# MASTERARBEIT | MASTER'S THESIS

Titel | Title

Blink Rate as a Possible Measure for the Valence of High Arousal Moments During a Walk in the City

verfasst von | submitted by

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# Abstract

A walk in the city, particularly in green spaces, has been shown to improve both physiological and psychological health. This includes effects on stress, anxiety and mood. While moments of high arousal can be detected precisely within time and space from individuals' immediate physiological reactions, the valence of these reactions remains an open question. This study investigates the suitability of blinking as a physiological measure of valence in two steps: In the first study, we recorded 32 participants as they walked along a predetermined urban route, using continuous geo-located recordings of electrodermal activity and simultaneous video recordings with a portable eye-tracker. Based on this data, we extracted twelve locations of interest along the route, all of which elicited a high arousal response. For the second study, we prepared a rating study to assess valence. For each location, a set of four images was presented to 145 subjects who rated the locations with the PANAS-sf and the Affective Slider, so we could calculate an average valence per location. Combining the two studies allowed us to investigate the relationship between location valence and blink rate as measured by eye-tracking. Although prior research has found blink rate to correlate with certain emotional states, in the field, no significant relationship between valence and blink rate or blink rate variability could be found. However, this study serves as a foundation for future research on emotional responses to urban environments with eye-tracking in field research. This knowledge will allow us to design cities that benefit the wellbeing of people and the planet.

# Index

# 1. General Introduction

*Living in Cities and Urban Green Spaces*

Although most of humans' evolutionary past occurred in natural habitats, rapid urbanization shapes our living environments all over the world. Today, half the world's population lives in cities, and this is expected to increase to 70 percent over the next 20 to 30 years (United Nations, 2018). As urbanization progresses, the investigation of its consequences on health and well-being also gains relevance. Understanding how the urban environment influences both physiological, but also psychological well-being, is essential when designing cities in a way that supports healthy living. Additionally, sustainable cities are main actors in strategies to combat climate change. Well-designed cities can mitigate present and future challenges of progressing climate change (Bowler et al., 2010; Nieuwenhuijsen et al., 2017; Shishegar, 2014; Sturiale & Scuderi, 2019).

So-called *urban green spaces*, e.g. spaces within the urban environment that include natural elements (van den Berg et al., 2015) are of particular interest. There is long-standing evidence that green spaces support health and well-being on multiple levels, from cardiovascular disease to psychological health and mood (Douglas et al., 2017; James et al., 2015; Kondo et al., 2018; Nieuwenhuijsen et al., 2017; van den Berg et al., 2015). Several established theories propose causal mechanisms underlying this beneficial effect: *Attention Restoration Theory* claims that directed focus on natural elements restores attention capacities by recovering mental fatigue (Kaplan, 1995); *Stress Restoration theory* finds that contact to nature mediates recovery from stress more efficiently than the built environment (Ulrich, 1979, 1983; Ulrich et al., 1991); the *Biophilia* hypothesis suggests that humans have an innate preference for nature and other living organisms, which has driven adaptive emotional responses over many generations (Heerwagen & Orians, 1993; Wilson, 1993). Given their potential to improve well-being and offset potential negative effects of urban living, urban green spaces present themselves as a valuable candidate for improving city design.

*Moving out of the Laboratory with Moments of Stress*

Numerous studies have examined the effects of green, natural elements in highly-controlled laboratory settings (Jo et al., 2019). However, it is complementary studies in real, complex, multi-stimuli environments that most genuinely capture the influence of green spaces on stress physiology, thereby enhancing ecological validity of contemporary stress research. Furthermore, exploring green spaces specifically in the city allows us to investigate how they act within the urban context, rather than simply approximating this by a comparison of the urban, built environment to a remote, natural environment (Kondo et al., 2018). Monitoring people as they perceive different elements in our environment provides data on how these elements can be integrated within the design of cities to minimize stress and promote well-being. But to carry out such field-based study designs, a key aspect is recording technologies that support such experimental setups.

The *Moments of Stress* (MOS) methodology is a novel and mobile tool to detect stress. As emotional states and stress have physiological components, these can be detected by suitable sensor technology (Tobón Vallejo & El Saddik, 2020). Kyriakou et al. proposed an algorithm for the detection of so-called *Moments of Stress* from physiological measures, which have previously been shown to reflect autonomous nervous system activity related to stress (Kyriakou et al., 2019). This algorithm was recently refined and now takes individual differences between people into account (Moser et al., 2023). MOS are detected by features extracted from electrodermal activity, which is based on the flow of electricity through the skin. Even small amounts of sweat, which occur with the activation of the autonomous nervous system during stress, can be identified by the skin's electrical conductivity (Giannakakis et al., 2022). Additionally, each MOS is paired with simultaneously measured GPS data. Consequently, MOS can be attributed to specific locations. Each location can then be evaluated based on the number of MOS recorded, providing information on their potential stress-inducing character. Importantly, the MOS approach relies only on small, non-invasive, wearable sensors, which makes it an ideal tool for real-world research in urban environments.

### *Experiencing a Walk in the City*

Recent approaches to urban design aim to improve walkability not only for general health benefits but also as a sustainable mode of transportation (Baobeid et al., 2021; Sundling & Jakobsson, 2023). The United Nations climate report names walkable urban environments as a key strategy to combat climate change (United Nations et al., 2023). For walking as a mode of travel, good design and diversity of built environments are most strongly correlated to the likelihood of walking (Ewing, 2010). However, the success of city design should not only be defined by changes in travel behavior alone, but also in the qualitative experience of these walks (Adkins, 2012; Johansson, 2016). Even micro-level design features of urban environments can impact attractiveness and perceived walkability of urban environments (Johansson, 2016), and when walkability is increased, this benefits health and emotional well-being (Johansson et al., 2011; Kelly et al., 2017, 2018).

A recent study by Brunner et al. (2025) identified elements that have a positive impact on the walking experience in the city: Varied facades, historic buildings, pedestrianized areas, greenery and access to services. A central idea is the prioritization of people; i.e. reallocating space to pedestrian areas and restricting vehicles and levels of noise and pollution (Brunner et al., 2025). For restoration purposes in particular, numerous studies find restorative benefits in parks and gardens. Relatively small patches of green increase the restorative potential of a built environment (Nordh et al., 2009; Weber & Trojan, 2018). But also certain built structures, such as cultural-historical sites, have similar potential for restoration (Weber & Trojan, 2018). On the other hand, in any city, there are elements that cause stress; by applying the MOS methodology discussed in the previous section, lack of space, followed by noise, interruption of desired line of movement and the quality of infrastructure result in the most MOS during a walk in the city (Schmidt-Hamburger & Zeile, 2023). This is just a glimpse into the many elements that individually and through their interactions determine our affective experience – elements, which good urban design aims to decode and apply effectively.

The present study aims to contribute to a deeper understanding of how environments affect physiological and psychological wellbeing.

# 2. Study 1: Field Study

## 2.1. Introduction

This study aims to investigate how green spaces affect stress experience during a walk in the city. It applies a within-subject design, where the subjective psychological state before and after the test is evaluated in addition to taking continuous physiological measurements. These continuous recordings allow us to extract specific parts of the walk for further evaluation. With these tools, this study assesses a predetermined route in an urban environment, where study participants experience a variety of stimuli in their immediate surroundings, ranging from busy streets to residential areas to public green parks. Thus, we can represent the diversity of sceneries in an urban environment as they would be experienced in everyday life.

By comparing emotional states before and after the walk, we aim to reproduce previous studies (as compiled by Kondo et al., 2018) that found improvements after going on a walk. This validates both the route and the experimental setup as suitable for further investigation. The continuous recording during the walk allows us to pinpoint stress in time and space. This serves as a foundation to identify elements in the environment which contribute to stress or the restoration thereof. By employing *Moments of Stress* to investigate a walk in the city, we explore a non-invasive, easily available method for stress research in the field, bringing state-of-the-art technologies into a research field that has been established but, in the face of the climate crisis, is now more important than ever.

In conclusion, the first study addresses the following research question:

(I) During a walk in the city, do urban green spaces differ in *Moments of Stress* from not-green sections?

Based on prior research that found beneficial effects of green spaces reducing stress, we hypothesize:

1) Participants experience fewer *Moments of Stress* in urban green spaces than in non-green spaces.

## 2.2. Methods

### 2.2.1. Data Collection

*Participants*

Thirty-two adults participated in the study, 24 women and 8 men. They were recruited via a combination of online advertisements and in-person recruitment at the University of Vienna, resulting in a sample predominantly composed of university students. Participants were between 18 and 35 years old (*M* = 23 years, *Mdn* = 23 years, *SD* = 3 years) and fluent in German. Due to insufficient German language proficiency that was observed during the testing, two participants had to be excluded retrospectively from language-dependent parts in the data analysis. All participants were compensated with 10 Euros for their participation.

*Procedure*

Data collection took place on weekdays between May 9th and May 27th, 2024 between 13:00 and 17:00. Participation took approximately 45 minutes in total. All testing was conducted in moderate to warm weather (sunny, cloudy, windy, light drizzle), with temperatures ranging from 17°C to 26°C as by local weather stations. Sessions were rescheduled in cases of inclement weather.

Participants started the experiment at a designated starting point outside the University of Vienna Biology Building (Djerassiplatz 1, 1030 Vienna). Participants were informed on the details of the study in written and verbal form. After having provided informed consent, they received the instructions regarding procedure and equipment. After setting up physiology recordings, participants filled out the digital questionnaires for assessment of affective and psychological state in a seated position. As this was concurrently serving as an individual baseline recording for following physiology measurements, participants had to remain seated for at least 4 minutes. Unless requiring assistance, they were instructed to remain quiet and wait for the signal that the baseline recording was concluded.

In the second part, participants completed a 20-minute guided walk. Two experimenters were accompanying each participant: One walked ahead to guide participants along the route and

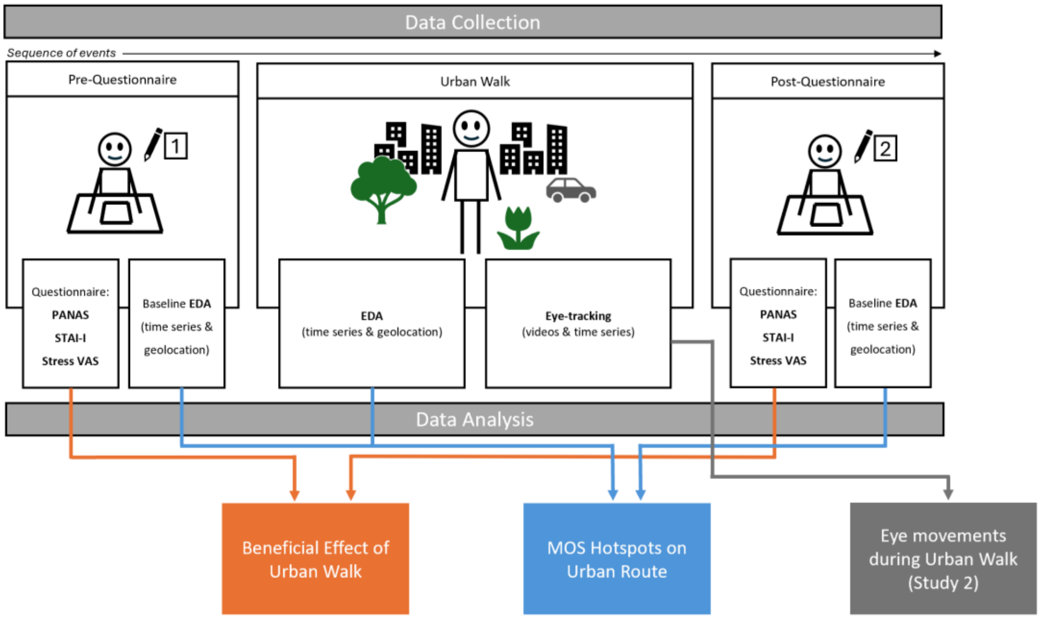


**Figure 1: Flow-Diagram of experimental procedure.** For each step in the data collection, the measures applied are depicted, as well as where they are applied in the data analysis. EDA = Electrodermal Activity, PANAS = Positive Affect and Negative Affect Schedule, STA-I = State-Trait-Anxiety Inventory, VAS = Visual Analogue Scale, MOS = *Moments of Stress*.

maintain the required pace, the other followed behind the participant to monitor device connectivity. Any interruptions (e.g., device disconnection, environmental disturbances) were documented and the walk was paused until proper function was restored. Participants were instructed to follow the first experimenter maintaining a fixed distance to the first experimenter and refrain from conversation and mobile phone use during the walk. Physiological measurements and eye-movements were recorded during the entire walk.

After the walk, participants filled out the post-walk questionnaires during a second baseline physiology recording at the university building, following the same experimental conditions as above. The entire experimental procedure can be reviewed in Fig. 1.

*Walking Route*

The walking route was a circuit through urban environments surrounding the University of Vienna Biology Building in Vienna’s third district (Fig. 2). This included broad and narrow streets with or without greenery, residential or slightly industrial scenes; thereby offering a diverse visual experience. Most notably, a considerable portion of the route followed the Schlachthausgasse, a wide, heavy-traffic road. In contrast, the route also passed through a secluded park featuring both maintained, but also more natural greenery (Fig. 3). The total route length is estimated at approximately 1.6 km based on *Google Maps* (retrieved July 2024). The target duration of the walk

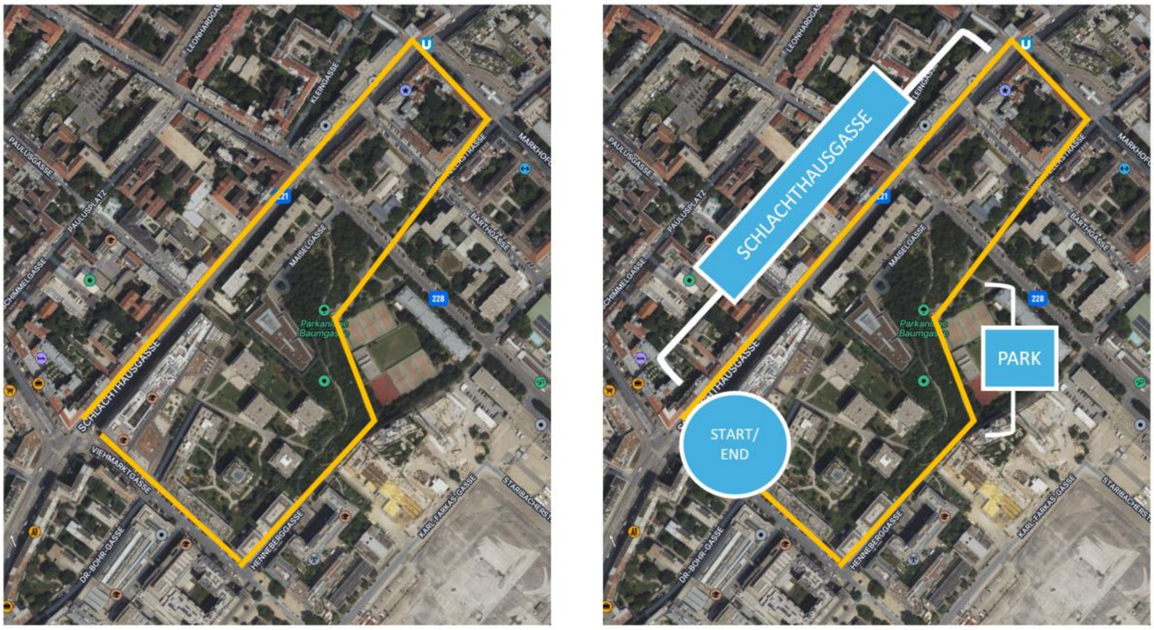


**Figure 2: Planned route of urban walk.** Image taken from Google Maps (retrieved July 2024). Yellow lines indicate the routes that were walked. Left: Raw Image of Route. Right: Details of walking route. Start and End at the university. Schlachthausgasse

**Figure 3: Different environments on the walking route.** Left: Park; Middle: Residential area between Park and university; Right: Schlachthausgasse

was 20 minutes. To control for potential directional effects, the starting direction was alternated across subjects. Walking speed was monitored and maintained at around 5 km/h by the experimenters using the mobile app "*Einfaches Tachometer*" by developer Tevik Yucek, available in the IOS App Store (May 2024).

*Measurements*

Participants completed a series of questionnaires before and after the walk out on their smartphones. This included the following measures: The Positive and Negative Affect Schedule (PANAS) for assessing positive and negative mood states (Krohne et al., 1996), the State-Trait Anxiety Inventory

(STAI-S) for determining perceived anxiety levels (Grimm, 2009; Spielberger et al., 1970) and a Visual Analogue Scale (VAS) for Stress to evaluate momentary perceived stress levels.

During the walk, the participants were equipped with multiple recording devices: An Empatica E4 Wristband and Zephyr BioHarness chip sensor (installed in a BioHarness chest strap) for the measurement of physiological parameters, as well as the Pupil Invisible Eye-Tracker (Pupil Labs) to record video data of visual field and eye-tracking during the walk. The Empathica E4 wristband measures electrodermal activity with a sampling frequency of 4 Hz, the data are stored via an eDiary Android App, which was developed at the University of Salzburg (Petutschnig et al., 2022). The Pupil Invisible Eye-Tracker records scene videos at 30 Hz, two infrared cameras are angled at the eye and record videos at 200 Hz. The eye tracker was paired with a OnePlus 8 device running Pupil Core software v3.5. To reduce artifacts due to the light sensitivity of the eye-tracker, participants carried a white umbrella during the walk.

For stress physiology, *Moments of Stress* (MOS) were identified using a pre-established algorithm that detects increased stress based on electrodermal activity (Moser et al., 2023). The exact location of each MOS was determined by combining physiological data with GPS data. Based on this, locations along the route, where MOS were increased or reduced, could be identified in the following analysis.

### 2.2.2. Data Analysis

Two participants were excluded from analysis due to insufficient German language proficiency. The questionnaires of the 30 remaining participants were analyzed in R (version 4.3.2; R Core Team, 2023). All analyses of Study 1 were done in R (version 4.3.2; R Core Team, 2023). Additional packages used for the analysis were: *ggpubr* (v0.6.0), *ggridges* (v0.5.6), *stringr* (v1.5.1), *tidyr* (v1.3.1), *ggplot2* (v3.5.2), *tidyverse* (v2.0.0), *dplyr* (v1.1.4). A Shapiro Wilk Test was performed on the data for anxiety, stress, positive and negative mood. Depending on data structure, a paired *t*-test for or a Wilcoxon test was used to compare pre- and post-responses.

The analysis of MOS was conducted in collaboration with the University of Salzburg, who assessed each participant's stress response during the walk by EDA measurements. Following Moser et al. (2023), a preprocessing procedure was applied to the EDA signal, in which the proper frequency filters for non-stationary study settings were used to filter out noise. Individual-based baseline parameters were used to determine threshold values for a rule-based algorithm to detect MOS. The MOS detected were assigned to their recorded GPS location. From the aggregated MOS across all participants, the frequency of MOS was geolocated and visualized as a heatmap of MOS frequency.

## 2.3. Results

Although 32 participants completed the walk, data from three participants was excluded due to incomplete recordings from at least one of the devices.

The results of this study show a significant reduction in self-reported negative mood, anxiety and stress after the walk (negative mood: V = 271, $p < 0.001$; anxiety: t(29) = 3.20, $p = 0.003$; stress: V = 286.5, $p < 0.001$). For positive mood, there is no significant difference before and after the walk (t(29) = 1.64, $p = 0.112$; Fig. 4)

In the detailed analysis of the walk, *Moments of Stress* (MOS) on the route were visualized using a heatmap. Hotspots with significantly higher concentrations of MOS could be found both in the green space (park), as well as the Schlachthausgasse – a wide and highly built, high-traffic street (Fig. 5). Across all participants, there is no visible reduction of MOS in green spaces. However, the MOS-analysis by walking directions revealed visible differences in the spatial distribution of high-MOS areas along the route. For the participants starting towards the park area, high-MOS areas

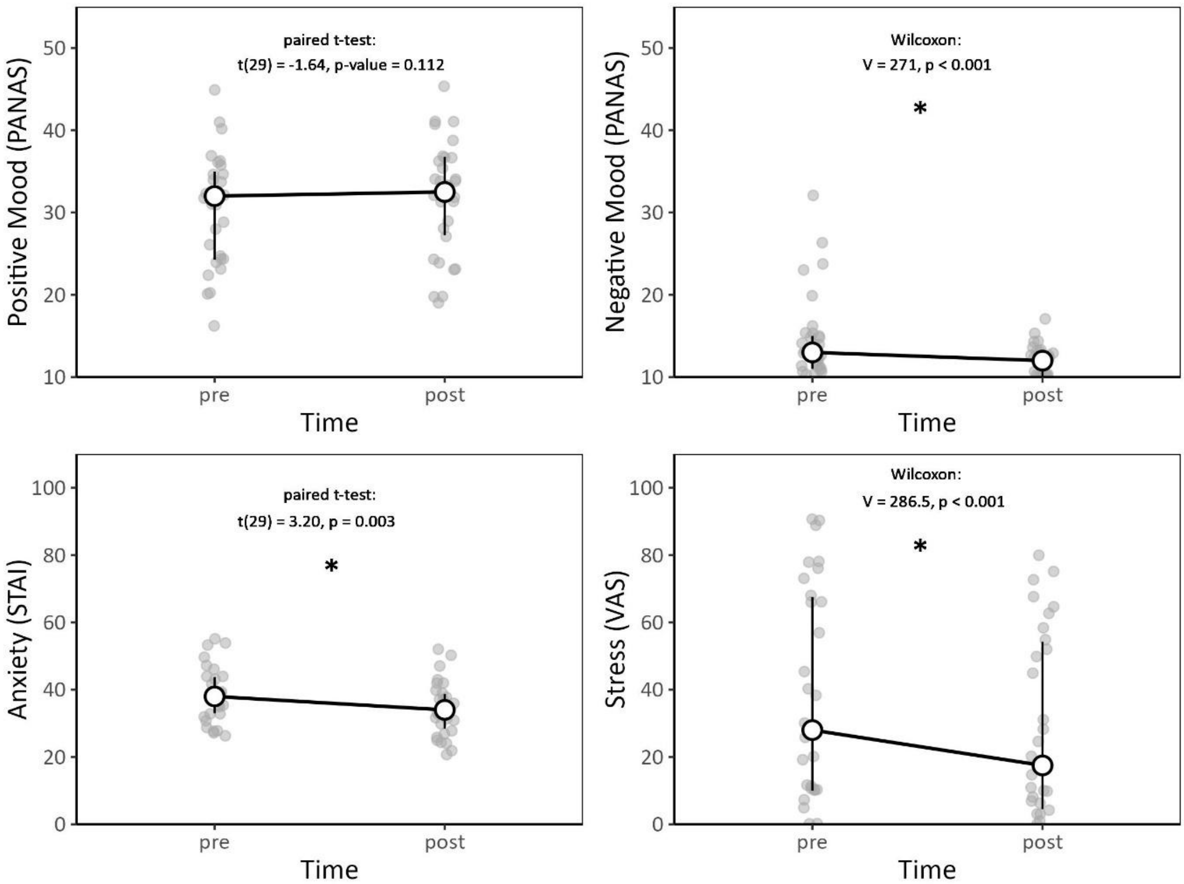


**Figure 4: Pre- and Post-evaluation of positive mood (PANAS), negative mood (PANAS), anxiety (STAI) and stress (VAS).** Data are the median ± *IQR*, significant results indicated by asterisk. $N = 30$.

areas accumulate at the Schlachthausgasse, but they experience fewer MOS at the park. For the participants starting towards the Schlachthausgasse, there is continuous high-MOS areas at the park section and fewer instances of high MOS-areas at the Schlachthausgasse. Additionally, the number of MOS increases over the duration of the walk for both directions.

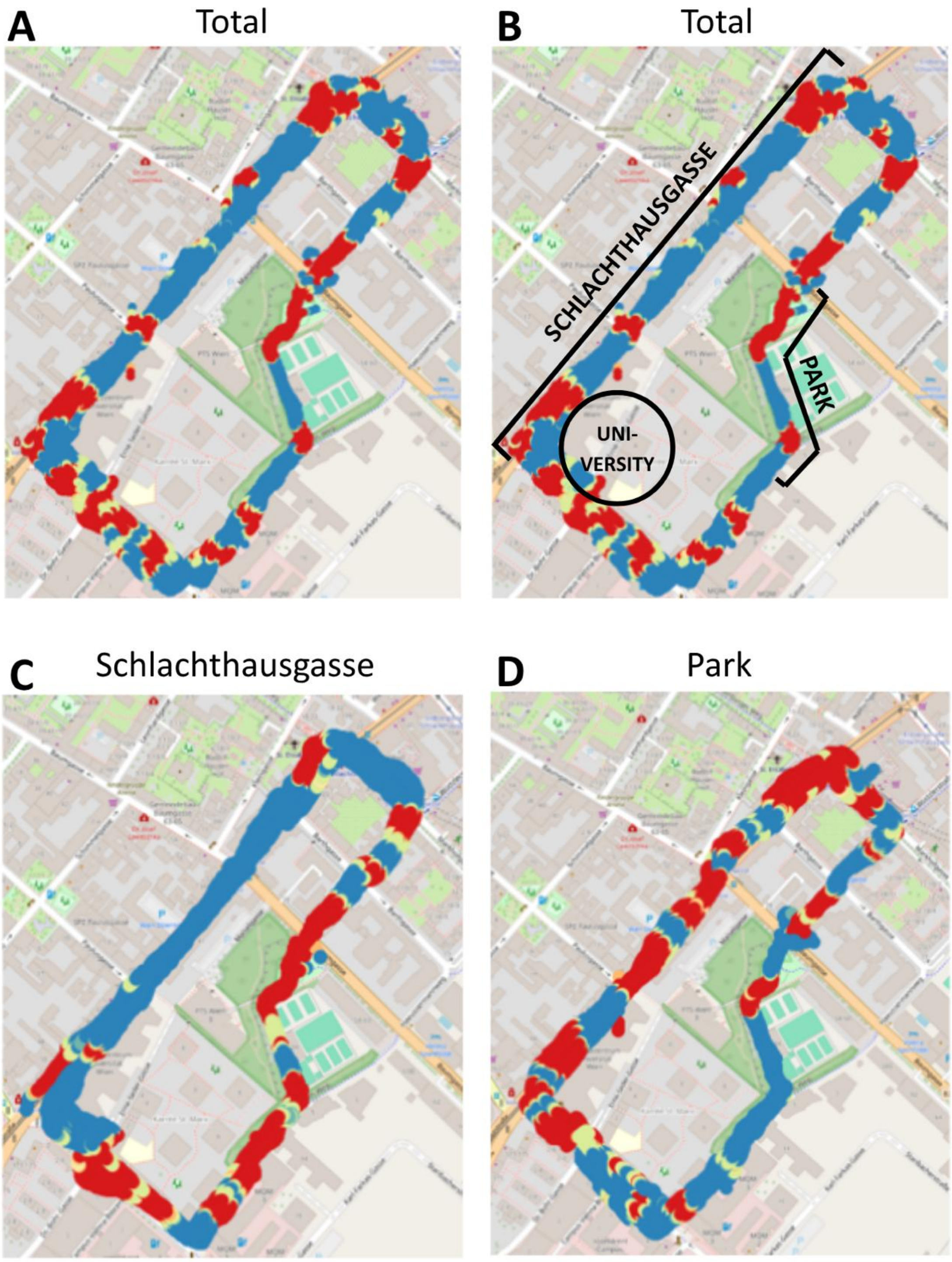


**Figure 5: Heatmap of MOS during Walk.** Blue areas indicate a MOS concentration below the baseline at rest, red areas indicate a MOS concentration higher than the baseline at rest. A & B: All MOS regardless of starting direction. C: MOS with starting direction to Schlachthausgasse. D: MOS with starting direction to Park. $N = 32$.

## 2.4. Discussion

This study investigated how different urban environments influence the experience of stress during a walk in the city. In particular, it focuses on the effect of urban green spaces, which are known to benefit health and well-being (Kondo et al., 2018; Liu et al., 2022; Nieuwenhuijsen et al., 2017; Olszewska-Guizzo et al., 2022a; van den Berg et al., 2015). Consistent with previous works, this study reproduced findings that show beneficial effects of going on a walk in an urban environment (Johansson et al., 2011; Kelly et al., 2017, 2018). In the present study, participants reported a significant decrease in negative mood, anxiety and stress (measured from PANAS, STAI and VAS scale for stress). Since no significant difference in positive mood was found, this indicates that the walk doesn't promote positive mood. These results suggest that a walk can remedy negative affective states (stress, anxiety, negative mood) but does not elicit positive affective states as by self-reported positive mood (PANAS).

However, the spatial distribution of *Moments of Stress* along the walk does not support the hypothesis that green spaces elicit fewer *Moments of Stress* (MOS) than non-green sections. This conflicts with pre-existing literature that compared the stress levels elicited by green and non-green environments (Kinnafick & Thøgersen-Ntoumani, 2014; LaJeunesse et al., 2021). For example, the Schlachthausgasse – a broad, traffic heavy street with little green and wide, grey paved areas – would typically be expected to produce higher MOS frequency. But despite accounting for about a third of the entire route, high MOS frequencies were limited to short segments, usually where roads intersect. This is notable given that many of the traits that are usually rated negatively are present: Broad and heavily frequented streets (LaJeunesse et al., 2021), busyness and crowding (Bornioli et al., 2019) especially at intersections, noise and interruption of the desired line of movement (Schmidt-Hamburger & Zeile, 2023), perceived oppressiveness assumed by high vehicle density (Luo & Jiang, 2022), road and landscape monotony (Fumagalli et al., 2020; Larue et al., 2011) with little architecture or greenery to alleviate these.

On the other hand, the park section elicits high MOS frequencies throughout. As a green space, this park shows a variety of presumably beneficial traits; it is not just a typical homogenous, segregated plot of grass, but rather a mixture of natural areas: A small, open elevated grass hill (providing Depth of View; in reference to restorative traits of the Contemplative Landscape Model) with benches for seating (Character of Peace and Silence), an asphalted sports area surrounded by bushes and trees and a forest-like path (Vegetation, Biodiversity) where people come to play with their dogs (Olszewska-Guizzo et al., 2022b). This diverse layout may provide high complexity and compatibility with many activities (Kaplan, 1995), and may visually resemble rural, non-artificial natural environments, which are typically slightly more restorative than constructed green spaces

(Korpela et al., 2010; Tyrväinen et al., 2014; White et al., 2013). The sports area, though constructed and less green, has restorative potential as an activity and hobby area (Korpela et al., 2010) – though such exercise areas have also shown reduced restoration compared to other green spaces before (White et al., 2013).

However, a notable factor influencing the results appears to be the starting direction. To account for this, MOS were also analyzed separately by the starting direction of the walk. In dense urban architecture with limited overview over the area, a single geolocation may potentially comprise two highly varied sceneries. This is an important consideration given that humans heavily rely on visual information (Sussman & Hollander, 2021) – even though we know that other sensory stimuli, such as noise, are also associated with increased MOS (Schmidt-Hamburger & Zeile, 2023). Consequently, the direction of the walk, and thereby the different visual scenery, plays a crucial role in the analysis. The directional results emphasized this, showing two distinct patterns: Participants that started with the green space experienced more stress in the non-green section, whereas participants starting with the non-green section recorded more MOS in the green space. It is worth mentioning that for both directions, MOS increased during the second half of the walk. This raises the question whether this increase of MOS is caused by exhaustion that arises after the first half of the walk, or whether the stress accumulated in the noisy street is carried over to the more tranquil second part of the walk. The final, combined heatmap highlights sections shared by the directional heatmaps. For one, the university entrance is a visible MOS hotspot. Though given that this participant sample consists mostly of students, this could potentially reflect the social or vocational associations rather than the environmental design. Excluding this location, other high-MOS areas are found at intersections along the route and, unexpectedly, at the park.

Overall, these results suggest that the presence or absence of greenness does not act as the leading driver of stress on this walk in the city, despite its appeal as an intervention target. However, in reference to preexisting literature (Kondo et al., 2018), it is likely that green elements play an important part in our experience of the environment. Present and future research should aim to untangle the complex interplay of sensory inputs and pre-existing internal states that shape stress experiences in the city. Secondly, perhaps previously recognized benefits of green spaces are not direct results of acute sensory exposure but result from indirect facilitation of healthy, restorative behaviors in these green spaces; behaviors such as sitting down to rest, meeting people, doing sports, mind-wandering or taking a break from more intense activities. During a continuous, paced walk, there are only limited opportunities to engage in such restorative behaviors, which potentially explains why green spaces do not visibly benefit MOS-concentration. Thus, the beneficial effects of green spaces may be distinct from the mechanisms that caused the reduction in stress, anxiety and negative mood after the walk. This distinction should serve as a guide for future directions.

Regardless of potential benefits of green spaces, any such effect could be masked by concurrent stressors in the same environment. First, as previously mentioned, the imposition of a fixed walking pace may have induced physical exhaustion that appears as spikes in physiological parameters, indistinguishable from MOS. Second, intersections consistently triggered a high number of MOS, possibly due to obstruction of direct paths by traffic rules or pedestrian congestion (Schmidt-Hamburger & Zeile, 2023). Third, structural elements within the park (e.g. multiple gated entrances, tunnel) corresponded to stress elevations; such elements are known to reduce the attractiveness of an environment (Adkins, 2012). Finally, prolonged monotony of straight, traffic-heavy streets may evoke hypovigilance akin to driver's fatigue (Larue et al., 2011), which leads to reduced perception of potential stressors. Stress response could also have been decreased for participants that were familiar with the route of the Schlachthausgasse, as familiarity with an environment is known to influence mental states when navigating a space (Harms et al., 2021).

Crucially, the divergence of the present MOS analysis to similar studies on beneficial green spaces raises a critical question: Do these moments genuinely portray stress, or are there other psychological or physiological markers that could have captured by these measuring devices? The MOS algorithm is based on electrodermal activity (EDA) and detects a particular pattern of change for each participant (Moser et al., 2023). While EDA is a reliable indicator for the arousal state, this was not seen for emotional valence (Greenwald et al., 1989; Sato et al., 2020). Arousal and valence are two dimensions on which emotional affect is mapped in the Circumplex model of emotional affect (Russell, 1980). This model illustrates how even though EDA-derived MOS may capture the arousal dimension of affect, they may not be informative on valence. Consequently, distinguishing different states of high arousal (in particular, stress and elation) accurately could turn out to be a challenge. Before we can interpret the role of the various elements – e.g. green spaces – along the walking route, it is essential to differentiate the MOS elicited by stress and other states of increased arousal. Therefore, we suggest a relabelling of MOS into *Moments of Arousal* (MOA). For studies designed for the identification of problematic areas in pedestrian and bicycle traffic, MOS might suffice, but for a more general analysis of urban space, adding the dimension of valence to the MOA seems essential.

Since concurrent eye-tracking data was collected during the walk, we used the recordings to annotate potential indicators of emotional valence. From the recordings, which comprises videos of gaze and scene view, it is possible to extract specific eye metrics like fixations, saccades or blinks. Blinks have been linked to cognitive, but also emotional states before – particularly stress (Skaramagkas et al., 2023). With the existing tools and data processing, Study 1 failed to make conclusions on how green spaces and non-green areas are experienced differently in terms of arousal and valence. Study 2 attempts to address the issue of attributing valence to the MOA.

# 3. Study 2: Survey + Eye-tracking Study

## 3.1. Introduction

*The Circumplex Model of Affect*

While Study 1 laid an important foundation by moving research into the real-world urban environment, it also revealed ambiguity surrounding arousal and stress. For a comprehensive understanding of stress, Study 2 implements the Circumplex model of affect (Russell, 1980) as a framework for the categorization of affective experiences during the walk. Incorporating such theories of emotion research might help the investigation of stress and simultaneously acknowledges the interdependence of this research field with emotion and affect, responding to pre-existing critique (e.g. Lazarus, 1999) of the separation of stress research from research of affect and emotion.

The Circumplex model introduces two dimensions to describe emotions: arousal and valence. Arousal describes the level of activation elicited by an emotion. The valence of an emotion is defined on a scale of positive (also: pleasure) to negative (displeasure; Colombetti & Kuppens, 2024; Lim et al., 2023; Russell, 1980). These dimensions serve as axes to a two-dimensional grid, where various adjectives representative of emotions are placed. Typically *stress* is situated on the top-left corner between high arousal and negative valence (see Fig. 6; Posner et al., 2005b). On the exact same activation level, but with positive valence, one can find *elation*. This emphasizes how valence transforms the affective experience.

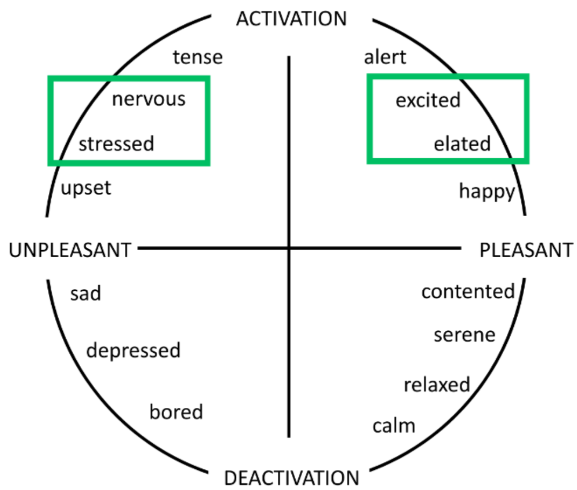


**Figure 6: Circumplex model of affect, adapted from Posner et al., 2005.** Note that emotions at same level of arousal = activation differ substantially on valence (pleasant, unpleasant). Stressed and nervous can be found at same level as excited and elated. Original model supplied in Appendix.

The Circumplex model has been widely used to evaluate affective responses to real-world environments. For instance, it has been applied to explore affect in regards to everyday travel (Westman et al., 2013), exercise (Evmenenko & Teixeira, 2022), cycling (Lim et al., 2023) or walking (Bornioli et al., 2019; Mouratidis & Hassan, 2020; Piga et al., 2023). A recent study by Brunner et al. (2025) was able to extract *improvement of buildings and facades* as key feature for excitement (high arousal & positive valence) during a walk in the city. In particular, they name improving greenery or lighting and scaling facades down to human size to be beneficial. In contrast, good sidewalk quality improves valence but not arousal, leading to a relaxing walk instead. These findings are derived from video-based evaluation of 10 urban walking environments. An expert panel systematically determined the present environmental properties and features, while 311 online participants provided subjective ratings. Responses could be integrated into the arousal and valence dimension by principal component analysis and were related to prior expert-identified properties. Thereby, this study demonstrates a differentiated evaluation of specific urban design features of real environments by arousal and valence.

Emotional affect, including emotional stress, can also be assessed by physiological measures. Among these physiological measures, electrodermal activity (EDA) – which was used for the MOS analysis (Moser et al., 2023) in Study 1 – has been shown to correlate with the level of emotional arousal, similarly to heart rate or certain fMRI or EEG signals in relevant brain regions (Greenwald et al., 1989; Sato et al., 2020). However, EDA has not yet been successful in capturing valence – physiological measures are confined to e.g. facial EMG activity (Cacioppo et al., 1986; Lang et al., 1993; Posner et al., 2005). The underlying mechanism for valence seems to lie in the mesolimbic pathway, one of the major dopaminergic pathways, which is suggested to be involved in the experience of negative emotions, and potentially acts as a neural substrate for the valence dimension (Greenwald et al., 1989). Identifying a physiological measure for valence, which is as easily obtainable in non-laboratory settings as sensor-based EDA, would bring a considerable advantage for field studies.

*Blinking as an Indicator for Emotional Affect*

In recent years, the rapidly growing availability of eye-tracking technologies increases interest in non-invasive eye- and pupil-derived measures (Eckstein et al., 2017). Regulated by the autonomous system, eye and pupil metrics have been linked to emotional and cognitive processes (Skaramagkas et al., 2023). One such metric is spontaneous blinking, which describes the closing of the eyelids without any external stimuli (Cruz et al., 2011). The primary function of blinking is to sustain tear film of the eye, previously found tear breakup times imply a theoretically necessary blink rate as low as 3-4 blinks per minute (Al-Abdulmunem, 1999). In reality, typical blink rate at rest is between

10-20 blinks per minute (Eckstein et al., 2017), implying that there are additional factors modulating blink activity.

Spontaneous blink activity is an established marker of dopaminergic activity in the brain and has been observed frequently in neurological conditions like Parkinson's disease or schizophrenia (Cruz et al., 2011; Eckstein et al., 2017; Lenskiy & Paprocki, 2016). Variations in spontaneous blinking have been related to processes of engagement, vigilance and mental load in particular (Lenskiy & Paprocki, 2016; Maffei & Angrilli, 2019; Nishizono et al., 2023; Ren et al., 2019). Recent studies demonstrated a significant increase in spontaneous blink rate during emotional stress (Giannakakis et al., 2017; Haak et al., 2009; Skaramagkas et al., 2023). Furthermore, the utilization of machine-learning-based models revealed that blinking patterns can classify different psychological states and allow us to build complex emotion-recognition systems; this includes blink rate and blink rate variability (Ren et al., 2019), blink duration variability (Sarma & Barma, 2021) and distribution of inter-blink intervals (Korda et al., 2021). These studies also emphasize to target the details in the dynamics of blinking specifically. Compared to blink rate, blink rate variability (which is based on the variation in intervals between each blink) has shown an added sensitivity in recognizing changes in blink dynamics at least in studies on reading and memory (Lenskiy & Paprocki, 2016; Paprocki et al., 2016; Paprocki & Lenskiy, 2017), which potentially also translates to emotional processes.

Although there is as yet limited research investigating the effect of valence on blink rate, existing findings indicate that spontaneous blinking is modulated differently depending on specific affective states. In Maffei & Angrilli (2019), participants were watching video clips of different emotional content while recording spontaneous blinking – which is typically lower with the higher attentional states occurring during video watching. The analysis revealed a significant effect of valence on blink modulation: Blink rate increases with negative self-evaluated valence and decreases with positive self-evaluated valence. Additionally, participants rated the emotional video clips. They rated fear highest in unpleasantness (negative valence) and high in arousal, whereas erotic and scenery clips were both rated as highly arousing, positive valence scenes. The patterns revealed in this study were time dependent, with differences between categories prominent in the beginning and in the end of the video stimulus (Maffei & Angrilli, 2019) – which points towards closer inspection of blink rate dynamics in immediate responses.

*The Present Study*

While study 1 successfully replicated the general beneficial effect of going on a walk – as measured through subjective well-being questionnaires, it raised questions on the EDA-based MOS detection of stress. The recorded responses may not have been exclusive to stress, which is typically defined by high arousal and negative valence, but could also have recorded high arousal moments with positive valence, found e.g. with excitement or elation (Posner et al., 2005). There is need for clarification on the valence of these moments previously characterized *"Moments of Stress"* (Kyriakou et al., 2019; Moser et al., 2023) – to address this, they will be reframed *"Moments of Arousal"* (MOA) from this section on.

Study 2 aims to further investigate the MOA identified in Study 1 by examining their valence. To obtain necessary data on the valence of MOA, we set up a rating study to evaluate the valence of the high-arousal locations of Study 1. This distinguishes high arousal moments with negative valence, suggesting genuine *Moment of Stress*, from high arousal moments with positive valence.

Additionally, Study 2 introduces blinking as a potential physiological indicator of the emotional experience during a walk in the city. As per Maffei et al. (2019), spontaneous blink rate responds differently to specific emotional states. This leads to the question whether there are differences in blink rate which can be correlated to positive and negative valence of high arousal moments. To answer this question, we specifically look at blink rate and its variability, which should provide additional insights into the dynamics of blink rate and deepen our understanding of blinking with emotional arousal.

There is practical value in this approach: Blinking, as a non-subjective, non-invasive measure, which is easily obtained via eye-tracking, has the potential to complement or even replace additional physiological sensors. It might replace the need for post-hoc evaluation of valence by subjective rating and could provide information on valence from objective, physiological measurements in continuous time-resolution. In the context of urban environments, this opens new opportunities to study how people experience different elements in the environment, which can be used to center human well-being in the design and planning of future cities.

In summary, Study 2 addresses the following research question:

(I) Can blinking serve as a measure to differentiate between high-arousal moments of positive and negative valence during a walk in the city?

We hypothesize that there is a significant correlation between valence and blink rate. Based on currently available literature, we propose:

1) Blink rate is higher with negative valence than with positive valence.
2) Blink rate variability is higher with negative valence than with positive valence.

If supported by the data, these findings would position blink rate as a promising, non-invasive, physiological indicator of emotional valence during a walk in the city.

## 3.2. Methods

### 3.2.1. Valence Rating

*Participants*

In total, 145 participants completed the questionnaire, 119 female, 21 male and 3 non-binary "diverse" (gender-diverse). Two participants chose not to answer the question. The participants had a mean age of 25 years (*Mdn* = 25 years, *SD* = 5 years).

By recruiting a large sample from a similar demographic as the first study, a close representation to how this group experienced the walk was targeted. Consequently, the same requirements as for the previous study were used. Participants had to be between 18-35 years old and speak German fluently. The participants were recruited through a combination of flyer advertisements at university sites and online recruitment in various student groups. A priori power analysis calculated 67 participants for medium effect size.

*Stimuli*

Twelve locations were selected from the route of Study 1 based on a high frequency of MOA at this location. Therefore, all locations were high arousal locations, to which we aimed to attribute a valence rating. Each location was represented by 4 images, which, in combination, showed the entire surroundings of each location (Fig. 7, 8). This methodology has shown to be feasible in previous studies, which demonstrated that the effect of experiencing nature can also be measured from viewing environments in photos or videos (Jo et al., 2019; Lin, 2021). The images were extracted from the frontal scene eye-tracking video recordings during Study 1. For image extraction, the recordings of participants, who did experience a MOA at this location, were prioritised. For five locations, since sufficient high-quality image material could not be extracted from the high arousal video recordings alone, images from medium-low MOA recordings at the same location were used complementarily. Recordings were matched in date, weather and experimenter identity. Images were presented in a 2x2 grid layout, with a fixed order roughly equating to the natural sequence in which one would encounter them during a walk.

*Procedure*

The online questionnaire was designed to be flexible in terms of timing and location. However, to ensure that images were displayed accurately, participants were instructed to use devices with screens larger than smartphones. While this could not be controlled, this requirement was emphasized multiple times during both recruitment and the study itself.


**Figure 7: Questionnaire Stimuli representing locations 1 – 6 of urban walk.** For each location, four images from eye-tracking videos are shown, the sequence resembling the order in which they were encountered.

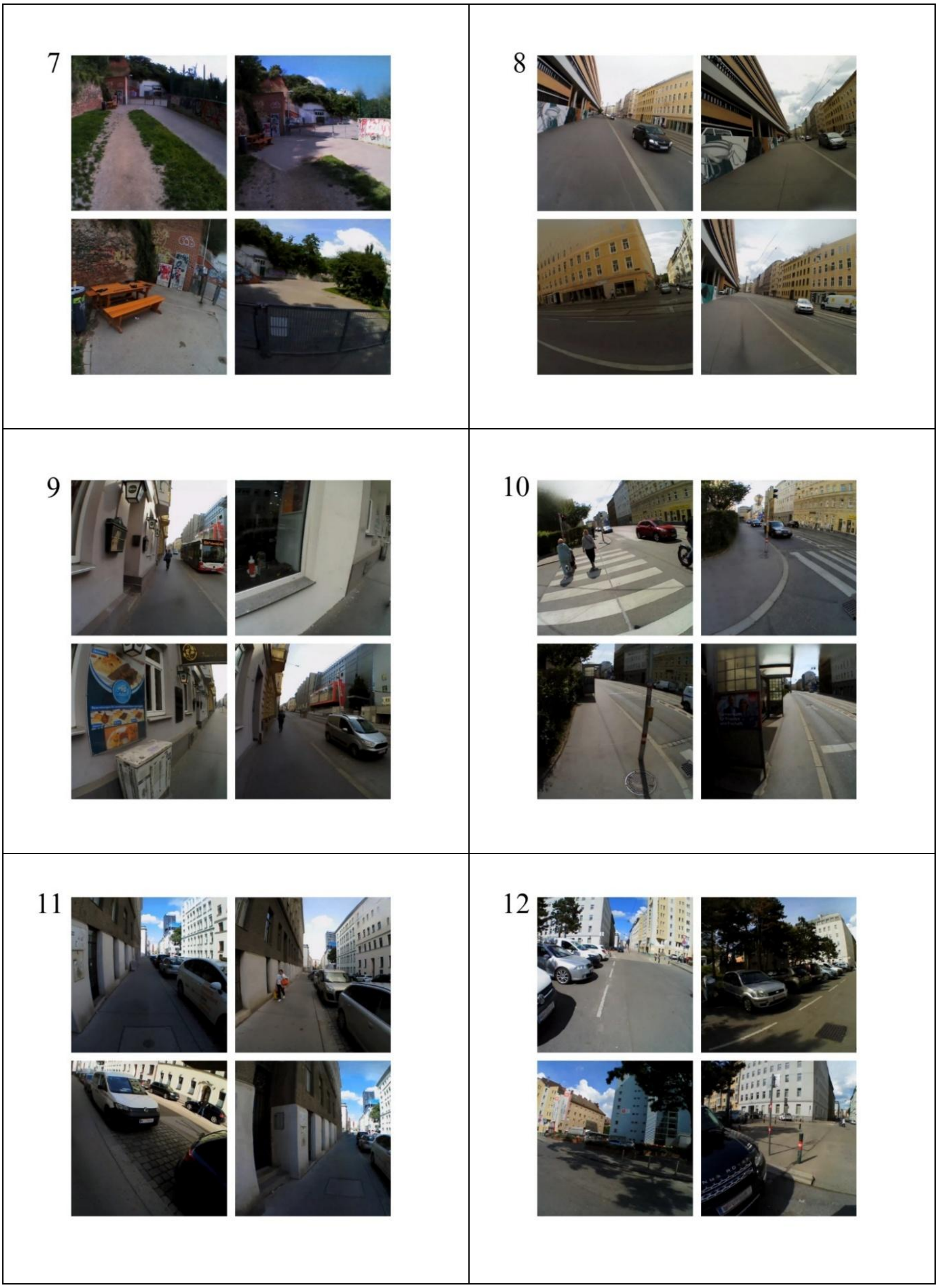


**Figure 8: Questionnaire Stimuli representing locations 7 – 12 of urban walk.** For each location, four images from eye-tracking videos are shown, the sequence resembling the order in which they were encountered.


**Figure 9: Questionnaire interface (German).** Each location has its own page in the questionnaire, starting with the 4-image stimuli (See Fig. 7, 8 ). Below the image stimuli, participants evaluate the location with the *Affective Slider*, positioning Slider between two faces. *Affective Slider* for valence was adapted from Betella & Verschure, 2016. Below, ten PANAS-sf adjectives (Krohne et al., 1996; Thompson, 2007) are displayed in randomized order (bold, left side). On right side to each adjective, participants rate how well this adjective resembles their feelings at this location. Below: Drop-down selection to choose if familiar with location. Below: Textbox for optional comments. On bottom right (blue), participants click to continue to next location page.

Participants viewed the 12 locations in randomized order. For each location, they were asked to observe the images and imagine walking through this area. Then, they completed a verbal and non-verbal rating: The non-verbal rating used the Valence Slider from the *Affective Slider* Tool (Betella & Verschure, 2016), which is based on the well-established Self-Assessment Manikin (Bradley & Lang, 1994) but functions as an updated tool for digital devices. Participants indicated their emotional response to the images by adjusting the position of the Slider between two stylized faces (upturned or downturned expression; Fig. 9). For the verbal rating, the sf-PANAS was used (Thompson, 2007). Since the study was conducted in German, we used the validated translation (Krohne et al., 1996) of the 10 items by Thompson (2007). The items were displayed in random order per location for each participant. The participants were instructed to select how well each word represents their emotional state after seeing the images.

Additionally, participants supplied their familiarity with the location ("yes", "no", "I don't know") and were provided with a textbox for optional comments. Each location was presented on a separate page, requiring participants to click to advance to the next location. After the evaluation of the locations was completed, demographic information (age, gender, highest level of education) was collected.

### 3.2.2. Eye-Tracking

Blinks were extracted from the eye video recordings collected during the walk in Study 1 using the Pupil Labs' Pupil Invisible glasses. For details on the data collection, refer to section *2.2.1. Data Collection*.

The Pupil Invisible recorded 200 Hz videos of the left and right eye. Blink detection was performed using the automatic blink extractor algorithm by Pupil Labs integrated in the Pupil Cloud service. The detected blinks for each recording were exported. The accuracy of the automated detected was validated by manual coding of the eye videos using BORIS (v8.27.10) software. This was done with a subset of the 13 video recordings, which were manually annotated for four 1-minute intervals. A representative sample was selected based the total blink number during recording, the date and walk direction + length – which varies the location of the intervals along the route. Since Pupil Invisible records videos of both eyes, both videos were coded, and blink counts averaged. So-called half-blinks (partial closing of eyelids) were included in manual coding, but there is no information how Pupil Labs blink algorithm handles this.

The quality of blink detection is described by mean absolute error, the standard deviation of absolute error and mean relative error (Tab. 1). The two methods were compared, both including

**Table 1: Reliability of automated blink detection.** MAE = Mean average error, SD = Standard deviation. Correlation describes the correlation of detected blinks by automated and by manual annotation.

| *Condition* | *N* | *MAE* | *SD Absolute Error* | *Mean % Error* | *Correlation* |
|---|---|---|---|---|---|
| All | 6 | 5 | 7 | 18.9 | Spearman's $\rho$ = 0.873, $p$ < 0.01 |
| Glasses | 3 | 13 | 11 | 40.5 | Pearson's $r$ = 0.915, $p$ < 0.01 |
| No Glasses | 10 | 4 | 3 | 12.4 | Pearson's $r$ = 0.987, $p$ < 0.01 |

and excluding poor quality data of people wearing personal glasses, which obstructs eye cameras. When comparing these methods, the blink detector detects a significantly higher number of blinks than with manual coding (Paired *t*-test: t(39) = 5.260048, $p < 0.001$). Additionally, the Pearson and Spearman correlation between automated and manual annotation describes how these methods align. The correlation tests between the two methods show that the detector tracks blinking as well as manual coding, especially when excluding data of participants wearing glasses, with the Correlation coefficient being nearly 1 (Pearson's $r = 0.987$, $p < 0.01$).

The blink data were then merged with the geo-recordings by global timestamps, applying a GPS-location to each blink and grouping them by location.

### 3.2.3. Analysis

All analyses of Study 2 were done in R (v4.3.2; R Core Team, 2023). Additional packages used for the analysis were: *ggpubr* (v0.6.0), *extrafont* (v0.19), *report* (v0.6.1), *DHARMa* (v0.4.7), *lme4* (v1.1-37), *Hmisc* (v5.2-3), *sf* (v1.0-21), *lubridate* (v1.9.4), *forcats* (v1.0.0), *stringr* (v1.5.1), *purrr* (v1.0.4), *tidyr* (v1.3.1), *tibble* (v3.2.1), *ggplot2* (v3.5.2), *tidyverse* (v2.0.0), *dplyr* (v1.1.4).

*Valence Ratings*

Valence ratings of every location were extracted from the questionnaire responses. The *Affective Slider* produced a numerical value from 1 to 1000 for each location. For the verbal evaluation, responses were handled separately for the five positive and five negative words of the sf-PANAS scale, resulting in a positive affect and a negative affect score. Standard descriptive statistics were computed for all rating variables (mean, median, standard deviation, interquartile range, minimum, maximum). Given the non-normality of the distribution of the data, the median response of the collected sample served as the final valence rating of each location. Thus, each location received three valence ratings, one each for the *Affective Slider*, positive PANAS-sf and negative PANAS-sf evaluation.

*Blink data*

Using the timestamps of blinks at each location, Blink rate (Eq. 1) and Blink Rate Variability (Eq. 2) were calculated. For Blink Rate Variability, to calculate the inter-blink intervals, the blink preceding the first blink at the location (-1) and the blink following the last blink at the location (+1) were added. This ensured that Blink Rate Variability could be calculated even in cases where only a single blink occurred at a location.

$$Blink\ Rate\ [min^{-1}] = \frac{Blink\ Count}{duration\ [min]} \tag{1}$$

$$Blink\ Rate\ Variability\ [ms] = \sqrt{\frac{\sum duration\ Interblinkintervals\ [ms]^2}{N(Interblinkintervals)}} \tag{2}$$

To account for individual differences in blinking of participants, a baseline approximation for blink rate was calculated by averaging blink rates across all 6 locations for each participant. The deviation from this baseline was then calculated for each location per participant, which could then be compared across locations. The same procedure was repeated for blink rate variability, providing the deviation of blink rate variability. This procedure provided both an absolute measure of blink rate and blink rate variability, but also a relative measure that takes individual participant differences into account.

*Correlation and Modeling*

Blink metrics were plotted against location valence for the visualization of potentially emerging patterns. To statistically test the relationship between valence and blinking behavior, Spearman's rank correlation test was conducted. To account for ties in the dataset, which affects the resulting p-value of the Spearman correlation test, Kendall's Tau correlation test was conducted in addition. Finally, the Spearman's rank correlation test was repeated with a transformed version of the dataset that introduced minimal jitter to the datapoints, thereby minimizing the issue of ties in the data structure.

To further explore the available data structure, a linear mixed-effects model with participant identity as a random effect was fitted.

## 3.3. Results

### 3.3.1. Valence

A total of 145 participants submitted a complete questionnaire for evaluation. Because participants were recruited both on site and online, they reported their familiarity with the depicted locations. For all 12 locations, fewer than 0.5% of participants confirmed familiarity (Tab. 2).

Valence was assessed with the *Affective Slider*, which rates ranges on a scale from 1 to 1000, with 1 being the most positive valence and 1000 representing the most negative valence possible. Both positive and negative affect, measured using the PANAS-sf, are rated on a scale of 5 to 25, with higher scores indicating a greater level of positive or negative affect.

A Shapiro-Wilk test for normality revealed that not all location valence ratings followed normal distribution (Tab. 3; additional density plots and Q-Q plots are provided in the Appendix). Consequently, both mean and median values are depicted to describe the data, as well as well as measures of dispersion and response range (Tab. 4). Due to the non-normality of these results, the final valence ratings of the locations were based on the median of valence scores. Overall, there was a wide variety in how locations were rated by participants. On the *Affective Slider*, all but one location received ratings that spanned the entire scale from 1 to 1000, the remaining location very close with a response from 1 to 997.

Most of the locations were rated in the middle third of the *Affective Slider* scale (Fig. 10). Only location 1, 4 and 5 deviate from this; location 1 and 5 were rated with a low value (positive), while location 4 was rated with a high value (negative). Negative affect ratings (PANAS-sf) were in the lower half for all scenes. Positive affect ratings were centered around the middle of the scale for all locations. Neither positive nor negative affect showed distinct patterns between the locations (Fig. 11).

**Table 2: Individuals indicating familiarity with locations.** N = 145.

| *Location* | *familiar* | *% familiar* |
|---|---|---|
| 1 | 2 | 0.014 |
| 2 | 4 | 0.028 |
| 3 | 3 | 0.021 |
| 4 | 3 | 0.021 |
| 5 | 5 | 0.034 |
| 6 | 5 | 0.034 |
| 7 | 3 | 0.021 |
| 8 | 25 | 0.172 |
| 9 | 19 | 0.131 |
| 10 | 21 | 0.145 |
| 11 | 3 | 0.021 |
| 12 | 2 | 0.014 |

*Note. Familiar* indicates the number of individuals that chose "yes" when asked if they were familiar with the location.

**Table 3: Shapiro-Wilk test of questionnaire responses for each scene.** N = 145.

| *Location* | *valence (Affective Slider)* | | *positive affect (PANAS-sf)* | | *negative affect (PANAS-sf)* | |
|---|---|---|---|---|---|---|
| | *W* | *p-value* | *W* | *p-value* | *W* | *p-value* |
| 1 | 0.93 | <0.01 | 0.99 | 0.14 | 0.45 | <0.01 |
| 2 | 0.98 | 0.02 | 0.97 | 0.01 | 0.71 | <0.01 |
| 3 | 0.98 | 0.10 | 0.97 | <0.01 | 0.77 | <0.01 |
| 4 | 0.93 | <0.01 | 0.98 | 0.01 | 0.92 | <0.01 |
| 5 | 0.93 | <0.01 | 0.99 | 0.24 | 0.65 | <0.01 |
| 6 | 0.99 | 0.18 | 0.97 | <0.01 | 0.84 | <0.01 |
| 7 | 0.98 | 0.08 | 0.96 | <0.01 | 0.85 | <0.01 |
| 8 | 0.98 | 0.11 | 0.94 | <0.01 | 0.81 | <0.01 |
| 9 | 0.98 | 0.09 | 0.94 | <0.01 | 0.81 | <0.01 |
| 10 | 0.99 | 0.24 | 0.96 | <0.01 | 0.71 | <0.01 |
| 11 | 0.99 | 0.17 | 0.92 | <0.01 | 0.81 | <0.01 |
| 12 | 0.98 | 0.11 | 0.95 | <0.01 | 0.76 | <0.01 |

**Table 4: Valence Ratings of 12 locations from urban walk.** *N* = 145. *M* = Median, *SD* = Standard deviation, *Mdn* = Median, *IQR* = Interquartile Range.

| *Location* | *Pleasure (Affective Slider)* | | | | |
|---|---|---|---|---|---|
| | *M* | *SD* | *Mdn* | *IQR* | *Range* |
| 1 | 238.38 | 162.60 | 220 | 184.00 | 1 - 1000 |
| 2 | 432.75 | 230.62 | 402 | 329.00 | 1 - 1000 |
| 3 | 525.42 | 213.63 | 539 | 326.50 | 1 - 1000 |
| 4 | 750.39 | 191.38 | 792 | 248.00 | 1 - 1000 |
| 5 | 336.07 | 234.80 | 282 | 274.00 | 1 - 1000 |
| 6 | 547.72 | 216.02 | 576 | 324.00 | 1 - 1000 |
| 7 | 592.73 | 208.21 | 612 | 312.00 | 1 - 1000 |
| 8 | 610.57 | 216.57 | 635 | 276.00 | 1 - 1000 |
| 9 | 636.60 | 184.00 | 635 | 249.50 | 1 - 1000 |
| 10 | 501.13 | 195.96 | 498 | 280.00 | 1 - 997 |
| 11 | 641.37 | 188.17 | 655 | 260.00 | 1 - 1000 |
| 12 | 547.82 | 210.79 | 538 | 316.00 | 1 - 1000 |
| *Location* | *Positive Affect (PANAS-sf)* | | | | |
| 1 | 13.32 | 4.18 | 13.00 | 6.00 | 5.00 - 24.00 |
| 2 | 12.27 | 4.28 | 12.00 | 6.00 | 5.00 - 22.00 |
| 3 | 11.78 | 4.31 | 12.00 | 7.00 | 5.00 - 25.00 |
| 4 | 12.10 | 4.22 | 12.00 | 6.00 | 5.00 - 25.00 |
| 5 | 14.16 | 4.17 | 14.00 | 6.00 | 5.00 - 25.00 |
| 6 | 11.78 | 3.93 | 12.00 | 7.00 | 5.00 - 21.00 |
| 7 | 11.57 | 4.40 | 11.00 | 7.00 | 5.00 - 23.00 |
| 8 | 10.06 | 3.85 | 9.00 | 6.00 | 5.00 - 20.00 |
| 9 | 9.94 | 3.56 | 9.00 | 6.00 | 5.00 - 21.00 |
| 10 | 11.09 | 4.13 | 11.00 | 6.00 | 5.00 - 21.00 |
| 11 | 9.37 | 3.54 | 9.00 | 5.00 | 5.00 - 20.00 |
| 12 | 10.41 | 3.81 | 10.00 | 6.00 | 5.00 - 19.00 |
| *Location* | *Negative Affect (PANAS-sf)* | | | | |
| 1 | 5.66 | 1.62 | 5.00 | 1.00 | 5.00 - 17,00 |
| 2 | 7.23 | 3.17 | 6.00 | 3.00 | 5.00 - 20,00 |
| 3 | 7.79 | 3.41 | 7.00 | 4.00 | 5.00 - 25,00 |
| 4 | 10.37 | 4.18 | 9.00 | 6.00 | 5.00 - 23,00 |
| 5 | 7.03 | 3.30 | 6.00 | 2.00 | 5.00 - 25,00 |
| 6 | 8.32 | 3.36 | 7.00 | 4.00 | 5.00 - 22,00 |
| 7 | 9.00 | 4.02 | 8.00 | 5.00 | 5.00 - 22,00 |
| 8 | 7.89 | 3.27 | 7.00 | 4.00 | 5.00 - 23,00 |
| 9 | 7.99 | 3.45 | 7.00 | 4.00 | 5.00 - 22,00 |
| 10 | 6.76 | 2.58 | 6.00 | 2.00 | 5.00 - 19,00 |
| 11 | 8.00 | 3.48 | 7.00 | 5.00 | 5.00 - 22,00 |
| 12 | 7.35 | 3.15 | 6.00 | 5.00 | 5.00 - 22,00 |

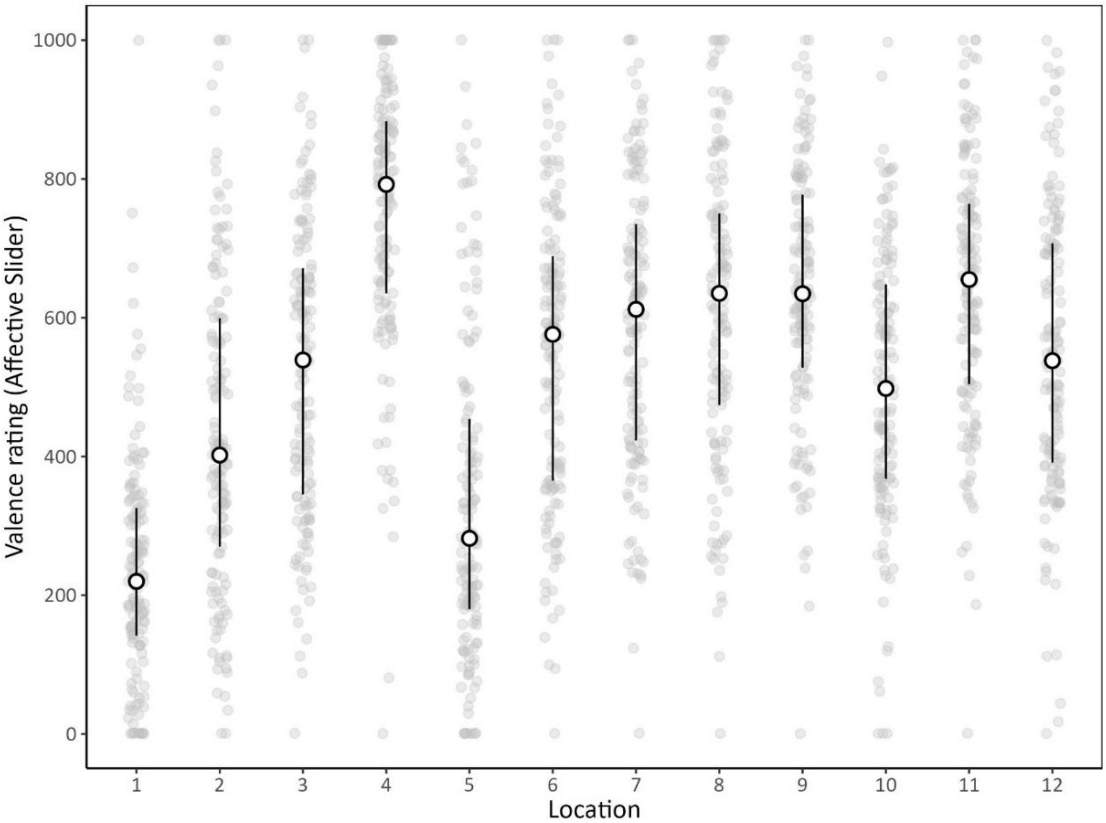


**Figure 10: Valence rating by *Affective Slider***. Note that a low score on valence scale represents positive valence, while a high score represents negative valence. For each location, pointrange shows median and interquartile range. Grey datapoints indicate distribution of individual responses. $N = 145$.

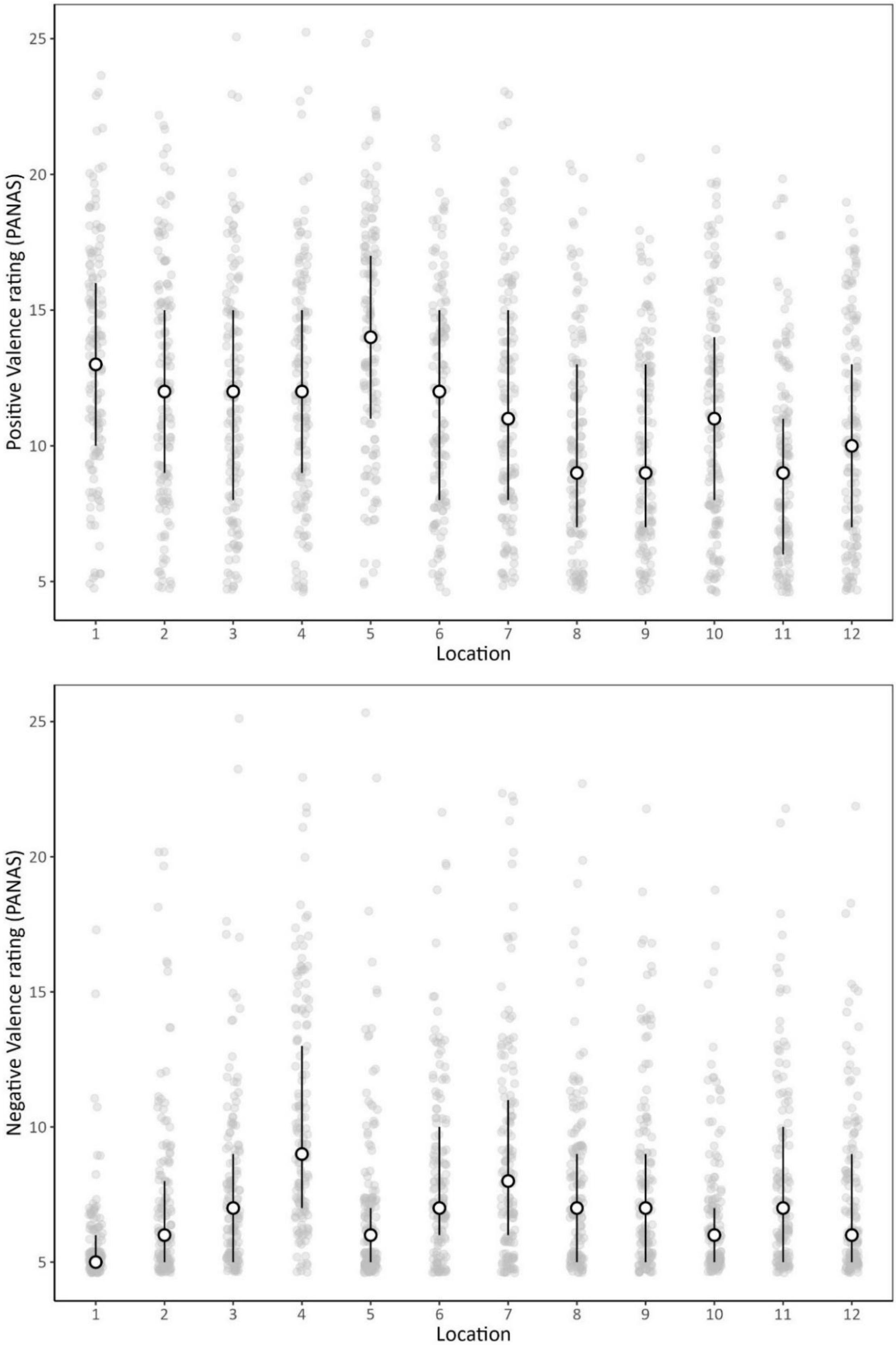


**Figure 11: Valence rating by positive mood and negative mood (PANAS-sf).** Top = positive mood, Bottom = negative mood. For each location, pointrange shows median and interquartile range. Grey datapoints indicate distribution of individual responses. $N = 145$.

### 3.3.2. Blinking

Blink data were extracted from the same eye-tracking recordings collected during Study 1's walk in the city. However, during the quality check, 11 participants had to be excluded for not inclusion criteria. Automatic blink detection by eye-tracking software was verified against manual coding: This led to exclusion of participants 1,3, 4, 6, 9, 10, 13, 15, 18, 19 and 29. The majority of these exclusions were due to participants wearing personal glasses beneath the eye-tracker. While acceptable in laboratory studies, in the field, this led to sunlight-induced reflections which interfered with consistent pupil detection and, consequently, accurate blink detection. Additionally, participants 4,6,9 and 10 were excluded due to insufficient GPS signal, which prevented complete geolocation coverage across all locations.

The final sample comprised 21 participants (15 female, 6 male). They had a mean age of 23 (*Mdn* = 23 years, *SD* = 3 years). Across 12 locations of interest, a total of 2357 blinks were recorded. For each participant and location, blink rate (BR) and blink rate variability (BRV) were calculated. Although there was some variation across locations (Fig. 12, 13), no consistent patterns emerged. Location 12 shows the highest mean BR and location 11 the lowest, location 11 the highest mean BRV (Tab. 5).

It is noteworthy that on the individual level, there were notable differences when comparing BR and BRV between locations. To make sure such effect wouldn't be masked, the deviation of BR and BRV from an approximate blinking baseline were also calculated. After these adjustments, the initial findings held true: Despite some individual variation, no universal patterns persisted at the group level.

**Table 5: Blink parameters during the urban walk per location.** BR = blink rate, BRV = Blink rate variability; BR given in Hz, BRV in ms. ΔBR describes deviation from individual's baseline BR; same for ΔBRV. *M* = Mean, *SD* = Standard deviation. *N* = 21.

| *Location* | *BR* | | ΔBR | | *BRV* | | ΔBRV | |
|---|---|---|---|---|---|---|---|---|
| | *M* | *SD* | *M* | *SD* | *M* | *SD* | *M* | *SD* |
| 1 | 36.87 | 18.55 | 1.35 | 8.83 | 2426 | 2224 | 293 | 1569 |
| 2 | 29.95 | 13.31 | -5.57 | 7.41 | 2748 | 1312 | 615 | 588 |
| 3 | 40.64 | 24.50 | 5.12 | 13.37 | 2303 | 1543 | 170 | 827 |
| 4 | 36.92 | 15.75 | 2.36 | 12.77 | 1618 | 631 | -652 | 763 |
| 5 | 34.38 | 19.09 | -2.79 | 11.33 | 2316 | 1353 | 333 | 639 |
| 6 | 40.83 | 15.33 | 5.31 | 8.11 | 1744 | 969 | -389 | 618 |
| 7 | 34.28 | 12.13 | -3.61 | 13.36 | 2578 | 946 | 127 | 744 |
| 8 | 44.96 | 22.28 | 7.07 | 15.26 | 2216 | 1283 | -235 | 800 |
| 9 | 33.13 | 18.90 | -4.76 | 12.78 | 2580 | 1960 | 129 | 1244 |
| 10 | 41.41 | 13.90 | 3.52 | 10.18 | 1788 | 864 | -662 | 1148 |
| 11 | 22.73 | 10.48 | -15.16 | 10.36 | 3912 | 2070 | 1461 | 1419 |
| 12 | 50.83 | 13.49 | 12.94 | 14.81 | 1631 | 670 | -820 | 972 |

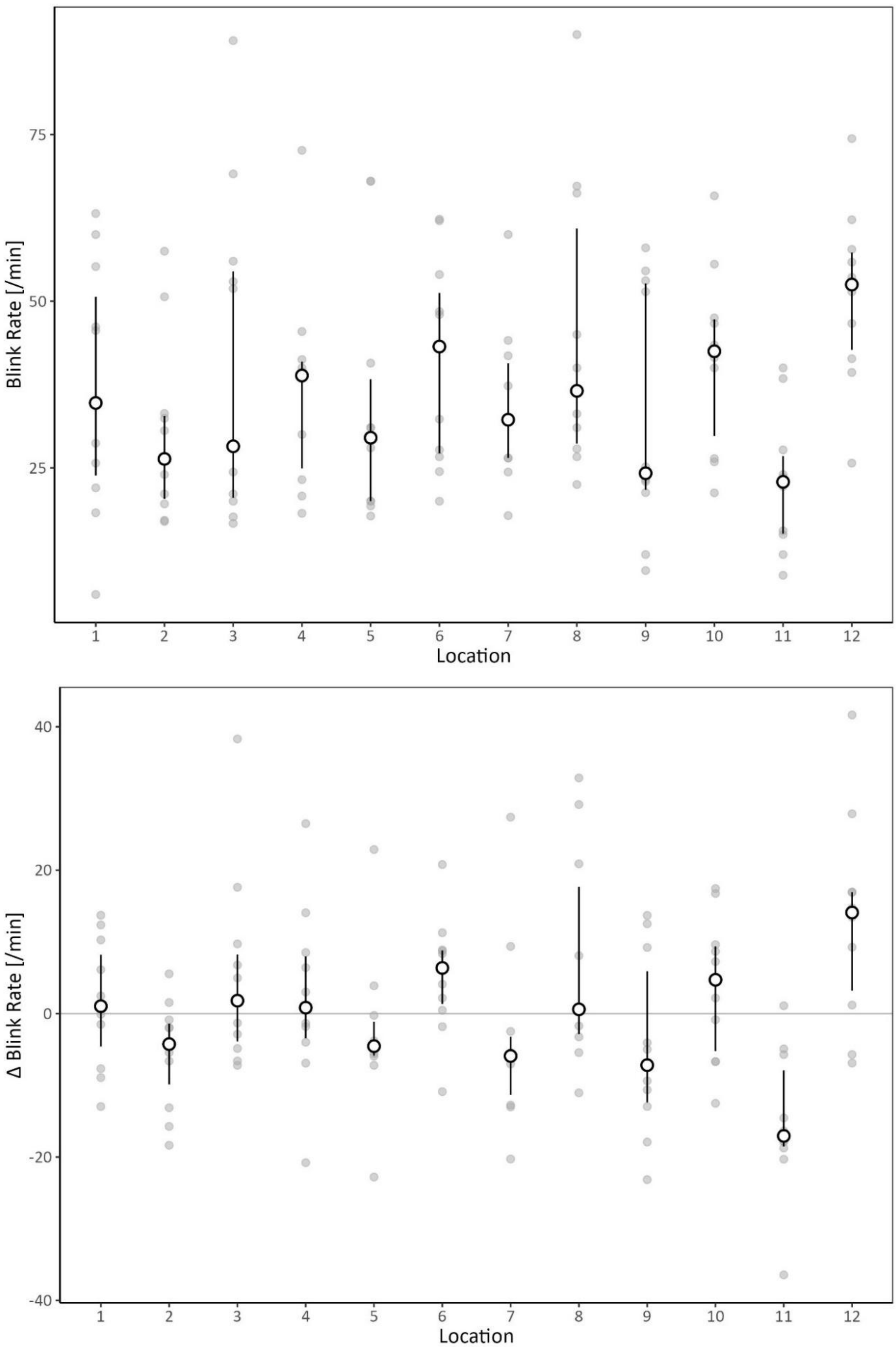


**Figure 12: Blink rate and Δ Blink rate per location.** Pointrange shows median and interquartile range. Grey datapoints indicate distribution of individual responses. ΔBR describes deviation from individual's baseline BR. $N = 21$.

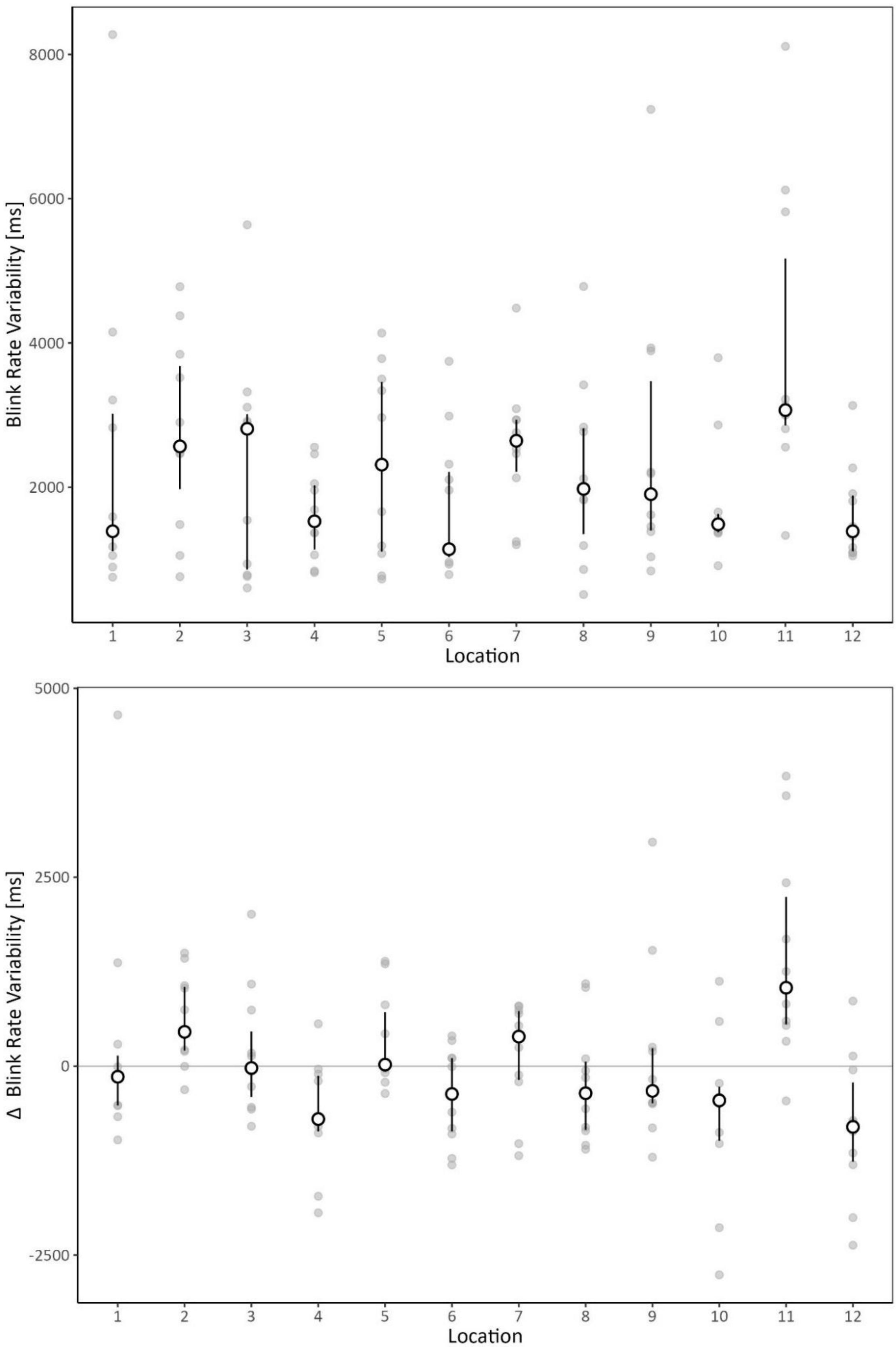


**Figure 13: Blink rate variability and Δ Blink rate variability per location.** Pointrange shows median and interquartile range. Grey datapoints indicate distribution of individual responses. ΔBRV describes deviation from individual's baseline BRV. $N = 21$.

### 3.3.3. Correlation Analysis

To test the hypothesis that blink rate (BR) and blink rate variability (BRV) are significantly correlated with the valence during high arousal moments on a walk in the city, we plotted the aggregated data of all participants and performed a spearman correlation test. We predicted that both BR and BRV are higher with negative valence than with positive valence.

BR and BRV were plotted against valence scores obtained from the *Affective Slider* and the PANAS-sf. The *Affective Slider* data yielded a more uniform distribution of locations across the scale, whereas with the PANAS-sf ratings, locations clustered around certain values – limiting their utility in the correlational analysis. Therefore, this section presents mainly the *Affective Slider* results (Fig. 14, 15); supplementary PANAS-sf figures are supplied in the Appendix.

Spearman correlation analysis revealed no correlation between valence and BR or valence and BRV neither for the *Affective Slider* (Spearman's $r_S = -0.07$, $p = 0.450$, $N = 21$) nor the PANAS-sf (positive affect: Spearman's $r_S = -0.01$, $p = 0.935$, $N = 21$; negative affect: Spearman's $r_S = -0.06$, $p = 0.481$; $N = 21$; Tab. 6). To address the influence of ties in our data, the non-significance of the correlation was verified using a Kendall correlation test, as well as a second Spearman correlation test of our data after a transformation that introduced slight jitter to the raw data. This process was repeated for the relative ΔBR and ΔBRV; the baseline-corrected variables showed no significant correlation with valence.

A linear mixed model was fit from the final 21 participants (124 observations) to examine the relationship between blink rate and valence. While valence did not predict blink rate ($\beta = 0.0020$, 95% CI [-0.02, 0.02], $t(120) = 0.22$, $p = 0.826$; Std. $\beta = 0.02$, 95% CI [-0.14, 0.17]), including the participant identity substantially improved model fit (AIC (mixed model) = 1048.8, AIC (linear model) = 1069.0). Individual differences between participants accounted for the majority of the explained variance (conditional $R^2 = 0.36$, marginal $R^2 = 0.0003$, ICC = 0.36) and highlights the importance of accounting for participant-dependent differences when modeling blink behavior. Similar results were found modeling blink rate variability ($\beta = -0.76$, 95% CI [-2.25, 0.74], $t(120) = -1.00$, $p = 0.318$; Std. $\beta = -0.08$, 95% CI [-0.24, 0.08]).

**Table 6: Correlation analysis (Spearman, Kendal correlation test) of blink variables with valence ratings (pleasure, positive affect, negative affect).** N = 21, df = 19. BR = blink rate, BRV = blink rate variability. Δ indicates the deviation from individual's average of according blink parameter across all of the measured high arousal.

| *Blink variable* | *pleasure (Affective Slider)* | | *positive affect (PANAS-sf)* | | *negative affect (PANAS-sf)* | |
|---|---|---|---|---|---|---|
| | *Spearman's $r_S$* | *p-value* | *spearman's $r_S$* | *p-value* | *spearman's $r_S$* | *p-value* |
| BR | -0.07 | 0.450 | -0.01 | 0.935 | -0.06 | 0.481 |
| ΔBR | -0.09 | 0.296 | 0.08 | 0.353 | -0.08 | 0.383 |
| BRV | 0.08 | 0.358 | -0.14 | 0.123 | 0.07 | 0.46 |
| ΔBRV | -0.04 | 0.681 | 0.07 | 0.421 | 0.01 | 0.878 |
| *Blink variable* | *pleasure (Affective Slider)* | | *positive affect (PANAS-sf)* | | *negative affect (PANAS-sf)* | |
| | *Kendall's τ* | *p-value* | *Kendall's τ* | *p-value* | *Kendall's τ* | *p-value* |
| BR | -0.04 | 0.488 | -0.01 | 0.899 | -0.05 | 0.513 |
| ΔBR | -0.06 | 0.314 | 0.05 | 0.414 | -0.06 | 0.393 |
| BRV | 0.06 | 0.367 | -0.11 | 0.114 | 0.05 | 0.467 |
| ΔBRV | -0.03 | 0.693 | 0.05 | 0.439 | 0.01 | 0.871 |
| *Blink variable* | *pleasure (Affective Slider)* | | *positive affect (PANAS-sf)* | | *negative affect (PANAS-sf)* | |
| | *Spearman's $r_S$* | *p-value* | *spearman's $r_S$* | *p-value* | *spearman's $r_S$* | *p-value* |
| BR* | -0.07 | 0.469 | -0.01 | 0.939 | 0.02 | 0.793 |
| ΔBR* | -0.09 | 0.307 | 0.06 | 0.536 | -0.04 | 0.694 |
| BRV* | 0.09 | 0.339 | -0.14 | 0.130 | 0.03 | 0.746 |
| ΔBRV* | -0.03 | 0.740 | 0.08 | 0.390 | 0.01 | 0.951 |

*Note*. * blink variables transformed with minimal jitter to avoid ties in data.

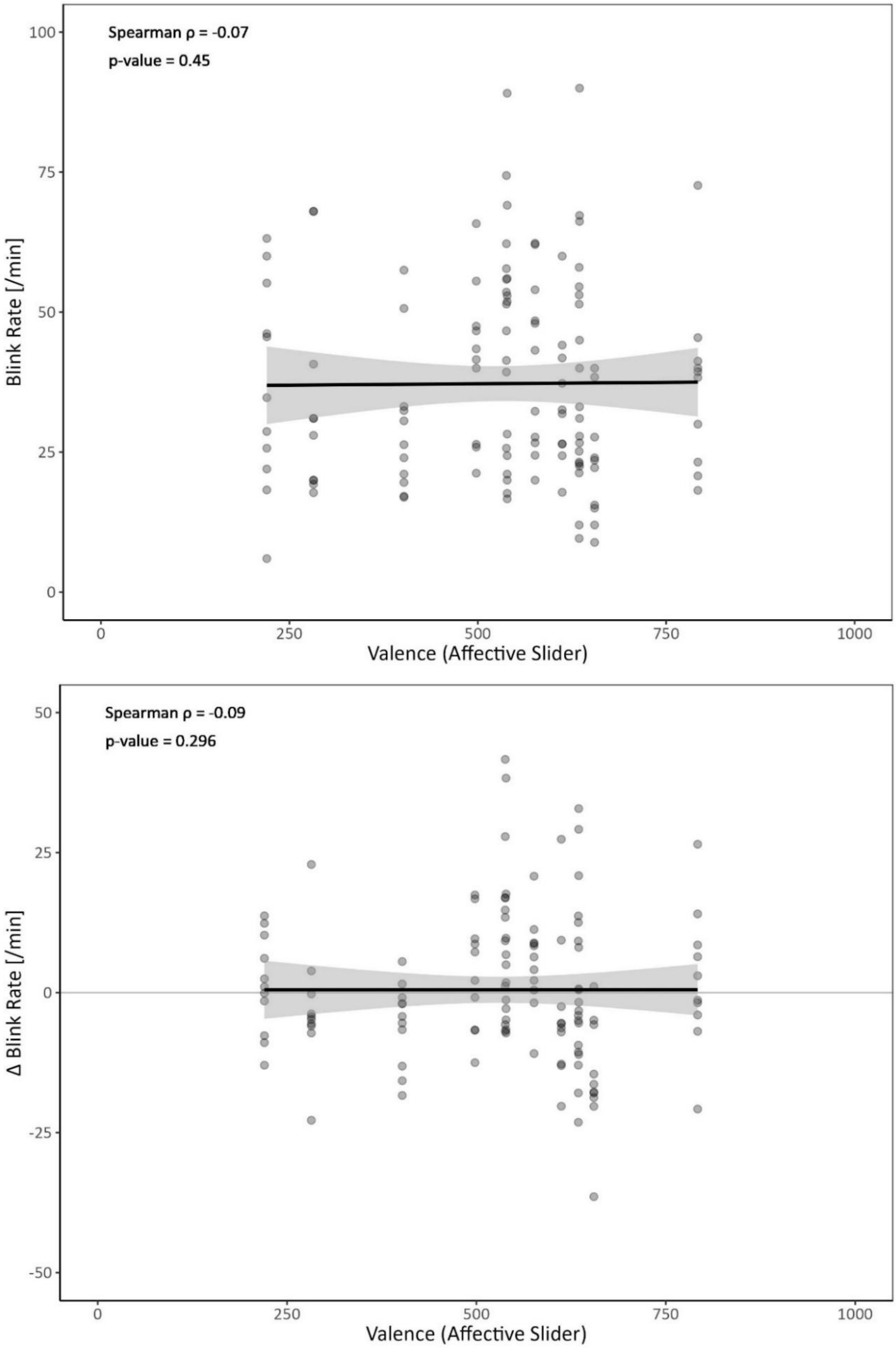


**Figure 14: Blink rate and Δ Blink rate per Valence (*Affective Slider*).** Low Valence score indicates positive valence, high Valence score indicates negative valence. ΔBR describes deviation from individual's baseline BR. $N = 21$.

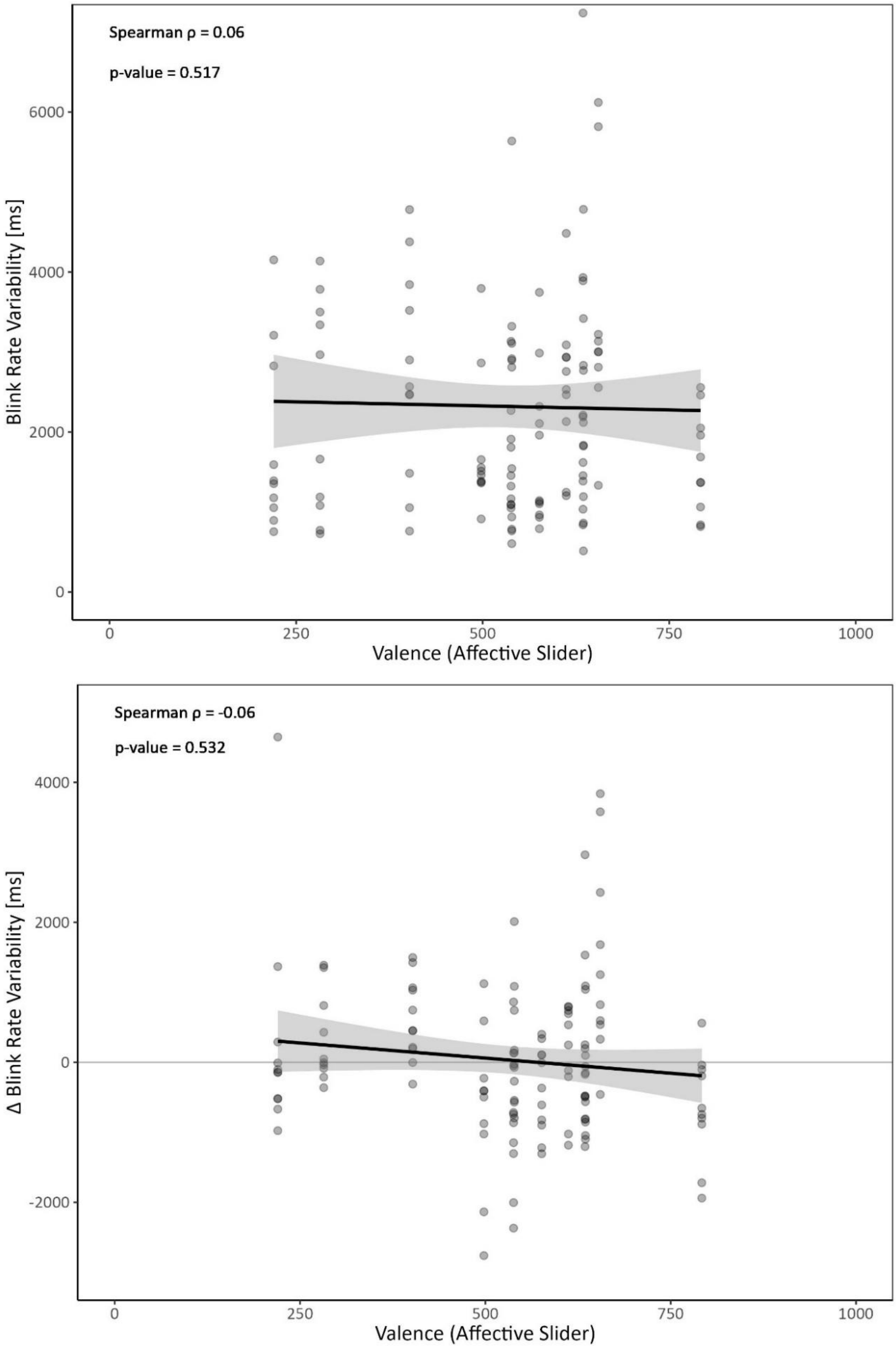


**Figure 15: Blink rate variability and Δ Blink rate variability per Valence (*Affective Slider*).** Low Valence score indicates positive valence, high Valence score indicates negative valence. ΔBRV describes deviation from individual's baseline BRV. $N = 21$.

## 3.4. Discussion

In Study 2, we aimed for a deeper understanding of the data that was collected during Study 1, while simultaneously exploring blink rate as a potential measure for valence. The results of this study do not suggest that blink rate is a reliable indicator for the valence of high arousal moments during a walk in the city. When examining data across all 21 participants for 12 high-arousal locations, neither blink rate nor blink rate variability showed a significant relationship with valence ratings. Among the three valence rating methods, the *Affective Slider* produced the most distinctive classification of the 12 scenes. Still, combining this with blink rate or blink rate variability did not reveal any discernable trend: Regression slope barely deviated from 0 and, more importantly, correlations were non-significant according to Spearman's rank correlation test. This diverges from Maffei & Angrilli (2019), who found a significant correlation between blink rate and valence in laboratory settings. Blink rate variability, as a measure, has the potential to display the time-dependent response patterns they found with different emotions. Despite that, the results of this study see blink rate variability no better than blink rate in differentiating the valence of high arousal moments. Generally, it can be observed that all locations have a high variety in (1) how they are evaluated on valence and (2) blink rates and their variability that were recorded on-site. PANAS-sf ratings for positive and negative affect yielded similar results.

Although the valence and blink data showed no correlation, individual participants exhibited noticeable variation in blink rates between one location and another during the walk. This means that blink rate at one location could be, for example, double the blink rate at another location – suggesting that participants do show variation in blinking behavior and potentially experience locations differently. However, since there seems to be no consensus how locations compare to one another among the participants, no generalized blinking difference between locations is visible when aggregating data of all participants. Similarly, an explorative linear mixed-effects model revealed that roughly one third of the total variance in blink rate stemmed from participant identity. This is in line with previous literature that found blinking to differ with age and sex (Sforza et al., 2008), certain neurological conditions (e.g. schizophrenia, Parkinson's) and medications (Eckstein et al., 2017). To account for this individuality and prohibit inter-subject differences from overshadowing location-dependent effects, an additional step was incorporated into the analysis: Here, we calculated a theoretical baseline blink rate for high arousal moments for each participant, derived from the collected data at all locations. This allowed the analysis of locations by the changes of blink rate from each individual's baseline blinking. However, despite these efforts, the results didn't reveal more than the basic analysis; while participants may show changes in their blinking at different locations, no general patterns emerged across the participants.

The attractiveness of blink rate as a measure for valence lies in the easy data collection provided by emerging eye-tracking technologies. This makes blink rate increasingly attractive for field research. Nevertheless, external, environmental factors can still put limitations on its use. For example, changes in lighting conditions – as seen in this study, when exiting tunnels, walking under dense top-foliage or in the cover of construction scaffolds – can disrupt regular blinking behavior. Bright light has been shown to increase blink rate (Hackley & Johnson, 2023), as well as other stimuli that trigger reflexive blinking. Wind can increase blinking by accelerating tear film evaporation (Himebaugh et al., 2009). Similarly, people wearing contact lenses can also show an increased blink rate and modified inter-blink intervals (Navascues-Cornago et al., 2022). Although contact lenses are preferred to wearing personal glasses in combination with eye-trackers, as this favors correct blink detection, the use of contact lenses creates different physiological conditions for this subset of participants that needs to be corrected for. If the experimental setup is not able to overcome these methodological challenges, these external factors can conceal the underlying relationship between blinking and valence.

The exploration of the valence of location-based MOA was made possible through the rating study. This was an online study with a new sample of participants, using two self-report tools on pre-selected images of each location. The importance of collecting data in the field was already discussed in *1. General Introduction*. It is possible that – while image and video of environment were able to evoke similar effect in previous studies (Jo et al., 2019; Lin, 2021) – the online format might only provide a diluted valence response compared to the multi-sensory, immersive field-based assessments. Thereby, results of the valence rating may not be representative. This limitation is particularly relevant given the greatest weakness of the present study: The disconnect between the two collected samples, blinking in the field study (1) and valence in the survey + eye-tracking study (2). It should be stressed that this was a compromise that had to be made to be able to collect the data on valence, which until then was missing from our study. To progress the study, the rating study was designed under the assumption that there is a general agreement on what constitutes a pleasant or unpleasant environment, based on a sensory and perceptive system that is based on the evolutionary history that all humans share (Heerwagen & Orians, 1993). In addition, since the urban environments should serve all its inhabitants, there is practical value in the use of an average rating from a general population.

The results of the rating study showed that valence ratings for the selected high-arousal moments were predominantly neutral. Notably, all but one location's *Affective Slider* score spanned the full 0-1000 range, the exception missing the extreme end by a mere 3 points. Despite this wide range, averaged ratings fell in the middle third of the scale for most locations. PANAS-sf ratings further supported this neutrality, with moderate to low positive affect and low negative affect scores.

Exceptions could be seen for locations 1 and 5, which leaned towards positive, and 4, which was distinctly negative in the *Affective slider* rating and was highest in negative affect PANAS-sf rating. This corresponds to the visual scenery visible in the images (See *3.2.1. Valence Rating*): Both locations 1 and 5 are abundant in green and natural elements, which are commonly evaluated positively (Johansson et al., 2016). Interestingly, location 2, although spatially close to location 5, scored near neutral. This could relate to the dense foliage obstructing prospect, which has previously impeded restorative green spaces (Gatersleben & Andrews, 2013). Alternatively, perhaps the muted, less green color palette did not trigger the same aesthetic preference. In contrast, at location 4, participants were presented with a construction site with steel girders on the side and above, which produces not only a highly built, non-green scene, but potentially causes additional discomfort due to a reduced overview (Gatersleben & Andrews, 2013) or safety concerns (Sundling & Jakobsson, 2023).

For the remaining locations, emotional responses were either generally mild, or they varied so substantially between participants that final scores converged to neutrality. This raises another important question: Can such ambiguous, mixed experiences truly be the drivers of general short- or long-term stress and well-being? Importantly, before such conclusions can be drawn, it needs to be confirmed that the method used represented the experience of our walking participants accurately. Despite there being a theoretical basis for using a generalized rating, the results suggest that this might not be specific enough to display more subtle differences, as could be the valence of different high arousal moments. This is especially the case when working with such a small sample size (n=21). This limitation demonstrates the importance to close the gap between valence and blinking by reporting valence ratings from every individual that participates in the walk. But even with a larger sample, having individualized valence ratings would be extremely beneficial, as valence ratings covered a wide range and individual blink behavior accounted for a large portion of blinking variation. Linking valence and blinking by specific moments of interest has the potential to directly display the relationship between these variables.

This leads to the practical challenge of how to collect this information during the walk – which is the very issue that demonstrates the appeal of blink rate as a measure in the first place. Until such a tool is available, one approach is to add post-walk annotations by the participants. However, this relies on memory and retrospective, subjective reconstruction of the affective experience. Alternatively, real-time check-ins during the walk could be introduced, but this disrupts immersion and in turn distorts the natural walk experience. In contrast, a non-invasive, non-disruptive physiological measure such as blink rate could be recorded automatically and continuously, without disrupting the experimental procedure. Furthermore, this also resolves common challenges of questionnaire-format studies like recall errors (Lance et al., 2009). Such a tool, which can be reliably attributed to an emotional experience, opens doors for research of all disciplines that consider emotional affect, including stress research.

Even if blink rate and blink rate variability ultimately end up unsuitable for the automatic measurement of valence, other eye-derived parameters remain promising. For instance, blink duration variability was found to be more useful than blink rate for the development of an algorithm discerning emotional states (Sarma & Barma, 2021). However, blinking might just not be suitable in a non-laboratory setting; in Maffei & Angrilli (2019), there were time-dependent patterns in the blinking response to differing valence. The decrease in blink rate following a high-arousal, positive-valence stimulus was strongest in the immediate post-stimulus period, while for a high-arousal, negative-valence stimulus, the responding blink rate increase was most pronounced in later time intervals. In real life settings, a plethora of stimuli can act in quick succession, potentially obstructing the response in later time intervals. This can be addressed by downsizing the time-window of blink investigation to the very immediate response. However, shorter time-windows may limit the suitability of blink rate, given its baseline number of occurrences (In Eckstein et al. (2017): 10-20 blinks per minute = 0.17-0.3 blinks per second). Measures with higher baseline occurrences may provide better sensitivity when examining the immediate seconds after a *Moment of Arousal* occurs. As an alternative to blinks, certain fixation features have also been found to reflect positive and negative emotional arousal (Skaramagkas et al., 2023). Whether it is blinking or another eye-derived measure, the result is a single tool – the eye-tracking methodology – which not only captures the features in the environment (visual field, fixations) but already provides the responding valence to this feature. With the advance of machine-learning algorithms in all technological and scientific fields, general emotion recognition is foreseen to benefit from this as well. The progressing field of emotion recognition research offers a wide range of applications (Khare et al., 2024), there is potential for this to serve health and well-being in our living spaces as well.

In conclusion, while this study could not provide a clear link between valence and blink rate nor blink rate variability in real-world settings, it should be stressed that this study specifically targeted high arousal moments and combined them with supplementary valence information from a second data collection. This entailed a multi-step process with some compromises due to situational constraints that may have impeded the correlational analysis. Yet, rather than discouraging future investigation of blinking-based measures, this thesis reveals the areas for improvement in refined procedures and improved samples, specifically in the area of individual blinking behavior variation.

# 4. General Discussion

Negative effects of urban environments often refer to the experience of high arousal, discounting that high-arousal experiences may also come with positive valence – as can be illustrated by the Circumplex Model of Affect (Russell, 1980). By employing the dimension of emotional valence, the urban walking experience can be investigated in more detail than just relying on arousal-based stress detection alone. The importance of this differentiation is also reflected in the results of Study 1; although there is a beneficial effect of the walk in total, this does not show up as acute, relaxing, de-stressing states in urban green spaces. Instead, multiple hotspots of high arousal are found in areas that are deemed beneficial on stress experience. In sustainable city design, it is important to understand the specific mechanisms that green spaces enable as they are used by its inhabitants.

With the emergence of eye-tracking technologies, previous studies have also applied this to investigate how urban environments are perceived and processed (Hollander et al., 2020). As eye-derived metrics can also provide insights into emotional processes (Skaramagkas et al., 2023), there is potential to use measures like blinking, which varies with emotional content (Maffei & Angrilli, 2019), as a physiological measure for a holistic representation of urban green spaces and other elements in the urban environment. Although Study 2 was not able to find blink rate or blink rate variability indicative of emotional valence, there is reason to believe that, with improved study design, future studies can reveal such a tool to evaluate environments. This tool can then be applied in the investigation of elements such as urban green spaces, so we learn how to implement them effectively in urban design. By focusing on eye-derived metrics, we aim for a physiological indicator of valence that can be seamlessly integrated into the existing experimental procedure of eye-tracking studies in the environment.

Improving the affective walking experience not only encourages walking, but this in turn has wide-ranging benefits on both people and the planet (Adkins, 2012; Brunner et al., 2025; De Vos et al., 2023; Johansson, 2016). On the level of people, walking benefits health and well-being both as physical but also as a recreational activity (Kelly et al., 2017, 2018). Improving walkability in cities improves effective public transport (Yanis et al., 2025) and combats social inequity (Baobeid et al., 2021). Reducing private vehicles and supporting sustainable mobility reduces greenhouse gas emissions (Piracha & Chaudhary, 2022). Implementing green spaces in city helps with specific issues like air quality (Nieuwenhuijsen et al., 2017) and urban heat island effect (Shishegar, 2014). Adding the psychological benefit of green environments, this improves livability of cities on multiple layers and contributes to overall well-being of the planet. Thereby, this thesis acts as a foundation for a large number of study objectives in the field of urban design.

# 5. Conclusion

The results of this study do not propose that blink rate is a reliable indicator for the valence of high arousal moments during a walk in the city. This does not necessarily mean that blinking is not indicative of valence at all: The external factors in the real-life environments might be too disruptive for this to be informative. To make more meaningful claims on the suitability of eye-tracking-derived blink measures in the field, an increased sample size would be beneficial. Moreover, this study collected valence ratings by independent, external raters. Having individualized valence ratings from each person that experienced the walk could yield a more accurate valence rating and thereby more accurate insights into the relationship between blinking and emotional valence. As urbanization progresses, this provides additional knowledge for tools to study how we perceive varying elements in the urban environment. These tools are essential if we want to center human well-being in the design and planning of future cities.

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# List of Figures



# List of Tables

# Appendix

## Circumplex Model of Affect

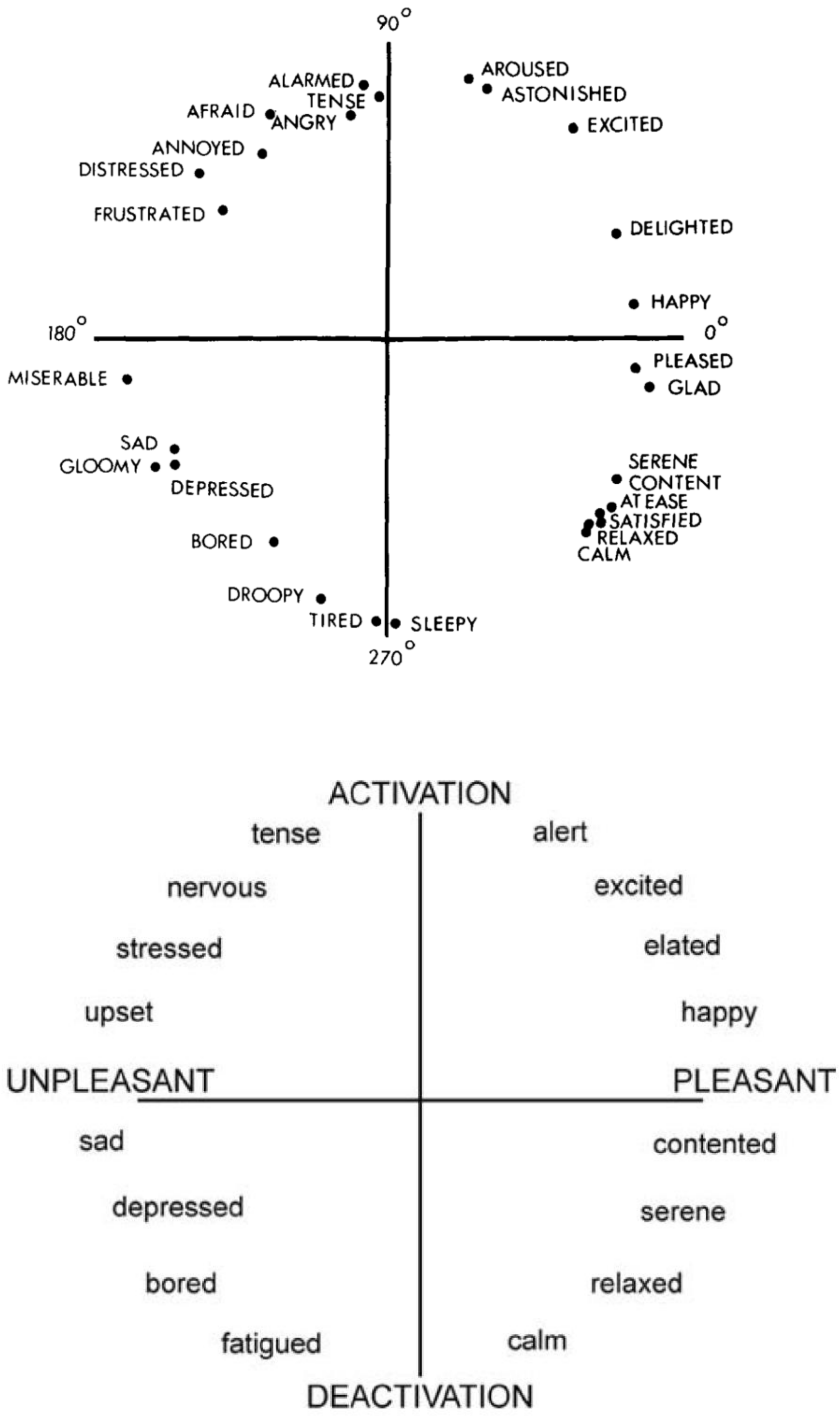


**Figure 16: Circumplex model of affect.** Top: Circumplex model as designed and published by Russel, 1980. Bottom: Adapted version of Circumplex model published by Posner et al., 2005.

## Affective Slider Response Distribution

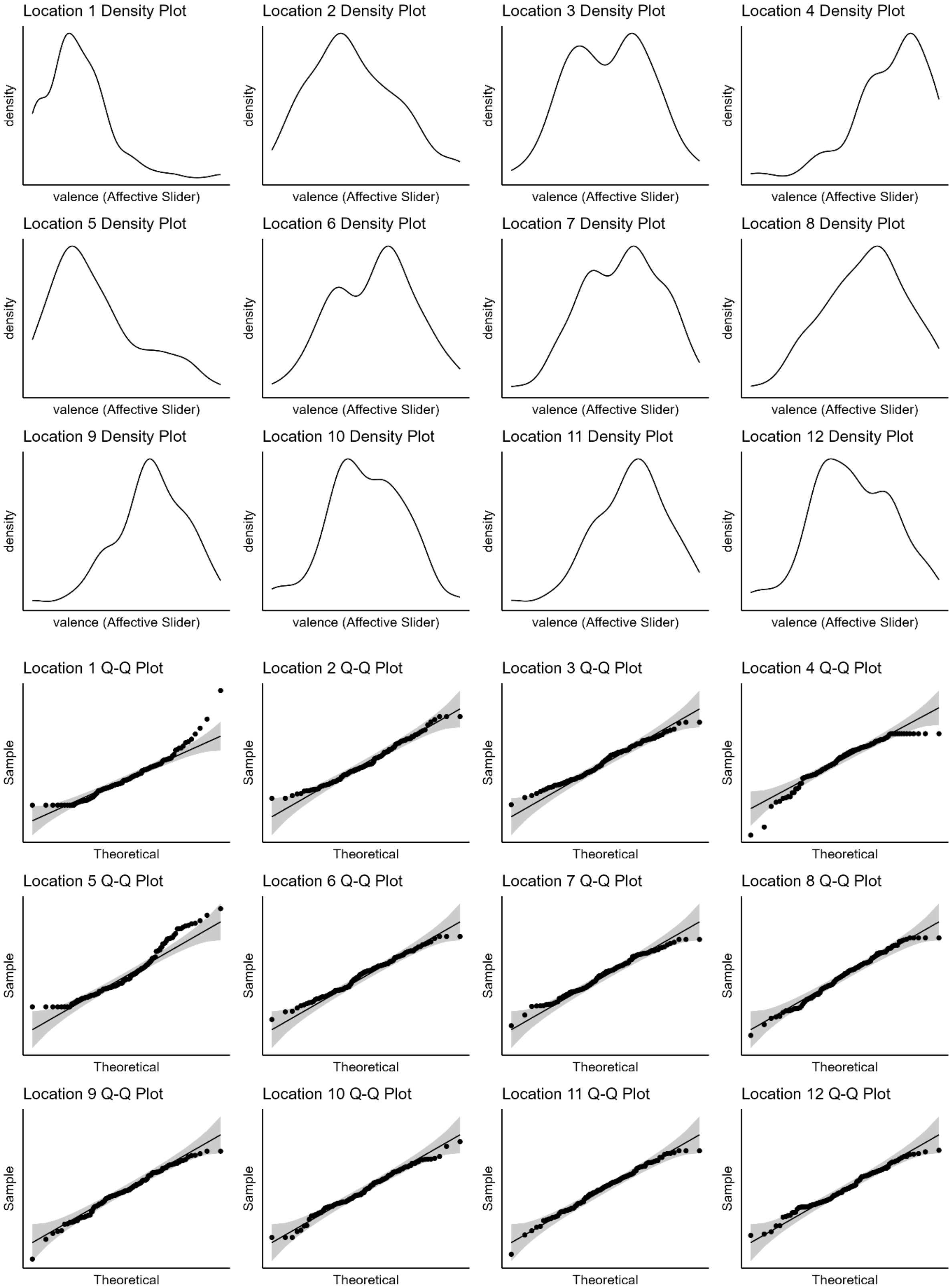


**Figure 17: Questionnaire *Affective Slider* Response.** Top: Density plot. Bottom: Q-Q plot. N = 145.

## Positive Affect Response Distribution

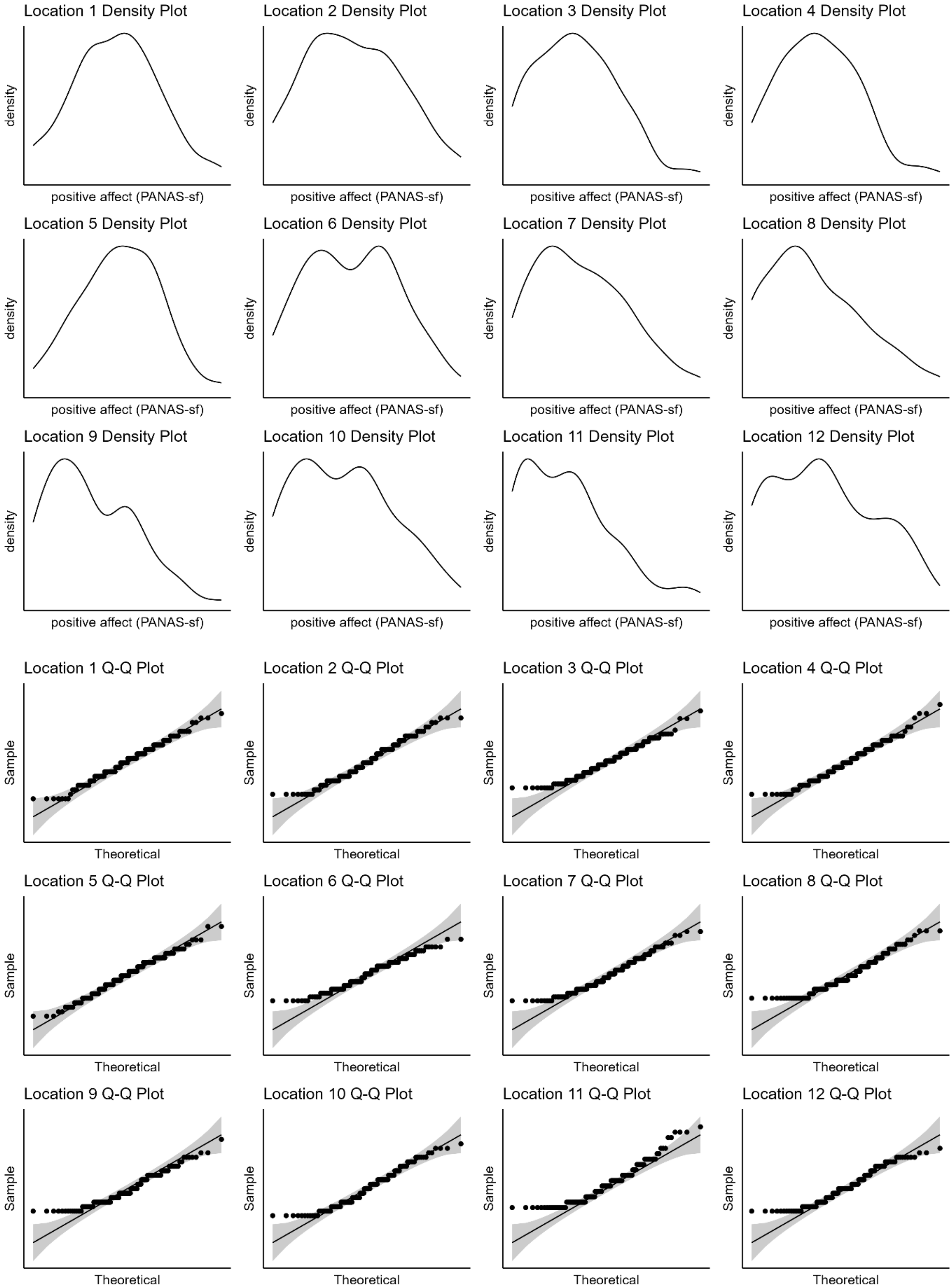


**Figure 18: Questionnaire positive Affect (PANAS-sf) Response.** Top: Density plot. Bottom: Q-Q plot. N = 145.

## Negative Affect Response Distribution

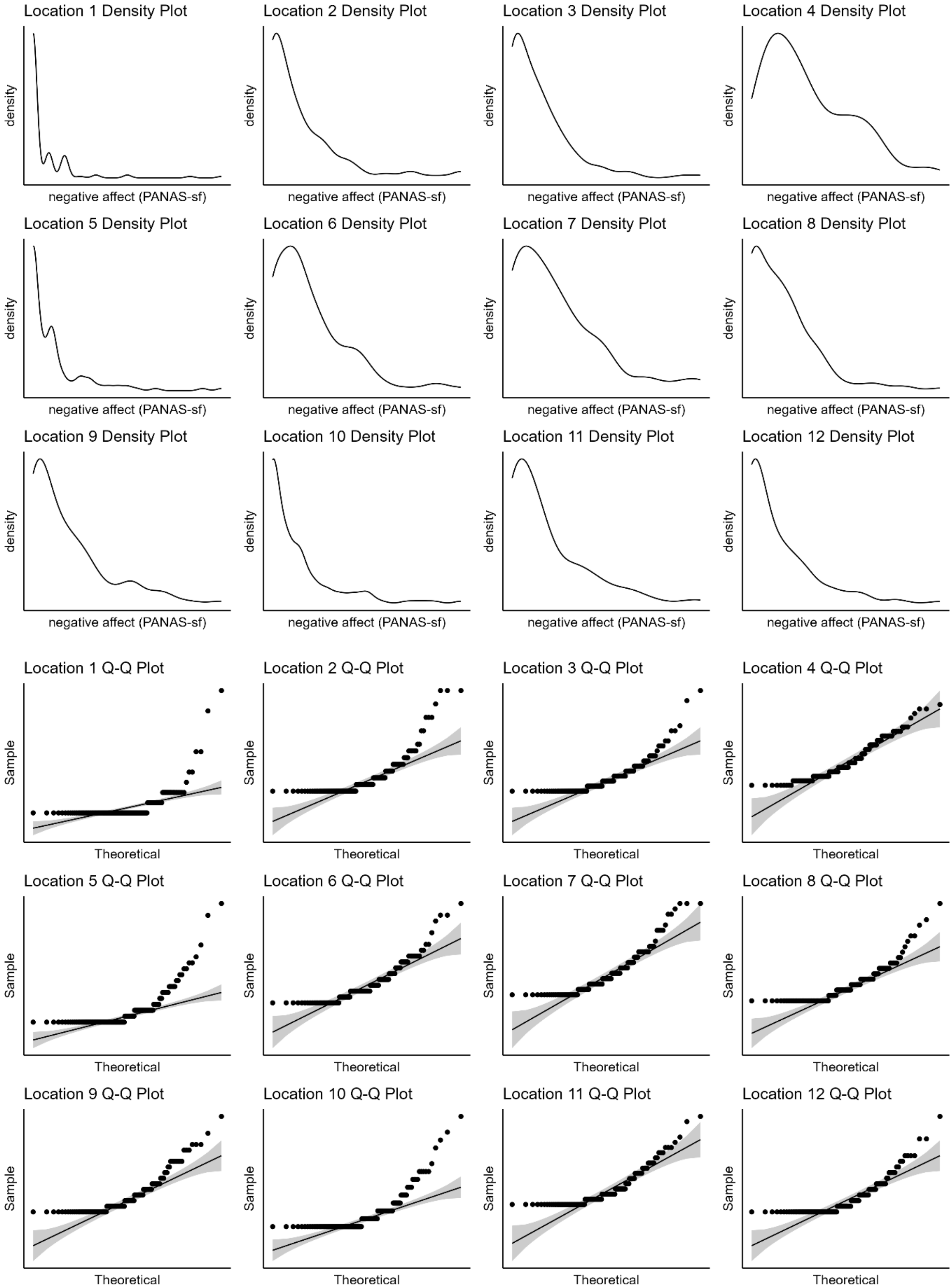


**Figure 19: Questionnaire negative Affect (PANAS-sf) Response.** Top: Density plot. Bottom: Q-Q plot. N = 145.

## Correlative Analysis Positive Affect

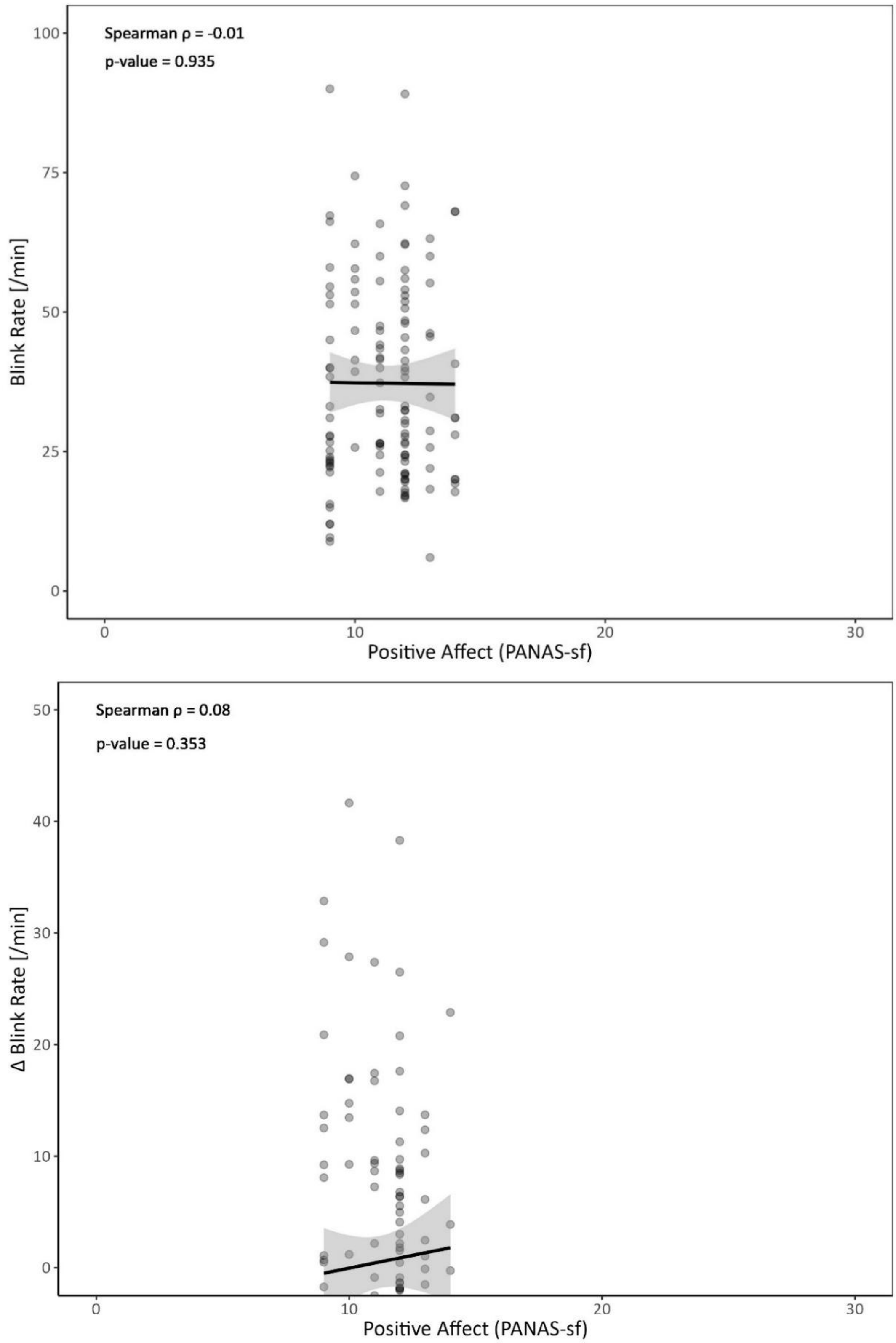


**Figure 20: Blink rate and Δ Blink rate per positive Affect (PANAS-sf).** Low Valence score indicates positive valence, high Valence score indicates negative valence. ΔBR describes deviation from individual's baseline BR. N = 21.

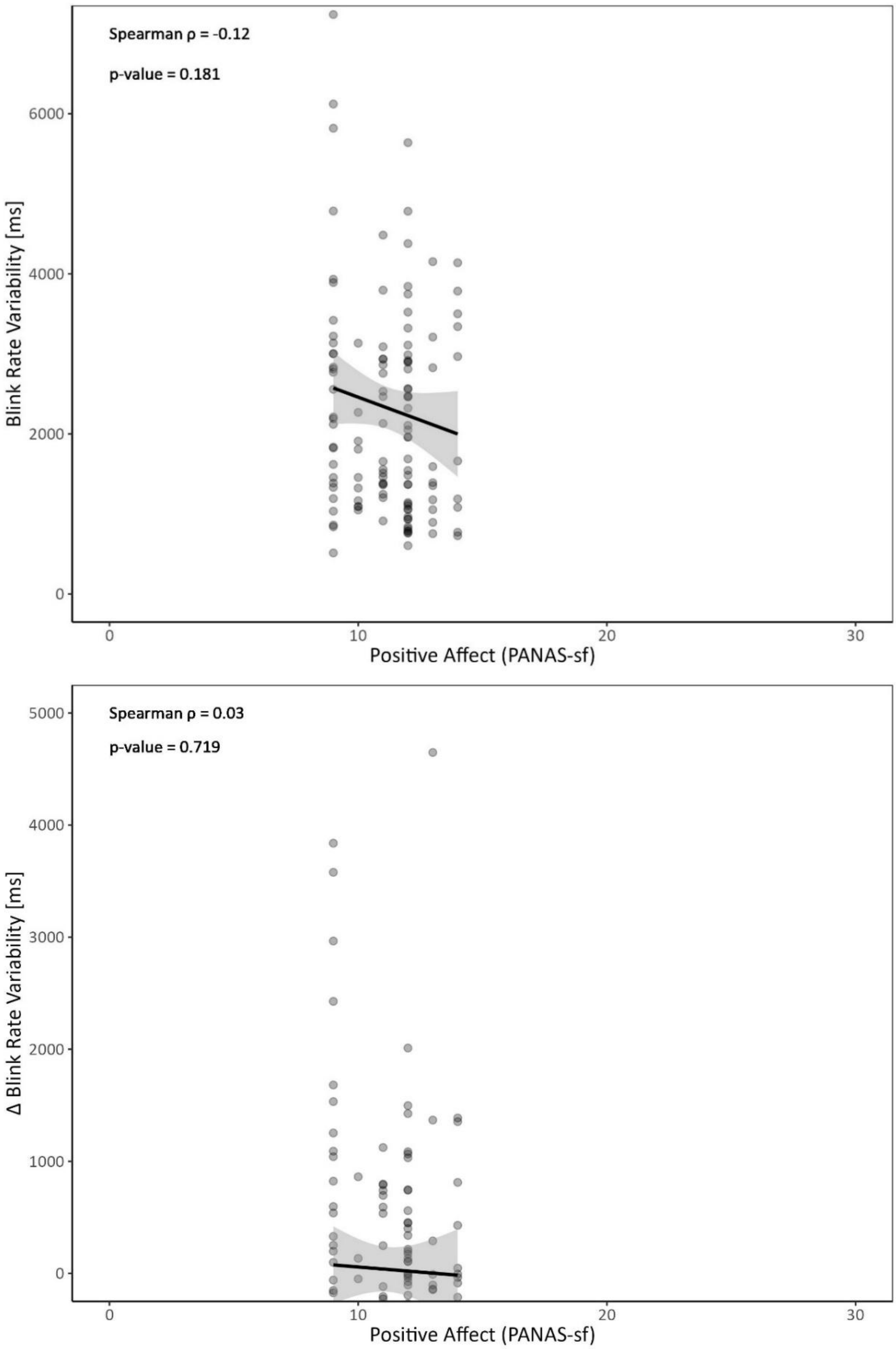


**Figure 21: Blink rate variability and Δ Blink rate variability per positive Affect (PANAS-sf).** Low Valence score indicates positive valence, high Valence score indicates negative valence. ΔBR describes deviation from individual's baseline BR. N = 21.

## Correlative Analysis Negative Affect

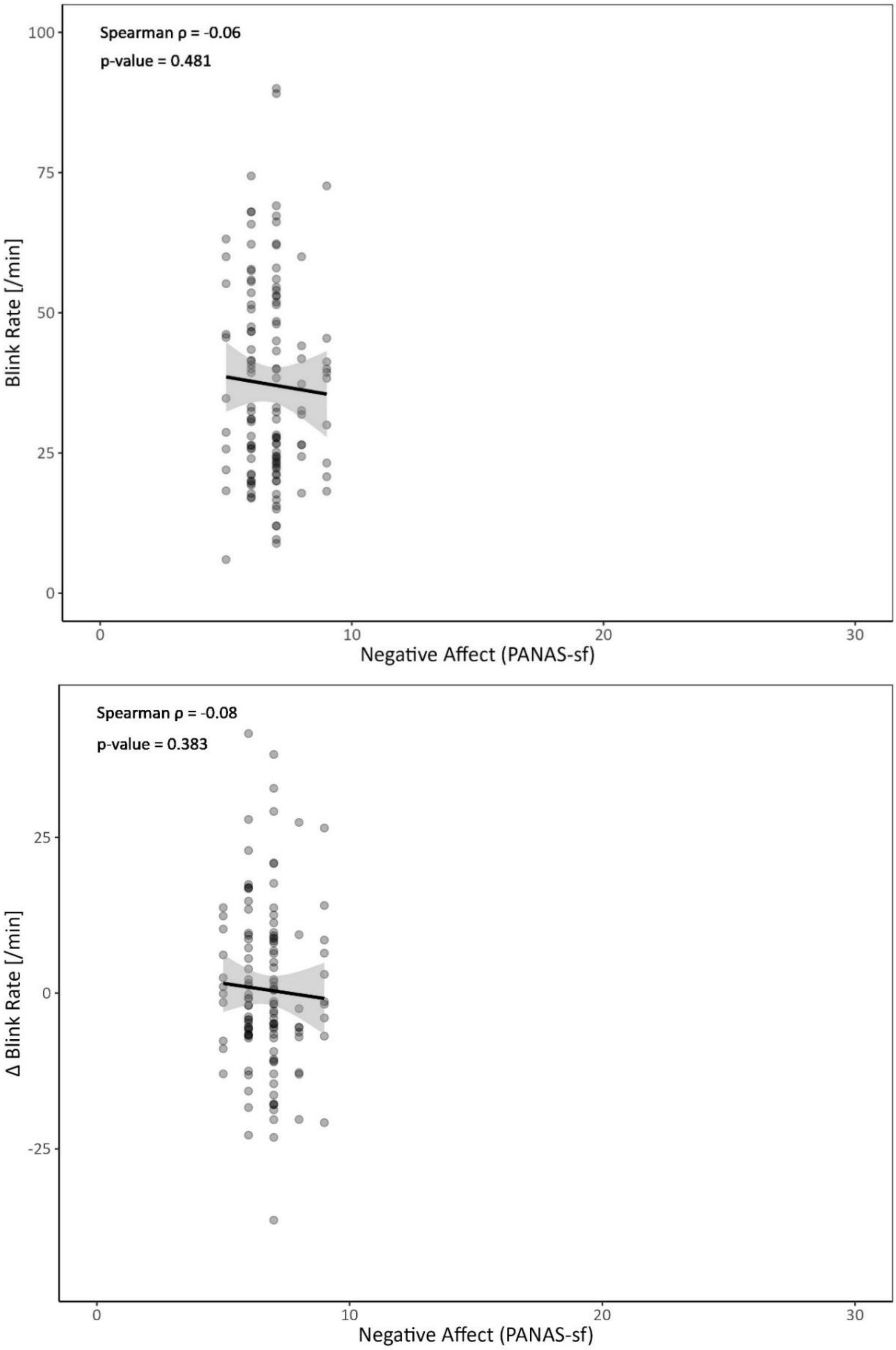


**Figure 22: Blink rate and Δ Blink rate per negative Affect (PANAS-sf).** Low Valence score indicates positive valence, high Valence score indicates negative valence. ΔBR describes deviation from individual's baseline BR. N = 21.

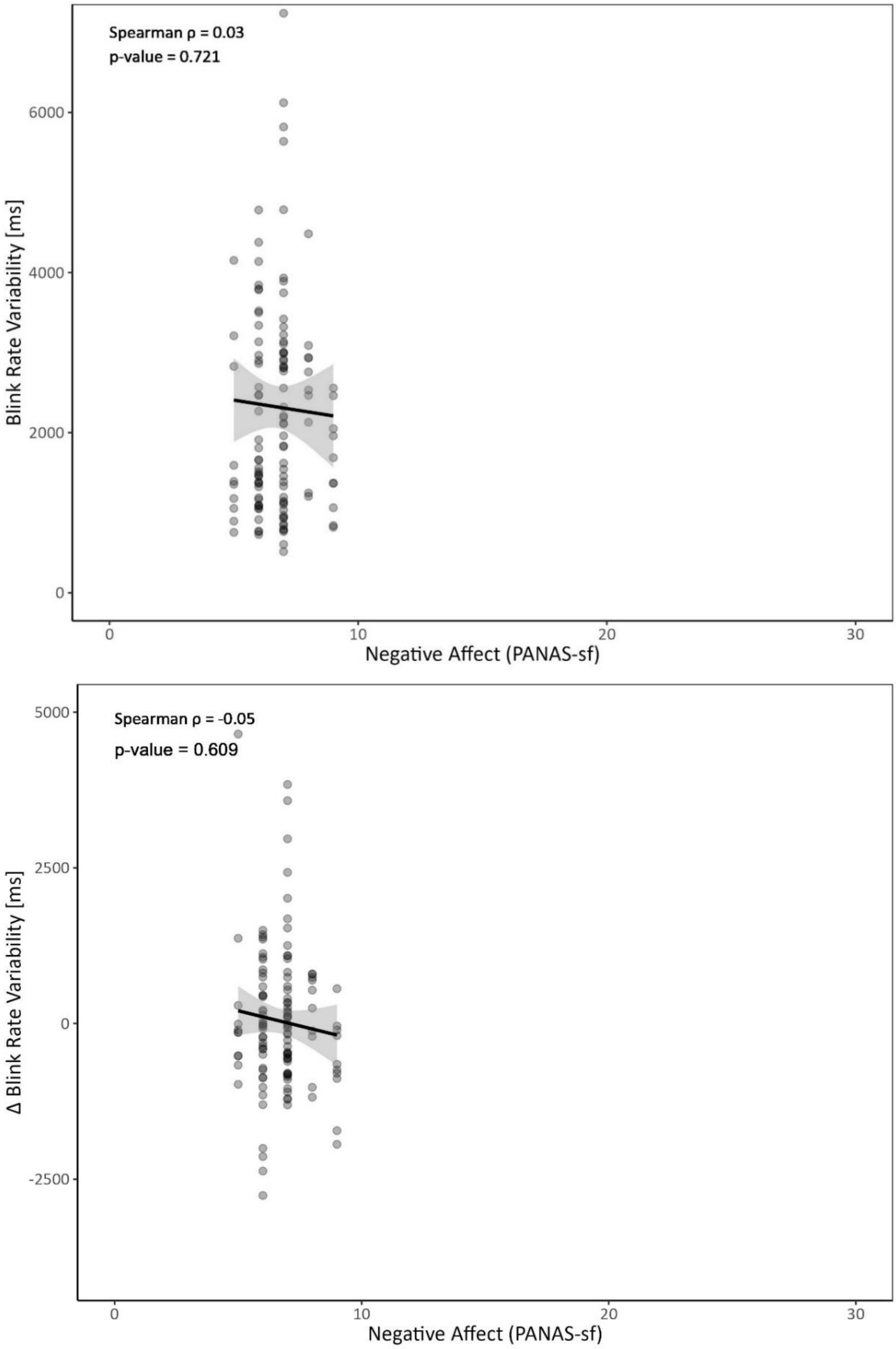


**Figure 23: Blink rate variability and Δ Blink rate variability per negative Affect (PANAS-sf).** Low Valence score indicates positive valence, high Valence score indicates negative valence. ΔBR describes deviation from individual's baseline BR. N = 21.

## German Summary: Zusammenfassung

Sogenannte *Urban Green Spaces* wirken positiv auf die Gesundheit, etwa in Bezug auf Stressempfinden oder Stimmung. So hat auch ein Spaziergang in der Stadt, besonders in *Urban Green Spaces*, zahlreiche positive Effekte. Dabei können einzelne Momente mit erhöhter emotionaler Erregung („*Arousal*“) über die Messung akuter physiologischer Parameter zuverlässig identifiziert werden. Jedoch ist es in Studien außerhalb des Labors nur eingeschränkt möglich, die Valenz dieser Momente zu bestimmen. Die hier vorliegende Studie untersucht Blinzeln als ein potenzielles physiologisches Maß für Valenz. Im ersten Teil wurden 32 Studienteilnehmer:innen bei einem Spaziergang auf einer vorbestimmten Route durch die Stadt begleitet. Dabei wurden elektrodermale Aktivität und Eyetracking, sowie GPS-Daten aufgezeichnet. Zwölf spezifische Orte auf dieser Route wurden ausgewählt, die alle eine hohe Erregung während des Spaziergangs aufwiesen. Im zweiten Teil wurde eine Bewertungsstudie durchgeführt, um die Valenz an diesen zwölf Orten zu bestimmen. Für jeden Ort wurde ein vierteiliges Bildset 145 Studienteilnehmer:innen präsentiert, das diese mithilfe des PANAS-sf und des *Affective Sliders* bewerteten. Die Zusammenführung beider Teile ermöglichte uns Zusammenhänge zwischen Valenz und Blinzelrate an einem Ort zu untersuchen. Obwohl frühere Studien eine Korrelation zwischen Blinzelrate und bestimmten emotionalen Zuständen gefunden hatten, zeigte sich in der hier vorliegenden Studie keine signifikante Korrelation zwischen Valenz und Blinzelrate oder deren Variabilität. Dennoch liefert diese Studie eine wichtige Grundlage für Forschung, die portables Eyetracking zur Untersuchung des Empfindens von unterschiedlichen urbanen Umgebungen einsetzen möchte. Dies wiederum kann uns dabei helfen, Städte zu designen, die sowohl uns Menschen als auch der Umwelt zugutekommen.