Understanding the Relationship Between People and Their Environments Using Smartphone Data: A Study of Personality, Places Visited, and Emotional Experiences

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Much has been theorized about the relationship between people and their environments. Certain people may be more inclined to visit certain types of places (e.g., campus, pub) and display different patterns of mobility as they move among them (e.g., number of places visited, distances traveled). Moreover, even the same place may affect people differently, depending on their psychological characteristics (e.g., personality). In this dissertation, I draw upon recent technological advances in smartphone-sensing methods to investigate the relationship between people's psychological characteristics and their physical movements through space.

I begin by reviewing the existing psychological literature. I next describe features that can be extracted from GPS data and categorize them to provide a framework for collecting, analyzing, and discussing mobility. Then, I conduct an empirical investigation demonstrating this methodology at work. One-hundred and eighteen participants provided ecological momentary assessments, reporting their places visited and emotional states (e.g., feeling stressed, relaxed, sad) four times per day for two to four weeks. In addition to these ecological momentary assessments, place and mobility data were also automatically collected for forty students using their smartphone's GPS sensors. I supplemented these data by collecting place attributions from an independent sample of 267 participants who evaluated the situational characteristics (e.g., sociality, positivity) of the most commonly visited locations. Lastly, I look at how people perceive places and whether their judgments about a location (e.g., predictions about the personality of those most likely to visit a location) demonstrate consensus or accuracy. A lens model analysis highlights the cues underlying these perceptions.

The results show how places visited (based on self-reported places) and mobility patterns (based on sensed GPS data) are related to people's in-the-moment emotional experiences and their enduring psychological characteristics, such as their personality and wellbeing. I also examine how one's personality interacts with the situational characteristics of a place to affect emotional states. For instance, one key finding reveals that, in general, participants experienced more positive emotions in social places (e.g., common rooms, pubs) but that this was especially true for more extraverted individuals. Lastly, I find that though people demonstrate consensus in their judgments when virtually visiting a place, they do not show significant accuracy.

My discussion focuses on the benefits of using place and GPS-based mobility measures to understand the relationship between people and their environments, as well as the unique methodological and logistical challenges inherent to this. I conclude by discussing potential implications for privacy and research ethics and point to promising directions for future research.

Declaration

This dissertation is the result of my own work and includes nothing that is the outcome of work done in collaboration except as declared in the Preface and specified in the text. It is not substantially the same as any that I have submitted, nor is it being concurrently submitted for a degree or diploma or other qualification at the University of Cambridge or any other university or similar institution except as declared in the Preface and specified in the text. This dissertation has about 38,000 words including appendices (but not Appendix H containing published material), bibliography, footnotes, and equations and has 44 figures and tables (excluding appendices). It does not exceed the prescribed word limit for the Degree Committee of the School of Biological Sciences.

Sandrine Ruth Müller
2018

To my parents

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Chapter 1. Introduction

Background

Traditional ways of studying mobility include surveys on commute trajectories or plane flight paths. With the advent of recent technological developments, research on human mobility has been changed dramatically. Mobility information about individuals has become widely available via applications that access a phone's global positioning system (GPS) data nearly continuously. The GPS is one of the most reliable, readily and often near-continuously available sensor data sources in a smartphone. Without requiring a phone or Internet connection, it captures information about places visited, distances traveled, and daily routines.

However, this rich source of information on human mobility and its psychological significance are not well-understood. Here I examine how GPS measures are related to psychological states and traits. Human mobility describes individuals' movement in the physical space that surrounds them (McInerney, Stein, Rogers, & Jennings, 2013). Understanding human mobility has applications in areas as far ranging as the spreading of diseases, city planning, and traffic engineering (see Harari, Müller, Aung, & Rentfrow, 2017 for an overview). By studying human mobility patterns and locations visited using the capabilities of modern smartphones, it may be possible to uncover new insights into human psychology.

It is also important to note, however, that the advent of recent technological advances, such as the widespread availability of GPS data, has enabled more and more companies to access their customers' detailed location histories. While the primary focus of this dissertation is to advance our psychological understanding, the general discussion relates to the potential implications of this technology for privacy and research ethics.

I begin by reviewing the existing psychological literature. I then describe features that can be extracted from GPS data and categorize them to provide a framework for collecting, analyzing, and discussing mobility.

Smartphone sensing.

Previous studies using more traditional research methods have uncovered many valuable findings about the relationship between people's minds and their movements through space. However, like all research, these investigations suffer from some limitations. The most significant limitation is that most data are cross sectional rather than longitudinal. As a result, the fine-grained daily behavioral patterns that might reveal more detail about people's psychology remain unexamined. Questionnaires are also costly to administer, subject to reporting biases, and do not scale well.

Smartphone apps can help us overcome these limitations. Smartphones are ubiquitous, computationally powerful mobile sensors with a penetration rate of up to 91% among 18-24 year olds in the United Kingdom (Google, 2013). As no face-to-face interaction with the participants is required (because applications can be downloaded online), they allow researchers to easily recruit large and diverse samples at low cost, while providing comprehensive longitudinal data that can be collected automatically without taxing participants. Such technologies also enable experience sampling methods, such that thoughts, feelings, physiological measures, and behavior can be reported by participants in the natural, spontaneous contexts in which they occur. This methodology offers researchers the capability to obtain higher resolution data (and make much more accurate estimations of the frequency of events) than traditional forms of psychological assessment.

Variables related to student wellbeing that can be recorded include:

- Physical activity, mobility (from the accelerometer, GPS / Wi-Fi),
- Socializing / isolation, emotional affect (from Bluetooth, microphone, call & text logs, social media APIs, contacts),
- Environmental factors (from the light / temperature / pressure sensors, photographs),
- Interests (browser history, running / installed apps, music/image/video files),
- Activities engaged in (e.g., shopping),
- Context (e.g., location) (e.g., Harari et al., 2016; Harari, Müller, & Gosling, 2018; Harari, Müller, Aung, & Rentfrow, 2017).

Additionally, participants can respond to ad hoc questionnaires that measure various psychological constructs (e.g., mood, stress level, or current behaviors).

***Capturing and processing location data from smartphones*.**

Most relevant for the work presented in this dissertation is the ability of smartphones to capture location. Virtually all smartphones have a Global Positioning System (GPS) receiver. GPS is the world's most prevalent global navigation satellite system and is owned by the U.S. government (Crato, 2010; National Coordination Office for Space-Based Positioning, Navigation, 2017). GPS receivers are able to receive signals from satellites orbiting Earth and compute their position from it using triangulation. Receivers are passive and do not send signals out, but in combination with mobile communication systems, phones may pass position data onto third parties. The accuracy of GPS location detection depends on numerous factors, such as satellite geometry, receiver quality, and whether an obstacle (such as a building) blocks the direct line of sight between the receiver and the satellite. GPS-enabled smartphones are usually accurate within a 4.9m radius (van Diggelen & Enge, 2015), although accuracy decreases near obstacles and GPS receivers vary in quality, some phones may have full GPS chips, while others combine GPS data with cell tower data (LaMance, Jarvinen, & DeSalas, 2002).

According to the National Coordination Office for Space-Based Positioning Navigation (2017) wrong locations are more often caused by issues with mapping software than with GPS hardware. Mapping software converts the GPS position into longitude, latitude, and altitude data. Examples of mapping software include Google Maps and Apple Maps. By combining this typically accurate location data with a time stamp, researchers can nearly continuously measure where people spend their time and how they move between these places in a way that was never before possible.

Practically, many steps need to be performed to get GPS data into a usable format. A researcher working with this data must remove outliers and data points with very low accuracy or very little data and then identify and remove possible duplicate GPS recordings (this is so higher quality readings can be kept if there are multiple). Depending on the research question, one might also want to remove data that has been generated while the device was non-stationary (e.g., the user might have been moving from one place to another).

Missing data requires special consideration. Gaps in the GPS recordings could be due to a device having run out of battery or having been switched off, the location services having been disabled, or no signal being available in a specific place. This is of particular importance when setting up a mobile sensing system. Usually developers opt to collect sensor data such as GPS recordings either through periodic or adaptive sampling (or, ideally, through a combination of both). An app might maintain a constant connection to the GPS service or check the GPS location periodically and only record location changes. While purely adaptive sensing is more difficult to interpret due to a lack of information about why data may be missing, an app that collects data periodically tends to get force-quit by the operating system sooner and thus, might not be able to collect data as continuously. Figure 1 provides an example of GPS data collected via a smartphone.

time	timeMillis	latitude	longitude	bearing	altitude	provider	accuracy	speed
2018-01-08T13:39:03.449+01:00	1515415143450	50.28497065549101	19.01416527467964	0.0	354.5770097147841	gps	192.0	0.80142
2018-01-08T13:39:04.397+01:00	1515415144397	50.284743971330585	19.01284676332055	0.0	446.6360255917781	gps	192.0	0.38110745
2018-01-08T13:39:05.382+01:00	1515415145382	50.2847898632255	19.012942008451844	0.0	445.76333837372823	gps	192.0	0.5107907
2018-01-08T13:39:06.380+01:00	1515415146381	50.284735728773605	19.014055642493624	0.0	384.63564747982736	gps	96.0	0.64313567
2018-01-08T13:40:26.909+01:00	1515415226909	50.284898789953964	19.013831349838522	0.0	389.0035218563274	gps	200.0	1.8857148
2018-01-08T13:40:27.919+01:00	1515415227919	50.28460638064444	19.014045043155154	0.0	353.5199843073529	gps	64.0	0.63065493
2018-01-08T13:40:28.942+01:00	1515415228942	50.28483970003967	19.01396440308273	0.0	358.08804444561997	gps	64.0	0.16002706
2018-01-08T13:40:29.934+01:00	1515415229934	50.2848873071775	19.013901643292346	0.0	374.24019101499334	gps	64.0	0.19561744
2018-01-08T13:40:30.934+01:00	1515415230934	50.28483679036941	19.013939187981116	0.0	367.31603672682	gps	64.0	0.21775605
2018-01-08T13:40:31.936+01:00	1515415231936	50.28485382834336	19.01400035768771	0.0	361.27143787561243	gps	64.0	0.5869531

Figure 1. Example smartphone GPS data output

Depending on the research question, scientists might then want to convert the raw GPS readings into features. As such, it might be insightful to get an overview of the quality of the data collected first (e.g., compute the number of hours a user has valid data for in a given day). This can be used to filter out users or days (or a combination thereof) that don't meet a certain threshold. For example, Wang et al. (2019) suggested a threshold of 12 hours with at least one GPS recording per day, but the granularity and coverage needed may vary depending on the research question at hand. Setting a high threshold might significantly reduce the size of the dataset.

Moreover, to identify specific places a person visited and the duration of his or her stay, a researcher must first cluster the GPS data. As location data is scattered around the true location of a user (e.g., a certain coffee shop), the raw location data cannot be used to determine whether two of a user's GPS traces were in the same place as they will differ at least slightly. Therefore, researchers usually opt to cluster the data points and determine what are known as 'significant' locations, which correspond to cluster midpoints. One such clustering procedure is presented in Tsapeli & Musolesi (2015), who suggested excluding GPS recordings with more than 50 meters accuracy and those recorded while users were moving. The algorithm then iterates over all GPS samples and creates clusters for which each location point is at most 200m away from the centroid.

In general, unlike traditional methods, working with mobile sensing data requires a significant amount of pre-processing and some technical expertise. However, this burden may be outweighed by the benefits this methodology offers to enhance our understanding of psychological phenomena, such as human mobility.

Mobility as a dimension of persons.

Human mobility refers to people's physical movement through space and the patterns underlying this behavior. These patterns can be highly individual and highly predictable (McInerney et al., 2013).

The advent of sensing methodologies has inspired many new studies on physical movement. These studies typically measure physical activity and mobility patterns (Harari et al., 2017). Physical activity refers to behaviors such as being stationary, walking, or running and is normally measured using the accelerometer sensor (Lane et al., 2010; Miluzzo et al., 2008). Mobility patterns refer to the trajectories of human travel and are typically measured using GPS, cell network, and WiFi data (Harari et al., 2017). They can include the distances a person travels, the number of places they visited, and the amount of time they spent in transit (Saeb, Lattie, Schueller, Kording, & Mohr, 2016). In recent years, researchers have begun to study human mobility patterns more closely to understand what these patterns reveal about us. Here, I review the existing work to offer insight into how to integrate mobility data into psychological research.

There has been a considerable amount of work on mobility in other fields. This includes research exploring population-level mobility (i.e., commute patterns), epidemiological investigations into how diseases spread based on mobility patterns, or studies examining the spread of information. For example, Castro, Zhang, & Li (2012) built future traffic density and air quality prediction models for a Chinese city based on the GPS traces of 5,000 taxis collected over one month. Molnar et al. (2013) used data from GPS devices installed in cars to compare participants' self-reported driving behavior with their actual driving patterns.

De Montjoye, Hidalgo, Verleysen, & Blondel (2013) studied a large dataset of mobility traces recorded for 1.5 million people over the course of 15 months. They found that human mobility is highly unique, such that only four spatio-temporal points were required to uniquely identify 95% of individual mobility traces in their dataset – and at most eleven points were required to identify all traces. This highlights that only coarsening a dataset, which is when the number of available location records per person are reduced, does very little to increase anonymity.

Analyzing the location traces for 100,000 mobile phone users collected over a six-month period, Gonzalez, Hidalgo, & Barabasi (2008) found that human mobility patterns display significant regularity as people frequently return to a few locations (e.g. work, home). More recently, topics such as the relationship between mobility and social network interactions have also garnered attention. De Domenico, Lima, & Musolesi (2012) found that location predictions could be further improved by additionally considering the movements of related entities, such as friends and acquaintances. Further underlining the importance of one's social network, Farrahi & Gatica-Perez (2009) showed that one's location and one's proximity to others are so highly related that one can be used to accurately predict missing data for the other. Beyond social ties, network proximity, and friendship, mobility behaviors have been linked to a variety of psychological characteristics, such as mood, well-being, anxiety, personality, and mental health disorders, including depression, schizophrenia, and bipolar disorder. I will explore each in turn below.

Mood: Epstein et al. (2014) found mood, stress, and drug cravings to be related to the characteristics of the particular neighborhood 27 drug users found themselves in over the course of 16 weeks. Kaspar, Oswald, Wahl, Voss, & Wettstein (2015) found a particularly strong effect between mood in older adults and mobility patterns related to recreational and social activities (based on self-reported mobility patterns). In addition, they found a relationship between mood on the weekends and time spent out-of-the-home (based on GPS data). Further support for this relationship was uncovered by Chow et al. (2017), who found that affect was related to time spent at home using a sample of 72 students whose GPS data was recorded for two weeks. Relatedly, Sandstrom, Lathia, Mascolo, & Rentfrow (2017) found that participants reported more positive moods in social places (compared to being at home) and at home (compared to being at work). These relationships held for both self-reported location (n=6759 participants) and sensed locations (n=3646 participants). Taken together, these studies suggest that those who spend more time outside of the home, particularly in social and recreational settings, experience more positive moods.

Servia-Rodríguez et al. (2017) found strong relationships between behavioral routines that can be passively captured via smartphones and psychological variables, such as personality, wellbeing, and mood in a large dataset collected over 3 years on 18,000 users. In particular, they were able to predict mood with an accuracy of about 70%. These predictions were primarily based on accelerometer, microphone, and call/text data. With regards to location data, they extracted number of locations visited per day, time spent at each location, and location changes. They found number of locations visited per day to be corelated with age, occupational status and education, but not with any of the psychological variables, such as personality or well-being. As a result, they did not include location sensor data as inputs to the deep neural network used to predict mood from passively sensed behaviors.

Well-being: Jaques et al. (2015) studied 68 students using tracking devices over the course of one month. From participants' mobility behaviors, the authors extracted the radius enclosing location samples, time spent indoors and outdoors, time spent on campus each day, as well as irregularity measures. In their analyses, the authors found that time spend outdoors and deviation from one's normal routine were strongly related to daily feelings of happiness.

Anxiety: Boukhechba et al. (2017) studied the correlates of social anxiety in a sample of 54 students, who provided smartphone data over the course of a two week period. The GPS data was semantically labeled using the OpenStreetMap database, allowing the authors to compute time spent in different types of locations as well as measure the diversity of the places visited. Time spent in restaurants as well as place diversity were found to be significantly negatively corelated with social anxiety. Huang et al. (2016) labeled the locations 18 students visited over ten days using Foursquare. They found that places visited and location transitions are related to social anxiety. However, Saeb, Lattie, Kording, & Mohr (2017) found no consistent relationship between depression or anxiety and the time spent at different types of places in a sample of 208 participants tracked over six weeks (with semantically labeled locations from Foursquare). Chow et al. (2017) studied 72 students who used the Sensus smartphone app over the course of two weeks. They found that higher social anxiety was related to more time spent at home, and that in students with higher social anxiety, negative affect in a day was related to more time spent at home during the next day, possibly suggesting a positive feedback loop leading to both greater negative emotions and more sedentary behaviors.

Stress: Jin, Xue, Li, & Feng (2016) studied 57 teenagers over the course of six months. They found that the congruence between the time/location of any given mobility segment and participant's typical lifestyle predicted lower stress. Sano & Picard (2013) recruited 18 participants who provided location data over five days. They extracted the mean, the standard deviation, and the median of the radius and distance. They did not find mobility to be related to stress in their correlation analysis, but only the mean of the standard deviation of the radius were selected as significant predictors in their machine learning model. Counter to the findings regarding positive mood, Tsapeli & Musolesi (2015) found that for the 48 participants in the StudentLife dataset (collected via a smartphone app over ten weeks) spending time outside of one's home and working environment had a positive effect on stress. No other GPS-based metrics were used outside of semantically labeled locations. Werner et al. (2012) studied 76 older adults with cognitive impairments as well as those caring for them using tracking device over the course of four weeks. Mobility in care-recipients was negatively related to the burden on those providing care. The strongest relationships were with the number of places visited, the time spent walking, and the average number of walking tracks per day.

Personality: In an explorative investigation using the location data of five participants tracked over a period of six months, Kim, Koo, & Song (2016) show that personality can be used to predict participants' probability to be in different locations at different times of the day. For example, higher neuroticism was related to a higher probability of being at school at midnight. As described earlier, Servia-Rodríguez et al. (2017) found no relationships in their large-scale study between personality and mobility behaviors – operationalized as the number of locations visited per day, the time spent at each location, and the number of location changes. Sandstrom et al. (2017) found evidence for a moderating effect of personality traits on the relationship between location and mood. However, the effects found were small and inconsistent between self-reported locations and sensed locations. Sokasane & Kim (2015) studied the relationship between mobility and personality. In their sample of 30 users, who provided data for one month, they found that the mobility metrics they employed - number of locations visited and the distance covered - were correlated with extraversion from the Myers-Briggs Type Indicator. It is important to note that the Myers-Briggs Type Indicator has been widely challenged by personality psychologists (Boyle, 1995; Pittenger, 2005). Srivastava, Ahuja, & Tyagi (2013) used a dataset of 150 users, collected over two years by Microsoft Research Asia, to study the relationship between Keirsey Temperament classes and sensed locations (as well as to what extent this relationship could be predicted by raters). They processed the GPS data to extract the categories of visited places as well as the occurrence of each category type.

Mental health - depression: Using their MoodTraces smartphone app, Canzian & Musolesi (2015) studied 28 people over two weeks. From the GPS data, they extracted distance covered, maximum distance between two locations, radius of gyration, standard deviation of displacements, maximum distance from home, number of different places visited, number of different significant places visited, and routine index. They found that maximum distance between two locations and the routine index were the strongest predictors of depression. A model designed to detect depression based on the collected mobility metrics achieved good performance. Using the Purple Robot smartphone app, Saeb et al. (2015) studied 28 people over two weeks. They found depression was related to a number of GPS-based mobility metrics, such as circadian rhythm and location variance. Moreover, they were able to build a model that accurately distinguished between participants with and without depressive symptoms (accuracy=86.5%). In a follow-up study, conducted on the StudentLife dataset (collected on 48 students over the course of ten weeks), Saeb et al. (2016) replicated their findings, and additionally found that the relationships between depression and mobility metrics were stronger if the features were measured on weekends, compared to weekdays. In their study of 208 participants, who logged their locations over the course of six weeks, Saeb et al. (2017) show that a combination of phone sensor data and Foursquare queries can be used to detect semantic locations with good accuracy. However, they find that the type of places people visit only accounts for a small proportion of participants' anxiety and depression.

Mental health - schizophrenia: Wang et al. (2017) found that changes in behavior in schizophrenic patients could be predicted by a variety of data passively collected from smartphones. They captured distance traveled, number of places visited, and location entropy from the GPS sensor, but only found number of visits to places in the morning to be a relevant predictor in a linear regression model. Their study was based on 36 patients with multiple months of data for each individual.

Mental health - bipolar disorder: In a similar vein, Gruenerbl et al. (2014) showed that in bipolar patients, GPS-based metrics could help detect behavioral changes linked to the patients' condition. They conducted their investigation on 12 patients who provided 12 weeks of data on average. The extracted GPS-based metrics included number of locations visited, distances traveled, and metrics related to outdoor stays.

How can we quantify GPS-based mobility?

To facilitate research in this area, I provide a list of mobility features that can be extracted from GPS data, so that other researchers have a common platform for talking about, evaluating, collecting, and analyzing this data. Table 1 presents a summary of daily mobility metrics that can be computed based on GPS data. I grouped them into the categories of distance measures, place measures, sequence and routine metrics, entropy metrics, and other metrics. All references to the literature containing the exact formulae have also been included in Table 1. A tile sequence refers to a time series of locations sampled at 10-minute intervals.

Distances measures include the total distance covered, the spatial coverage by tiles (number of unique tiles visited), the spatial coverage by convex hull (smallest Euclidian space that contains all location points), the maximum distance between two locations, the maximum distance from home, the standard deviation of the displacements (standard deviation of the distances between each place and the subsequent one), and the location variance (combined variance of latitude and longitude values).

Places measures include number of places visited (in a stricter definition, Servia, Rachuri, & Mascolo (2017) consider a place visited only if a person has spent at least one hour there), location changes per day, time spent at home, time spent at each location, and transition time.

Sequences and routines measures quantify how different the places visited by a user are across days. More precisely, this is operationalized as the similarity between two sequences of tiles (i.e., the minimum number of insertions, deletions, and substitutions required to transform one string of tiles into the other). A similar metric can be calculated on the place sequence (the similarity between two sequences of place identifiers). Circadian movement describes regularity in 24-hour rhythm. It captures to what extent a participant's sequence of locations follows a 24-hour rhythm. If a participant visits the same places at similar times each day, the circadian movement will be high, while it will be low for participants with irregular patterns.

Entropy measures capture how a participant's time was distributed over different locations. High entropy indicates that a participant spent his or her time evenly distributed across different location clusters, while low entropy indicates that the time was unevenly spent. Normalized entropy is the entropy controlling for the number of location clusters; hence, it always lies between 0 (all location data points belong to the same cluster) and 1 (all location data points are uniformly distributed across all clusters). Raw entropy is entropy based on GPS data points before clustering. Displacement entropy describes the predictability of daily movement patterns and is computed as the entropy of distances travelled in 10-minute time windows during the day. The radius of gyration is the deviation from the centroid of the places visited, weighed by time spent in each place.

Other measures include the mean of the instantaneous speed (in degrees/sec) at each GPS data point, the variance of the instantaneous speed (in degrees/sec) at each GPS data point, and indoor mobility.

Table 1

Summary of Daily Mobility Metrics Computed Based on GPS Data

Metric	Description	Reference
	Distance metrics	
Total distance		
• Total Distance Covered	Sum of the distance between each longitude/latitude pairs and the subsequent pair	(Canzian & Musolesi, 2015; Saeb et al., 2015)
• Spatial coverage by tiles approximation	Number of unique tiles visited (square tiles with 50m long sides mapped onto space)	(Mehrotra & Musolesi, 2017)
• Spatial coverage by convex hull approximation	Smallest Euclidian space that contains all location points	(Mehrotra & Musolesi, 2017)
Span and variations		
• Maximum distance between two locations	Maximum span of the area covered	(Canzian & Musolesi, 2015)
• Standard deviation of the displacements	Standard deviation of the distances between each place and the subsequent one	(Canzian & Musolesi, 2015)
• Maximum distance from home*	Maximum distance from the location cluster labeled as home (see *Note*)	(Canzian & Musolesi, 2015)
• Location variance	Combined variance of latitude and longitude values	(Saeb et al., 2015)
	Place metrics	
Amounts		
• Number of locations visited per day	Number of locations visited	(Canzian & Musolesi, 2015; Saeb et al., 2015)
Time spent		
• Time spent at each location	Average time spent at each location	(Servia-Rodríguez et al., 2017)
• Home* stay	Percentage of time spent at home	(Chow et al., 2017; Saeb et al., 2015)
• Transition time	Percentage of time spent in transit	(Saeb et al., 2015)
Variations		
• Location changes	Number of location changes	(Servia-Rodríguez et al., 2017)

Note. Home (*) can be operationalized as the location where the user is most often found at 2:00 a.m., 6:00 a.m., and 8:30 p.m. during weekdays (Canzian & Musolesi, 2015). Depending on the research question at hand, these metrics could of course also be computed with respect to a different location, e.g., a user's workplace.

Summary of Daily Mobility Metrics Computed Based on GPS Data - continued

Metric	Description	Reference
	Distance metrics	
Total distance		
• Total Distance Covered	Sum of the distance between each longitude/latitude pairs and the subsequent pair	(Canzian & Musolesi, 2015; Saeb et al., 2015)
• Spatial coverage by tiles approximation	Number of unique tiles visited (square tiles with 50m long sides mapped onto space)	(Mehrotra & Musolesi, 2017)
	Entropy measures	
Radius of gyration	Deviation from the centroid of the places visited, weighed by time spent in each place	(Canzian & Musolesi, 2015)
Entropy	Measurement of how a participant's time was distributed over different locations	(Saeb et al., 2015)
Normalized entropy	Entropy controlling for the number of location clusters (mobility between favorite locations)	(Saeb et al., 2015)
Raw entropy	Entropy based on GPS data points before clustering	(Saeb et al., 2015)
Displacement entropy	Predictability of daily movement patterns as entropy of displacements (distances travelled in 10 minute time windows during the day)	(Mehrotra & Musolesi, 2017)
	Sequences and routines	
Routine index	Quantification of how different the places visited by a user are across days	(Canzian & Musolesi, 2015)
• Circadian movement	Regularity in 24-hour rhythm as amount of energy (power spectral density) that fell into the frequency bins within a day period	(Saeb et al., 2015)
Tiles sequence	Similarity between two sequences of tiles (time series of locations at 10 minute intervals) as minimum number of insertions, deletions, and substitutions required to transform one string into the other.	(Mehrotra & Musolesi, 2017)
Place sequence	Similarity between two sequences of place identifiers as minimum number of insertions, deletions, and substitutions required to transform one string into the other.	(Mehrotra & Musolesi, 2017)
	Other	
Speed mean	Mean of the instantaneous speed (in degrees/sec) at each GPS data point,	(Saeb et al., 2015)
Indoor mobility	Measure of how much a student is moving in buildings during a day	(Wang et al., 2014)

Note. Home (*) can be operationalized as the location where the user is most often found at 2:00, 6:00 and 20:30 during weekdays (Canzian & Musolesi, 2015). Depending on the research question at hand, these metrics could of course also be computed with respect to a different location, e.g., a user's workplace.

Places as a dimension of environments.

Environments are important—everything we do happens within a physical context. People make decisions about where to go multiple times a day. One might go for a walk to clear one's thoughts or go to work in the buzzy environment of a lively coffee shop or watch a movie from the comfort of one's sofa at home. Places evoke emotions, create a backdrop for activities, and shape the situation a person experiences (Graham & Gosling, 2011). Features of a space may influence activities (e.g., reading, talking to a friend), which affect emotions (e.g., relaxation), but ambient features might also directly impact mood (Küller, Ballal, Laike, Mikellides, & Tonello, 2006). Buss (1987) proposed that people alter their environments by selection (e.g., by choosing to seek out or avoid certain people or places), manipulation (e.g., changing an environment or a person), and evocation (i.e., by eliciting reactions from others).

To date, psychology has paid much more attention to understanding persons rather than their environments. As such, characteristics such as personality traits are well-studied (Mccrae et al., 1991). However, only more recently have the characteristics of situations and environments started receiving more attention (Rauthmann et al., 2014).

Recent technological developments such as the advent of smartphones make it easy to capture information about both people and their environments continuously as they go about their day (Harari et al., 2017). Yet, the empirical psychological literature says very little about how we can use people's mobility patterns or the continuous stream of places they visit to learn more about their psychology.

Google Streetview and the Google Places API.

In addition to pure location data, publicly available datasets and API's have made it possible to further enrich this data by merging in additional information. This could be socio-economic ZIP code level data from statistical offices, weather data, or popularity among

Foursquare users. For example, the longitude/latitude coordinates collected by a smartphone app via the GPS sensor can be processed using the Google Maps API (Google, 2018), via the googleway package (Cooley, 2018) in R (R Core Team, 2013). This returns information related to this place, such as nearby places of interest (e.g., shops, public institutions, or sights, but not residential places) for which, in turn, more information can be accessed (e.g., category labels, address, contact details, and opening hours). Longitude/latitude coordinates can also be directly entered into Google Maps to access Streetview images of the outside of a place and its surroundings.

The present research

This present research complements and extends upon past work in this area in the following ways.

First, there are many different metrics used in the literature, and each study only employs a limited number of them with little consistency regarding the metrics used. As such, it is difficult to conclude which GPS-based mobility metrics are the most promising for psychological research or how they compare to each other in predicting psychological traits. Thus, I begin by providing an overview organizing the diverse mobility metrics into a unifying framework. I then conduct a study using a broad range of 22 GPS-based metrics, allowing for between-metric comparisons. Together, I hope these approaches better inform our understanding of different metrics and help psychologists identify which mobility metrics they should adopt in future research.

Second, past research is also limited in terms of the psychological rigor of the measures used. For instance, the psychological instruments used in past work are sometimes less valid than those used in academic psychology (e.g., using Myers-Briggs Type Indicator instead of the Big Five to capture personality). Moreover, as with mobility metrics, many studies use only a small and distinct set of psychological measures typically capturing only traits or states, which precludes comparisons between studies.

To address these issues, in the present research, I deploy a broader set of psychological measures capturing stable individual differences (i.e., personality, well-being), transitory psychological states (i.e., ecological momentary assessments of mood) and consensual characterizations of locations (i.e., situational characteristics of places). I also use measures that have been previously-validated in academic psychology (i.e., BFI-44, WHO-5, DIAMONDS) and provide estimates of their reliability in the samples collected. Furthermore, rather than simple correlations, when appropriate, I utilize more advanced statistical and methodological techniques (e.g., lens model analysis, linear mixed-effects modeling, hierarchical regression) to more adequately investigate the complex relationships between psychology and mobility. Through these additions, I hope to strengthen the rigor and validity of the psychological conclusions drawn.

In this dissertation, I conduct an empirical investigation demonstrating how smartphone sensing methodologies and related technologies can be used to study the relationship between people's psychology and their physical movement through space. One-hundred and eighteen participants provided ecological momentary assessments, reporting the places they visited and their emotional states (e.g., feeling stressed, relaxed, sad) four times per day for two to four weeks. In addition to these ecological momentary assessments, place and mobility data were also collected for forty students using their smartphone's GPS sensors. I supplemented these data with an independent sample of 267 participants who evaluated the situational characteristics of places visited (e.g., sociality, positivity). The results show how places visited (based on self-reported places) and mobility patterns (based on sensed GPS data) are related to people's in-the-moment emotional experiences and their enduring psychological characteristics, such as their personality and wellbeing. I also examine how one’s personality interacts with the situational characteristics of a place to affect one’s momentary emotional states. Thus, these new methods can shed light on some long-standing questions in psychology.

Chapter 2. The Student Wellbeing Study

The aim of the Student Wellbeing Study was to study daily behavioral patterns and how these patterns relate to a person's psychological states and traits. Participants tracked their psychological states and daily activities in social, academic, and health domains (e.g., stress and emotional levels, patterns of sleep, physical exercise and work). This was done using ecological momentary assessments (EMAs) and, for a subset of participants, smartphone tracking software as well. The tracking portion of the study involved two phases. The first phase occurred for two weeks during the middle of the academic year (February 2016), and the second phase occurred at the end of the school year (May/June 2016). See Figure 2 for an overview of the timeline.

Participants

One-hundred and eighteen undergraduate students at the University of Cambridge participated in the first phase of data collection. Ninety-one of these students participated in the second phase as well. Forty participants (33.9% of the sample) during the first phase and 28 (30.77% of the sample) during the second phase had a smartphone compatible with our tracking software (i.e., Android), enabling us to collect such data. The sample was 62.61% female, with an average age of 19.10 years. Students were enrolled in 28 different courses, and were members of 30 (out of 31) colleges at the University of Cambridge. Eighty-five students were originally from the UK (73.91%), 15 (13.04%) from the EU, and 15 (13.04%) were other internationals. Fifteen (12.71%) were first generation students, and the dominant ethnicity was White (68.64%), followed by Asian (20.34%).

Procedure

At the beginning and end of both phases of data collection, participants filled out longer, comprehensive questionnaires (see Appendix A) that included psychological scales measuring wellbeing, where individuals turn for advice and support within and outside of the university, health, adjustment to university life, personality, and sociability. Moreover, participants kept a digital diary, in which they indicated at the end of each day whether and when they had engaged in sleeping, working, eating, relaxing, socializing, or other activities (see Figure 3). The EMA questionnaires were hosted on Qualtrics.com with reminders sent to participants via SMS by SurveySignal (Hofmann & Patel, 2015), and the diary was hosted on a website by heroku.com (Salesforce) with reminders displayed at the end of the final EMA survey for the day and sent via email (see Table 2).

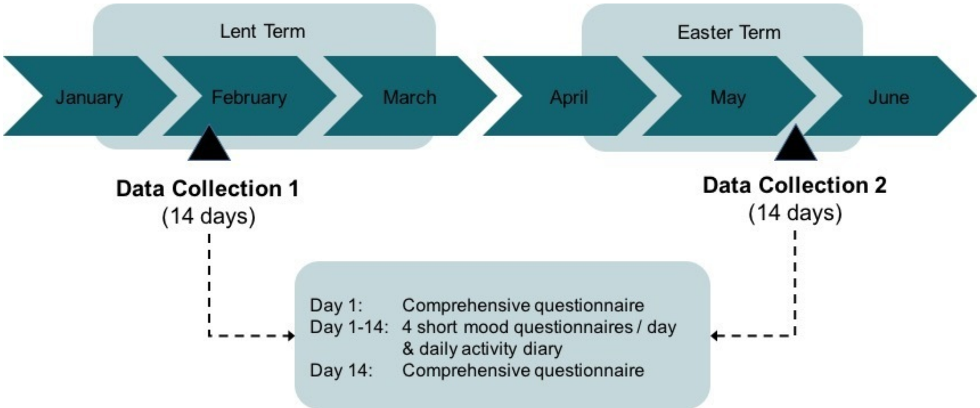

Figure 2. Timeline of the study during the second and third term of the academic year 2015/2016 at the University of Cambridge.

Table 2 provides an overview of the specific tools employed to collect each type of data. The study procedures received ethical approval from the Cambridge Psychology Research Ethics Committee at the University of Cambridge on December 21, 2015 and May 11, 2016 (amended) under protocol number PRE.2015.102.

Tools and measures

Table 2 provides an overview of the data collection tools employed. Table 3 provides an overview of the data collected, including the survey measures. The EMA measures collected only during Phase 2 (satisfaction with self, narcissistic rivalry and admiration) will not be discussed in this dissertation. However, the results of all analyses performed for the other affective states can be found for these additional variables in Appendix C as well. Descriptive statistics for the survey measures can be found in Table 4.

Due to the originally selected smartphone sensing application becoming unavailable shortly before the start of data collection, the data was collected with the help of a set of different tools. During the first phase, all participants responded to the longer pre and post surveys, as well as the short ecological momentary assessments (EMAs) on Qualtrics.com. The diary was hosted on a website by heroku.com. Participants received reminders to respond to the EMAs via text message (sent by SurveySignal). Reminders for the pre and post questionnaires, as well as the daily diary entries, were sent via email. The last EMA of the day also redirected participants from Qualtrics.com to the diary website. In addition, Android users downloaded the EasyM application that collected sensor data from their GPS (location) and accelerometer (movement) sensors, as well as call and text log data.

During the second phase, the same system was used for non-Android users, and all users responded to pre and post questionnaires through Qualtrics.com. However, Android phone users were able to download the MyLifeLogger application (Mehrotra, 2016) that allowed them to respond to EMAs and fill out the diary within the app. The application collected objective behavioral information through mobile sensing—e.g., sensing physical activity from the accelerometer, location from the GPS, and socializing from in and outgoing texts and calls. In addition, the app also collected notification and app usage data. Figure 3 depicts examples of the MyLifeLogger user interface.

The EasyM application for Android, which was used during the first phase of the study, was developed by Neal Lathia (then at the Computer Laboratory at the University of Cambridge) and colleagues, but has since been discontinued (Lathia, 2019). The MyLifeLogger Android app used during the second phase was developed by Abhinav Mehrotra in the Department of Geography at University College London (Mehrotra, 2016).

Details regarding both applications are provided below. However, the primary focus will be on the MyLifeLogger app as it was more heavily used in the present research, and I was involved in the creation of this application. Moreover, publicly available documentation for EasyM can be found online (Lathia, Rachuri, Mascolo, & Roussos, 2013).

EasyM used the ESSensorManager to obtain passively sensed information from smartphone sensors, which is described in detail in Lathia et al. (2013). As opposed to MyLifeLogger, EasyM did not rely on adaptive sampling, which adds a new record for location only when the location has changed. EasyM also allowed researchers to prompt participants to respond to questionnaires, though this functionality was not used in the current research. EasyM was solely loaded on participants' phones to perform passive data collection. The EasyM application has been used in past studies, such as Moran, Culbreth, & Barch (2017), Lee, Efstratiou, & Bai (2016), and Galante et al. (2018).

MyLifeLogger performed continuous sensing in the background, logging:

- Notifications (arrival and removal time of notifications, as well as the name of the application that triggered the notification)
- Application usage (name of used application, time of launch and time when usage was completed)
- Phone interaction (time at which the phone was locked or unlocked; time, type and application used during interactions with the phone screen such as clicking or scrolling)
- Call and text logs
- Location (geo-location)
- Activity (physical activities, such as walking and running)

Like EasyM, MyLifeLogger uses the ESSensorManager (Lathia et al., 2013) to obtain context information. Specifically, MyLifeLogger connects to Android's

NotificationListenerService (Google, 2016a) and UsageStatsManager (Google, 2016b) to track notifications, as well as application and phone usage. The app relies on the LocationManager (Google, 2016c) to capture geo-location and the Activity API (Google, 2016d) to record physical activities. Call and text logs are retrieved from CallLog (Google, 2016e) and Telephony.Sms (Google, 2016f), respectively. Information from the activity API is requested once per minute, while full logs are recorded for notifications, application usage, phone interaction, call logs and text logs. Adaptive sampling was chosen for the location – recording the location only when the user changes their location. Among all of the data collected by the MyLifeLogger app, the data that requires the most energy to record is the location data (Canzian & Musolesi, 2015). The procedure described in Canzian & Musolesi (2015) was therefore implemented to determine what location sampling rate, provider and accuracy would be appropriate for research while also energy efficient. When individuals download and install the MyLifeLogger app, they are required to agree to a consent form as well as to permission requests mandated by the Android operating system to ensure they are aware of the types of data captured by the app.

In addition to the passive sensing component, MyLifeLogger allows users to actively log their responses to short mood surveys and to record their daily activities (eating, sleeping, working, exercising, socializing, relaxing, other). Mood surveys were initiated four times per day and a reminder to log daily activities was sent once at the end of each day (see Figure 3).

The main limitations of this approach are that no API is available to retrieve location information in a more intuitively usable format. Instead, raw locations are obtained and need to be processed before including them in any analysis. Location clustering, labeling, and feature extraction was hence performed following the procedures described in Capturing and Processing Location Data from Smartphones (pp. 3-6) and Mobility as a Dimension of Persons (pp. 6-7). A further limitation is that, while adaptive sampling of location is more energy efficient, gaps between locations can be difficult to interpret. For example, a longer gap between two location recordings could be due to the user not moving, the phone being switched off or the app's permission to access location information being revoked. Moreover, only an Android app was available and hence no passive sensing information was collected from iOS users. Survey data regarding mood and daily activities was collected from all participants via the application.

Table 2

Data Collection Tools Employed in the Student Wellbeing Survey

Study element	Phase 1	Phase 2
In-the-moment experiences via Ecological Momentary Assessment surveys (EMA)	Questionnaires made available on Qualtrics.com, links sent via text message by SurveySignal	App users: MyLifeLogger app Non-app users: Questionnaires made available on Qualtrics.com, links sent via text message by SurveySignal
Activities via diary	Website hosted by herokuapp, daily email reminders with link	App users were able to keep an in-app activity diary (see Figure 3). Non-app users used the website used during phase 1, hosted by herokuapp, and received daily email reminders with the link. The last EMA of the day also allowed them to directly proceed to the website.
Activities and environments via passive sensing	EasyM app	MyLifeLogger app
Traits and demographics via pre and post study questionnaires	Questionnaires made available on Qualtrics.com, links sent via email	Questionnaires made available on Qualtrics.com, links sent via email

Note. References for the tools are as follows:

Activity diary:	https://mydiaryweb.herokuapp.com, website set up by Srivigneshwar R. Prasad, then in the Department of Psychology at the University of Cambridge;
EasyM app:	Smartphone sensing application for research projects developed by Neal Lathia, then at the Computer Laboratory at the University of Cambridge, originally available for iPhone and Android, although only the Android app was available at the time of this study and both have since been discontinued;
MyLifeLogger app:	Android application, developed by Abhinav Mehrotra in the Department of Geography at University College London, https://play.google.com/store/apps/details?id=com.nsds.mystudentlife;
Qualtrics:	Website enabling the collection of questionnaire data, https://www.qualtrics.com/;
SurveySignal:	Survey distribution service, http://surveysignal.com (Hofmann & Patel, 2015)

Table 3

Overview of the Data Collected During the Student Wellbeing Study

Study element	Phase 1	Phase 2

Ecological momentary assessment surveys (EMA; four times per day)	• Affective states (Lane, Zareba, Reis, Peterson, & Moss, 2011; Rachuri et al., 2010; Staats, Cosmar, & Kaffenberger, 2007)
	  ◦ Arousal [1-5]
	  ◦ Valence [1-5]
	  ◦ Tension [1-7]
	  ◦ Stress [1-7]
	  ◦ Relaxation [1-7]
	  ◦ Excitement [1-7]
	  ◦ Sadness [1-7]
	• Current location [‘pub/party’, ‘café/restaurant’, ‘university’, ‘college (common area)’, ‘friend’s house’, ‘home/own room’, ‘in transit’, or ‘other’]
		Same as phase 1 with the following additional affective states:
		• Satisfaction with self [1-4] (Rosenberg, 1965)
		• Narcissistic admiration [1-6] (Back et al., 2013)
		• Narcissistic rivalry [1-6] (Back et al., 2013)

Activity diary	• Activities engaged in during that day with start and end times [sleeping, eating, socialising, working, exercising, other relaxation, other]	Same as phase 1
Sensing	• Accelerometer (raw data) • Call logs • Text logs • GPS location	• Accelerometer (activity labels) • Call logs • Text logs • GPS location • Phone usage • Notifications
Pre- (1) and post- (2) study questionnaires	• Academic achievement[1, 2] • Connectedness[1] (Deters & Mehl, 2013) • Health[1, 2] (Atherton, Robins, Rentfrow, & Lamb, 2014) • Life satisfaction[1, 2] (Diener, Emmons, Larsen, & Griffin, 1985) • Personality (TIPI[1] (Lane et al., 2011), BFI[2] (Soto & John, 2017) • Self determination[1] (Sheldon, Ryan, & Reis, 1996) • Sociability[1, 2] (Diener & Seligman, 2002) • University adjustment[1] (Pennebaker, 2013) • Wellbeing[1, 2] Psychiatric Research Unit WHO Collaborating Centre in Mental Health, 1998) • Demographics[1, 2]	Same as phase 1, and in addition: • Narcissism[1, 2] (Back et al., 2013) • Self-esteem[1, 2] (Rosenberg, 1965)

Note. [1] Measure included in the first phase of the study, [2] measure included in the second phase of the study. Values in square brackets describe the scale ranges.

Table 4

Descriptive Statistics for Survey Measures Collected in the Student Wellbeing Study

	Phase 1		Phase 2	
	Pre	Post	Pre	Post
Academic achievement	2.97 (0.93)	3.01 (0.90)	3.01 (0.94)	2.96 (0.92)
Connectedness	19.38 (5.23)	-	19.71 (5.93)	-
Health	0.00 (3.95)	0.09 (4.26)	0.00 (5.11)	0.00 (5.17)
Life satisfaction	24.03 (6.72)	24.78 (6.86)	24.98 (7.03)	25.39 (7.06)
Personality (TIPI)				
Openness	5.04 (1.15)	4.98 (1.02)	4.92 (1.16)	4.89 (1.26)
Conscientiousness	4.97 (1.30)	4.87 (1.41)	4.88 (1.35)	5.04 (1.34)
Extraversion	4.11 (1.56)	4.23 (1.43)	4.14 (1.49)	4.17 (1.58)
Agreeableness	4.76 (1.20)	4.84 (1.24)	4.89 (1.17)	4.94 (1.27)
Neuroticism	4.12 (1.57)	4.21 (1.58)	4.19 (1.66)	4.09 (1.57)
Personality (BFI)				
Openness	-	3.52 (0.60)	-	3.51 (0.61)
Conscientiousness	-	3.44 (0.74)	-	3.46 (0.73)
Extraversion	-	3.14 (0.8)	-	3.10 (0.85)
Agreeableness	-	3.71 (0.55)	-	3.70 (0.60)
Neuroticism	-	3.21 (0.86)	-	3.18 (0.82)
Self determination	3.65 (0.80)	-	3.67 (0.77)	-
Sociability				
Satisfaction with friends	4.93 (1.47)	4.92 (1.40)	4.73 (1.56)	4.85 (1.54)
Satisfaction family life	3.68 (1.76)	5.25 (1.72)	5.08 (1.78)	5.18 (1.57)
Satisfaction romantic life	3.68 (2.05)	3.81 (1.98)	3.95 (1.93)	3.87 (1.97)
University adjustment	80.85 (15.99)	-	78.30 (14.54)	-
Wellbeing	12.04 (4.48)	11.66 (4.37)	15.62 (4.55)	16.19 (4.52)
Narcissism	-	-	2.55 (0.73)	2.63 (0.68)
Self-esteem	-	-	18.18 (6.22)	18.16 (6.35)

Note. All variables are normally distributed. Variable means are presented with standard deviations in parentheses.

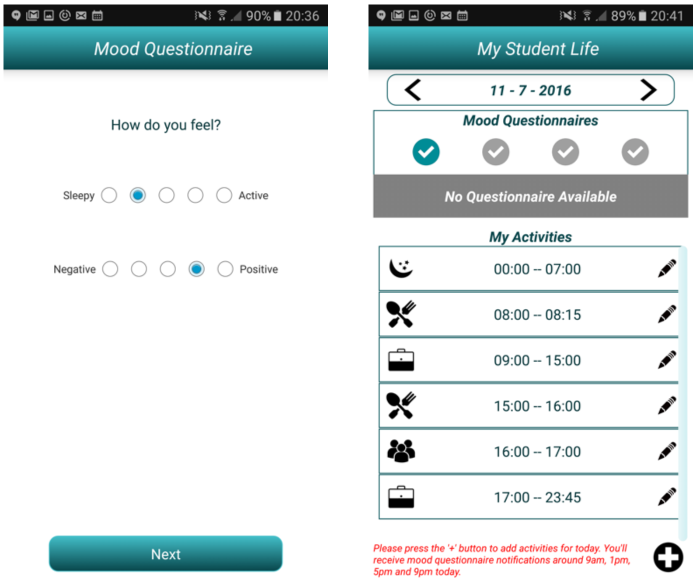

Figure 3. Left panel: Measuring mood in the MyLifeLogger app. Right panel: An example of how users log their daily activities.

Chapter 3. The Relationship between Psychology and Mobility

First, I present the quantities and accuracies of the raw GPS samples collected in the two phases of the Student Wellbeing Study. As such, I compare the average quantities of GPS recordings per day and per participant. I compare the accuracies per day and per participant across the two phases that employed different sensing apps and different sampling strategies as well. GPS recordings allow for both pinpointing a specific place and looking into movements between places. I present the results of investigations into the possibility of using GPS recordings to classify places using information retrieved via the Google Maps API.

Later analyses in this chapter focus on mobility features computed from the raw GPS recordings. All features presented in Table 1 were computed. Some mobility metrics are based on raw GPS recordings, while others are based on clustered data (see Table 1 for more details). I identified location clusters—the midpoints of which are defined as participants' significant places—using existing clustering procedures presented in Tsapeli & Musolesi (2015), excluding GPS recordings with more than 50 meters accuracy and those recorded while users were moving. The algorithm iterates over all GPS samples and creates clusters for which each location point is at most 200m away from the centroid.

I describe the daily mobility patterns of participants, the observed relationships of those mobility patterns with wellbeing and personality, as well as affective states employing, for example, correlation analyses and linear mixed-effect modeling.

How Well Can We Capture Location Patterns?

Quantities recorded and accuracy of GPS samples.

Table 5 compares the GPS records captured by the two different apps during phase one and phase two of data collection. During the first phase, the average daily number of GPS stamps was 48.81 (*sd*: 33.07) for the 33 participants (ranging from 0.07 to 93.93), and the mean standard deviation was 21.93 (*sd*: 14.49). The app was programmed to sample GPS location data continuously. However, on average, 33.76% of participant days had no GPS location data recorded at all, and 56.71% of participant days had less than 48 time stamps within 24 hours.

During the second phase, the average daily number of GPS stamps was 165.87 (*sd*: 88.47) for the 25 participants (ranging from 2.50 to 366.79), and the mean standard deviation was 73.33 (*sd*: 36.13). The app was set up to sample GPS location data adaptively (i.e. record the GPS location as soon as it changes). On average, 12.29% of participant days had no GPS location data recorded at all, and 21.71% of participant days had less than 48 time stamps within 24 hours.

It is unclear what led to the differences with regards to the collected data quantities. Anecdotally, an app that checks the GPS location periodically gets force-quit by the operating system sooner than an application that maintains a constant connection to the GPS service and observes (i.e. triggers the recording of) location changes. This might have led to the discrepancies. Because of the large discrepancies in terms of data recorded, analyses based on the sensed GPS locations will focus on the data collected during the second phase.

Table 5

Comparison of Recorded GPS Data Quantities and Accuracy During the Two Phases

	Phase 1	Phase 2
App	EasyM	MyLifeLogger
Sampling frequency	Periodically	Adaptive
Number of participants with GPS data	33	25
GPS records per participant per day		
Average mean	48.81 (*33.07*)	165.87 (*88.47*)
Average standard deviation	21.93 (*14.49*)	73.33 (*36.13*)
Range	0.07 to 93.93	2.50 to 366.79
GPS records per day across participants		
Mean	48.81 (*6.06*)	178.15 (*57.49*)
Range	39.18 to 57.24	91.82 to 375.50
% of participant days with no GPS records	33.76	12.29
% of participant days with less than 48 GPS records	56.71	21.71
Accuracy (in m) per participant		
Mean	238.92 (*182.39*)	201.95 (*228.79*)
Range	25.56 to 901.90	20.00 to 856.51
Accuracy (in m) per day		
Mean	270.04 (*58.98*)	241.02 (*40.72*)
Range	152.00 to 396.92	175.36 to 298.68
Overall accuracy (in m)		
Mean	262.22 (*549.37*)	242.02 (*673.06*)
Range	1.50 to 9282.80	6.00 to 20287.49

Note. Standard deviations are presented in parenthesis. The average mean of daily GPS records per participant ("row means"), and the average number of GPS records per day ("column means") are identical for the first phase as the study participation period was the same for all participants (February 1-14, 2016). During the second phase participants took part for 14 days during May 25 - June 9, 2016 and hence, not all participants participated on all days of the study.

Validation of sensed locations using self-reports.

The longitude/latitude coordinates collected by the smartphone app via the GPS sensor can be processed using the Google Maps API (Google, 2018). I did so using the googleway package (Cooley, 2018) in R (R Core Team, 2013). This returns information related to this place, such as nearby places of interest (e.g., shops, public institutions, or sights, but not residential places) for which, in turn, more information can be accessed (e.g., category labels, address, contact details, and opening hours). Table 7 (individual labels) and Table 8 (label categories) list the labels the Google Maps API returned for the closest places of interest to the sensed GPS locations.

Furthermore, this can be validated using EMAs. As the EMAs contained a question asking participants to indicate where they currently are (pub/party, coffee shop/restaurant, gym/sports facility, university, college common area, friend's house, home/own room, in transit, or other), the category labels provided by the Google Maps API for the closest place of interest to the longitude/latitude coordinates can be matched to the EMA category. I only matched GPS location readings if they were captured within 15 minutes of responding to an EMA.

Table 6 shows the resulting sample sizes when EMAs are merged with GPS locations. Locations refer to the midpoints of the cleaned and clustered raw GPS recordings. Across both time points, 1,721 EMAs can be matched to highly accurate, stationary GPS recordings, which is approximately 50% of all EMAs collected for 38 app users (and 19% of all EMAs collected in the study). Those 1,721 EMAs represent 250 locations from 38 users.

Table 9 shows that even for categories that should be clearly labeled on Google Maps, such as cafes and restaurants, the Google labels for the corresponding GPS point match only the EMA category chosen by the participant in 11.11% of cases. The overall accuracy lies below 10%. I have therefore decided to not use additional information extracted from the Google Places' API for further analyses into the effects of specific places.

Table 6

Resulting Sample Sizes when Merging EMAs with GPS Locations

	Phase 1	Phase 2
All participants	118	83
All EMAs	4882	4389
- a) Locations matched to EMAs -		
App users (38 across both time points)	33	27 (1 app user with no location data)
Unique EMAs from app users	1359	2104
EMAs that can be matched to a GPS recording	855 (62.91%)	1560 (74.14%)
EMAs that can be matched to high quality, non-moving GPS recordings	609 (44.81%)	1112 (52.85%)
- b) EMAs matched to Locations -		
Raw location samples	39,694	150,867
Unique locations (clustered high accuracy, stationary raw GPS samples)	426	1372
Locations with associated EMA	110 (25.82%)	140 (10.20%)

Table 7

Frequencies and Percentages of Google Place Labels for Sensed Locations

Google Place Label	Frequency	Percentage
store	136	7.56
food	115	6.40
restaurant	88	4.89
lodging	51	2.84
bar	46	2.56
transit_station	42	2.34
park	36	2.00
health	33	1.84
bus_station	32	1.78
finance	28	1.56
clothing_store	27	1.50
home_goods_store	22	1.22
cafe	21	1.17
place_of_worship	21	1.17
church	20	1.11
university	19	1.06
meal_takeaway	15	0.83
school	14	0.78
electronics_store	13	0.72
travel_agency	13	0.72
hair_care	11	0.61
parking	11	0.61
grocery / supermarket	10	0.56
jewelry_store	10	0.56
furniture_store	9	0.50
atm	8	0.44
bank	8	0.44
museum	8	0.44
bakery	7	0.39
general_contractor	7	0.39
shoe_store	7	0.39
dentist	6	0.33
doctor	6	0.33
supermarket	6	0.33
night_club	5	0.28
art_gallery	4	0.22
bicycle_store	4	0.22
book_store	4	0.22
car_rental	4	0.22
lawyer	4	0.22
liquor_store	4	0.22
real_estate_agency	4	0.22
shopping_mall	4	0.22
accounting	3	0.17
beauty_salon	3	0.17
gas_station	3	0.17
laundry	3	0.17
library	3	0.17
light_rail_station	3	0.17
florist	2	0.11
gym	2	0.11
hospital	2	0.11
locksmith	2	0.11
meal_delivery	2	0.11
movie_theater	2	0.11
painter	2	0.11
pharmacy	2	0.11
post_office	2	0.11
train_station	2	0.11
car_repair	1	0.06
convenience_store	1	0.06
electrician	1	0.06
funeral_home	1	0.06
local_government_office	1	0.06
police	1	0.06
taxi_stand	1	0.06
Not Found	71	3.95

Note. The following general level labels have been removed from the overview: point_of_interest (40.49%), establishment (40.43%), locality (33.09%), route (21.97%), premise (3.17%), administrative_area_level_2 (0.22%), sublocality_level_1 (0.06%).

Table 8

Frequency of Google Place Categories Returned for the Significant Places Sensed via the GPS Sensor

Place category	Google Place Labels included in category	Frequ.	Perc.
Transport	airport, bus_station, parking, taxi_stand, train_station, transit_station, intersection, route, subway_station	448	24.92
Store	bicycle_store, book_store, car_dealer, clothing_store, convenience_store, department_store, electronics_store, furniture_store, florist, gas_station, hardware_store, home_goods_store, jewelry_store, liquor_store, pet_store, real_estate_agency, shoe_store, shopping_mall, store, supermarket, grocery_or_supermarket	146	8.12
Eating	cafe, meal_delivery, meal_takeaway, restaurant, food, bakery	116	6.45
Lodging	lodging	52	2.89
Nightlife	bar, night_club, casino	48	2.67
Business / Service	moving_company, electrician, painter, plumber, roofing_contractor, general_contractor, lawyer, storage, veterinary_care, car_rental, car_repair, car_wash, travel_agency, insurance_agency, locksmith, laundry, movie_rental	38	2.11
Nature	campground, park, rv_park, natural_feature	36	2.00
Work	library, school, university	36	2.00
Medical	dentist, doctor, physiotherapist, hospital, health, pharmacy	35	1.95
Finance	accounting, atm, bank, finance	28	1.56
Religious institution	church, hindu_temple, mosque, synagogue, place_of_worship	21	1.17
Beauty	beauty_salon, hair_care, spa	13	0.72
Culture	art_gallery, museum	12	0.67
Public service	city_hall, courthouse, embassy, local_government_office, political, post_box, post_office	3	0.17
Recreation	amusement_park, aquarium, bowling_alley, movie_theater, stadium, zoo	2	0.11
Sports	gym	2	0.11
Memorial	cemetery, funeral_home	1	0.06
Emergency	fire_station, police	1	0.06
Not Found		71	3.95
Other	point_of_interest, establishment, locality, premise	1323	73.58

Note. N=1798 significant places, by 38 participants. The Google place labels were grouped into superordinate categories by a naïve research assistant. Google place labels providing geographical information (e.g., administrative_area_level, sublocality) have not been included in the overview. They were associated with 5 places (0.28%). As places are frequently associated with multiple labels, the sum of the percentage column exceeds 100%.

Table 9

Validation of Google Place labels for GPS Readings Using Corresponding Self-Reported Location

EMA label	GPS reading correctly labelled	GPS reading wrongly labelled as	Total count
In transit	13.56% (8)	Café/restaurant (5.08%), Pub/party (1.69%), Other (79.66%)	59
Café / restaurant	11.11% (3)	Pub/party (3.70%), In transit (3.70%), Other (81.48%).	27
University	4.65% (2)	Café/restaurant (2.33%), Other (93.02%)	43
Pub_Party	0.00% (0)	Other (100.00%)	5
Other	100.00% (39)		39
College (common area)	Not identifiable	University (1.18%), Other (98.82%)	(85)
Home / own room	Not identifiable	In transit (7.19%), Café /restaurant (0.28%), Other (92.52%)	(709)
Friend's house	Not identifiable	In transit (3.16%), Café /restaurant (1.05%), Other (95.79%)	(95)
Overall	*30.06% (52)*		*173*
Overall (without Other)	*9.70% (13)*		*134*

Note. Number of GPS readings matched is 1068. Google Places labels do not provide a categorization for residential and private places. As such, the Google Places API would not produce identifiable labels for places that would have been marked as 'home,' 'friend's house,' or 'college' by participants. These categories have been included for completeness but are not included in the computation of overall accuracy.

Students' Daily Mobility Behaviors

For all mobility behaviors, more variance was observed within individuals than between. Person mean reliabilities were high except for total distance covered, radius of gyration, and mean speed. The standard deviations tend to be large compared to the variable means.

Distances: The average total distance covered was .01 (*sd*: .03). The average spatial coverage by tiles approximation (number of unique tiles visited) was 12.03 (*sd*: 7.78). The average spatial coverage by convex hull approximation (smallest Euclidian space that contains all location points) was .16 (*sd*: .27). The average maximum distance between two locations was 2981.42 (*sd*: 4663.56), while the average maximum distance from home was 7470.51 (*sd*: 21027.49). The average standard deviation of the displacements (standard deviation of the distances between each place and the subsequent one) was 479.60 (*sd*: 723.34). The average location variance (combined variance of latitude and longitude values) was 15.72 (*sd*: 7.70).

Places: On average, students visited 3.20 (*sd*: 1.58) places, made 7.33 (*sd*: 3.25) location changes per day, and spent 86% (*sd*: 10%) of their time at home. The average time spent at each location was 9.08 (*sd*: 4.74). The average transition time was .60 (*sd*: .45).

Sequences and routines: The routine index quantifies how different the places visited by a user are across days on average and was 21.31 (*sd*: 13.17). The tiles sequence describes the average similarity between two sequences of tiles (time series of locations at 10-minute intervals) as minimum number of insertions, deletions, and substitutions required to transform one string into the other and was 7.69 (*sd*: 5.24). The average place sequence (similarity between two sequences of place identifiers as minimum number of insertions, deletions, and substitutions required to transform one string into the other) was 19.49 (*sd*: 11.89).

Entropy: The average radius of gyration (deviation from the centroid of the places visited, weighed by time spent in each place) was 2677.31 (*sd*: 5063.40). Entropy measures how a participant's time was distributed over different locations and was .45 (*sd*: .30) on average. The average normalized entropy (entropy controlling for the number of location clusters) was .35 (*sd*: .17). The average raw entropy (entropy based on GPS data points before clustering) was 1.12 (*sd*: .61). The average displacement entropy describes the predictability of daily movement patterns and is computed as the entropy of distances traveled in 10-minute windows during the day and was .63 (*sd*: .34).

Speed: The average mean of the instantaneous speed (in degrees/sec) at each GPS data point was .02 (*sd*: .03). The average variance of the instantaneous speed (in degrees/sec) at each GPS data point was -1.93 (*sd*: 3.76).

Table 10

Variance Between and Within Individual for Daily Mobility Behaviors and Average Daily Affective States

	Average daily mean	Standard deviation	Average daily standard deviation	Variance between individuals	Variance within individuals	Person mean reliability
Mobility behaviors						
convex_hull	.16	.27	.27	.12	.88	.62
dis_ent	.63	.34	.33	.45	.55	.91
displacement_var	479.60	723.34	760.52	.14	.86	.65
distance	.01	.03	.03	.00	1.00	.00
ent	.45	.30	.33	.37	.63	.87
loc_var	-15.72	7.70	10.25	.19	.81	.73
location_change	7.33	3.25	4.26	.23	.77	.78
max_dis	2981.42	4663.56	4799.30	.14	.86	.66
max_dis_from_home	7470.51	21027.49	12357.85	.21	.79	.76
norm_ent	.35	.17	.22	.26	.74	.80
num_cluster	3.20	1.58	1.72	.34	.66	.86
per_at_home	.86	.10	.14	.22	.78	.77
place_seq	19.49	11.89	15.38	.27	.73	.81
rad_gyration	2677.31	5063.40	5439.79	.09	.91	.53
raw_ent	1.12	.61	.62	.42	.58	.90
routine_index	21.31	13.17	9.52	.56	.44	.94
speed_mean	.02	.03	.04	.02	.98	.22
speed_var	-1.93	3.76	4.09	.21	.79	.76
tile_seq	7.69	5.24	4.72	.37	.63	.88
tiles	12.03	7.78	8.50	.27	.73	.82
time_at_each_loc	9.08	4.74	4.91	.39	.61	.88
transition_time	.60	.45	.42	.48	.52	.92
Affective states						
Arousal	3.20	.46	.51	.39	.61	.88
Valence	3.45	.46	.55	.36	.64	.87
Tense	2.49	.72	.63	.51	.49	.93
Stressed	2.89	.87	.85	.41	.59	.89
Relaxed	3.41	1.09	.85	.57	.43	.94
Excited	2.91	1.21	.76	.66	.34	.96
Sad	1.75	.70	.61	.48	.52	.92

Note. 21 participants, 4-14 days. ICC1s (variance between individuals) and ICC2s (individual mean reliability) were computed using a multilevel modeling approach as the group sizes (i.e. number of days per participant) were not balanced. I used the multilevel package in R, following the procedure suggested for estimating multiple ICC values in Bliese (2016).

Relationships of Mobility with Personality and Wellbeing

All GPS-based mobility measures were found to be strongly related to each other. In addition, wellbeing is strongly related to almost all measures, neuroticism and conscientiousness are each related to a number of measures, extraversion is positively related to wellbeing, consistent with past work, age is only related to the number of location changes, and gender, openness, and agreeableness seem statistically independent from mobility and other measures (see Table 11).

Table 11

Correlation Matrix for Mobility Metrics, Personality, and Wellbeing

	1	**2**	**3**	**4**	**5**
1 Age		[-.23, .60]	[-.62, .23]	[-.35, .52]	[-.47, .42]
2 Gender	.23 (.320)		[-.47, .41]	[-.61, .23]	[-.25, .60]
3 Openness	-.24 (.312)	-.03 (.884)		[-.47, .42]	[-.15, .66]
4 Conscientiousness	.11 (.659)	-.23 (.319)	-.03 (.896)		[-.39, .49]
5 Extraversion	-.03 (.905)	.22 (.357)	.31 (.182)	.07 (.783)	
6 Agreeableness	-.18 (.438)	-.30 (.203)	-.02 (.920)	-.01 (.965)	.28 (.231)
7 Neuroticism	-.15 (.524)	-.39 (.088)	.11 (.635)	**-.45 (.044)**	-.42 (.066)
8 Wellbeing	.17 (.463)	.19 (.418)	.12 (.621)	.07 (.757)	**.46 (.041)**
9 convex_hull	.19 (.417)	-.02 (.946)	-.18 (.453)	**.55 (.011)**	-.06 (.798)
10 dis_ent	.10 (.658)	-.17 (.453)	.06 (.812)	**.52 (.020)**	.16 (.490)
11 displacement_var	.05 (.841)	.00 (1.00)	-.07 (.768)	**.55 (.013)**	.06 (.788)
12 distance	.14 (.537)	.00 (1.00)	-.20 (.404)	.44 (.053)	-.05 (.837)
13 ent	.15 (.517)	.11 (.634)	.18 (.436)	.26 (.268)	.36 (.123)
14 loc_var	.12 (.617)	-.17 (.453)	.11 (.636)	**.61 (.004)**	.14 (.564)
15location_change	**.46 (.035)**	.22 (.337)	.09 (.715)	.31 (.183)	.34 (.149)
16 max_dis	.08 (.741)	.00 (1.00)	-.08 (.727)	**.55 (.011)**	.04 (.857)
17 maxdisfrom_home	.48 (.112)	-.10 (.765)	-.40 (.193)	.17 (.601)	-.17 (.600)
18 norm_ent	.05 (.845)	-.03 (.892)	.31 (.180)	.33 (.150)	.34 (.146)
19 num_cluster	.38 (.089)	.13 (.563)	.12 (.627)	.22 (.347)	.32 (.165)
20 per_at_home	-.43 (.163)	.00 (1.00)	.02 (.957)	-.08 (.795)	-.11 (.736)
21 place_seq	.28 (.222)	.22 (.337)	.07 (.785)	-.02 (.942)	.15 (.538)
22 rad_gyration	.24 (.301)	-.05 (.839)	-.22 (.356)	**.46 (.043)**	-.08 (.740)
23 raw_ent	.07 (.748)	.03 (.892)	.08 (.725)	**.47 (.037)**	.20 (.409)
24 routine_index	.40 (.075)	.14 (.540)	.02 (.932)	-.01 (.962)	.02 (.947)
25 speed_mean	.37 (.103)	.08 (.734)	-.22 (.354)	**.57 (.009)**	.04 (.877)
26 speed_var	.24 (.292)	-.06 (.786)	-.01 (.957)	**.70 (.001)**	.17 (.480)
27 tile_seq	.40 (.069)	.09 (.684)	-.04 (.874)	.18 (.449)	.10 (.688)
28 tiles	.35 (.125)	.03 (.892)	-.11 (.643)	**.51 (.022)**	.04 (.872)
29 time_at_each_loc	-.03 (.881)	.00 (1.00)	-.21 (.379)	-.40 (.080)	-.24 (.311)
30 transition_time	.16 (.495)	-.22 (.337)	-.17 (.477)	.34 (.143)	.05 (.830)

Note. Spearman correlation coefficients are presented. P values are presented in parentheses and have been corrected for multiple comparisons using the method presented in (Benjamini & Hochberg, 1995). Coefficients and p values are presented in bold if $p < .05$. Confidence intervals are presented in square brackets.

Correlation Matrix for Mobility Metrics, Personality, and Wellbeing - continued

	6	**7**	**8**	**9**	**10**
1 Age	[-.58, .28]	[-.56, .31]	[-.29, .57]	[-.27, .57]	[-.34, .51]
2 Gender	[-.65, .17]	[-.71, .06]	[-.27, .58]	[-.44, .42]	[-.56, .28]
3 Openness	[-.46, .42]	[-.35, .53]	[-.34, .53]	[-.58, .29]	[-.40, .49]
4 Conscientiousness	[-.45, .43]	[-.75, -.01]	[-.38, .50]	[.15, .80]	[.10, .78]
5 Extraversion	[-.19, .64]	[-.73, .03]	[.02, .75]	[-.49, .39]	[-.30, .57]
6 Agreeableness		[-.66, .15]	[-.02, .73]	[-.38, .50]	[-.39, .49]
7 Neuroticism	-.31 (.179)		[-.81, -.18]	[-.72, .04]	[-.68, .12]
8 Wellbeing	.43 (.060)	**-.57 (.008)**		[.04, .76]	[.09, .78]
9 convex_hull	.08 (.739)	-.41 (.071)	**.47 (.035)**		[.64, .93]
10 dis_ent	.06 (.802)	-.34 (.137)	**.51 (.020)**	**.84 (<.001)**	
11 displacement_var	.09 (.701)	**-.51 (.022)**	**.55 (.011)**	**.95 (<.001)**	**.87 (<.001)**
12 distance	.10 (.661)	**-.45 (.046)**	**.54 (.013)**	**.93 (<.001)**	**.76 (<.001)**
13 ent	.14 (.547)	**-.49 (.027)**	**.63 (.003)**	**.65 (.001)**	**.83 (<.001)**
14 loc_var	.12 (.627)	-.39 (.089)	**.51 (.022)**	**.87 (<.001)**	**.90 (<.001)**
15location_change	-.02 (.937)	**-.53 (.017)**	**.64 (.002)**	**.58 (.006)**	**.75 (<.001)**
16 max_dis	.09 (.720)	**-.52 (.018)**	**.55 (.012)**	**.95 (<.001)**	**.85 (<.001)**
17 maxdisfrom_home	.13 (.677)	.01 (.965)	.28 (.371)	**.99 (<.001)**	**.76 (.005)**
18 norm_ent	.21 (.380)	-.44 (.053)	**.51 (.021)**	**.60 (.004)**	**.81 (<.001)**
19 num_cluster	-.01 (.977)	-.41 (.074)	**.65 (.002)**	**.62 (.003)**	**.82 (<.001)**
20 per_at_home	.08 (.810)	.07 (.819)	-.28 (.377)	**-.73 (.007)**	**-.73 (.007)**
21 place_seq	.04 (.859)	-.32 (.169)	**.48 (.031)**	**.45 (.04)**	**.52 (.016)**
22 rad_gyration	-.08 (.748)	-.23 (.334)	.43 (.056)	**.91 (<.001)**	**.84 (<.001)**
23 raw_ent	.02 (.919)	-.40 (.085)	**.48 (.032)**	**.81 (<.001)**	**.92 (<.001)**
24 routine_index	.06 (.792)	-.23 (.328)	**.49 (.030)**	**.53 (.013)**	**.48 (.027)**
25 speed_mean	-.03 (.889)	-.41 (.074)	**.49 (.029)**	**.93 (<.001)**	**.81 (<.001)**
26 speed_var	.14 (.543)	**-.56 (.010)**	**.59 (.006)**	**.87 (<.001)**	**.82 (<.001)**
27 tile_seq	-.06 (.814)	-.35 (.136)	**.57 (.009)**	**.66 (.001)**	**.69 (.001)**
28 tiles	-.10 (.661)	-.29 (.208)	**.46 (.044)**	**.83 (<.001)**	**.82 (<.001)**
29 time_at_each_loc	-.02 (.927)	.41 (.075)	**-.54 (.014)**	**-.75 (<.001)**	**-.93 (<.001)**
30 transition_time	.08 (.751)	-.21 (.375)	**.47 (.039)**	**.81 (<.001)**	**.93 (<.001)**

Note. Spearman correlation coefficients are presented. P values are presented in parentheses and have been corrected for multiple comparisons using the method presented in (Benjamini & Hochberg, 1995). Coefficients and p values are presented in bold if $p < .05$. Confidence intervals are presented in square brackets.

Correlation Matrix for Mobility Metrics, Personality, and Wellbeing - continued

	11	12	13	14	15
1 Age	[-.39, .47]	[-.31, .54]	[-.30, .55]	[-.33, .52]	[.04, .74]
2 Gender	[-.43, .43]	[-.43, .43]	[-.34, .52]	[-.56, .28]	[-.23, .60]
3 Openness	[-.50, .38]	[-.59, .27]	[-.28, .58]	[-.35, .53]	[-.37, .51]
4 Conscientiousness	[.14, .80]	[.00, .74]	[-.21, .63]	[.23, .83]	[-.15, .66]
5 Extraversion	[-.39, .49]	[-.48, .40]	[-.10, .69]	[-.32, .55]	[-.13, .68]
6 Agreeableness	[-.37, .51]	[-.35, .52]	[-.32, .55]	[-.34, .53]	[-.46, .43]
7 Neuroticism	[-.78, -.09]	[-.74, -.01]	[-.77, -.07]	[-.71, .06]	[-.79, -.11]
8 Wellbeing	[.15, .80]	[.13, .79]	[.26, .84]	[.08, .78]	[.28, .85]
9 convex_hull	[.89, .98]	[.82, .97]	[.31, .85]	[.71, .95]	[.20, .81]
10 dis_ent	[.70, .95]	[.48, .90]	[.63, .93]	[.76, .96]	[.48, .89]
11 displacement_var		[.86, .98]	[.41, .88]	[.75, .96]	[.26, .83]
12 distance	**.94 (<.001)**		[.26, .83]	[.51, .90]	[.22, .82]
13 ent	**.72 (<.001)**	**.62 (.003)**		[.34, .86]	[.68, .94]
14 loc_var	**.89 (<.001)**	**.77 (<.001)**	**.67 (.001)**		[.27, .83]
15location_change	**.62 (.003)**	**.60 (.004)**	**.86 (<.001)**	**.63 (.002)**	
16 max_dis	**.99 (<.001)**	**.95 (<.001)**	**.71 (<.001)**	**.88 (<.001)**	**.62 (.003)**
17 maxdisfrom_home	**.90 (<.001)**	**.76 (.004)**	**.58 (.048)**	**.73 (.007)**	.39 (.208)
18 norm_ent	**.67 (.001)**	**.53 (.014)**	**.95 (<.001)**	**.69 (.001)**	**.75 (<.001)**
19 num_cluster	**.65 (.001)**	**.60 (.004)**	**.93 (<.001)**	**.65 (.002)**	**.94 (<.001)**
20 per_at_home	**-.75 (.005)**	**-.63 (.028)**	**-.81 (.001)**	**-.71 (.009)**	**-.57 (.051)**
21 place_seq	.43 (.052)	.41 (.063)	**.78 (<.001)**	**.45 (.042)**	**.74 (<.001)**
22 rad_gyration	**.85 (<.001)**	**.79 (<.001)**	**.64 (.002)**	**.79 (<.001)**	**.57 (0.007)**
23 raw_ent	**.82 (<.001)**	**.72 (<.001)**	**.88 (<.001)**	**.81 (<.001)**	**.78 (<.001)**
24 routine_index	**.47 (.033)**	**.48 (.027)**	**.65 (.001)**	**.51 (.018)**	**.63 (.002)**
25 speed_mean	**.85 (<.001)**	**.82 (<.001)**	**.65 (.001)**	**.81 (<.001)**	**.69 (.001)**
26 speed_var	**.90 (<.001)**	**.85 (<.001)**	**.64 (.002)**	**.90 (<.001)**	**.68 (.001)**
27 tile_seq	**.64 (.002)**	**.63 (.002)**	**.75 (<.001)**	**.70 (<.001)**	**.79 (<.001)**
28 tiles	**.75 (<.001)**	**.70 (<.001)**	**.68 (.001)**	**.80 (<.001)**	**.72 (<.001)**
29 time_at_each_loc	**-.81 (<.001)**	**-.68 (.001)**	**-.93 (<.001)**	**-.78 (<.001)**	**-.80 (<.001)**
30 transition_time	**.79 (<.001)**	**.75 (<.001)**	**.74 (<.001)**	**.79 (<.001)**	**.70 (<.001)**

Note. Spearman correlation coefficients are presented. P values are presented in parentheses and have been corrected for multiple comparisons using the method presented in (Benjamini & Hochberg, 1995). Coefficients and p values are presented in bold if $p < .05$. Confidence intervals are presented in square brackets.

Correlation Matrix for Mobility Metrics, Personality, and Wellbeing - continued

	16	**17**	**18**	**19**	**20**
1 Age	[-.37, .49]	[-.13, .83]	[-.39, .47]	[-.06, .70]	[-.81, .19]
2 Gender	[-.43, .43]	[-.64, .51]	[-.46, .41]	[-.32, .53]	[-.57, .57]
3 Openness	[-.51, .37]	[-.79, .22]	[-.15, .66]	[-.34, .53]	[-.56, .59]
4 Conscientiousness	[.15, .80]	[-.45, .68]	[-.13, .68]	[-.24, .61]	[-.63, .51]
5 Extraversion	[-.41, .48]	[-.68, .45]	[-.12, .68]	[-.14, .67]	[-.64, .50]
6 Agreeableness	[-.37, .51]	[-.48, .66]	[-.26, .60]	[-.45, .44]	[-.52, .62]
7 Neuroticism	[-.78, -.10]	[-.56, .58]	[-.74, .00]	[-.72, .04]	[-.52, .62]
8 Wellbeing	[.14, .80]	[-.35, .74]	[.09, .78]	[.29, .85]	[-.74, .35]
9 convex_hull	[.88, .98]	[.95, 1.00]	[.23, .82]	[.26, .83]	[-.92, -.26]
10 dis_ent	[.66, .94]	[.32, .93]	[.58, .92]	[.60, .92]	[-.92, -.26]
11 displacement_var	[.99, 1.00]	[.66, .97]	[.34, .85]	[.30, .84]	[-.92, -.31]
12 distance	[.89, .98]	[.33, .93]	[.12, .78]	[.23, .82]	[-.88, -.09]
13 ent	[.40, .87]	[.01, .87]	[.89, .98]	[.84, .97]	[-.95, -.44]
14 loc_var	[.73, .95]	[.28, .92]	[.36, .86]	[.30, .84]	[-.91, -.24]
15location_change	[.26, .83]	[-.24, .79]	[.48, .89]	[.86, .98]	[-.86, .00]
16 max_dis		[.58, .96]	[.31, .85]	[.30, .84]	[-.94, -.38]
17 maxdisfrom_home	**.87 (<.001)**		[-.06, .85]	[-.01, .86]	[-.92, -.26]
18 norm_ent	**.66 (.001)**	.53 (.075)		[.62, .93]	[-.95, -.48]
19 num_cluster	**.65 (.001)**	.56 (.056)	**.83 (<.001)**		[-.89, -.12]
20 per_at_home	**-.78 (.003)**	**-.73 (.007)**	**-.83 (.001)**	**-.65 (.022)**	
21 place_seq	.43 (.050)	.58 (.048)	**.70 (<.001)**	**.77 (<.001)**	**-.80 (.002)**
22 rad_gyration	**.83 (<.001)**	**.92 (<.001)**	**.57 (.007)**	**.65 (.001)**	**-.66 (.020)**
23 raw_ent	**.81 (<.001)**	**.66 (.020)**	**.84 (<.001)**	**.85 (<.001)**	**-.66 (.020)**
24 routine_index	**.48 (.029)**	**.69 (.013)**	**.59 (.005)**	**.64 (.002)**	**-.97 (<.001)**
25 speed_mean	**.84 (<.001)**	**.92 (<.001)**	**.56 (.009)**	**.70 (<.001)**	**-.63 (.028)**
26 speed_var	**.90 (<.001)**	**.62 (.031)**	**.60 (.004)**	**.63 (.002)**	**-.67 (.017)**
27 tile_seq	**.66 (.001)**	.52 (.080)	**.65 (.001)**	**.81 (<.001)**	**-.78 (.003)**
28 tiles	**.75 (<.001)**	**.78 (.003)**	**.60 (.004)**	**.77 (<.001)**	-.52 (.085)
29 time_at_each_loc	**-.79 (<.001)**	-.54 (.071)	**-.92 (<.001)**	**-.86 (<.001)**	**.77 (.003)**
30 transition_time	**.78 (<.001)**	**.69 (.013)**	**.66 (.001)**	**.77 (<.001)**	**-.54 (.071)**

Note. Spearman correlation coefficients are presented. P values are presented in parentheses and have been corrected for multiple comparisons using the method presented in (Benjamini & Hochberg, 1995). Coefficients and p values are presented in bold if $p < .05$. Confidence intervals are presented in square brackets.

Correlation Matrix for Mobility Metrics, Personality, and Wellbeing - continued

	21	22	23	24	25
1 Age	[-.17, .63]	[-.22, .61]	[-.37, .49]	[-.04, .71]	[-.08, .69]
2 Gender	[-.23, .60]	[-.47, .39]	[-.41, .46]	[-.31, .54]	[-.37, .49]
3 Openness	[-.39, .49]	[-.60, .25]	[-.37, .51]	[-.43, .46]	[-.60, .25]
4 Conscientiousness	[-.46, .43]	[.02, .75]	[.03, .75]	[-.45, .43]	[.17, .81]
5 Extraversion	[-.32, .55]	[-.50, .38]	[-.27, .59]	[-.43, .46]	[-.41, .47]
6 Agreeableness	[-.41, .48]	[-.50, .38]	[-.42, .46]	[-.39, .49]	[-.47, .42]
7 Neuroticism	[-.67, .14]	[-.61, .24]	[-.71, .06]	[-.61, .24]	[-.72, .04]
8 Wellbeing	[.05, .76]	[-.01, .74]	[.05, .76]	[.05, .76]	[.06, .77]
9 convex_hull	[.02, .74]	[.79, .96]	[.59, .92]	[.13, .78]	[.82, .97]
10 dis_ent	[.11, .78]	[.63, .93]	[.81, .97]	[.06, .76]	[.59, .92]
11 displacement_var	[.00, .73]	[.65, .94]	[.61, .93]	[.04, .75]	[.65, .94]
12 distance	[-.02, .72]	[.54, .91]	[.42, .88]	[.06, .76]	[.60, .92]
13 ent	[.52, .91]	[.29, .84]	[.72, .95]	[.31, .85]	[.30, .84]
14 loc_var	[.02, .74]	[.55, .91]	[.58, .92]	[.10, .77]	[.59, .92]
15location_change	[.46, .89]	[.19, .81]	[.53, .91]	[.28, .84]	[.36, .86]
16 max_dis	[.00, .73]	[.62, .93]	[.58, .92]	[.05, .75]	[.63, .93]
17 maxdisfrom_home	[.01, .87]	[.74, .98]	[.13, .89]	[.20, .91]	[.72, .98]
18 norm_ent	[.38, .87]	[.18, .80]	[.64, .93]	[.21, .81]	[.17, .80]
19 num_cluster	[.52, .90]	[.31, .85]	[.66, .94]	[.29, .84]	[.38, .87]
20 per_at_home	[-.94, -.41]	[-.89, -.13]	[-.89, -.13]	[-.99, -.90]	[-.88, -.09]
21 place_seq		[.02, .74]	[.28, .84]	[.78, .96]	[.10, .77]
22 rad_gyration	**.45 (.043)**		[.51, .90]	[.14, .79]	[.84, .97]
23 raw_ent	**.63 (.002)**	**.77 (<.001)**		[.10, .77]	[.59, .92]
24 routine_index	**.90 (<.001)**	**.54 (.012)**	**.51 (0.018)**		[.16, .80]
25 speed_mean	**.51 (.018)**	**.93 (<.001)**	**.82 (<.001)**	**.56 (0.009)**	
26 speed_var	.41 (.064)	**.78 (<.001)**	**.74 (<.001)**	**.49 (0.024)**	**.87 (<.001)**
27 tile_seq	**.73 (<.001)**	**.68 (.001)**	**.72 (<.001)**	**.73 (<.001)**	**.71 (<.001)**
28 tiles	**.55 (.009)**	**.88 (<.001)**	**.86 (<.001)**	**.51 (0.017)**	**.94 (<.001)**
29 time_at_each_loc	**-.62 (.003)**	**-.76 (<.001)**	**-.93 (<.001)**	**-.52 (0.016)**	**-.73 (<.001)**
30 transition_time	**.49 (.024)**	**.82 (<.001)**	**.86 (<.001)**	**.47 (0.033)**	**.79 (<.001)**

Note. Spearman correlation coefficients are presented. P values are presented in parentheses and have been corrected for multiple comparisons using the method presented in (Benjamini & Hochberg, 1995). Coefficients and p values are presented in bold if $p < .05$. Confidence intervals are presented in square brackets.

Correlation Matrix for Mobility Metrics, Personality, and Wellbeing - continued

	26	27	28	29	30
1 Age	[-.21, .61]	[-.03, .71]	[-.10, .68]	[-.46, .40]	[-.29, .55]
2 Gender	[-.48, .38]	[-.35, .51]	[-.41, .46]	[-.43, .43]	[-.60, .23]
3 Openness	[-.45, .43]	[-.47, .41]	[-.53, .35]	[-.60, .26]	[-.57, .30]
4 Conscientiousness	[.37, .87]	[-.29, .58]	[.09, .78]	[-.72, .05]	[-.12, .68]
5 Extraversion	[-.30, .57]	[-.36, .52]	[-.41, .47]	[-.62, .23]	[-.4, .48]
6 Agreeableness	[-.32, .55]	[-.49, .40]	[-.52, .35]	[-.46, .42]	[-.38, .50]
7 Neuroticism	[-.80, -.16]	[-.68, .11]	[-.65, .17]	[-.04, .72]	[-.60, .26]
8 Wellbeing	[.20, .82]	[.17, .81]	[.02, .75]	[-.79, -.13]	[.03, .75]
9 convex_hull	[.70, .95]	[.32, .85]	[.63, .93]	[-.89, -.47]	[.58, .92]
10 dis_ent	[.60, .92]	[.37, .86]	[.61, .93]	[-.97, -.84]	[.83, .97]
11 displacement_var	[.76, .96]	[.29, .84]	[.48, .89]	[-.92, -.58]	[.54, .91]
12 distance	[.67, .94]	[.27, .83]	[.38, .87]	[-.86, -.36]	[.46, .89]
13 ent	[.28, .84]	[.47, .89]	[.35, .86]	[-.97, -.84]	[.44, .89]
14 loc_var	[.76, .96]	[.38, .87]	[.56, .91]	[-.90, -.52]	[.55, .91]
15location_change	[.36, .86]	[.55, .91]	[.41, .88]	[-.92, -.57]	[.38, .87]
16 max_dis	[.77, .96]	[.33, .85]	[.46, .89]	[-.91, -.54]	[.53, .91]
17 maxdisfrom_home	[.08, .88]	[-.07, .84]	[.36, .93]	[-.85, .05]	[.20, .91]
18 norm_ent	[.23, .82]	[.30, .84]	[.22, .82]	[-.97, -.81]	[.33, .85]
19 num_cluster	[.27, .83]	[.57, .92]	[.52, .90]	[-.94, -.69]	[.51, .90]
20 per_at_home	[-.90, -.16]	[-.94, -.38]	[-.84, .08]	[.35, .93]	[-.85, .05]
21 place_seq	[-.02, .72]	[.43, .88]	[.16, .80]	[-.83, -.25]	[.07, .76]
22 rad_gyration	[.53, .91]	[.36, .86]	[.72, .95]	[-.90, -.49]	[.60, .92]
23 raw_ent	[.45, .89]	[.43, .88]	[.69, .94]	[-.97, -.84]	[.69, .94]
24 routine_index	[.07, .76]	[.44, .88]	[.10, .77]	[-.78, -.11]	[.04, .75]
25 speed_mean	[.70, .95]	[.40, .87]	[.85, .98]	[-.88, -.44]	[.55, .91]
26 speed_var		[.30, .84]	[.49, .90]	[-.88, -.41]	[.40, .87]
27 tile_seq	**.65 (.002)**		[.50, .90]	[-.86, -.37]	[.43, .88]
28 tiles	**.76 (<.001)**	**.77 (<.001)**		[-.89, -.48]	[.59, .92]
29 time_at_each_loc	**-.71 (<.001)**	**-.69 (.001)**	**-.75 (<.001)**		[-.92, -.59]
30 transition_time	**.71 (<.001)**	**.73 (<.001)**	**.81 (<.001)**	**-.81 (<.001)**	

Note. Spearman correlation coefficients are presented. P values are presented in parentheses and have been corrected for multiple comparisons using the method presented in (Benjamini & Hochberg, 1995). Coefficients and p values are presented in bold if $p < .05$. Confidence intervals are presented in square brackets.

Relationship of Mobility with Daily Affective States

Multilevel models were fitted to predict affective states from mobility behaviors. Corresponding to the data structure (i.e., multiple EMA responses being nested within persons), random intercepts were used and set to vary within persons. The models did not converge when including further random effects of the predictor variables. Table 12 presents the fixed effects of the fitted linear mixed-effects models predicting affective states from mobility metrics. Maximum distance from home and percentage of time spent at home were removed from the models as they were only available for a small subset of participants and hence would have reduced the sample size to a fraction if included.

Arousal: A shorter distance traveled in a day (B = -5.54, p = .024), higher mean speed (B = 5.86, p =.034) and shorter transition times (B = -.40, p =.015) are associated with significantly higher arousal.

Valence: Higher displacement entropy (B =.45, p =.035), lower entropy (B = -1.07, p =.048), and shorter transition times (B = -.36, p =.041) were associated with significantly greater self-reported positive feelings. Entropy measures how a participant's time was distributed over different locations and displacement entropy describes the predictability of daily movement patterns, computed as the entropy of distances traveled in 10-minute time windows during the day.

Tense: The radius of gyration (deviation from the centroid of the places visited, weighed by time spent in each place; B =.00, p =.032), as well as a lower tile sequence (B = -.03, p =.012) were associated with more tense feelings. The tiles sequence describes the average similarity between two sequences of tiles (time series of locations at 10-minute intervals).

Stressed: A larger location variance (computed as the combined variance of latitude and longitude values; B =.03, p =.022) and a lower tile sequence (B =-.04, p =.013) were associated with more stress.

Relaxed: A larger spatial coverage (by convex hull approximation) (B =1.55, p =.005), the standard deviations of the displacements (computed as the standard deviation of the distances between each place and the subsequent one; B =.00, p =.025), the maximum distance between two locations (B =.00, p =.003), radius of gyration (B =.00, p =.001), and a larger tile sequence (B =.03, p =.039) were related to greater feelings of relaxation.

Excited: radius of gyration (B =.00, p =.041), a larger tile sequence (B =.03, p =.026) were associated with greater excitement.

Sad: Less spatial coverage (by convex hull approximation; B =-1.10, p =.023), as well as the radius of gyration (B =.00, p =.022), were associated with increased feelings of sadness.

Table 12

Linear Mixed-Effects Models Predicting Affective States from Mobility Metrics (Random Intercepts Model)

	Arousal			Valence			Tense			Stressed		
	B	SE	p	B	SE	p	B	SE	p	B	SE	p
Intercept	2.83	.31	<.001	2.45	.33	<.001	2.81	.39	<.001	4.28	.53	<.001
convex_hull	-.10	.35	.772	.39	.38	.304	-.68	.42	.107	-.53	.59	.364
dis_ent	.28	.20	.159	**.45**	.21	.035	.10	.23	.657	-.32	.33	.331
displacement_var	.00	.00	.980	.00	.00	.466	.00	.00	.235	.00	.00	.904
distance	**-5.54**	2.44	.024	-2.86	2.63	.279	3.23	2.94	.274	6.64	4.11	.108
ent	.21	.50	.673	**-1.07**	.54	.048	.66	.60	.276	.86	.84	.307
loc_var	-.01	.01	.415	-.01	.01	.058	.01	.01	.353	**.03**	.01	.022
location_change	-.02	.02	.226	.00	.02	.839	-.03	.02	.213	-.03	.03	.292
max_dis	.00	.00	.836	.00	.00	.337	.00	.00	.073	.00	.00	.541
norm_ent	-.24	.47	.601	.81	.51	.112	-.46	.56	.408	-.60	.78	.445
num_cluster	.02	.07	.791	.10	.07	.200	-.03	.08	.724	-.13	.12	.261
place_seq	.00	.00	.403	.00	.00	.339	.00	.00	.641	.01	.01	.177
rad_gyration	.00	.00	.702	.00	.00	.169	**.00**	.00	.032	.00	.00	.196
raw_ent	.08	.22	.711	.23	.24	.332	.07	.27	.784	.17	.38	.645
routine_index	.01	.01	.108	.01	.01	.183	.00	.01	.499	-.01	.01	.150
speed_mean	**5.86**	2.74	.034	2.30	2.97	.439	-2.64	3.30	.425	-4.04	4.61	.383
speed_var	.03	.02	.135	.03	.02	.084	.00	.02	.819	-.05	.03	.090
tile_seq	-.01	.01	.449	.02	.01	.061	**-.03**	.01	.012	**-.04**	.02	.013
tiles	.00	.01	.712	.00	.01	.909	.00	.01	.817	.00	.02	.924
time_at_each_loc	.01	.01	.487	.01	.01	.501	.02	.02	.306	.00	.02	.985
transition_time	**-.40**	.16	.015	**-.36**	.17	.041	.05	.20	.788	-.12	.28	.654

Note. N=21. This table features individuals who participated for 4-14 days. Table presents fixed effects. Models did not converge when adding random effects. I also removed variables denoting the maximum distance from home and percentage of time spent at home as they were only available for a small subset of participants.

Linear Mixed-Effects Models Predicting Affective States from Mobility Metrics (Random Intercepts Model) - continued

	Relaxed			Excited			Sad		
	B	SE	p	B	SE	p	B	SE	p
Intercept	2.59	.52	<.001	2.96	.49	<.001	2.19	.44	<.001
convex_hull	**1.55**	.55	.005	.68	.50	.179	**-1.10**	.48	.023
dis_ent	.11	.31	.724	-.13	.28	.641	-.02	.27	.932
displacement_var	**.00**	.00	.025	.00	.00	.199	.00	.00	.175
distance	-5.68	3.87	.144	-1.22	3.57	.733	-3.71	3.37	.273
ent	-.21	.79	.789	.60	.73	.413	.83	.69	.231
loc_var	-.01	.01	.524	.00	.01	.878	-.01	.01	.514
location_change	-.01	.03	.823	-.05	.03	.075	-.02	.02	.394
max_dis	**.00**	.00	.003	.00	.00	.101	.00	.00	.147
norm_ent	.53	.73	.471	-.29	.67	.672	-.83	.64	.196
num_cluster	.08	.11	.450	.00	.10	.975	-.08	.10	.393
place_seq	.00	.01	.385	.00	.00	.534	.01	.00	.143
rad_gyration	**.00**	.00	.001	**.00**	.00	.041	**.00**	.00	.022
raw_ent	-.31	.36	.383	.22	.33	.499	-.20	.31	.528
routine_index	.01	.01	.476	.00	.01	.643	.00	.01	.525
speed_mean	5.53	4.34	.204	3.01	4.00	.453	3.88	3.79	.307
speed_var	.03	.03	.271	.00	.02	.897	.01	.02	.667
tile_seq	**.03**	.02	.039	**.03**	.01	.026	-.01	.01	.503
tiles	.01	.02	.640	-.01	.02	.496	.00	.01	.848
time_at_each_loc	.01	.02	.723	-.02	.02	.210	-.03	.02	.154
transition_time	.12	.26	.645	.07	.24	.777	.13	.23	.566

Note. N=21. This table features individuals who participated for 4-14 days. Table presents fixed effects. Models did not converge when adding random effects. I also removed variables denoting the maximum distance from home and percentage of time spent at home as they were only available for a small subset of participants.

Discussion and Conclusion

Methodologically, I demonstrate a novel approach for examining the relationship between people's minds and their trajectories through space. I show that GPS locations can be captured fairly well over a long duration from smartphones, especially when adaptive sampling was used as in phase 2. However, matching EMAs to information retrieved from Google API for the same location was not successful and hence discarded as a strategy. Mobility features showed high stability day-to-day, and all GPS-based mobility measures were found to be strongly related to each other.

Theoretically, this investigation uncovered some new insights about the relationship between people's patterns of physical movement and their inner mental lives. The variation within people was generally higher for mobility metrics than the variation between people. This suggests that mobility may function more as a state than a trait. Nonetheless, the individual differences between people in mobility do predict some psychological individual differences.

In particular, mobility metrics were significantly related to conscientiousness, neuroticism, and wellbeing. Conscientiousness predicted traveling farther distances and with greater speed. This may be because conscientious individuals have and keep more obligations than others, requiring them to travel more frequently and efficiently. This could also be due to exercise, such as walking or jogging, which conscientious people may be more inclined to do. On the other hand, neurotic individuals traveled shorter distances and with at a slower speed. Mobility does seem to be positively associated with wellbeing, as those who reported higher wellbeing traveled farther, to more places, more unpredictably, and faster, spending less time at each location. While the data is only correlational, it could be plausible that encouraging people to move more could increase their wellbeing. In other work, I am investigating this by collaborating with a popular smartphone sensing app designed to help people with depression. Age is only related to the number of location changes, and gender, openness, and agreeableness seem statistically independent from mobility and other measures.

In addition, multilevel modeling showed that many mobility features were related to daily affective states. People with more positively valence emotions traveled to fewer locations, in an unpredictable manner, and with shorter transition times. People who were more stressed or tense had less similarity in their travel sequence, while the opposite was true for those who were relaxed. Consistent with the trait findings for neuroticism and wellbeing, those who were sadder traveled less than others. Spatial coverage (operationalized by convex hull), radius of gyration, and entropy were related to many emotions and might be especially promising metrics going forward.

Chapter 4. The Relationship between Psychology and Places Visited

This chapter investigates how spaces and their psychological characteristics are related to the emotions individuals experience in those locations and the personality traits of those that frequent these locations. I examine where people generally spend their time and how they generally feel, how people feel in particular locations, whether there are relationships between stable psychological traits and frequency of visits to different locations, and how psychological traits interact with situational factors to affect people's in-the-moment experiences. Thus, I investigate: (a) In general, where do people go and how do they feel? (b) How do people feel in different places? (c) Where do different people go? (d) How do different people feel in different situations?

Methods

This investigation is based on the EMA data collected from 83 participants during the second wave of the Student Wellbeing Study (see Chapter 0). In addition, another study was conducted to supplement this dataset with information about the psychological characteristics of these places. In this additional study, 27 place types were rated on 33 variables by 279 participants on Amazon's Mechanical Turk. The place types were selected to represent spaces in which the EMA participants typically spent time. They were compiled by merging students' self-reported place types (taken from each EMA) with the place categories trained research assistants used to classify each student's location (see Chapter 0). To identify these additional place types, raters manually checked the GPS coordinates of the places students had spent the most time in during the study period (see Table 15 for the full list, including highlights of which location options were also found in the EMAs).

The full questionnaire is available in Appendix B. All place types were rated on their situational characteristics using the situational DIAMONDS, see Table 14 (Rauthmann et al., 2014), ambience (Hanyu, 2000), the typical personality of the people who visit that place (adapted from TIPI; Gosling, Rentfrow, & Swann, 2003), and its restorativeness (the four highest loading items for each of the sub dimensions – being away, fascination, coherence, and compatibility – of the Perceived Restorativeness Scale (PRS); Hartig, Korpela, Evans, & Gärling, 1997). Here, I will focus on the situational DIAMONDS. In addition, the raters responded to items about how often (and for how long) they typically visit each place type, how much they enjoy spending time there, as well as scales capturing their personality (BFI-2; Soto & John, 2017) and wellbeing (WHO-5; Psychiatric Research Unit WHO Collaborating Centre in Mental Health, 1998). This study received approval from both the Columbia University Morningside Institutional Review Board (under Protocol Number IRB-AAAR8167) and the Stanford University Institutional Review Board 2 (under Protocol Number IRB-44891).

The survey was posted on Amazon's Mechanical Turk. Three-hundred and forty completed responses were recorded, out of which 61 had to be excluded because of failed attention checks (34), because they belonged to participants who took the survey repeatedly (8), or because Amazon's Mechanical Turk reported a gender reporting consistency of less than 95% for those participants (19). The final sample consists of 279 responses, with each location type being rated by 47 to 55 raters. Each participant rated 5 randomly selected place types.

The ICCs for all place types (across variables, see Table 15) range from .93 to .98, and the ICCs for the rated variables (across locations, see Table 14) range from .98 to 1 (all *p-values* <.001) and hence are satisfactory. Mean ratings were computed for each situational DIAMONDS dimension (see Table 16 for a full list and Table 17 for an overview of the place types that were rated highest and lowest on each DIAMONDS dimension).

Table 13 show how the ratings gathered via Amazon's Mechanical Turk mapped onto the EMA place categories. Two additional ratings were computed to parallel the EMA options ('Café/restaurant' from 'café' and 'restaurant, and pub/party from 'pub' and 'party'). The ratings were centred prior to analysis.

Table 13

EMA Place Categories and Matched DIAMONDS Ratings

EMA place category (Student Wellbeing Study)	Matched DIAMONDS ratings (MTurk study)
Café / restaurant	Mean of ratings for 'Coffee shop and 'restaurant
College common room	Ratings for 'Common room (in a dorm)'
Friend's house	Ratings for 'Friend's house'
Home/own room in college	Ratings for 'Home/private room (in a dorm)'
In transit	No ratings matched
Pub / party	Mean of ratings for 'Bar/pub' and 'Dance club'
University	Ratings for 'Campus'
Other	No ratings matched

Note. Differences reflect American wording (e.g., dorm) to be intuitively understandable by American participants on Amazon's Mechanical Turk who are not familiar with the college system at the University of Cambridge.

Table 14

Items and Interrater Agreements for Situational DIAMONDS

Classification	Item wording	Interrater agreement	
		ICC2k	ICC2
Duty (Du)	In a typical [*PLACE*], a job needs to be done.	.99 [.99, 1.00]	.34 [.24, .50]
Intellect (I)	A typical [*PLACE*] affords an opportunity to demonstrate intellectual capacity.	.99 [.99, 1.00]	.25 [.25, .50]
Adversity (A)	In a typical [*PLACE*], a person may be criticized directly or indirectly.	.99 [.98, .99]	.20 [.13, .32]
Mating (M)	In a typical [*PLACE*], potential romantic partners are present.	.99 [.98, .99]	.24 [.16, .37]
Positivity (O)	In a typical [*PLACE*], situations are playful.	1.00 [.99, 1.00]	.51 [.39, .66]
Negativity (N)	In a typical [*PLACE*], situations are potentially anxiety inducing.	.99 [.99, 1.00]	.32 [.22, .47]
Deception (De)	In a typical [*PLACE*], someone might be deceitful.	.99 [.98, 1.00]	.25 [.17, .38]
Sociality (S)	In a typical [*PLACE*], social interaction is possible.	.99 [.98, .99]	.24 [.16, .38]

Note. N=1395 ratings of each situational DIAMONDS. 279 participants rated five (out of 27) different place types each. Average ICCs (ICC2k) and single ICCs (ICC2) with confidence intervals in parentheses are presented. ICCs are all highly significant (p<.001). The items were adapted from Rauthmann et al. (2014). Participants rated their responses on a 7-point scale ranging from 'Extremely uncharacteristic of the place' (1) to 'Extremely characteristic of the place' (7). They were prompted to respond to "Think of a typical [*PLACE*]. Indicate to what extent you agree with the following statements with regards to this type of place:" [*PLACE*] is a place holder for the different places evaluated using this scheme. See Table 15 for a full list of places evaluated.

Table 15

Interrater Agreements for Place Types

Place type	No. of raters	Interrater agreement	
		ICC2k	ICC2
Airport	55	.98 [.97, .99]	.46 [.35, .60]
Bar/pub *	51	.96 [.93, .98]	.30 [.22, .44]
Bus stop	54	.97 [.95, .98]	.37 [.27, .51]
Campus *	51	.97 [.95, .98]	.40 [.29, .54]
Club/party *	53	.98 [.97, .99]	.49 [.38, .63]
Coffee shop *	52	.96 [.94, .98]	.33 [.24, .47]
Common room in college *	50	.95 [.93, .97]	.29 [.20, .40]
Fraternity/sorority	53	.97 [.96, .98]	.40 [.30, .55]
Friend's house *	51	.98 [.97, .99]	.47 [.36, .61]
Green space	49	.97 [.95, .98]	.37 [.27, .52]
Gym	51	.97 [.95, .98]	.38 [.28, .52]
Health facility	55	.98 [.97, .99]	.50 [.39, .64]
House	50	.96 [.94, .98]	.34 [.25, .48]
Industrial building	51	.96 [.94, .98]	.34 [.24, .48]
Lake/River	53	.97 [.96, .99]	.42 [.32, .56]
Library	50	.98 [.97, .99]	.49 [.38, .63]
Mall	53	.97 [.95, .98]	.36 [.26, .50]
Museum	53	.98 [.96, .99]	.44 [.33, .58]
Parking	48	.97 [.96, .99]	.44 [.33, .58]
Religious institution	54	.96 [.94, .98]	.30 [.21, .43]
Residential building	52	.96 [.93, .97]	.30 [.21, .43]
Restaurant *	47	.97 [.96, .99]	.45 [.34, .59]
Private room/home *	52	.96 [.94, .98]	.33 [.24, .47]
Store	54	.97 [.95, .98]	.36 [.26, .50]
Street	50	.93 [.89, .96]	.21 [.14, .32]
Trail	53	.97 [.95, .98]	.35 [.25, .48]
Train station	50	.96 [.94, .98]	.34 [.24, .47]

Note. Each of 279 raters evaluated 5 randomly selected place types. Average ICCs (ICC2k) and single ICCs (ICC2) with confidence intervals in parentheses are presented. ICCs are all highly significant (p<.001). Asterisks (*) indicate place types that were listed as response options to the EMA question "Where are you right now?" in the Student Wellbeing Study.

Table 16

Average Ratings of Situational DIAMONDS for Different Place Types

Place type	Duty		Intellect		Adversity		Mating		Positivity		Negativity		Deception		Sociality	
	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Airport	5.65	*1.58*	3.11	*1.73*	4.40	*1.59*	3.62	*1.72*	2.24	*1.25*	5.98	*1.16*	4.38	*1.42*	6.00	*1.14*
Bar	3.43	*2.10*	3.45	*1.71*	5.10	*1.47*	5.76	*1.58*	5.65	*1.43*	4.35	*1.95*	5.43	*1.53*	6.39	*1.28*
Bus	4.33	*2.02*	2.15	*1.23*	3.91	*1.71*	3.04	*1.74*	2.17	*1.36*	4.22	*1.72*	4.13	*1.85*	5.43	*1.44*
Coffeeshop	4.81	*1.83*	4.10	*1.79*	3.79	*1.64*	4.56	*1.43*	3.75	*1.34*	3.10	*1.66*	3.58	*1.53*	6.25	*0.84*
Common	4.10	*1.87*	4.52	*1.55*	4.00	*1.63*	4.40	*1.86*	5.06	*1.20*	2.96	*1.67*	3.06	*1.58*	6.04	*1.26*
Dance club	2.49	*1.61*	2.32	*1.54*	4.68	*1.70*	6.02	*1.20*	6.06	*0.89*	4.43	*1.94*	5.17	*1.66*	6.49	*1.10*
Frat	3.45	*1.87*	3.72	*1.96*	5.72	*1.34*	4.55	*1.98*	5.77	*1.27*	5.08	*1.40*	5.45	*1.39*	6.70	*0.80*
Friends	2.45	*1.47*	4.69	*1.39*	3.37	*1.67*	3.10	*1.87*	5.53	*1.25*	2.41	*1.58*	2.33	*1.37*	6.47	*0.92*
Green space	2.96	*1.71*	3.47	*1.62*	2.94	*1.49*	3.82	*1.59*	5.06	*1.30*	2.06	*1.16*	2.84	*1.49*	5.00	*1.27*
Gym	5.63	*1.47*	2.22	*1.32*	4.73	*1.81*	4.39	*1.54*	3.96	*1.25*	4.59	*1.73*	4.18	*1.68*	5.88	*1.19*
House	5.22	*1.49*	4.46	*1.53*	4.56	*1.55*	4.66	*2.04*	4.98	*1.27*	3.40	*1.67*	3.76	*1.77*	6.22	*1.15*
Industrial building	6.27	*1.31*	4.24	*1.75*	4.47	*1.65*	2.31	*1.42*	2.02	*1.14*	4.29	*1.74*	3.92	*1.67*	4.57	*1.70*
Library	5.00	*1.36*	5.74	*1.37*	2.82	*1.77*	3.40	*1.75*	2.50	*1.43*	1.86	*1.28*	2.58	*1.68*	4.48	*1.64*
Mall	5.45	*1.39*	2.53	*1.53*	3.79	*1.69*	4.32	*1.75*	4.15	*1.49*	4.21	*1.63*	4.85	*1.34*	6.11	*0.89*
Medical	6.56	*0.83*	4.44	*1.94*	4.62	*1.69*	2.45	*1.50*	1.64	*1.11*	6.25	*1.14*	3.69	*1.75*	5.60	*1.41*
Museum	3.62	*2.15*	5.91	*1.01*	3.11	*1.78*	4.09	*1.79*	2.94	*1.61*	2.09	*1.52*	2.66	*1.56*	5.28	*1.45*
Parking	4.63	*2.06*	1.94	*1.45*	3.63	*1.97*	2.52	*1.62*	1.81	*1.35*	4.21	*1.99*	3.71	*1.89*	4.42	*1.89*
Religious	3.72	*1.86*	3.48	*1.87*	4.67	*1.85*	4.15	*1.78*	2.41	*1.49*	3.85	*1.80*	4.67	*1.74*	5.76	*1.47*
Residential	3.98	*1.75*	4.52	*1.23*	4.56	*1.47*	4.96	*1.39*	4.35	*1.25*	3.75	*1.77*	4.65	*1.15*	6.00	*0.97*
Restaurant	5.06	*2.03*	3.68	*1.76*	4.11	*1.48*	5.04	*1.33*	4.34	*1.61*	2.94	*1.65*	3.70	*1.59*	6.51	*0.62*
Room	3.58	*1.74*	4.37	*1.77*	2.94	*1.82*	3.63	*2.19*	3.65	*1.48*	2.88	*1.80*	3.00	*1.58*	4.31	*2.06*
Store	5.76	*1.24*	3.06	*1.58*	3.56	*1.56*	3.44	*1.64*	2.96	*1.35*	3.54	*1.77*	4.17	*1.31*	5.87	*1.06*
Street	3.76	*1.78*	2.72	*1.78*	4.04	*1.69*	3.22	*1.88*	3.08	*1.71*	4.46	*1.69*	4.28	*1.69*	4.56	*1.58*
Trail	2.57	*1.69*	3.06	*1.60*	2.40	*1.56*	3.25	*1.64*	4.26	*1.69*	2.91	*1.63*	2.62	*1.53*	4.36	*1.62*
Train station	5.34	*1.84*	2.44	*1.40*	3.86	*1.54*	3.42	*1.69*	2.30	*1.27*	4.32	*2.03*	4.40	*1.73*	5.50	*1.22*
University	6.00	*1.08*	6.22	*1.19*	5.41	*1.30*	5.25	*1.52*	4.59	*1.42*	5.04	*1.54*	5.06	*1.50*	6.55	*0.86*
Water	2.62	*1.69*	2.77	*1.42*	3.02	*1.88*	4.42	*1.67*	5.77	*1.22*	2.79	*1.85*	2.66	*1.73*	5.38	*1.36*

Note. M= Mean. SD = Standard Deviation. The scale ranged from 1 to 7. Mean values above the scale midpoint (=4) are highlighted in green, and mean values below the scale midpoint are in red. Two-hundred seventy nine participants rated 5 place types each. Each place type received 48-55 ratings (see Table 15).

Table 17

Top Three and Bottom Three Location Types for each Situational DIAMONDS by Mean Rating

Duty	**Intellect**	**Adversity**	**Mating**	**Positivity**	**Negativity**	**Deception**	**Sociality**
Health facility (6.56, *0.83*)	Campus (6.22, *1.19*)	Fraternity/sorority (5.71, *1.34*)	Club/party (6.02, *1.20*)	Club/party (6.06, *0.89*)	Health facility (6.25, *1.14*)	Fraternity/sorority (5.45, *1.39*)	Fraternity/sorority (6.70, *0.80*)
Industrial build. (6.27, *1.31*)	Museum (5.91, *1.01*)	Campus (5.41, *1.30*)	Bar/pub (5.76, *1.58*)	Fraternity/sorority (5.77, *1.27*)	Airport (5.98, *1.16*)	Bar/pub (5.43, *1.53*)	Campus (6.55, *0.86*)
Campus (6.00, *1.08*)	Library (5.74, *1.37*)	Bar /Pub (5.10, *1.47*)	Campus (5.25, *1.52*)	Lake/river (5.77, *1.22*)	Fraternity/sorority (5.08, *1.40*)	Club/party (5.17, *1.66*)	Restaurant (6.51, *0.62*)
[…]	[…]	[…]	[…]	[…]	[…]	[…]	[…]
Trail (2.56, *1.69*)	Gym (2.22, *1.32*)	Green space (2.94, *1.49*)	Parking (2.52, *1.62*)	Industrial build. (2.02, *1.14*)	Museum (2.09, *1.52*)	Trail (2.62, *1.53*)	Parking (4.42, *1.89*)
Club/party (2.49, *1.61*)	Bus stop (2.15, *1.23*)	Library (2.82, *1.77*)	Health facility (2.45, *1.50*)	Parking (1.81, *1.35*)	Green space (2.06, *1.16*)	Library (2.58, *1.68*)	Trail (4.36, *1.62*)
Friend's place (2.45, *1.47*)	Parking (1.94, *1.45*)	Trail (2.40, *1.56*)	Industrial build. (2.31, *1.42*)	Health facility (1.64, *1.11*)	Library (1.86, *1.28*)	Friend's place (2.33, *1.37*)	Private room (4.31, *2.06*)

Note. Shown in parentheses are the mean ratings, alongside their standard deviations in italics. Each place type was rated by 47 to 55 raters out of the total rater population of 279. Each situational DIAMONDS received 279*5=1395 ratings. Scale ranges from 1 to 7.

Results

Inter-item correlations.

The majority of personality traits (i.e., openness, conscientiousness, agreeableness and neuroticism) were not correlated with frequency of place visits (see Table 18). Only extraversion was found to be positively related to how often one visited pubs/parties (.24, $p<.05$). However, wellbeing was found to be strongly related to a number of place visiting frequencies. In particular, people with higher wellbeing visited college common areas (.40, $p<.001$), pubs and parties (.29, $p<.01$), and other places (.31, $p<.01$) more frequently, and reported being in transit more often (.24, $p<.05$).

Table 18

Correlation Matrix for Frequencies of Visits to Different Place Types, Personality and Wellbeing

	1	**2**	**3**	**4**	**5**	**6**
1 Age		[-.16, .27]	[.06, .46]	[-.17, .26]	[-.23, .21]	[-.09, .35]
2 Gender	.11		[.05, .46]	[.01, .42]	[-.12, .31]	[-.34, .09]
3 EMA count	**.31****	**.25***		[.30, .63]	[-.28, .16]	[-.27, .17]
4 App participation	.12	**.22***	**.42*****		[-.19, .25]	[-.49, -.08]
5 Openness	.00	.12	-.05	.04		[-.12, .32]
6 Conscientiousness	.15	-.13	-.09	**-.33****	.11	
7 Extraversion	-.05	.08	-.06	-.18	.19†	.14
8 Agreeableness	-.14	**-.24***	-.13	-.13	**.26***	**.25***
9 Neuroticism	.01	**-.38*****	-.19†	-.22†	-.15	-.18
10 Wellbeing	**.35****	.18	.13	.14	.02	.04
11 Café / restaurant	.14	-.13	.08	-.21†	.06	.22†
12 College common room	**.24***	.07	**.29****	**.28****	-.12	-.10
13 Friend's house	.08	-.07	.12	.15	.00	-.10
14 Home/own room	.09	**.34****	**.71*****	**.32****	-.07	-.13
15 In transit	.16	.02	**.24***	**.26***	-.07	-.05
16 Pub / party	-.01	.01	.13	-.12	.00	-.10
17 University	-.08	-.10	**-.40*****	-.21†	.00	.08
18 Other	.14	-.13	.17	.02	.09	.06

Note. † $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$. Variables 11-18 represent frequencies of visits to these place types. Spearman correlation coefficients are presented. P values have been corrected for multiple comparisons using the method presented in (Benjamini & Hochberg, 1995). Coefficients and p values are presented in bold if $p < .05$. Confidence intervals are presented in square brackets.

Correlation Matrix for Frequencies of Visits to Different Place Types, Personality and Wellbeing (continued)

	7	8	9	10	11	12
1 Age	[-.28, .16]	[-.40, .02]	[-.14, .30]	[.07, .48]	[-.31, .12]	[.01, .42]
2 Gender	[-.14, .30]	[-.45, -.03]	[-.54, -.15]	[-.04, .39]	[-.36, .07]	[-.22, .21]
3 EMA count	[-.35, .08]	[-.28, .16]	[-.36, .07]	[-.14, .30]	[-.3, .13]	[.12, .51]
4 App participation	[-.39, .04]	[-.33, .10]	[-.41, .01]	[-.10, .34]	[-.43, -.02]	[.05, .45]
5 Openness	[-.04, .39]	[.02, .44]	[-.34, .09]	[-.19, .25]	[-.37, .06]	[-.44, -.03]
6 Conscientiousness	[-.02, .40]	[.01, .43]	[-.40, .03]	[-.17, .27]	[-.11, .33]	[-.42, .00]
7 Extraversion		[-.11, .32]	[-.56, -.19]	[.06, .47]	[.07, .48]	[-.26, .18]
8 Agreeableness	.10		[-.31, .13]	[-.29, .15]	[-.13, .31]	[-.31, .13]
9 Neuroticism	**-.38*** **	-.04		[-.56, -.18]	[-.37, .06]	[-.29, .15]
10 Wellbeing	**.26***	-.08	**-.39*** **		[-.20, .25]	[.18, .56]
11 Café / restaurant	.14	.02	.10	-.16		[-.08, .35]
12 College common room	.05	-.20†	-.14	**.40*** **	-.04	
13 Friend's house	.00	.16	.07	.18	-.10	.21†
14 Home/own room	-.15	-.11	-.15	-.07	**-.33** **	-.12
15 In transit	-.04	.03	-.14	**.24***	-.15	**.32** **
16 Pub / party	**.24***	.07	-.05	**.29** **	-.06	**.27***
17 University	-.01	-.13	.07	.01	-.09	-.10
18 Other	.03	-.13	-.11	**.31** **	-.08	**.26***

Note. † $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$. Variables 11-18 represent frequencies of visits to these place types. Spearman correlation coefficients are presented. P values have been corrected for multiple comparisons using the method presented in (Benjamini & Hochberg, 1995). Coefficients and p values are presented in bold if $p < .05$. Confidence intervals are presented in square brackets.

Correlation Matrix for Frequencies of Visits to Different Place Types, Personality and Wellbeing (continued)

	13	**14**	**15**	**16**	**17**	**18**
1 Age	[.12, .51]	[-.11, .32]	[.10, .49]	[-.08, .34]	[-.21, .22]	[.00, .42]
2 Gender	[-.26, .17]	[.15, .53]	[-.17, .26]	[-.14, .28]	[-.25, .18]	[-.33, .10]
3 EMA count	[-.10, .32]	[.55, .78]	[.07, .47]	[-.17, .26]	[-.53, -.15]	[-.14, .29]
4 App participation	[-.17, .26]	[.10, .49]	[.13, .52]	[-.30, .13]	[-.41, .00]	[-.17, .26]
5 Openness	[-.27, .17]	[-.30, .14]	[-.28, .16]	[-.25, .19]	[-.17, .27]	[-.09, .34]
6 Conscientiousness	[-.26, .18]	[-.33, .10]	[-.26, .18]	[-.33, .11]	[-.15, .29]	[-.20, .24]
7 Extraversion	[-.11, .33]	[-.37, .06]	[-.31, .13]	[-.10, .34]	[-.11, .32]	[-.16, .28]
8 Agreeableness	[-.11, .33]	[-.31, .13]	[-.33, .10]	[-.26, .19]	[-.41, .02]	[-.28, .16]
9 Neuroticism	[-.17, .27]	[-.31, .12]	[-.35, .08]	[-.24, .20]	[-.14, .30]	[-.35, .08]
10 Wellbeing	[.13, .52]	[-.29, .15]	[.09, .49]	[.08, .48]	[-.10, .34]	[.17, .55]
11 Café / restaurant	[-.19, .25]	[-.54, -.17]	[-.34, .08]	[-.13, .30]	[-.24, .19]	[-.04, .38]
12 College common room	[.12, .51]	[-.24, .19]	[.14, .52]	[.00, .41]	[-.25, .18]	[.30, .64]
13 Friend's house		[-.39, .03]	[.06, .46]	[.09, .48]	[-.28, .15]	[-.03, .39]
14 Home/own room	**-.27***		[-.24, .19]	[-.27, .16]	[-.43, -.02]	[-.38, .04]
15 In transit	.14	-.04		[.12, .51]	[-.10, .32]	[.13, .51]
16 Pub / party	.16	-.07	.17		[-.04, .38]	[.10, .49]
17 University	-.11	**-.29****	-.02	-.04		[-.06, .36]
18 Other	.03	-.12	**.23***	.33**	-.09	

Note. † $p < .10$. * $p < .05$. ** $p < .01$. *** $p < .001$. Variables 11-18 represent frequencies of visits to these place types. Spearman correlation coefficients are presented. P values have been corrected for multiple comparisons using the method presented in (Benjamini & Hochberg, 1995). Coefficients and p values are presented in bold if $p < .05$. Confidence intervals are presented in square brackets.

Where do people go and how do they feel generally?

When responding to EMA surveys over the course of the study period, participants reported being in: a café/restaurant (*m*=2.83, *sd*=6.72), college common room (*m*=2.07, *sd*=3.18), friend's house (*m*=2.64, *sd*=4.68), home/own room (*m*=27.54, *sd*=13.25), in transit (*m*=1.67, *sd*=2.19), pub/party (*m*=0.52, *sd*=0.87), university (*m*=4.58, *sd*=6.03), and other places (*m*=2.2, *sd*=2.74).

For each place type, a majority of the participants reported to have been there at least once while responding to an EMA during the study (café/restaurant: 55.42%; college common room: 61.45%; friend's house: 62.65%; in transit: 57.83%; university 79.52%; other 65.06%). The exception is that only 34.94% of participants reported being in pub/at a party at least once. One-hundred percent of participants reported being at home / in their own room at least once.

For all place visiting frequencies, more variance was observed within individuals than between. The ICC1 measures the proportion of variance explained by participants and can be conceptualized as the correlation for the dependent variable for two randomly selected EMAs from the same participant. An ICC1=.05 represents a small to medium effect (LeBreton & Senter, 2008). With the exception of the frequency of being in transit (.04) and in pubs/at parties (.01), all frequency measures lie on or above that threshold. Person mean reliabilities were excellent for café/restaurant, college common room, friend's house, home/own room, and university, fair to good for in transit and other, and poor for pub/party visits (Fleiss, 1986).

Table 19

Variance Between and Within Individual for Places Visited and Affective States

	Percentage of participants who reported visiting the place at least once	Average frequency	Standard deviation	Variance between individuals	Variance within individuals	Person mean reliability
Places visited						
Café/restaurant	55.42	2.83	6.72	.32	.68	.95
College common room	61.45	2.07	3.18	.07	.93	.77
Friend's house	62.65	2.64	4.68	.19	.81	.91
Home/own room	100.00	27.54	13.25	.20	.80	.92
In transit	57.83	1.67	2.19	.04	.96	.65
Pub/party	34.94	0.52	0.87	.01	.99	.30
University	79.52	4.58	6.03	.22	.78	.93
Other	65.06	2.2	2.74	.05	.95	.71
Affective states		Average rating	Standard deviation			
Arousal		2.77	0.61	.23	.77	.93
Valence		3.46	0.56	.24	.76	.93
Tense		2.51	0.94	.40	.60	.97
Stressed		2.90	0.94	.34	.66	.96
Relaxed		3.18	0.98	.32	.68	.95
Excited		2.76	1.03	.37	.63	.96
Sad		1.85	0.84	.40	.60	.97

Note. N = 3657 EMAs, submitted by 83 participants, who participated for 3-14 days. ICC1s (variance between individuals) and ICC2s (individual mean reliability) were computed using a multilevel modeling approach as the group sizes (i.e. number of EMAs per participant) were not balanced. I used the multilevel package in R, following the procedure suggested for estimating multiple ICC values in Bliese (2016).

How do people feel in different places?

Multilevel models were fitted to predict affective states from places. Home was set as the reference category. Corresponding to the data structure (i.e., multiple EMA responses being nested within persons), random intercepts were used and set to vary within persons. The models did not converge when including further random effects of the predictor variables. Table 20 presents the fixed effects of the fitted models.

Arousal: Being in a pub or at a party was associated with significantly lower arousal compared to being at home, .36, p=.032 (see Table 19). This is roughly half a standard deviation. Being in a café or a restaurant predicted .35 lower arousal (p<.001) or half a standard deviation, and being on campus predicted .21 lower arousal (p=.002) or a third of a standard deviation.

Valence: Being in a pub or at a party (.53, p < .001), in transit (.38, p <.001), in a college common area (.35, p <.001), a friend's house (.34, p <.001), or in an 'Other' place (.29, p <.001) were associated with significantly higher self-reported positive feelings.

Tense: Being in a pub or at a party (-.46, p=.008), and being at a friend's house predicted significantly lower (-.37, p <.001) tense feelings, while being in a café or restaurant was associated with more (0.39, p <.001) tense feelings.

Stressed: Being in a pub or at a party (-.78, p <.001), being at a friend's house (-.46, p<.001), being in transit (-.41, p<.001), being in an 'Other' place (-.36, p<.001), or in a college common area (-.33, p=.002) were associated with less stress, while being in a café or restaurant (.45, p<.001) was associated with more stress.

Relaxed: Being in a pub or at a party (1.17, p<.001), being at a friend's house (.84, p<.001), being in transit (.43, p=.001), or in a college common area (.36, p=.001) were associated with greater feelings of relaxation compared to being at home, while being in a café or restaurant (-.52, p<.001) was related to reduced feelings of relaxation.

Excited: Being in a pub or at a party (.96, $p<.001$), being at a friend's house (.51, $p<.001$), and being in transit (.34, $p=.004$) were associated with greater excitement.

Sad: No place type was found to be significantly associated with students' feelings of sadness compared to being at home.

Table 20

Linear Mixed-Effects Models Predicting Affective States from Places (Random Intercepts Model)

	Arousal			Valence			Tense			Stressed		
	B	SE	p	B	SE	p	B	SE	p	B	SE	p
Intercept	2.84	.07	<.001	3.37	.06	<.001	2.52	.10	<.001	2.96	.10	<.001
Café / restaurant	**-.35**	.09	<.001	-.01	.08	.894	**.39**	.09	<.001	**.45**	.11	<.001
College common area	-.16	.09	.067	**.35**	.08	<.001	-.07	.09	.429	**-.33**	.11	.002
Friend's house	-.05	.08	.577	**.34**	.07	<.001	**-.37**	.09	<.001	**-.46**	.10	<.001
In transit	-.10	.10	.315	**.38**	.08	<.001	-.17	.10	.081	**-.41**	.11	<.001
Pub / Party	**-.36**	.17	.032	**.53**	.15	<.001	**-.46**	.17	.008	**-.78**	.20	<.001
University	**-.21**	.07	.002	.12	.06	.044	-.01	.07	.922	-.13	.08	.089
Other	-.10	.09	.228	**.29**	.08	<.001	-.13	.09	.154	**-.36**	.10	<.001

Note. Number of EMAs n = 3657, submitted by 83 participants, who participated for 3-14 days. The scales ranged from 1 to 5, and 'Home' was set as the reference category. Table presents fixed effects. Models did not converge when including random effects.

Linear Mixed-Effects Models Predicting Affective States from Places (Random Intercepts Model) - continued

	Relaxed			Excited			Sad		
	B	SE	p	B	SE	p	B	SE	p
Intercept	3.09	.11	<.001	2.65	.11	<.001	1.87	.09	<.001
Café / restaurant	**-.52**	.11	<.001	-.05	.11	.643	-.01	.08	.900
College common area	**.36**	.11	.001	.20	.11	.063	-.08	.08	.319
Friend's house	**.84**	.11	<.001	**.51**	.10	<.001	-.09	.08	.240
In transit	**.43**	.12	.001	**.34**	.12	.004	-.08	.09	.356
Pub / Party	**1.17**	.21	<.001	**.96**	.20	<.001	.14	.16	.389
University	-.01	.08	.895	.09	.08	.269	-.05	.06	.435
Other	**.44**	.11	<.001	**.60**	.10	<.001	-.06	.08	.461

Note. Number of EMAs n = 3657, submitted by 83 participants, who participated for 3-14 days. The scales ranged from 1 to 5, and 'Home' was set as the reference category. Table presents fixed effects. Models did not converge when including random effects.

Where do different people go?

Two-stage hierarchical negative binomial regressions were conducted with frequency of visits to different places as the dependent variables. Age, gender, total number of submitted EMAs, and mode of participation (app vs. text messages) were entered at step one of the regressions to control for demographics and participation metrics. Personality (BFI-44) and trait wellbeing (WHO-5) were entered at stage two. Intercorrelations between the regression variables are reported in Table 18, and the regression statistics are in Table 21-Table 24.

Café/restaurant: The hierarchical negative binomial regression revealed that at stage one, total number of submitted EMAs and mode of participation contributed significantly to the regression model (see Table 21). Introducing personality and trait wellbeing did not significantly improve the model (χ^2 (10, N = 85) = 13.91, p =.177), and the total number of submitted EMAs and mode of participation remained the only significant predictors. The total number of submitted EMAs has a statistically significant coefficient of .04 (p=.015), meaning that for each additional submitted EMA the expected log count of number of visits to cafes/restaurants increases by .04. The variable shown as app participation is the expected difference in log count between participants who responded via app and participations who responded using a survey link sent via text message. The expected log count for participants who responded via app is 1.27 lower (p=.014) than the log count for participants who responded via texted survey links.

Common area in college: At stage one, total number of submitted EMAs contributed significantly to the regression model (see Table 21). However, introducing personality and trait wellbeing significantly improves the model (χ^2 (10, N = 85) = 31.79, p <.001) and adds trait wellbeing as a significant predictor. The total number of submitted EMAs has a statistically significant coefficient of .05 (p=.004), meaning that for each additional submitted EMA the expected log count of number of visits to college common areas increases by .05. Trait wellbeing has a statistically significant coefficient of .55 (p=.001), meaning that for each increase of one standard deviation on the WHO-5 scale, the expected log count of number of visits to college common areas increases by .55.

Friend's house: At stage one, no predictors contributed significantly to the regression model (see Table 22). Introducing personality and trait wellbeing significantly improves the model (χ^2 (10, N = 85) = 29.46, p =.001) and adds agreeableness (.52, p=.005), neuroticism (.63, p<.001), and trait wellbeing (.73, p<.001) as significant predictors.

Home/own room: At stage one, age and total number of submitted EMAs contributed significantly to the regression model (see Table 22). Introducing personality and trait wellbeing significantly improves the model (χ^2 (10, N = 85) = 31.86, p <.001) and, while age is no longer a significant predictor, gender emerges as a significant predictor. Gender has a statistically significant coefficient of .17, meaning that the expected log count for men is .17 higher (p=.045) than the log count for women. Men were more likely to frequent their home/own room than women were. Total number of submitted EMAs has a statistically significant coefficient of .03 (p<.001).

In transit: At stage one, no predictors contributed significantly to the regression model (see Table 23). Introducing personality and trait wellbeing does not significantly improve the model (χ^2 (10, N = 85) = 17.29, p =.068), but adds trait wellbeing as a significant predictor to the model (.37, p=035).

Pub/party: At stage one, mode of participation contributed significantly to the regression model (see Table 23). Introducing personality and trait wellbeing significantly improves the model (χ^2 (10, N = 85) = 26.37, p <.001). While mode of participation is no longer a significant predictor, conscientiousness (-.44, p = .050) and trait wellbeing (.68, *p*=.002) significantly predict the expected log count of number of reported visits to pubs and parties.

University: At stage one, total number of submitted EMAs (-.04, p <.001) contributed significantly to the regression model (see Table 24). Introducing personality and trait wellbeing significantly improves the model (χ^2 (10, N = 85) = 27.80, p =.002), but did not add additional significant predictors.

Other: At stage one, gender and total number of submitted EMAs contributed significantly to the regression model (see Table 24). Introducing personality and trait wellbeing significantly improves the model (χ^2 (10, N = 85) = 32.34, p <.001) and, while removing total number of submitted EMAs, adds wellbeing (.40, *p*=.006) to gender (-.78, *p*=.007) as a significant predictor.

Table 21

Results of Hierarchical Negative Binomial Regression for Frequency of Visits to Café/Restaurant and College (Common area)

	Café / restaurant						College (Common area)					
	Step 1			Step 2			Step 1			Step 2		
	B	SE	p	B	SE	p	B	SE	p	B	SE	p
# of EMAs												
Intercept	-.80	.83	.331	-.88	.93	.342	-1.82	.81	.024	-2.00	.85	.019
Age	-.03	.20	.878	-.10	.22	.661	.20	.14	.163	-.01	.14	.960
Gender	-.55	.38	.154	-.66	.44	.141	-.51	.31	.105	-.50	.32	.119
EMA count	**.04**	.02	.007	**.04**	.02	.015	**.04**	.02	.004	**.05**	.02	.004
App participation	**-1.63**	.45	<.001	**-1.27**	.51	.014	.62	.33	.058	.27	.35	.435
Openness				-.20	.20	.334				-.15	.15	.320
Conscientiousness				.17	.22	.452				-.22	.17	.195
Extraversion				.27	.22	.214				-.06	.16	.728
Agreeableness				-.09	.21	.676				-.22	.15	.156
Neuroticism				-.31	.25	.212				-.12	.19	.535
Wellbeing				-.16	.23	.495				**.55**	.16	.001
AIC / 2LL	330.27 / -318.27			328.36 / -304.36			309.93 / -297.98			290.19 / -266.19		
χ^2 (10, N = 85)				13.91, p =.177						**31.79**, p <.001		

Note. n=83; Chi-squared tests for improved model fit were performed. The chi-squared statistic corresponds to the Δ 2x maximized log likelihood. Gender coding: Male=1, female=0. Continuous variables were z-scored.

Table 22

Results of Hierarchical Negative Binomial Regression for Frequency of Visits to Friend's house and Home/own room

	Friend's house						Home / own room					
	Step 1			Step 2			Step 1			Step 2		
	B	SE	p	B	SE	p	B	SE	p	B	SE	p
# of EMAs												
Intercept	.03	.71	.968	.10	.72	.890	1.28	.19	<.001	1.39	.20	<.001
Age	.15	.16	.368	-.03	.17	.859	**-.06**	.04	.101	-.04	.04	.395
Gender	-.47	.34	.163	.23	.38	.540	.15	.08	.055	**.17**	.09	.045
EMA count	.02	.01	.194	.01	.01	.661	**.04**	.00	<.001	**.03**	.00	<.001
App participation	.35	.37	.350	.54	.42	.192	-.08	.09	.352	-.11	.10	.268
Openness				-.13	.17	.437				-.02	.04	.698
Conscientiousness				-.06	.19	.731				-.03	.04	.500
Extraversion				.20	.18	.270				-.03	.04	.454
Agreeableness				**.52**	.18	.005				-.01	.04	.726
Neuroticism				**.63**	.23	.005				-.03	.05	.521
Wellbeing				**.73**	.19	<.001				-.07	.04	.113
AIC / 2LL	353.34 / -341.34			335.88 / -311.88			606.29 / -594.29			586.43 / -562.42		
χ^2 (10, N = 85)				**29.46**, p =.001						**31.86**, *p* <.001		

Note. n=83; Chi-squared tests for improved model fit were performed. The chi-squared statistic corresponds to the Δ 2x maximized log likelihood. Gender coding: Male=1, female=0. Continuous variables were z-scored.

Table 23

Results of Hierarchical Negative Binomial Regression for Frequency of Being in Transit and Visits to Pub/Party

	In transit						Pub / party					
	Step 1			Step 2			Step 1			Step 2		
	B	SE	p	B	SE	p	B	SE	p	B	SE	p
# of EMAs												
Intercept	-.66	.68	.333	-.61	.75	.421	-.09	.20	.650	-2.34	1.00	.020
Age	.13	.14	.359	.03	.15	.849	.04	.37	.921	-.20	.21	.325
Gender	-.12	.30	.694	-.17	.34	.614	.03	.02	.055	.30	.42	.482
EMA count	.02	.01	.149	.02	.01	.194	-.82	.45	.067	.03	.02	.160
App participation	.42	.32	.194	.18	.37	.624	**-2.32**	.96	.016	-.90	.47	.055
Openness				.01	.16	.931				-.07	.19	.725
Conscientiousness				-.13	.18	.468				**-.44**	.22	.050
Extraversion				-.20	.17	.237				.32	.19	.083
Agreeableness				.12	.16	.481				.31	.22	.143
Neuroticism				-.11	.20	.582				.19	.25	.454
Wellbeing				**.37**	.17	.035				**.68**	.22	.002
AIC / 2LL	296.63 / -284.63			291.35 / -267.34			168.31 / -156.31			153.94 / -129.94		
χ^2 (10, N = 85)				17.29, p =.068						**26.37**, p <.001		

Note. n=83; Chi-squared test for improved model fit were performed. The chi-squared statistic corresponds to the Δ 2x maximized log likelihood. Gender coding: Male=1, female=0. Continuous variables were z-scored.

Table 24

Results of Hierarchical Negative Binomial Regression for Frequency of Visits to University and Other

	University						Other					
	Step 1			Step 2			Step 1			Step 2		
	B	SE	p	B	SE	p	B	SE	p	B	SE	p
# of EMAs												
Intercept	3.67	.49	<.001	3.66	.51	<.001	-.33	.63	.599	-.19	.63	.757
Age	.10	.13	.469	.01	.14	.952	.16	.13	.222	.00	.13	.995
Gender	.04	.26	.883	.02	.28	.945	**-.61**	.28	.031	**-.78**	.29	.007
EMA count	**-.04**	.01	<.001	**-.04**	.01	<.001	**.03**	.01	.039	.02	.01	.072
App participation	-.25	.30	.398	-.47	.32	.151	-.03	.31	.912	-.12	.32	.699
Openness				.09	.13	.475				.25	.14	.062
Conscientiousness				.04	.14	.753				.06	.14	.679
Extraversion				.01	.14	.936				-.05	.14	.710
Agreeableness				-.21	.13	.112				-.20	.13	.138
Neuroticism				.03	.16	.855				-.09	.16	.600
Wellbeing				.13	.14	.348				**.40**	.14	.006
AIC / 2LL	426.15 / -414.16			410.35 / -386.35			333.82 / -321.82			313.47 / -289.47		
χ^2 (10, N = 85)				**27.80**, p =.002						**32.34**, *p* <.001		

Note. n=83; Chi-squared tests for improved model fit were performed. The chi-squared statistic corresponds to the Δ 2x maximized log likelihood. Gender coding: Male=1, female=0. Continuous variables were z-scored.

How do different people feel in different situations?

Pearson correlation coefficients were computed for the situational DIAMONDS. Overall, many dimensions show strong linear relationships with each other. Place intellect was not significantly related to any other place characteristics, and place duty only to place positivity and place negativity. However, place adversity, mating affordances, positivity, negativity, deception, and sociality were each moderately to very strongly related to three or four other dimensions.

Specifically, place duty was strongly negatively related to place positivity (r = -.61, p < .001), and moderately positively related to place negativity (r = .44, p = .018). Place intellect was not significantly related to any other place characteristics, although there were marginally significant, weak negative relationships with place negativity (r = -.31, p = .098) and place deception (r = -.31, p = .097). Place adversity was very strongly related to place deception (r = .84, p < .001), strongly related to place negativity (r = .73, p < .001) and place sociality (r = .65, p < .001), and moderately related to a place's mating affordances (r = .46, p = .013). A place's mating affordances were strongly related to place positivity (r = .74, p < .001) and place sociality (r = .70, p < .001), and moderately positively related to place deception (r = .49, p = .007), and moderately negatively related to place adversity (r = .46, p = .013). Place positivity was strongly positively related to a place's mating affordances (r = .74, p < .001) and place sociality (r = .65, p = .002), and strongly negatively related to place duty (r = -.61, p < .001). Place negativity was strongly related to place duty (r = .73, p < .001), place adversity (r = .73, p < .001), and place deception (r = .72, p < .001). Place deception was very strongly related to place adversity (r = .84, p < .001), strongly related to place negativity (r = .72, p < .001), and moderately related to place sociality (r = .52, p = .004) and a place's mating affordances (r = .49, p = .007). Place sociality was strongly positively related to a place's mating affordances (r = .70, p < .001), adversity ($r = .65$, $p < .001$), and place positivity ($r = .65$, $p = .002$), and moderately related to place deception ($r = .52$, $p = .004$).

Table 25

Correlation Matrix for Average Ratings of Situational DIAMONDS for Different Place Types

	Du	I	A	M	O	N	De	S
Duty (Du)		.448	.152	.121	<.001	.018	.373	.858
Intellect (I)	.15		.952	.793	.895	.098	.097	.737
Adversity (A)	.27	-.01		.013	.332	<.001	<.001	<.001
Mating (M)	-.29	.05	.46 *		<.001	.948	.007	<.001
Positivity (O)	-.61 ***	.03	.19	.74 ***		.237	.472	.002
Negativity (N)	.44 *	-.31 †	.73 ***	-.01	-.23		<.001	.174
Deception (De)	.17	-.31 †	.84 ***	.49 **	.14	.72 ***		.004
Sociality (S)	.03	.07	.65 ***	.70 ***	.54 **	.26	.52 **	

Note. Pearson correlation coefficients are displayed below and p values above the diagonal. All variables are normally distributed. N=79;
† *p* < .10. * *p* < .05. ** *p* < .01. *** *p* < .001.

Linear mixed models were fitted to assess the relationship between in-the-moment wellbeing (valence) with psychological characteristics of the place (DIAMONDS) and psychological traits of the visitor (i.e., personality of the EMA participants), including their interactions. The situational DIAMONDS dimensions were found to be strongly related to each other (see Table 25). Therefore, to avoid lack of interpretability due to multicollinearity, a separate model including each DIAMONDS dimension as a predictor was run. Time, gender, and trait wellbeing were included as control variables.

Time (*average beta* = .01), wellbeing (*average beta* = .19) and conscientiousness (*average beta* = .17) are significant predictors of valence in all models. Extraversion is significantly related to valence in the models containing place adversity (.11, p=.050) and place sociality (.13, p=.031), and neuroticism is significantly related to valence in the model containing place intellect (-.12, p=.043). Adversity (.06, p=.004), positivity (.14, p<.001), and sociality (.06, p<.001) are significantly related to valence in the respective models containing them.

The interaction between place intellect and extraversion (.10, p=.013) is a significant predictor of valence. The interaction is positive, indicating an enhancing effect: as extraversion increases, the relationship of place intellect and valence becomes stronger. Figure 4 visualizes this interaction. The significant interaction between place duty and extraversion (.07, p=.039) indicates that, as extraversion increases, the relationship between place duty and valence becomes stronger (Figure 5). The significant interaction between place intellect and agreeableness (.07, p=.043) indicates that, as agreeableness increases, the relationship between place intellect and valence becomes stronger (see Figure 6). The significant interaction between place adversity and extraversion (.06, p=.031) indicates that, as extraversion increases, the relationship between place adversity and valence becomes stronger (see Figure 7). The significant interaction between place positivity and agreeableness (.06, p=.026) indicates that, as agreeableness increases, the relationship between place positivity and valence becomes stronger (see Figure 8). The significant interaction between place sociality and extraversion (.05, p=.013) indicates that, as extraversion increases, the relationship between place sociality and valence becomes stronger (see Figure 9).

Table 26

Multilevel Models Predicting Valence from Place Duty/Intellect/Adversity/Mating Affordances and Personality (Random Intercepts Model)

DIAMONDS:	…Duty…			…Intellect…			…Adversity…			…Mating…		
	B	SE	p	B	SE	p	B	SE	p	B	SE	p
Intercept	3.33	.07	<.001	3.34	.07	<.001	3.37	.07	<.001	3.35	.07	<.001
Time	**.01**	.00	<.001	**.01**	.00	<.001	**.01**	.00	<.001	**.01**	.00	<.001
Gender	-.07	.11	.519	-.07	.11	.515	-.06	.11	.594	-.06	.11	.562
Wellbeing (WHO-5)	**.19**	.05	<.001	**.19**	.05	<.001	**.19**	.05	<.001	**.19**	.05	<.001
…DIAMONDS dimension…	-.01	.03	.675	.02	.03	.581	**.06**	.02	.004	.05	.03	.080
Openness	.00	.05	.956	.01	.05	.816	-.02	.05	.665	-.02	.05	.770
Conscientiousness	**.18**	.05	<.001	**.19**	.05	<.001	**.17**	.05	.002	**.18**	.05	.001
Extraversion	.08	.05	.129	.07	.05	.209	**.11**	.06	.050	.09	.06	.110
Agreeableness	.03	.05	.611	.02	.05	.691	.06	.06	.264	.04	.06	.483
Neuroticism	-.11	.06	.071	**-.12**	.06	.043	-.10	.06	.107	-.11	.06	.093
DIAMONDS*Openness	-.03	.03	.289	-.05	.04	.177	-.03	.02	.149	-.04	.03	.247
DIAMONDS*Conscientiousness	.02	.03	.510	.02	.04	.656	-.01	.02	.604	.00	.03	.986
DIAMONDS*Extraversion	**.07**	.03	.039	**.10**	.04	.013	**.06**	.03	.031	.04	.04	.252
DIAMONDS*Agreeableness	-.01	.03	.759	**.07**	.04	.043	.04	.02	.094	.01	.03	.793
DIAMONDS*Neuroticism	.04	.03	.191	.08	.04	.063	.02	.03	.408	.02	.04	.664

Note. Number of EMAs n = 3538, submitted by 79 participants, who participated for 6-14 days and provided personality reports (BFI-44). To avoid lack of interpretability due to multicollinearity between the DIAMONDS dimensions, a separate model including each dimension as a predictor was run. Table presents fixed effects. Models did not converge when including random effects for time and DIAMONDS. Time is represented by a continuous EMA count, ranging from 1-56 (4 EMAs per day for 14 days). Gender coding: Male=1, female=0.

Table 27

Multilevel Models Predicting Valence from Place Positivity/Negativity/Deception/Sociality and Personality (Random Intercepts Model)

DIAMONDS:	…Positivity…			…Negativity…			…Deception…			…Sociality…		
	B	SE	p	B	SE	p	B	SE	p	B	SE	p
Intercept	3.44	.08	<.001	3.34	.07	<.001	3.34	.07	<.001	3.39	.08	<.001
Time	**.01**	.00	<.001	**.01**	.00	<.001	**.01**	.00	<.001	**.01**	.00	<.001
Gender	-.04	.11	.742	-.07	.11	.513	-.07	.11	.512	-.04	.11	.706
Wellbeing (WHO-5)	**.17**	.05	.002	**.19**	.05	<.001	**.19**	.05	<.001	**.19**	.05	.001
…DIAMONDS dimension…	**.14**	.03	<.001	.03	.03	.275	.03	.03	.338	**.06**	.02	<.001
Openness	-.01	.06	.925	-.01	.05	.852	-.01	.05	.820	-.01	.06	.915
Conscientiousness	**.15**	.06	.010	**.19**	.05	<.001	**.19**	.05	<.001	**.14**	.05	.009
Extraversion	.12	.06	.055	.09	.05	.095	.09	.05	.098	**.13**	.06	.031
Agreeableness	.08	.06	.162	.05	.05	.376	.05	.05	.398	.06	.06	.269
Neuroticism	-.10	.07	.153	-.11	.06	.089	-.11	.06	.092	-.10	.07	.134
DIAMONDS*Openness	.00	.03	.865	-.05	.03	.131	-.04	.03	.207	-.01	.02	.737
DIAMONDS*Conscientiousness	-.04	.03	.140	.02	.03	.447	.02	.04	.489	-.03	.02	.098
DIAMONDS*Extraversion	.05	.03	.084	.06	.03	.086	.05	.04	.157	**.05**	.02	.013
DIAMONDS*Agreeableness	**.06**	.03	.026	.05	.03	.105	.04	.03	.300	.03	.02	.145
DIAMONDS*Neuroticism	.03	.03	.402	.04	.04	.234	.03	.04	.399	.02	.02	.441

Note. Number of EMAs n = 3538, submitted by 79 participants, who participated for 6-14 days and provided personality reports (BFI-44). To avoid lack of interpretability due to multicollinearity between the DIAMONDS dimensions, a separate model including each dimension as a predictor was run. Table presents fixed effects. Models did not converge when including random effects for time and DIAMONDS. Time is represented by a continuous EMA count, ranging from 1-56 (4 EMAs per day for 14 days). Gender coding: Male=1, female=0.

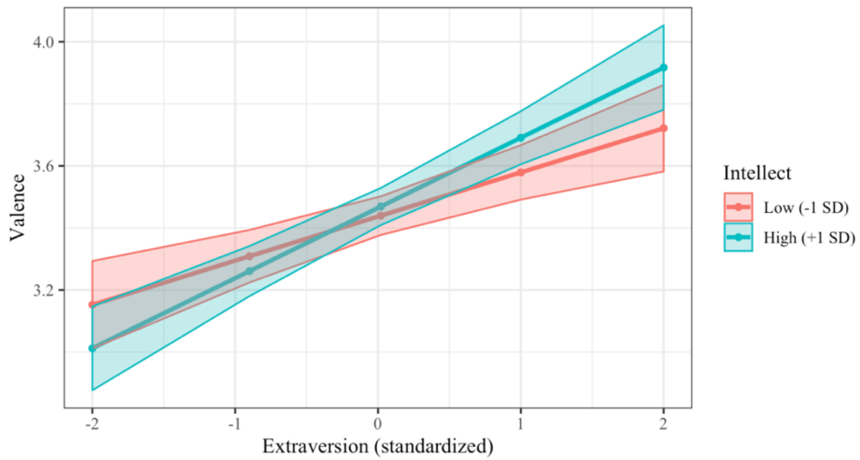

Figure 4. Effect of extraversion and place intellect on momentary valence

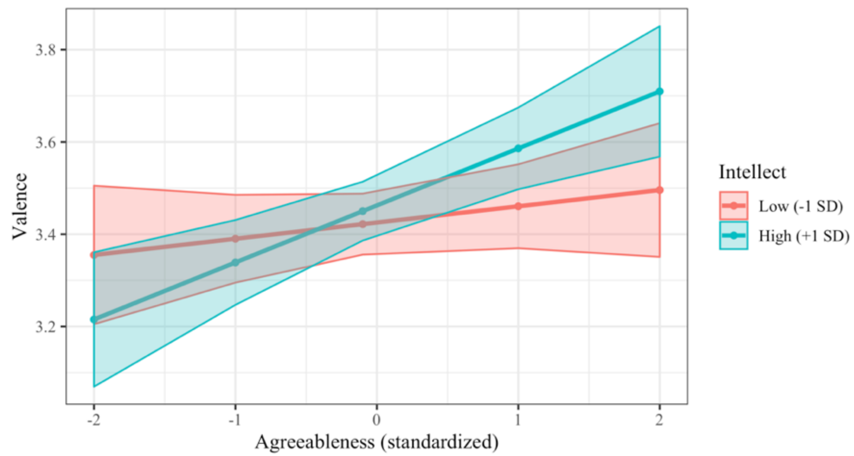

Figure 6. Effect of agreeableness and place intellect on momentary valence

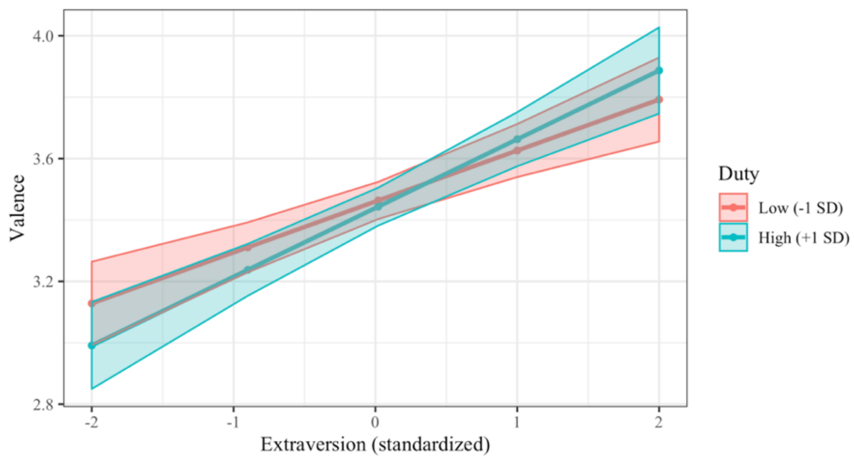

Figure 5. Effect of extraversion and place duty on momentary valence

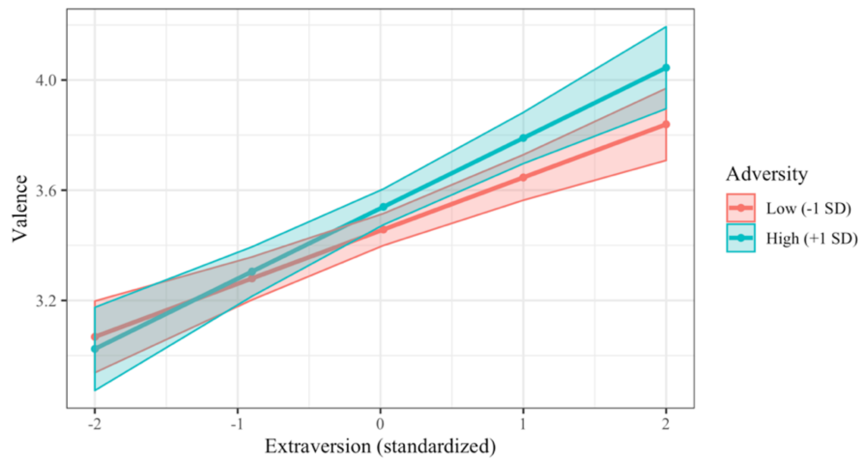

Figure 7. Effect of extraversion and place adversity on momentary valence

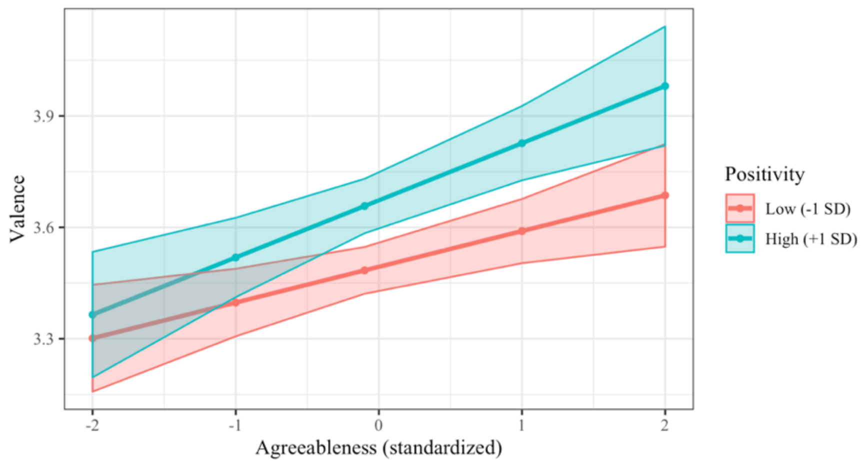

Figure 8. Effect of agreeableness and place positivity on momentary valence

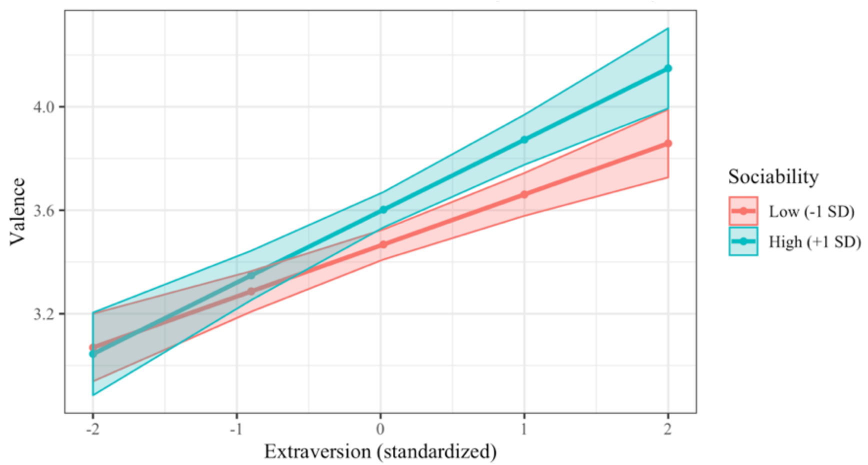

Figure 9. Effect of extraversion and place sociability on momentary valence

Discussion and Conclusion

This chapter investigates the psychology of places. I examine how affective states and psychological traits are related to place visits. Then, I test for interactions between personality and situational characteristics on momentary affect.

Being in a pub or at a party, in transit, in a college common area, or at a friend's house was associated with significantly higher self-reported positive feelings. Paralleling these results, being at a college common area, a friend's home, or a pub/party was associated with significantly higher wellbeing. It seems people tend to be happier at places that facilitate social interactions, and people who are happier tend to frequent these places more often.

However, surprisingly, participants reported being more stressed and tense at restaurants/cafes. This may be because it is common for students to study at these locations. Conscientious people were less likely to visit pubs/parties, as might be expected. Though the previous chapter suggests these individuals do travel more, they may not be going to such places. Agreeable and neurotic people were both more likely to spend time at a friend's house, but the underlying motivation for doing this may have differed (i.e., to be friendly vs. to soothe negative emotions).

The correlations in Table 18 also show that some places have a complimentary relationship (the more time people spend at pubs/parties, the more time they spend in common rooms) while other locations have a supplementary relationship (the more time people spend in cafes/restaurants, the less time they spend at home). Future research could investigate these inter-location dynamics, which may reveal things about the latent dimensions locations fall into.

Finally, this methodology has uncovered some interesting interactions between persons and situations. I find that stable psychological traits can interact with situational characteristics to predict in-the-moment emotional states. This demonstrates how our personality and the situation we find ourselves in can combine to shape our experiences.

While everyone felt more positively valenced emotions in positive environments, and this effect was especially prominent for agreeable individuals. Thus, the emotional states of agreeable people may be especially sensitive to the positivity of their environment. Similarly, as previously mentioned, participants generally felt happier in sociable environments. However, this was especially true for extraverted people. Over time, the different level of emotions people with different traits feel in the same environment might lead them to change their behavior. It may even lead to a feedback loop that causes them to change their personality.

In future work, researchers can examine these possibilities. It is also important to note that situational attributions were made by MTurk raters rather than the participants. While this allows for a more independent assessment of situational characteristics, it may be interesting to examine how the situational characteristics a place evokes depend on the rater's personality (e.g., perhaps more extraverted raters perceive pubs/parties to be more positive or less adverse).

Chapter 5. Personality Judgments of Visitors to a Place Based on Place Images

While the previous chapters focused on the objective links between places and people, in this chapter, I examine the subjective links between physical locations and human psychology. In particular, I investigate the perceptions people have of a place from a virtual visit. It is increasingly common in today's world to visit a place virtually, using services such as Google Maps. When a person visits a place in this way, what does he or she learn about the people who are likely to spend time in this location? In this chapter, I examine such judgments and whether these subjective ratings are consensual as well as accurate. I also adopt a lens model to examine which cues are utilized when forming these perceptions and whether they are valid.

In addition, this study showcases a novel approach, combining smartphone sensing technology, web mapping services, and psychological assessments to enhance our understanding of the psychological characteristics of places.

Background

Every day, people spend time in many distinct places as they go about their lives. In a typical day, most people may spend a majority of their time in their home or workplace. However, people also spend time in a variety of public places that have been described as "third places," such as cafes, shops, or parks (Oldenburg, 1997). Such places have been associated with relaxation and social activities (Mehta & Bosson, 2010), suggesting that the places we spend time in reflect our needs and values. Indeed, the previous chapter shows that there are some significant relationships between psychological traits and the places people visit. Here I examine to what extent virtual visitors can predict such relationships, whether their judgments are consensual, and what cues underlie these predictions.

Characteristics of different places.

Places can be described in terms of their objective or subjective characteristics. Objective characteristics include information about a place's "type" (e.g., whether the place is a café, shop, or park), or information about its sociodemographic characteristics (e.g., the socioeconomic status of the area it is located in). Subjective characteristics include information about a place's ambience or the psychological responses it invokes in its inhabitants, such as whether the place appears beautiful, clean, or lively.

Social scientists have studied people's impressions of places, such as how aesthetically appealing, interesting, or safe a location appears to be (Hanyu, 1997; Nasar, 1998). However, it is typically difficult for participants or coders to travel to many places and view them under the same conditions. Yet recent technological developments, such as Google Streetview, have enabled people to view a standardized 3D view of a location without needing to leave their home or office, and a growing body of research is using such tools to understand places (Salesses, Schechtner, & Hidalgo, 2013).

Psychological characteristics of people in different places.

Features of a space influence activities—e.g., reading, talking to a friend—which affect emotions (e.g., relaxation), but ambient features might also directly impact mood (Küller et al., 2006). Buss (1987) proposed that people alter their environments by selection (e.g., by choosing to seek out or avoid certain people or places), manipulation (e.g., changing an environment or a person), and evocation (i.e., by eliciting reactions from others). Environments are important—everything we do happens within a physical context, and people spend a lot of time thinking about where to go and make such decisions multiple times a day. As such, one might go for a walk to clear one's thoughts or go to work in the buzzy environment of a lively coffee shop or watch a movie from the comfort of one's sofa at home. Places evoke emotions, create a backdrop for activities and interact with both the people and situations in them (Graham & Gosling, 2011).

The present research.

The research presented in this chapter has three principal aims: (a) to examine whether people's subjective perceptions of a place are consensual, (b) to investigate to what extent these perceptions correspond to reality, and (c) to examine the utilization and validity of the cues underlying these subjective perceptions using a lens model.

Methods

Participants and procedure.

I began by examining participants from the Student Wellbeing Study who had used the Android applications and provided location data (N = 38). The sample consisted of 18 male and 20 female students (M=19.24 years, SD=1.88), who were enrolled in 19 different undergraduate courses. Twenty six percent (n=10) of the sample was non-British. After identifying the places participants had spent the most time in, I asked raters to navigate around those places on Google Streetview and code them on a number of characteristics.

Research design.

I collected data from three sources: (a) observer ratings of the personality of the typical person who spends time in a given place, (b) the average personality of visitors to a given place, and (c) ratings of objective and subjective place characteristics (e.g., safe, boring, pleasant). These data allow us to examine observer consensus regarding personality ratings of visitors to a place, the accuracy of the observers' impressions, and the degree to which various place features were associated with the observers' impressions and with the actual visitors' personalities.

Measures and data collection.

Places visited from location traces.

Unique longitude/latitude recordings (99,452) were collected across all users for the period of this study. As the raw GPS traces scatter around the true location, participants' significant places were identified using a clustering procedure presented in Tsapeli & Musolesi (2015). As such, GPS locations where users spend less than 10 minutes overall and where the accuracy exceeded 50 minutes were excluded. Location clusters were then created based on the raw GPS traces. Each GPS point gets either added to an existing cluster if it is less than 50 minutes away from its center point (in which case the center coordinates get updated accordingly) or becomes the center for a new cluster. For each user, I calculated the top ten places where the user had spent the most time during each of the study periods. In phase one, participants had visited an average of 14.10 places (SD = 8.58) where they spent an average of 23.96 minutes (SD = 17.42) in each of their top ten locations. In phase two, participants had visited an average of 52.73 places (SD = 63.90) and spent an average of 468.61 minutes (SD = 540.41) in their top ten places.

Table 28

Descriptive Statistics of Sensed Locations

	Phase 1 (n=30)	Phase 2 (n=26)
Avg no of places visited	14.10 (SD = 8.58)	52.73 (SD = 63.90)
Mean time spent in top 10	23.96 mins (SD = 17.42)	468.61 mins (SD = 540.41)
SD time spent	60.79 mins (SD = 41.48)	2012.25 mins (SD = 1444.62)
Total time in top 10	301.68 mins (SD = 188.40) = approx. 5 hours (range 0-12 hours)	14951.93 mins (SD = 6689.85) = approx. 250 hours (16 days) (range 0-380 hours)

Note. Only a subset of participants participated in both phases.

Observer ratings for place characteristics.

Next, I trained four raters to code each participant's top 10 locations for various psychological characteristics (see Appendix D for the coding manual.). Each rater used the GPS coordinates for a location to navigate to it using Google Maps Streetview (see Figure 10 for example images). All locations that did not have perfect rater agreement for the physical location of interest were reviewed by the author, who is very familiar with the city in which the participants reside. For the subjective criteria, inter-rater reliabilities were computed to evaluate rater agreement.

Figure 10. Example images of locations visited by users, Google Streetview data ©2017 Google.

The coding criteria consisted of locations of interest based on Google Place Types (Google, 2017) as well as affective appraisals (Hanyu, 1997; Nasar, 1998; Salesses et al., 2013), and personality. More specifically, each location was rated for the following subjective features: ambience characteristics (degree to which a location is pleasant, exciting, relaxing, interesting, safe, lively, happy, productive, clean, unique, modern, vacant, wealthy, and urban) and personality characteristics (openness: artistic vs. conservative; conscientiousness: organized vs. flexible; extraversion: outgoing vs. reserved; agreeableness: compassionate vs. critical; neuroticism: emotional vs. stable). The affective appraisals and personality traits were rated on a 7-point scale.

Results

To understand observers' impressions of different places, here I first describe how observers rated different place types in terms of ambience and personality and how the personality of actual visitors to a place type compares to observers' ratings. I then examined inter-observer consensus to evaluate agreement on observers' personality ratings, as well as accuracy to assess the extent to which observers made accurate personality impressions. Finally, to identify the underlying cues informing these perceptions, I conclude with a lens model.

Place characteristics.

Inter-rater reliability by location type.

The average inter-rater reliability across all different location types was .35, which indicates low to moderate agreement between raters and is typical for measurements of similar constructs with similar amounts of raters (Salesses et al., 2013). Some location types appear to have more typical representations that result in high agreement (e.g., shopping malls .56 and cafes .53), while others might have been represented by more diverse instances in this sample (e.g., university buildings .21 or pubs/club .19). Basing analyses on larger samples than the ones presented in this investigation (both raters and sample locations rated) could also be expected to yield higher agreement. For example, previous research (Salesses et al., 2013) recommended 22-32 ratings to achieve highly consistent measures. Consensus on personality measures will be reported below.

Ambience ratings.

Ambience ratings can help describe the character of a place by analyzing a specific location type's individual ambience profile. For example, streets are perceived as more lively, modern, and urban compared to green spaces, while green spaces are perceived as more pleasant, relaxing, and safe (see Figure 11). Depending on the question at hand, it might also be interesting to identify places that exhibit certain characteristics (e.g., how exciting different types of locations are perceived to be by human raters; see Figure 12). Shopping malls (M=5.37, SD=0.46) and cafés (M=5.00, SD=0.25) are the most exciting, while industrial business buildings (M=2.83, SD=0.52) and houses/apartment buildings (M=3.47, SD=0.68) are perceived to be the least exciting. Appendices E and F contain the ambience profiles for all places and zones, as well as comparisons of all places and zones on ambience and personality dimensions.

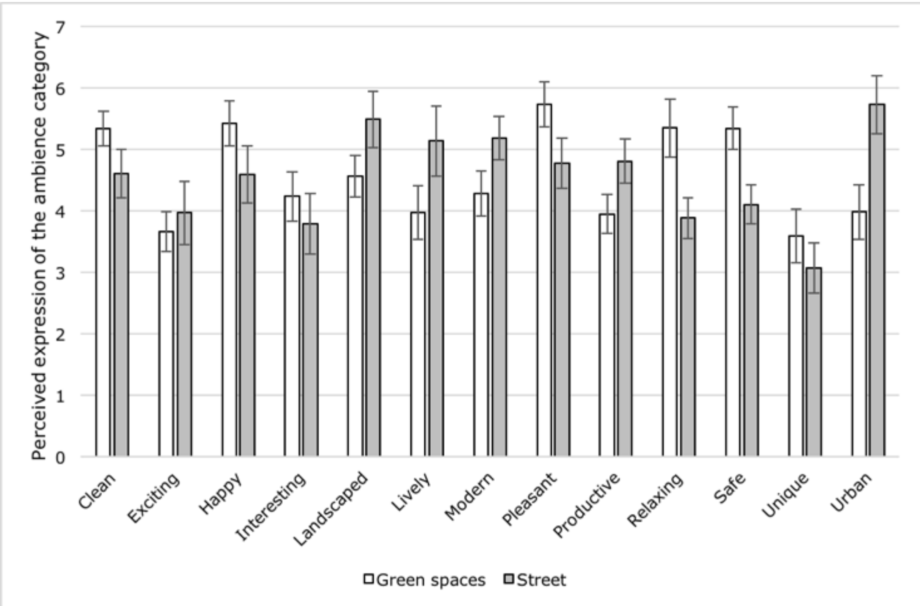

Figure 11. Ambience profiles for two different types of places.

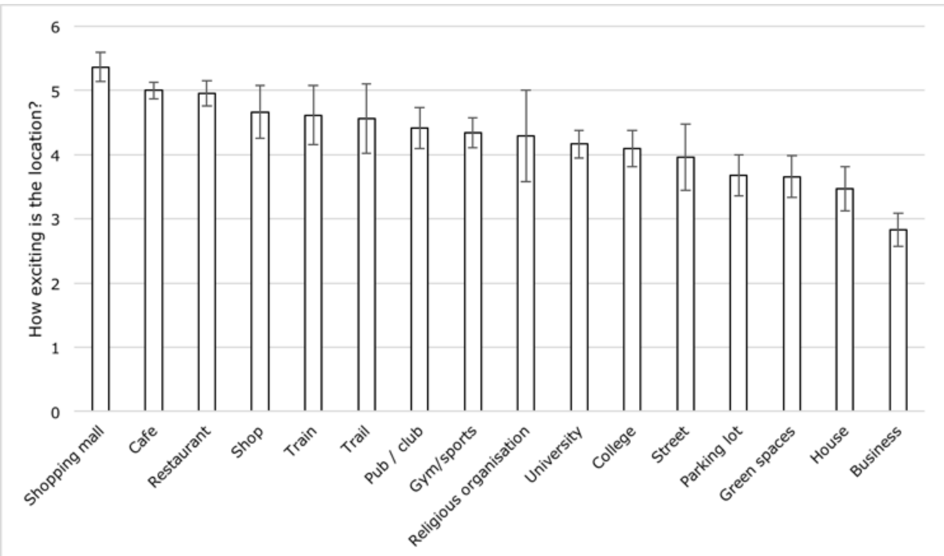

Figure 12. Ratings for how exciting different types of places are perceived to be by human raters.

Personality.

Locations can also be analyzed with regards to their perceived personality. Figure 13 (left) shows perceiver ratings for four location categories. The perceived personality profiles of train stations and shopping malls, as well as those of green spaces and religious organizations, appear to be similar. For example, both green spaces and religious organizations are perceived to be highly emotionally stable and agreeable spaces, while both train stations and shopping malls are perceived to be places characterized by high extraversion and openness to new experiences.

Interestingly, the perceived personality of a location can be compared with the actual personalities of the people who spend time there. Mapping the personality traits of the average visitor to these types of locations (weighed by time spent) yields similar patterns overall (see Figure 13, right). However, in this specific example, while shopping malls and train stations are similar in the types of people they attract, green spaces and religious organizations draw somewhat different types of individuals. Appendix G contains personality profiles for all place / zones types and visitors to those.

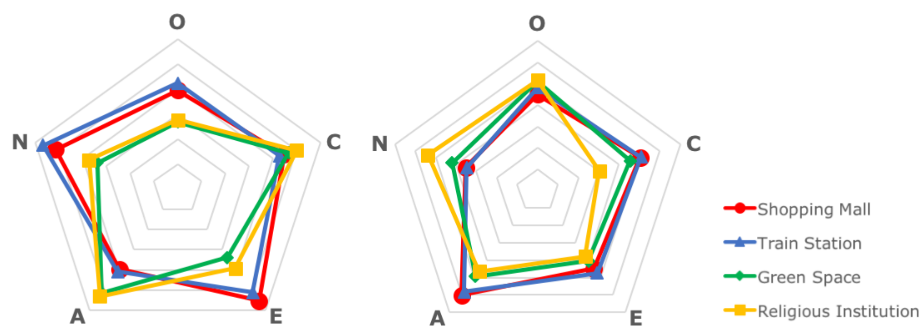

Figure 13. Perceiver ratings for four location categories (left) and aver-age personality of visitors to the location categories, weighted by time spent (right). Greater distance from the center represents a higher score on each of the five personality traits (O-openness, C-conscientiousness, E-extraversion, A-agreeableness, N-neuroticism).

Inter-observer consensus.

To evaluate inter-rater agreement on personality impressions, intra-class correlations (ICCs) were computed. A two-way inter-rater reliability agreement model was chosen as both subjects and raters were randomly chosen from a bigger pool of persons and to take mean rating differences between judges into account. Both single (ICC[2,1]) and average (ICC[2,k]) reliabilities were estimated (Shrout & Fleiss, 1979). As shown in Table 29, when forming impressions of personality of visitors to a place, raters showed moderate to high consensus for all personality dimensions. Openness showed the strongest consensus, followed by Agreeableness, and Conscientiousness. Extraversion and Neuroticism showed the least consensus (Table 29, Column 1). Overall, consensus was high (mean ICC = .59).

Table 29

Observer Consensus and Accuracy of Personality Impressions of Visitors to a Place

Traits Assessed	Consensus (ICC)	Accuracy (r)
Openness	.72*** $p < .001$ (.39*** $p < .001$)	-.01 (p=.85)
Conscientiousness	.60*** $p < .001$ (.27*** $p < .001$)	.07 (p=.17)
Extraversion	.50*** $p < .001$ (.20*** $p < .001$)	.06 (p=.19)
Agreeableness	.61*** $p < .001$ (.28*** $p < .001$)	.01 (p=.80)
Neuroticism	.52*** $p < .001$ (.21*** $p < .001$)	.11* (p=.02)

Note: Consensus is represented by intraclass correlations (ICCs) among 4 observers. Average and single ICCs (in parentheses) are presented. Accuracy is indexed by the correlation between observers' ratings and self-reports of visitors (N = 434).
*** $p < .001$. ** $p < .01$. * $p < .05$.

Inter-observer accuracy.

Correlations between the aggregated observer ratings and the targets' self-reports were computed to assess the extent to which observers made accurate personality impressions. As shown in Table 29, I found little evidence for accuracy of observer impressions. Accuracy was significant (but low) only for the personality dimension of Neuroticism (Table 29, Column 2).

Place cues.

I used a lens model analysis (Brunswik, 1956) to identify whether there is a systematic basis for the previously presented inaccurate impressions. I examined the relationship between observers' impressions and the characteristics (i.e. "cues") of the places, as well as the validity of the cues and how sensitive observers were to the valid cues.

Cue utilization.

To test the extent to which cues are related to observers' impressions, I regressed observer ratings onto the cue scores for each personality trait. *Table 30* presents these cue utilization scores (adjusted-R^2 values). Observers showed strong tendencies to use the captured cues in the Google Streetview images of the places across all personality dimensions (adjusted-R^2 ranging from .50 to .64, all ps<.001). The cues were most strongly related to extraversion ratings (adjusted-R^2 = .64, p<.001), followed by neuroticism (adjusted-R^2 = .59, p<.001) and agreeableness (adjusted-R^2 = .58, p<.001). Relationships were slightly weaker for openness (adjusted-R^2 = .52, p<.001) and conscientiousness (adjusted-R^2 = .50, p<.001).

A series of correlations was performed to determine which cues were related to impressions of each personality trait (Table 31). Average observer ratings were correlated with the cues using Pearson correlations. Most subjective cues and a large part of the objective cues were related to all personality traits, but the magnitude of these relationships varied. For example, places that appeared more open were rated as more exciting, lively, and interesting, and they were less likely to be residential areas or houses. Places that appeared to be more conscientious were rated as wealthier, cleaner, more pleasant, and more likely to be in a university area or be a university building. Places that appeared to be more extraverted were rated as more lively, exciting, crowded, and less likely to be in a residential area or green space. Places that appeared to be agreeable were rated as more relaxing, safe, pleasant, and more likely to be in a college area and to be a green space. Places that appeared to be neurotic were rated as more distressing, unsafe, unpleasant, and less likely to be a green space or in a college area.

Table 30

Cue Utilization, Validity, and Sensitivity of Personality Impressions of Visitors

Traits Assessed	Cue utilization	Cue validity	Cue sensitivity
Openness	.52 *** (*p* <.001)	.00 (*p*=.43)	-.26 † (*p*=.09)
Conscientiousness	.50 *** (*p* <.001)	.00 (*p*=.43)	.17 (*p*=.28)
Extraversion	.64 *** (*p* <.001)	.02 (*p*=.23)	.20 (*p*=.19)
Agreeableness	.58 *** (*p* <.001)	.02 (*p*=.18)	.09 (*p*=.56)
Neuroticism	.59 *** (*p* <.001)	.06 ** (*p*=.01)	.52 *** (*p*=.00)

Note: Cue utilization is represented by the adjusted-R^2 values when mean observer scores are regressed on cue scores. Cue validity is represented by the adjusted-R^2 values when visitors' self-reports are regressed on cue scores. Cue sensitivity is represented by vector correlations between absolute values of cue-utilization and cue-validity correlations. Mean correlations were computed using Fisher's *r*-to-z transformation.
*** $p <.001$ ** $p < .01$. * $p < .05$. † $p<.10$

Cue validity.

To test the extent to which the cues served as valid indicators of the personality of actual visitors to the place, I regressed visitors' self-reports onto the cue scores for each personality trait. *Table 30* presents cue validity scores (adjusted-R^2 values). The findings indicate that the cues had little validity as indicators of visitors' actual personality. Cue validities ranged from R^2 = .00 for openness to R^2 = .06 for neuroticism, with only the regression of neuroticism producing a significant result. I also computed the validity scores of the individual cues by correlating self-reported visitor personality traits with the cue values (see Table 31) and indeed found evidence for the validity of only a few cues.

Cue sensitivity.

For each personality trait, the observers' sensitivity to the (limited) validity of the cues was tested via column-vector correlations between the (Fisher's Z-transformed) cue utilization and the cue validity scores (Table 30). The findings indicate lower levels of observer sensitivity to the place cues than those previously reported in the literature; for example, when forming impressions on the basis of WoW usernames (Graham & Gosling, 2012) and *Second Life* avatars (Bélisle & Bodur, 2010).

Table 31

Lens Model Analysis of Observable Cues in Places

Cue validity O	C	E	A	N	Cues ("lens")	Cue utilization O	C	E	A	N
					Subjective criteria: Ambience characteristics					
.03	.04	.04	.04	-.12 *	Pleasant	.05	.36 ***	-.10 *	.58 ***	-.57 ***
-.03	-.01	.00	-.04	.05	Exciting	.59 ***	.06	.60 ***	-.13 **	.23 ***
.04	.02	-.03	.01	-.10 *	Relaxing	-.25 ***	.27 ***	-.47 ***	.67 ***	-.72 ***
-.03	.03	-.02	.00	.00	Interesting	.44 ***	.26 ***	.28 ***	.19 ***	-.05
-.02	.05	.01	-.01	-.08 †	Safe	-.27 ***	.41 ***	-.46 ***	.61 ***	-.60 ***
-.01	.09 †	.05	.04	-.07	Lively	.49 ***	.03	.69 ***	-.22 ***	.33 ***
-.04	.07	.07	.03	-.12 *	Happy	.15 **	.28 ***	.03	.55 ***	-.52 ***
.00	.02	.06	.03	-.02	Productive	.41 ***	.31 ***	.43 ***	-.29 ***	.39 ***
-.04	.01	.06	.06	-.14 **	Clean	-.07	.49 ***	-.24 ***	.56 ***	-.51 ***
.03	.00	-.03	-.05	.00	Unique	.38 ***	.27 ***	.12 *	.12 **	-.07
-.01	-.10 *	.07	.03	.01	Modern	.29 ***	-.11 *	.38 ***	-.32 ***	.33 ***
-.01	-.03	.00	.04	-.07	Vacant	-.28 ***	.13 **	-.50 ***	.31 ***	-.44 ***
.03	.01	.06	.01	-.08	Wealthy	.18 ***	.54 ***	.08 †	.37 ***	-.25 ***
.02	-.03	.06	.02	-.02	Urban	.16 **	.08 †	.36 ***	-.33 ***	.46 ***
.05	.01	.12 *	.10 *	-.05	Landscaped	.14 **	.28 ***	.24 ***	-.05	.19 ***
					Objective criteria: Outside vs inside					
.03	.02	-.02	.01	.07	Outside	-.11 *	-.16 ***	-.15 ***	.12 *	-.15 **
					Objective criteria: Land use zones					
.03	.03	.04	.00	.01	College	-.18 ***	.10 *	-.28 ***	.25 ***	-.31 ***
-.02	.00	-.07	.04	-.03	Nature	-.06	-.07	-.13 **	.18 ***	-.27 ***
.03	-.04	.02	.02	-.05	Residential	-.38 ***	-.16 ***	-.27 ***	.15 **	-.17 ***
.01	.07	.04	-.01	-.04	Transport	.18 ***	-.10 *	.15 **	-.11 *	.18 ***
-.03	-.04	-.07	-.03	.04	Campus	.09 †	.38 ***	-.05	-.16 ***	.15 ***
					Objective criteria: Specific location types					
-.08	.00	-.04	.02	.01	Airport	.08	-.02	.04	-.03	.07
.08 †	.00	-.01	-.11 *	.05	Bus	.00	-.08	.06	-.10 *	.06
-.05	-.01	.09 †	.01	.01	Café	.13 **	.05	.11 *	-.01	.07
.07	.02	.02	.02	-.03	College bg.	-.07	.09 *	-.12 **	.04	-.09 †
.01	.04	.00	-.01	-.04	Green sp.	-.17 ***	.00	-.30 ***	.38 ***	-.44 ***
.00	.04	-.02	-.04	-.06	Sports	.18 ***	.15 ***	.22 ***	-.07	.00
.05	-.06	.04	.00	.04	Health	-.03	-.02	-.03	.04	.09 †
.09 †	-.06	.06	.00	-.05	House	-.27 ***	-.07	-.20 ***	.14 **	-.13 **
-.02	.02	.12 **	.00	-.09 †	Industrial	-.06	-.01	-.01	-.06	.01
-.02	-.08 †	-.02	.06	-.02	Water	.01	-.03	.01	.00	-.05
.00	.05	-.01	.03	-.06	Library	.02	.12 **	-.15 **	.02	-.01
.06	.01	-.06	-.02	.05	Museum	.03	.06	-.05	.04	.00
-.04	.05	-.05	-.08 †	.09 †	Parking	-.03	.01	.02	-.05	.12 **
-.02	-.10 *	.00	.09 *	.04	Club	.07	-.04	.07	-.09 *	.04
.04	-.03	.00	.04	.01	Religious	-.06	.04	-.04	.17 ***	-.09 †
.01	.01	-.03	.00	.09 †	Restaurant	.11 *	-.06	.17 ***	-.02	.07
-.01	.00	-.04	-.03	.04	Shop	.16 ***	-.06	.25 ***	-.16 ***	.19 ***
-.08 †	-.06	-.01	.05	.07	Mall	.18 ***	-.08 †	.19 ***	-.08 †	.11 *
-.04	.05	.04	.05	-.04	Street	.01	-.16 ***	.11 *	-.19 ***	.17 ***
.03	.06	-.04	-.02	.11 *	trail	.02	.03	-.06	.01	-.03
.00	.05	.05	.04	-.04	train	.19 ***	-.08	.12 **	-.05	.13 **
-.10 *	-.09 †	-.06	.01	.01	Univ. bldg.	.02	.25 ***	-.06	-.13 **	.12 **

Note: O = Openness; C = Conscientiousness; E = Extraversion; A = Agreeableness; N = Neuroticism. Coefficients are indexed by Pearson correlations. Cue validity is the correlation between visitors' self-reported personality and the presence of a cue. Cue utilization is the correlation between observer ratings of personality and presence of a cue.
*** p <.001 ** p < .01. * p < .05. † p<.10.

Discussion and Conclusion

The results presented here show that observers virtually visiting a place (from the outside) tend to arrive at a consensual understanding of what that place is like. In particular, they agree on what kind of person is likely to visit a place. As the images do not show inside views of most locations, visitors must guess what the inner ambience of a place is. Considering this, it is quite impressive that they show consensus in their judgments. However, I also find that this consensual perception provides very little accuracy with regards to the personality of people who actually spend time in a place. This is likely due to shortcomings of the study design and the small sample size. With a larger sample, more people visiting the same location could be captured and their personalities averaged. Additionally, future work should include inside views, or ideally, let raters visit the locations they are asked to evaluate.

I also examine the specific cues used to form these consensual judgments. Subjective characteristics of places, such as how safe or modern they look, play a significant role in people's judgments of the kinds of people that visit a location. However, objective characteristics, such as place type, are also related to this judgment. In general, most of the cues people use to form their judgments about the visitors to a place are not valid, which explains why perceivers make inaccurate predictions.

The preliminary findings of this research show that virtual visits to places show consensus but not accuracy in their judgments and reveal the cues involved in these relationships. In addition, by combining mobile sensing with web mapping services and psychological assessments, the novel approach described here may be used to further our understanding of the psychological characteristics of places and the people who spend time in them.

Chapter 6. Discussion

In this dissertation, I presented how smartphone sensing methodologies can be used to study the relationship between people's psychology and their physical movement through space. One-hundred and eighteen participants provided ecological momentary assessments, reporting their places visited and emotional states (e.g., feeling stressed, relaxed, sad) four times per day for two to four weeks. In addition to these ecological momentary assessments, place and mobility data was also collected for forty students using their smartphone's GPS sensors. I supplemented these data with an independent sample of 267 participants who evaluated the situational characteristics of places visited (e.g., sociality, positivity). The results show how places visited (based on self-reported places) and mobility patterns (based on sensed GPS data) are related to people's in-the-moment emotional experiences and their enduring psychological characteristics, such as their personality and wellbeing. I also examine how one's personality interacts with the situational characteristics of a place to affect emotional states. Lastly, in a final study, I show that raters who virtually visit the most common destinations in the sample show consensus, but not accuracy, in their perceptions of participants.

I show that GPS locations can be captured fairly well over a long duration from smartphones. GPS-based mobility features showed high stability day-to-day and appear as a promising approach for examining the relationship between people's minds and their trajectories through space. This dissertation provides evidence to suggest that mobility behaviors show state like properties, but also significantly predict some psychological individual differences. In particular, they were found to be significantly related to conscientiousness, neuroticism, and wellbeing. Future work can assess the causal mechanism driving this relationship.

Multilevel modeling uncovered that many mobility features were related to daily affective states. For example, students who reported more positive feelings traveled to fewer locations, in an unpredictable manner and with shorter transition times. People who were more stressed or tense had less similarity in their travel sequence, while the opposite was true for those who were relaxed. Consistent with the trait findings for neuroticism and wellbeing, those who were sadder traveled less than others.

I also examined how affective states and psychological traits are related to place visits, and how interactions between personality and situational characteristics affect emotions. It seems people tend to be happier at places that facilitate social interactions, and people who are happier tend to frequent these places more often. Results also indicated that visits to some places have a complementary relationship while other locations have a supplementary relationship, and that stable psychological traits can interact with situational characteristics to predict in-the-moment emotional states. For example, participants generally felt happier in sociable environments. However, this was especially true for extraverted people.

Lastly, this dissertation shows that observers virtually visiting a place tend to arrive at a consensual understanding of what that place is like. Furthermore, they agree on what kind of person is likely to visit such a place; however, this shared consensus is generally inaccurate. A lens model analysis revealed the underlying characteristics driving these perceptions.

Methodological, Technical, and Ethical Challenges

GPS data can be captured via smartphones that generate individual, continuous records of mobility patterns. The GPS technology has been well-established, but the sampling rate for psychometric research has not yet been established. It would be very worthwhile for researchers to reach a consensus about what the gold standard should be and which mobility metrics should be used in analyses. GPS consists of longitude and latitude coordinates, which need to be processed further to be psychologically meaningful; this has so far proven challenging.

Despite the obvious potential of GPS data for research purposes, a major ethical problem currently prevents a more prevalent distribution of location data for scientific use. Hand-in-hand with the informativeness of location data goes the potential for privacy violations. These data are so commonly collected that it may not seem worrisome. However, GPS and location data can potentially reveal personal places like one's home, workplace, and other regularly visited locations. If visiting patterns of people are known, the identity of originally anonymous participants is in jeopardy. In the following section, I will illustrate how location data can identify the home of participants and which precautions can be taken in order to better protect individual privacy rights.

Every form of anonymization or aggregation inevitably leads to an associated loss of information in the process. In my opinion, no perfect solution to this dilemma yet exists. One approach is to remove decimals (de Montjoye et al., 2013): one can remove personal information from GPS data through the reduction of digits of the longitude and latitude measures. However, with a simple reduction of decimals, a significant loss of information is accrued. Depending on the type of analysis, this might prevent the detection of important relationships or prevent replication of the results.

Another possibility is to remove GPS positions of personal areas such as the home. A strong form of anonymization would be to assign only labels instead of locations—e.g., home, work, other—and remove coordinates altogether. However, this approach would require an experimenter to still know where participants' homes are located, at least initially. Future research may automate this process so that no human has access to this sensitive data. If such an algorithm could be trusted, this could serve as an adequate solution.

Next Steps and Open Questions

Past research studies have been done with small samples across different disciplines, without a clear, coherent research agenda. Here I propose three promising directions for future work in this space.

Methodologically, researchers can investigate which GPS features are the most predictive and useful and what these metrics can reveal about human psychology. Such developments could serve as the backbone for future research in this area.

From an applied perspective, applications of mobility research should also receive more attention (e.g., the ethics of personalized marketing based on location data; the ability of basic science research to inform context-sensitive location-based interventions). In this field, industry often leads academia with respect to technology. However, academics still contribute by studying the consequences of such technology and offering domain expertise (e.g., psychological insight).

Lastly, to extend extant theory, it is also necessary to further investigate the causal mechanisms generating the patterns described here. For instance, researchers have begun to explore what factors cause a person to have higher mobility, such as social network structure (Cho, Myers, & Leskovec, 2011). Such theories can inform academics, practitioners, and the general public. Overall, there remain many promising future avenues to explore in this nascent but rapidly emerging space.

To showcase some additional work I have conducted in this area with my collaborators, six papers and one book chapter published on topics related to this dissertation appear in the Appendix H.

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Appendix A: Questionnaire Measures Included in the Student Wellbeing Study

Connectedness (Deters & Mehl, 2013)

“Please indicate how often you feel the way described”:

“How often do you feel that there is no one you can turn to?”
[Never, Rarely, Sometimes, Always]
“How often do you feel alone?”
[Never, Rarely, Sometimes, Always]
“How often do you feel that you have a lot in common with the people around you?"
[Never, Rarely, Sometimes, Always]
“How often do you feel that you are no longer close to anyone?”
[Never, Rarely, Sometimes, Always]
“How often do you feel close to people?”
[Never, Rarely, Sometimes, Always]
“How often do you feel that no one really knows you well?”
[Never, Rarely, Sometimes, Always]
“How often do you feel isolated from others?”
[Never, Rarely, Sometimes, Always]
“How often do you feel that there are people who really understand you?”
[Never, Rarely, Sometimes, Always]
“How often do you feel that there are people you can talk to?”
[Never, Rarely, Sometimes, Always]
“How often do you feel that there are people you can turn to?”
[Never, Rarely, Sometimes, Always]

Personality (Gosling et al., 2003)

“Please rate the extent you think each pair of words applies to you:”

“Extraverted, Enthusiastic”
[“Disagree strongly", "Disagree moderately", "Disagree a little", "Neither agree/disagree", "Agree a little", "Agree moderately", "Agree strongly"]
“Critical, Quarrelsome”
["Disagree strongly", "Disagree moderately", "Disagree a little", "Neither agree/disagree", "Agree a little", "Agree moderately", "Agree strongly"]
“Dependable, Self-Disciplined”
["Disagree strongly", "Disagree moderately", "Disagree a little", "Neither agree/disagree", "Agree a little", "Agree moderately", "Agree strongly"]
“Anxious, Easily Upset”
["Disagree strongly", "Disagree moderately", "Disagree a little", "Neither agree/disagree", "Agree a little", "Agree moderately", "Agree strongly"]
“Open to New Experiences, Complex”
["Disagree strongly", "Disagree moderately", "Disagree a little", "Neither agree/disagree", "Agree a little", "Agree moderately", "Agree strongly"]
“Reserved, Quiet”
["Disagree strongly", "Disagree moderately", "Disagree a little", "Neither agree/disagree", "Agree a little", "Agree moderately", "Agree strongly"]

“Sympathetic, Warm”
["Disagree strongly", "Disagree moderately", "Disagree a little", "Neither agree/disagree", "Agree a little", "Agree moderately", "Agree strongly"]
“Disorganized, Careless”
["Disagree strongly", "Disagree moderately", "Disagree a little", "Neither agree/disagree", "Agree a little", "Agree moderately", "Agree strongly"]
“Calm, Emotionally Stable”
["Disagree strongly", "Disagree moderately", "Disagree a little", "Neither agree/disagree", "Agree a little", "Agree moderately", "Agree strongly"]
“Conventional, Uncreative”
[“Disagree strongly", "Disagree moderately", "Disagree a little", "Neither agree/disagree", "Agree a little", "Agree moderately", "Agree strongly"]

Self-determination (Sheldon, Ryan, & Reis, 1996)

Please read the pairs of statements, one pair at a time, and think about which statement within the pair seems more true to you at this point in your life. Indicate the degree to which statement A feels true, relative to the degree that Statement B feels true, on the 5-point scale shown after each pair of statements. If statement A feels completely true and statement B feels completely untrue, the appropriate response would be 1. If the two statements are equally true, the appropriate response would be a 3. If only statement B feels true and so on.

1. A. I always feel like I choose the things I do.
B. I sometimes feel that it’s not really me choosing the things I do.
[“Only A feels true = 1”, “2”, “3”, “4”, “5 = Only B feels true”]
2. A. My emotions sometimes seem alien to me.
B. My emotions always seem to belong to me.
[“Only A feels true = 1”, “2”, “3”, “4”, “5 = Only B feels true”]
3. A. I choose to do what I have to do.
B. I do what I have to do, but I don’t feel like it is really my choice.
[“Only A feels true = 1”, “2”, “3”, “4”, “5 = Only B feels true”]
4. A. I feel that I am rarely myself.
B. I feel like I am always completely myself.
[“Only A feels true = 1”, “2”, “3”, “4”, “5 = Only B feels true”]
5. A. I do what I do because it interests me.
B. I do what I do because I have to.
[“Only A feels true = 1”, “2”, “3”, “4”, “5 = Only B feels true”]
6. A. When I accomplish something, I often feel it wasn’t really me who did it.
B. When I accomplish something, I always feel it’s me who did it.
[“Only A feels true = 1”, “2”, “3”, “4”, “5 = Only B feels true”]
7. A. I am free to do whatever I decide to do.
B. What I do is often not what I’d choose to do.
[“Only A feels true = 1”, “2”, “3”, “4”, “5 = Only B feels true”]
8. A. My body sometimes feels like a stranger to me.
B. My body always feels like me.
[“Only A feels true = 1”, “2”, “3”, “4”, “5 = Only B feels true”]
9. A. I feel pretty free to do whatever I choose to.
B. I often do things that I don’t choose to do.
[“Only A feels true = 1”, “2”, “3”, “4”, “5 = Only B feels true”]

10. A. Sometimes I look into the mirror and see a stranger.
B. When I look into the mirror I see myself."
["Only A feels true = 1", "2", "3", "4", "5 = Only B feels true"]

University Adjustment (Pennebaker, 2013)

"Use a 7-point scale to answer each of the following questions, where:
1 2 3 4 5 6 7
not at all somewhat a great deal

Within the **LAST WEEK**, to what degree have you:
1. Missed your friends from high school ______
2. Missed your home _____
3. Missed your parents and other family members ______
4. Worried about how you will perform academically at university ______
5. Worried about love or intimate relationships with others ____
6. Worried about the way you look ____
7. Worried about the impression you make on others ____
8. Worried about being in university in general ____
9. Liked your classes ____
10. Liked your roommate(s) _____
11. Liked being away from your parents ____
12. Liked your social life _____
13. Liked university in general _____
14. Felt angry ____
15. Felt lonely ____
16. Felt anxious or nervous ____
17. Felt depressed ____
18. Felt optimistic about your future at university ____
19. Felt good about yourself ____

Demographics

"Gender. Are you...?"
[Male, Female, Other]
"Age. What year were you born...?"
[2000 or after, 1990 - 1999, 1980 - 1989, 1970 - 1979, 1960 - 1969, 1950 - 1959, 1940 - 1949, 1930 - 1939, 1920 - 1929, 1910 - 1919, Before 1910]
"What is your ethnic group...?"
[Asian, Black, Middle Eastern, White, Mixed Race, Other, Prefer Not to Say]
"Did your father go to university?"
[Yes, No, Unknown]
"Did your mother go to university?"
[Yes, No, Unknown]
"Are you an international student?"
[Yes, No]
"Which college are you in?"
[…]

"Which course are you matriculated in?" (e.g., BSc Chemistry)
[…]
"Which year of your studies are you in?"
[1, 2, 3]
"Which phone model are you using?"
[…]
"What software runs on your phone (e.g., iOS 8)?"
[…]

Self-esteem (Rosenberg, 1965)

Below is a list of statements dealing with your general feelings about yourself. If you strongly agree, circle SA. If you agree with the statement, circle A. If you disagree, circle D. If you strongly disagree, circle SD.

["Strongly Agree", "Agree", "Disagree", "Strongly Disagree"]

On the whole, I am satisfied with myself.
At times, I think I am no good at all.
I feel that I have a number of good qualities.
I am able to do things as well as most other people.
I feel I do not have much to be proud of.
I certainly feel useless at times.
I feel that I'm a person of worth, at least on an equal plane with others.
I wish I could have more respect for myself.
All in all, I am inclined to feel that I am a failure.
I take a positive attitude toward myself.

Narcissistic admiration and rivalry (Back et al., 2013)

Please indicate how much the following statements apply to you using a response format ranging from 1 = "not agree at all" to 6 = "agree completely."

[(1) "Not agree at all", (2), (3), (4), (5), (6) "Agree completely"]

I am great.
I will someday be famous.
I show others how special I am.
I react annoyed if another person steals the show from me.
I enjoy my successes very much.
I secretly take pleasure in the failure of my rivals.
Most of the time I am able to draw people's attention to myself in conversations.
I deserve to be seen as a great personality.
I want my rivals to fail.
I enjoy it when another person is inferior to me.
I often get annoyed when I am criticized.
I can barely stand it if another person is at the centre of events.
Most people won't achieve anything.

Other people are worth nothing.
Being a very special person gives me a lot of strength.
I manage to be the centre of attention with my outstanding contributions.
Most people are somehow losers.
Mostly, I am very adept at dealing with other people.

Sociability (Diener & Seligman, 2002)

“Compared to the average person, how satisfied are you with your relationships with your CLOSE FRIENDS?",
["Much below average", "Below average", "Slightly below average", "Average", "Slightly above average", "Above average", "Much above average"]
“Compared to the average person, how satisfied are you with your relationships with your FAMILY?",
["Much below average", "Below average", "Slightly below average", "Average", "Slightly above average", "Above average", "Much above average"]
“Compared to the average person, how satisfied are you with your ROMANTIC RELATIONSHIPS?",
["Much below average", "Below average", "Slightly below average", "Average", "Slightly above average", "Above average", "Much above average"]
“On an average week day, how many hours do you spend:
Alone?”
["No time", "0-1 hrs", "1-2 hrs", "2-3 hrs", "3-4 hrs", "4-5 hrs", "5-6 hrs", "6-7 hrs", "7-8 hrs", "More than 8 hrs"]
With family?”
["No time", "0-1 hrs", "1-2 hrs", "2-3 hrs", "3-4 hrs", "4-5 hrs", "5-6 hrs", "6-7 hrs", "7-8 hrs", "More than 8 hrs"]
With friends?”
["No time", "0-1 hrs", "1-2 hrs", "2-3 hrs", "3-4 hrs", "4-5 hrs", "5-6 hrs", "6-7 hrs", "7-8 hrs", "More than 8 hrs"]
“Do you currently have a romantic partner?”
["Yes", "No"]

> “If ["Yes"]:
> On an average week day, how many hours do you spend:
> With your partner?",
> ["No time", "0-1 hrs", "1-2 hrs", "2-3 hrs", "3-4 hrs", "4-5 hrs", "5-6 hrs", "6-7 hrs", "7-8 hrs", "More than 8 hrs"]

Wellbeing (Psychiatric Research Unit WHO Collaborating Centre in Mental Health, 1998)

“Please indicate for each of the five statements which is closest to how you have been feeling over the last two weeks. Notice that higher numbers mean better well-being.”
Over the last two weeks…

I have felt cheerful and in good spirits.
[“All of the time”, “Most of the time”, “More than half of the time”, “Less than half of the time”, “Some of the time”, “At no time”]
I have felt calm and relaxed.

[“All of the time”, “Most of the time”, “More than half of the time”, “Less than half of the time”, “Some of the time”, “At no time”]
I have felt active and vigorous.
[“All of the time”, “Most of the time”, “More than half of the time”, “Less than half of the time”, “Some of the time”, “At no time”]
I woke up feeling fresh and rested.
[“All of the time”, “Most of the time”, “More than half of the time”, “Less than half of the time”, “Some of the time”, “At no time”]
My daily life has been filled with things that interest me.
[“All of the time”, “Most of the time”, “More than half of the time”, “Less than half of the time”, “Some of the time”, “At no time”]

Health (Atherton et al., 2014)

“In general, would you say your health is”:
["Poor", "Fair", "Good", "Very Good", "Excellent"]
“During the past 4 weeks, have you accomplished less with your work or other daily activities than you would like as a result of your physical health?”
["No", "Yes"]
“During the past 4 weeks, how much did pain interfere with your normal work (including both work outside the home and housework)?”
["Not at all", "A little bit", "Moderately", "Quite a bit", "Extremely"]
“How much bodily pain have you had during the past 4 weeks?”
["None", "Very mild", "Mild", "Moderate", "Severe", "Very severe"]
“How much of the time during the past 4 weeks have you had a lot of energy?”
[“None of the time", "A little bit of the time", "Some of the time", "A good bit of the time", "Most of the time", "All of the time"]
“During the past 4 weeks, to what extent have your physical health or emotional problems interfered with your normal social activities with family, friends, neighbours or groups?”
["Not at all", "Slightly", "Moderately", "Quite a bit", "Extremely"]
“How much of the time during the past 4 weeks have you felt so down in the dumps that nothing could cheer you up?”
["All of the time", "Most of the time", "A good bit of the time", "Some of the time", "A little bit of the time", "None of the time"]
“During the past 4 weeks have you accomplished less than you would like with your work or other daily activities as a result of any emotional problem (such as feeling depressed or anxious)?”
["No", "Yes"]

Life Satisfaction (Diener et al., 1985)

“Below are five statements that you may agree or disagree with. Using the 1 - 7 scale below, indicate your agreement with each item by placing the appropriate number on the line preceding that item. Please be open and honest in your responding.”

In most ways my life is close to my ideal.
[“Strongly Agree”, “Agree”, “Slightly Agree”, “Neither Agree nor Disagree”, “Slightly Disagree”, “Disagree”, “Strongly Disagree”]

The conditions of my life are excellent.
[“Strongly Agree”, “Agree”, “Slightly Agree”, “Neither Agree nor Disagree”, “Slightly Disagree”, “Disagree”, “Strongly Disagree”]
I am satisfied with my life.
[“Strongly Agree”, “Agree”, “Slightly Agree”, “Neither Agree nor Disagree”, “Slightly Disagree”, “Disagree”, “Strongly Disagree”]
So far, I have gotten the important things I want in life.
[“Strongly Agree”, “Agree”, “Slightly Agree”, “Neither Agree nor Disagree”, “Slightly Disagree”, “Disagree”, “Strongly Disagree”]
If I could live my life over, I would change almost nothing.
[“Strongly Agree”, “Agree”, “Slightly Agree”, “Neither Agree nor Disagree”, “Slightly Disagree”, “Disagree”, “Strongly Disagree”]

Academic achievement (self-rated)

“Compared to your fellow classmates, how well would you say you are doing in your studies?”
["Poorly", "Below average", "Average", "Above average", "Outstanding"]

Thoughts about participating

I had trouble understanding the questions.
[“Strongly Agree”, “Agree”, “Neither Agree nor Disagree”, “Disagree”, “Strongly Disagree”]
I had trouble entering my responses.
[“Strongly Agree”, “Agree”, “Neither Agree nor Disagree”, “Disagree”, “Strongly Disagree”]
The notifications interfered with my activities.
[“Strongly Agree”, “Agree”, “Neither Agree nor Disagree”, “Disagree”, “Strongly Disagree”]
The questionnaires felt too long.
[“Strongly Agree”, “Agree”, “Neither Agree nor Disagree”, “Disagree”, “Strongly Disagree”]
Overall, this experience was pleasant.
[“Strongly Agree”, “Agree”, “Neither Agree nor Disagree”, “Disagree”, “Strongly Disagree”]
Overall, this experience was challenging.
[“Strongly Agree”, “Agree”, “Neither Agree nor Disagree”, “Disagree”, “Strongly Disagree”]
Overall, this experience was stressful.
[“Strongly Agree”, “Agree”, “Neither Agree nor Disagree”, “Disagree”, “Strongly Disagree”]
I would be interested in participating in similar studies in the future.
[“Strongly Agree”, “Agree”, “Neither Agree nor Disagree”, “Disagree”, “Strongly Disagree”]
I would recommend others participate in this study.
[“Strongly Agree”, “Agree”, “Neither Agree nor Disagree”, “Disagree”, “Strongly Disagree”]
Would you like to take part in future waves of this study?
[“Yes”, “No”, “Maybe”]
Would you like to receive an analysis of your data?
[“Yes”, “No”]

Appendix B: MTurk Place Rating Questionnaire

Note: Respondents filled the questionnaire out for five randomly selected place types. In addition, the questionnaire contained randomized attention checks that have not been included below.

<u>Personality</u> (Soto & John, 2017)

I am someone who...

[Disagree strongly (1); Disagree a little (2); Neutral; no opinion (3); Agree a little (4); Agree strongly (5)]

… Is outgoing, sociable.
… Is compassionate, has a soft heart.
… Tends to be disorganized.
… Is relaxed, handles stress well.
… Has few artistic interests.
… Has an assertive personality.
… Is respectful, treats others with respect.
… Tends to be lazy.
… Stays optimistic after experiencing a setback.
… Is curious about many different things.
… Rarely feels excited or eager.
… Tends to find fault with others.
… Is dependable, steady.
… Is moody, has up and down mood swings.
… Is inventive, finds clever ways to do things.
… Tends to be quiet.
… Feels little sympathy for others.
… Is systematic, likes to keep things in order.
… Can be tense.
… Is fascinated by art, music, or literature.
… Is dominant, acts as a leader.
… Starts arguments with others.
… Has difficulty getting started on tasks.
… Feels secure, comfortable with self.
… Avoids intellectual, philosophical discussions.
… Is less active than other people.
… Has a forgiving nature.
… Can be somewhat careless.
… Is emotionally stable, not easily upset.
… Has little creativity.
… Is sometimes shy, introverted.
… Is helpful and unselfish with others.
… Keeps things neat and tidy.
… Worries a lot.
… Values art and beauty.
… Finds it hard to influence people.
… Is sometimes rude to others.
… Is efficient, gets things done.
… Often feels sad.
… Is complex, a deep thinker.

… Is full of energy.
… Is suspicious of others' intentions.
… Is reliable, can always be counted on.
… Keeps their emotions under control.
… Has difficulty imagining things.
… Is talkative.
… Can be cold and uncaring.
… Leaves a mess, doesn't clean up.
… Rarely feels anxious or afraid.
… Thinks poetry and plays are boring.
… Prefers to have others take charge.
… Is polite, courteous to others.
… Is persistent, works until the task is finished.
… Tends to feel depressed, blue.
… Has little interest in abstract ideas.
… Shows a lot of enthusiasm.
… Assumes the best about people.
… Sometimes behaves irresponsibly.
… Is temperamental, gets emotional easily.
… Is original, comes up with new ideas.

Place visit frequency
On average, how often do you visit a [PLACE]?
Several times a day (1)
About once a day (2)
Every 2-3 days (3)
About once a week (4)
Every 2-3 weeks (5)
About once a month (6)
Every 2-3 months (7)
About once every 6 months (8)
Every 7-8 months (9)
About once a year (10)
Less than once a year (11)

Place visit duration
How much time do you spend on an average visit to a [PLACE]?
Less than 15 minutes (1)
15-30 minutes (2)
30minutes - 1 hour (3)
1-2 hours (4)
2-4 hours (5)
More than 4 hours (6)

Situational characteristics (modeled after Rauthmann et al., 2014)
Think of a typical [PLACE]. Indicate to what extent you agree with the following statements with regards to this type of place:
Extremely uncharacteristic (1); (2); (3); Neutral (4); (5); (6); Extremely characteristic (7)
In a typical [PLACE], a job needs to be done.
A typical [PLACE] affords an opportunity to demonstrate intellectual capacity.

In a typical [PLACE], a person may be criticised directly or indirectly.
In a typical [PLACE], potential romantic partners are present.
In a typical [PLACE], situations are playful.
In a typical [PLACE], situations are potentially anxiety inducing.
In a typical [PLACE], someone might be deceitful.
In a typical [PLACE], social interaction is possible.

<u>Restorativeness</u> (Hartig et al., 1997)
Think of a typical [PLACE]. Indicate to what extent you agree with the following statements with regards to this type of place:
Not at all (1); Slightly (2); Somewhat (3); Quite a bit (4); Very much (5); Completely (6)
Spending time in an [PLACE] gives me a good break from my day-to-day routine.
There is a great deal of distraction in an [PLACE].
Being in an [PLACE] suits my personality.
An [PLACE] has fascinating qualities.

<u>Ambience</u>
Rate a [PLACE] on the following scales, assessing the ambience <u>during a typical visit</u>.
[1-7]
Unpleasant --- Pleasant
Boring --- Exciting
Anxiety-inducing --- Relaxing
Uninteresting ---
Unsafe --- Safe
Quiet --- Lively
Sad --- Happy
Lazy --- Productive
Unclean --- Clean
Typical --- Unique
Historical --- Modern
Crowded --- Vacant
Poor --- Wealthy
Rural --- Urban
Wild --- Landscaped

<u>Place personality</u> (modeled after Gosling et al., 2003)
The people who typically spend time in a [PLACE] are...
[1-7]
Extraverted, Enthusiastic --- Reserved, Quiet
Critical, Quarrelsome --- Sympathetic, Warm
Dependable, Self-Disciplined --- Disorganized, Careless
Anxious, Easily Upset --- Calm, Emotionally Stable
Open to New Experiences, Complex --- Conventional, Uncreative

<u>Place enjoyment</u>
How much do you enjoy spending time in a typical [PLACE]?
Very much (1)
Quite a bit (2)
Somewhat (3)
Slightly (4)
Not at all (5)

<u>Demographics</u>
What kind of area do you spend most of your time in?
Rural (1)
Mix of rural and urban (2)
Urban (3)

What is your year of birth? *[...]*

Choose one or more races that you consider yourself to be:
White (1)
Black or African American (2)
American Indian or Alaska Native (3)
Asian (4)
Native Hawaiian or Pacific Islander (5)
Other (6): [...]

What is your gender?
Male (1)
Female (2)
Other (3)

<u>Wellbeing</u> (Psychiatric Research Unit WHO Collaborating Centre in Mental Health, 1998)
Over the last two weeks...
All of the time (1); Most of the time (2); More than half of the time (3); Less than half of the time (4); Some of the time (5); At no time (6)
I have felt cheerful and in good spirits (1)
I have felt calm and relaxed (2)
I have felt active and vigorous (3)
I woke up feeling fresh and rested (4)
My daily life has been filled with things that interest me (5)

Appendix C: Extensions of Tables for Affective States Satisfied, Admired, Criticized

Extension of Table 10

Variance Between and Within Individual for Average Daily Affective States

Affective states	Average daily mean	Standard deviation	Average daily standard deviation	Variance between individuals	Variance within individuals	Person mean reliability
Satisfied	2.72	.33	.39	.31	.69	.84
Admired	3.13	1.21	.61	.76	.24	.97
Criticized	1.88	.66	.46	.58	.42	.94

Note. 21 participants, 4-14 days. ICC1s (variance between individuals) and ICC2s (individual mean reliability) were computed using a multilevel modelling approach as the group sizes (i.e. number of days per participant) were not balanced. I used the multilevel package in R, following the procedure suggested for estimating multiple ICC values in Bliese (2016).

Extension of Table 12

Linear Mixed-Effects Models Predicting Affective States from Mobility Metrics (Random Intercepts Model)

	Satisfied			Admired			Criticized		
	B	SE	p	B	SE	p	B	SE	p
Intercept	2.22	.26	<.001	2.80	.45	<.001	2.15	.33	<.001
convex_hull	-.17	.30	.580	.69	.43	.109	-.59	.35	.095
dis_ent	.05	.17	.763	-.16	.24	.511	-.06	.20	.766
displacement_var	.00	.00	.536	.00	.00	.521	.00	.00	.222
distance	.79	2.08	.706	-.18	3.05	.952	-2.09	2.46	.398
ent	-.37	.43	.392	-.31	.63	.619	.07	.51	.884
loc_var	.00	.01	.457	-.01	.01	.515	.00	.01	.975
location_change	.01	.01	.679	.00	.02	1.000	.01	.02	.716
max_dis	.00	.00	.540	.00	.00	.449	.00	.00	.204
norm_ent	.04	.40	.914	-.35	.57	.542	.40	.47	.396
num_cluster	.01	.06	.900	.05	.09	.542	-.09	.07	.202
place_seq	.00	.00	.100	-.01	.00	.113	.00	.00	.956
rad_gyration	.00	.00	.575	.00	.00	.118	.00	.00	.086
raw_ent	.35	.19	.062	.43	.28	.128	-.09	.23	.686
routine_index	**.01**	.00	.013	.01	.01	.396	.00	.01	.770
speed_mean	-.88	2.35	.708	-.57	3.42	.869	2.84	2.76	.306
speed_var	-.02	.01	.213	.02	.02	.367	-.01	.02	.536
tile_seq	**.02**	.01	.013	**.03**	.01	.010	.00	.01	.904
tiles	-.01	.01	.448	-.02	.01	.153	.00	.01	.733
time_at_each_loc	.01	.01	.586	.00	.02	.775	-.01	.01	.437
transition_time	-.11	.14	.429	.01	.21	.970	-.10	.17	.570

Note. N= 21 participants, who participated for 4-14 days. This table features individuals who participated for 4-14 days. Table presents fixed effects. Models did not converge when adding random effects. I also removed variables denoting the maximum distance from home and percentage of time spent at home as they were only available for a small subset of participants.

Extension of Table 19

Variance Between and Within Individual for Places Visited and Affective States

Affective states	Average frequency	Standard deviation	Variance between individuals	Variance within individuals	Person mean reliability
Satisfied	2.68	0.45	.30	.70	.95
Admired	2.91	1.06	.45	.55	.97
Criticized	1.66	0.66	.39	.61	.97

Note. Number of EMAs n = 3657, submitted by 83 participants, who participated for 3-14 days. ICC1s (variance between individuals) and ICC2s (individual mean reliability) were computed using a multilevel modelling approach as the group sizes (i.e. number of EMAs per participant) were not balanced. I used the multilevel package in R, following the procedure suggested for estimating multiple ICC values in Bliese (2016).

Extension of Table 20

Multilevel Models Predicting Affective States from Places (Random Intercepts Model)

	Satisfied			Admired			Criticized		
	B	SE	p	B	SE	p	B	SE	p
Intercept	2.61	.05	<.001	2.79	.11	<.001	1.66	.07	<.001
Café restaurant	.07	.05	.196	-.09	.10	.363	.03	.07	.650
College common area	**.20**	.05	<.001	**.34**	.10	<.001	-.04	.07	.588
Friend’s house	**.22**	.05	<.001	**.71**	.09	<.001	-.05	.06	.418
In transit	**.16**	.06	.006	**.40**	.10	<.001	.06	.07	.429
Pub Party	**.30**	.10	.004	**.66**	.18	<.001	.25	.13	.053
University	**.12**	.04	.004	**.21**	.07	.004	-.01	.05	.800
Other	**.27**	.05	<.001	**.35**	.09	<.001	.00	.07	.952

Note. Number of EMAs n = 3657, submitted by 83 participants, who participated for 3-14 days. The scales ranged from 1 to 5, and ‘Home’ was set as the reference category. Table presents fixed effects. Models did not converge when including random effects.

Appendix D: GPS Location Coding Manual

Detailed GPS Location Coding Manual
- Cambridge, UK -

The following manual explains the process of coding the GPS location data. If you have any questions or anything is unclear, please do get in touch as it will help further clarify this manual and ensure all coders report information about the locations in the same way.

Thank you for your help!

Let's get started!
You are going to code objective as well as subjective information with the help of Google Maps.

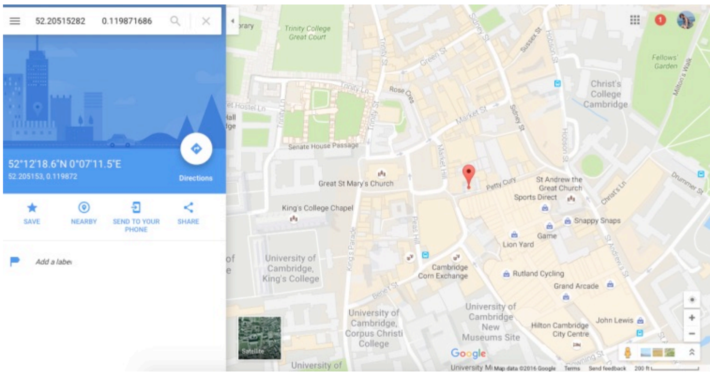
For all coding (objective and subjective), you will need to have two windows open on your computer:

- The Qualtrics web survey where you are going to enter the information: [Refer to email for your individual link]
- And Google Maps, where you are going to retrieve the information: https://www.google.com/maps

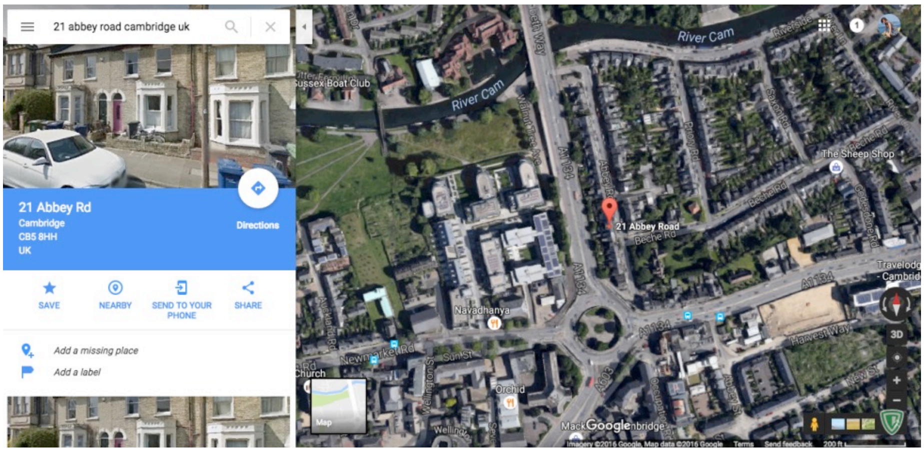
Note that you can interrupt the Qualtrics survey at any time and go back to it at a later point. This is possible because your Qualtrics link is individualised and Qualtrics keeps track of how many/which locations you have coded so far. It is also possible to go backwards in the survey in case you accidentally entered wrong information and there is an open text field provided at the very end of the survey in case you want to keep note of anything.

Step 1: Enter the location and get an overview.

Copy longitude and latitude (e.g. "52.20515282 0.119871686") from the Qualtrics survey into the Google Maps search field. Hit enter or click search. You should now see this:



Have a look at both the Google *Maps* and the *Satellite/Earth* view.



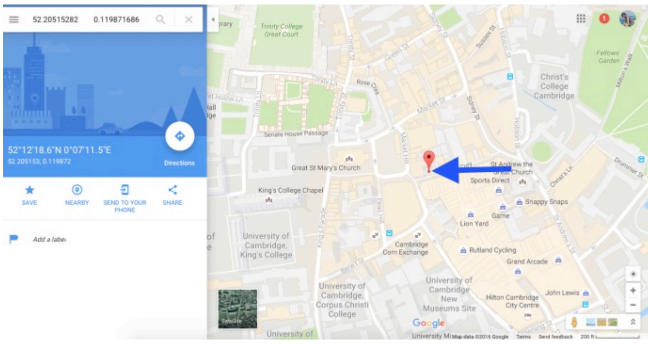
Now, navigate to Google *Streetview* [if available for the location] and do a 360 degree turn as if you were standing in the location yourself.

IMPORTANT:
Make sure again that the location hasn't "jumped" after doing this. You can do so by looking at the map in the lower left corner. The location tag should be located right next to the orange man icon. Please try as best as you can to get a view of the location. If they are too far apart/you can't see anything, please indicate that Google Streetview is not available for this location.

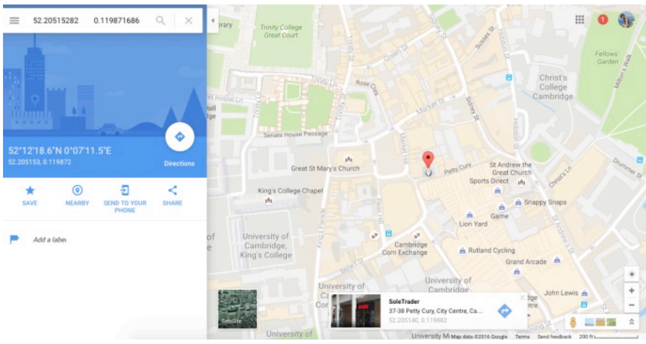
Coding objective information

<u>Step 2: Retrieve the address and the postcode.</u>

Go back to the *Maps* view and click on the center of the little red dot below the tear shaped tag:

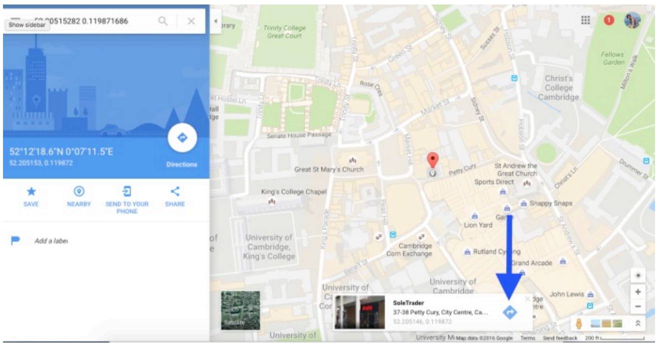


This will make the address appear:

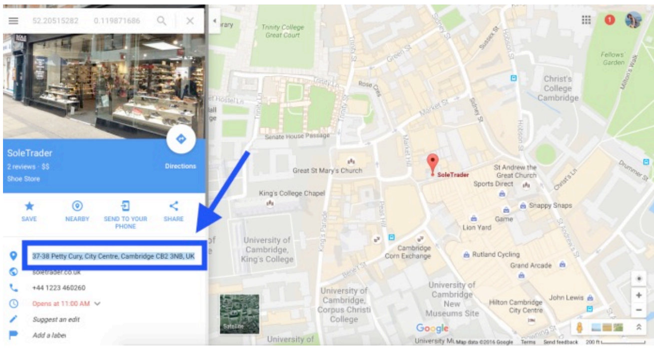


IMPORTANT:
Make sure that the location hasn't "jumped" after doing this (this can easily happen if the location is e.g. in the middle of an area without a specific address such as a park or in a large building such as a big supermarket). If this happens, click on the place tag (e.g. "Tesco Cambridge Newmarket Road" or "Midsummer Commons") and use the address that appears for the tag. Make sure the location has a postcode too (e.g. for parks often not the case). If the postcode is missing, add the one from the location the tag first jumped to. For some foreign locations, no postcode might be available.

Click on the arrow symbol in the address box:



This will put the address into the box on the left where you can copy it from (and paste it into the respective field of the Qualtrics survey):

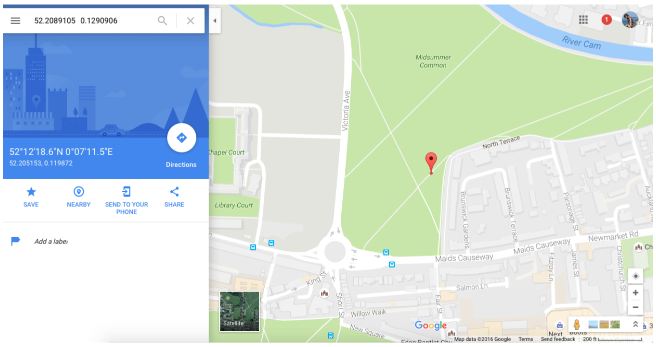


IMPORTANT:
Keep track of the postcode for <u>any</u> location, but <u>do not</u> enter the address (street name and house number) for residential locations. See Step 4 for an example of what a residential area looks like. We are only saving the postcode, but not details, of residential locations for privacy reasons. If you record a foreign residential location, record the country as well as the postcode.

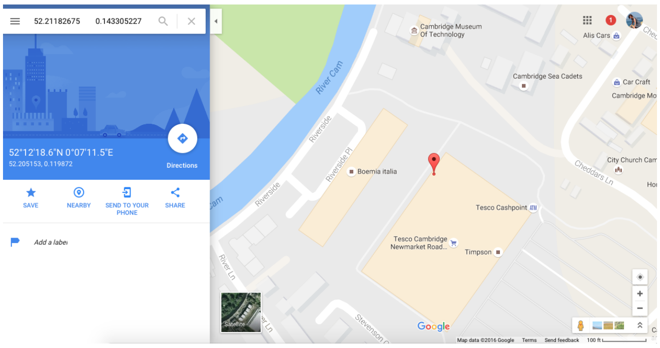
Step 3: Record whether the location is inside or outside.

Here are two examples of what an outside location and an inside location could look like:

→ Outside location: Tag appears in the middle of a park.



→ Inside location: Tag appears in a supermarket building



→ Unclear: Select if it is unclear, whether the location is inside or outside (e.g. the location falls onto the border of a building). Please don't select this option too easily. Try first to zoom into the location to determine whether it is inside or outside (and use common sense in your decision).

Step 4: Report the land use zone the location falls into.

Decide which land use zone the location falls into. The options are:

1. *College (Cambridge)*
2. *Commercial / urban*
3. *Nature*
4. *Residential*
5. *Transportation*
6. *University*

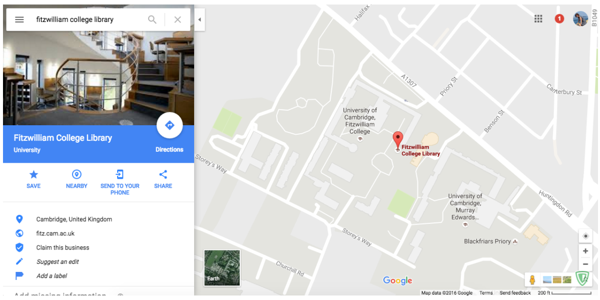
More details about the different options are given in the following.

1. College

→ Includes: College buildings (unspecified), libraries, gym/outdoor recreational sport areas, cafes, dining halls, houses/dorms.

IMPORTANT: Remember that colleges in Cambridge (UK) are more like Harry Potter houses and not 'colleges' in the US :)

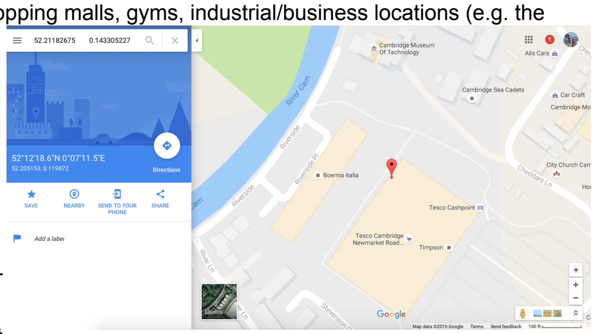
→ Example on the right:



2. Commercial and urban

→ Includes: Cafés, restaurants, shopping malls, gyms, industrial/business locations (e.g. the office building of an insurance company), retail shops, religious organizations (e.g. churches, YMCAs), museums, health related locations (e.g. medical practice).

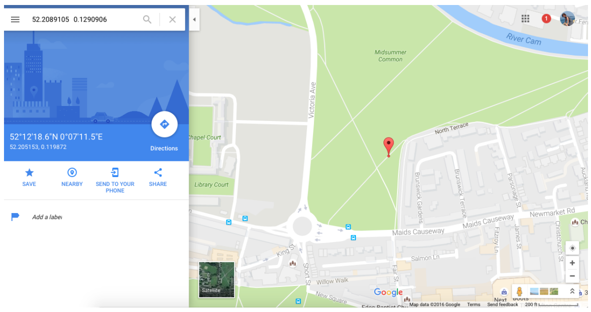
→ Example on the right: The building is labelled as a supermarket/shop and therefore commercial (when in doubt whether this is a commercial location, you can retrieve more information about the location by clicking on it's label, e.g. "Tesco Cambridge Newmarket Road" in this example)



3. Nature

→ Includes: Lakes, rivers, trails, public gardens, green spaces/parks.

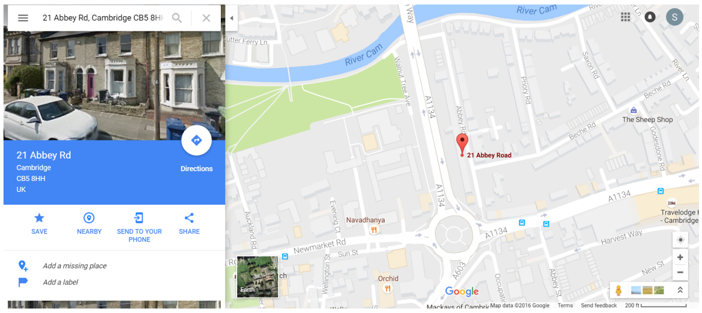
→ Example on the right: The tag falls into a park and is therefore nature related.



4. Residential

→ Includes: Houses, apartment buildings.

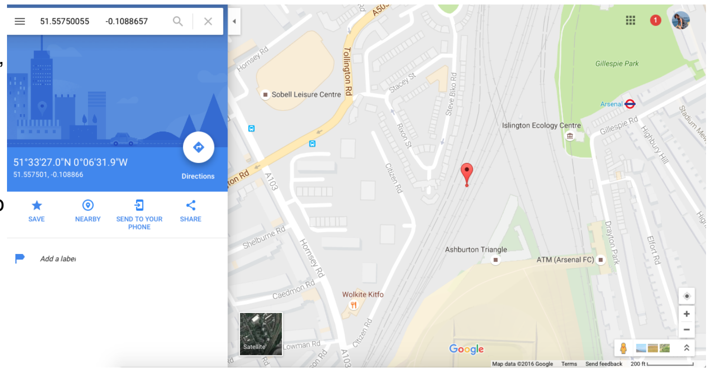
→ Example on the right:



5. Transportation

→ includes: Bus stops, train stations, train tracks, airport, motorways/highways.

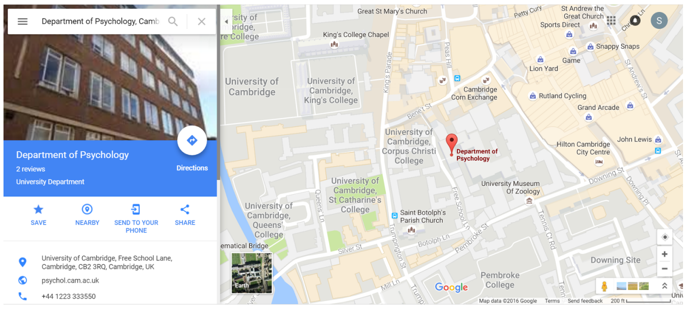
→ Example on the right: The tag falls onto train tracks and can therefore be labelled as transportation related.



6. University

→ Includes: University buildings (e.g. lecture halls, departments), libraries, gym/outdoor recreational sport areas, cafes, dining halls.

→ Example on the right:



Step 5: Report locations of interest.

After having coded the land use zone for the location, you will be asked to record more details about the location. For example, you will be able to select locations such as college building, university buildings, cafes, gyms, libraries, restaurants, shops, museums. See below for a complete overview of the options.

→ *Unclear / not codable*:
Select if not enough information is available to code the location on this level of detail (e.g. the location is a commercial/urban unit in a row of shops, but you cannot find out whether it is a cafe, shop or something else).

→ *Other*:
Select if the location does not fit into any of the options and enter details in the provided space so that we can adjust the coding scheme in the future if we forgot about something important.

Table: Overview of Coding Scheme for Land Use Zones and Locations of Interest

Level 1: Land use zone	**Level 2: Locations of interest**
College Commercial/(urban) Nature Residential Transportation University	Airport Bus Stop Cafe College Dining hall Green spaces/gardens/parks Gym/outdoor recreational sports Health House/apartment building Industrial/business Lake/river Library Museum Parking lot Religious organisation Restaurant Shop (retail) Shopping mall Street Train Trail/path University building (incl departments) Unclear/not codable Other [enter additional information]

Coding subjective information

Step 6: Personality
The people who typically spend time in this location are…

Extraverted, Enthusiastic	-----	Reserved, Quiet
Critical, Quarrelsome	-----	Sympathetic, Warm
Dependable, Self-Disciplined	-----	Disorganized, Careless
Anxious, Easily Upset	-----	Calm, Emotionally Stable
Open to New Experiences, Complex	-----	Conventional, Uncreative

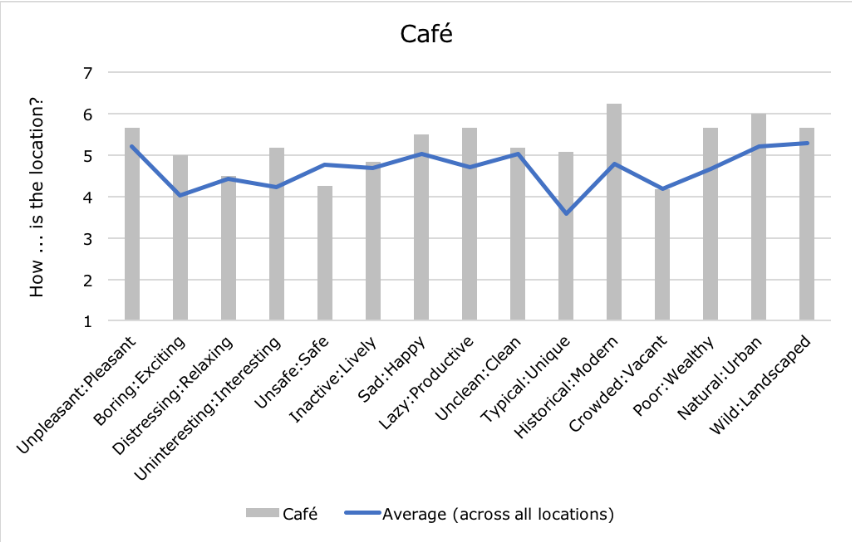
Step 7: Affective appraisals
Rate the location on the following scales, assessing the ambience of the area during the day. Don't let the weather influence your ratings.

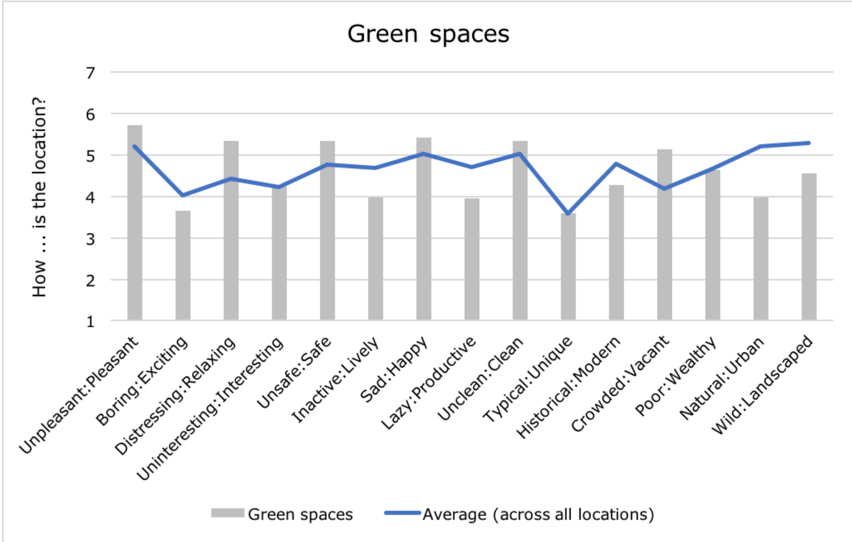
Unpleasant	-----	Pleasant
Boring	-----	Exciting
Distressing/anxious/tense	-----	Relaxing
Uninteresting	-----	Interesting
Unsafe	-----	Safe
Inactive	-----	Active/busy/lively
Sad	-----	Happy
Lazy	-----	Productive

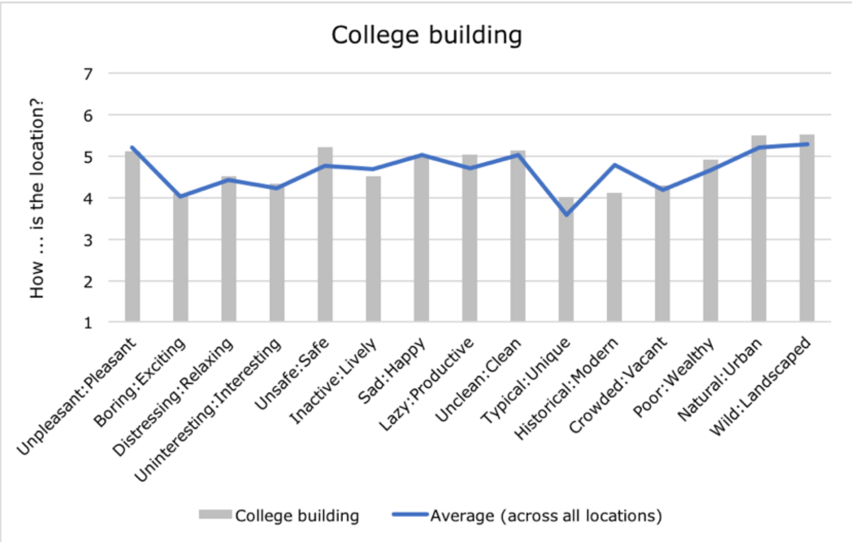
Unclean	-----	Clean
Typical	-----	Unique
Historical	-----	Modern
Poor	-----	Wealthy
Natural	-----	Built/urban
Landscaped/cultivated	-----	Wild/uncultivated
Crowded	-----	Vacant/open

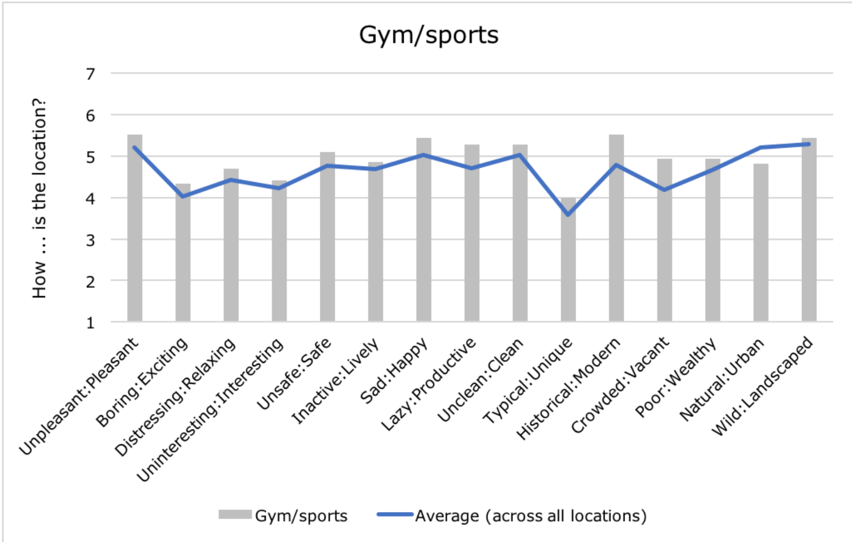
IMPORTANT:
Don't forget to take breaks regularly - try to not do more than 2 hours of coding in one sitting!

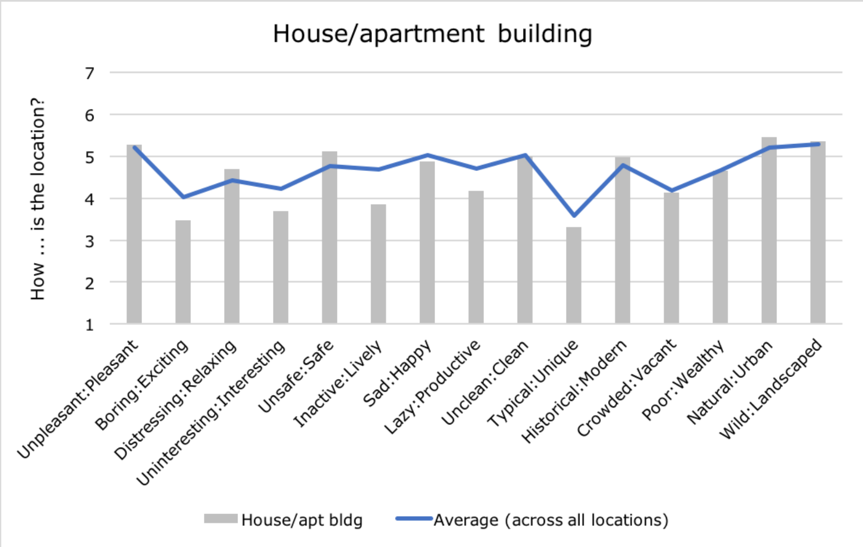
Appendix E: Ambience Profiles for All Places and Zones

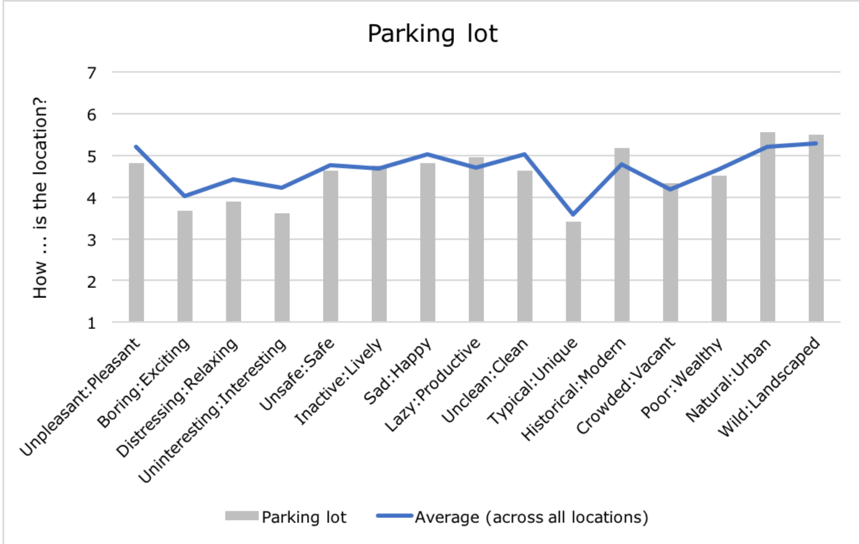


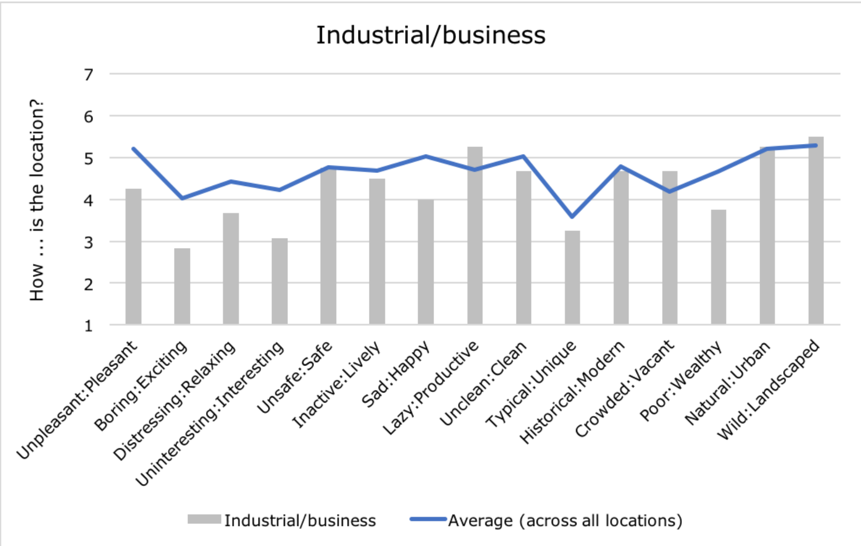


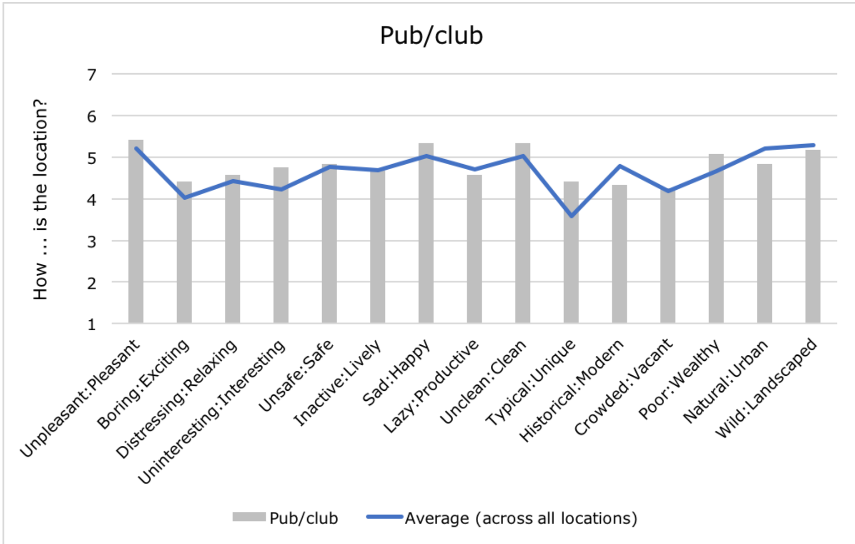


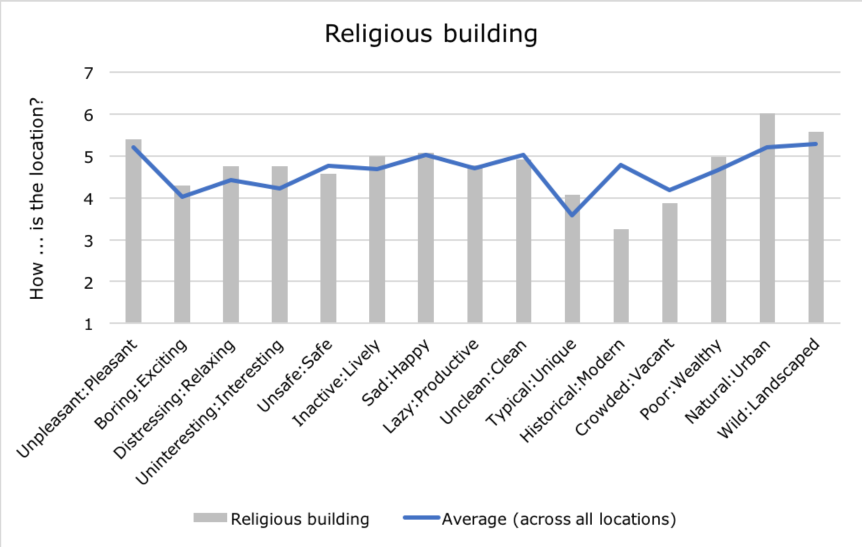


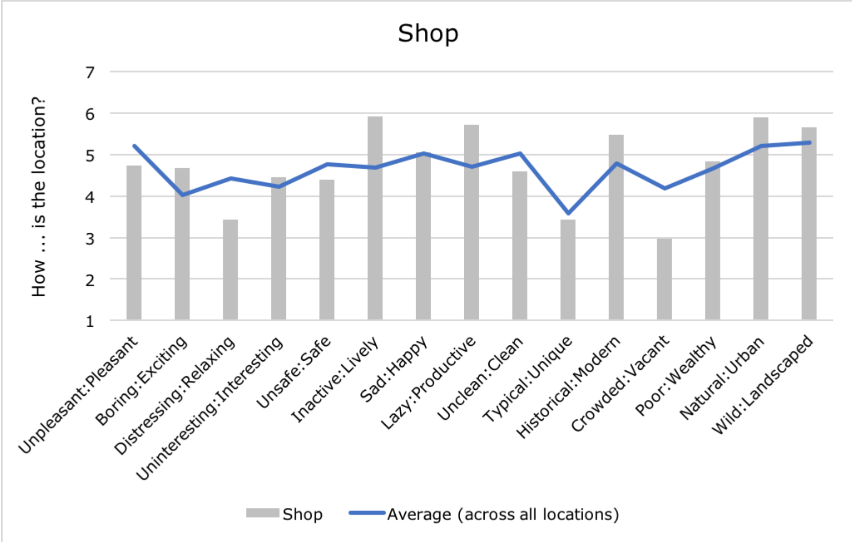

House/apartment building
How ... is the location?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
House/apt bldg
Average (across all locations)


Parking lot
How ... is the location?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Parking lot
Average (across all locations)

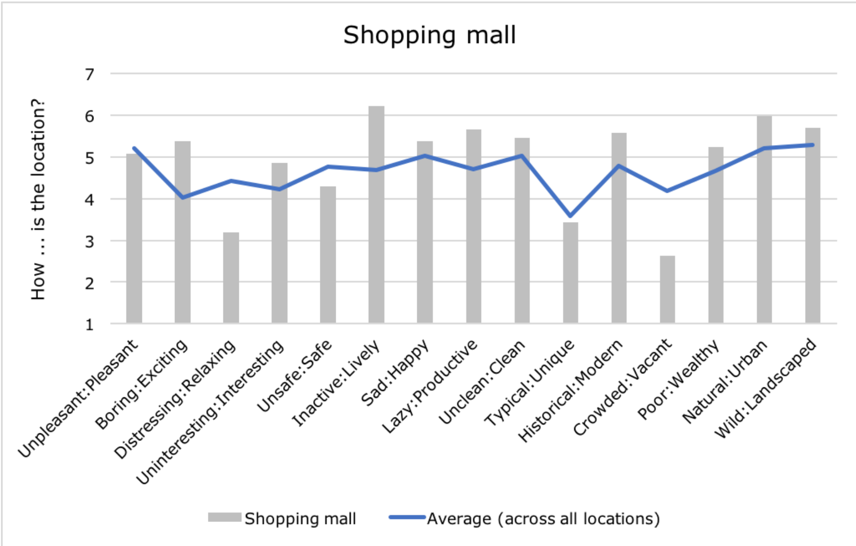

Industrial/business
How ... is the location?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Industrial/business
Average (across all locations)

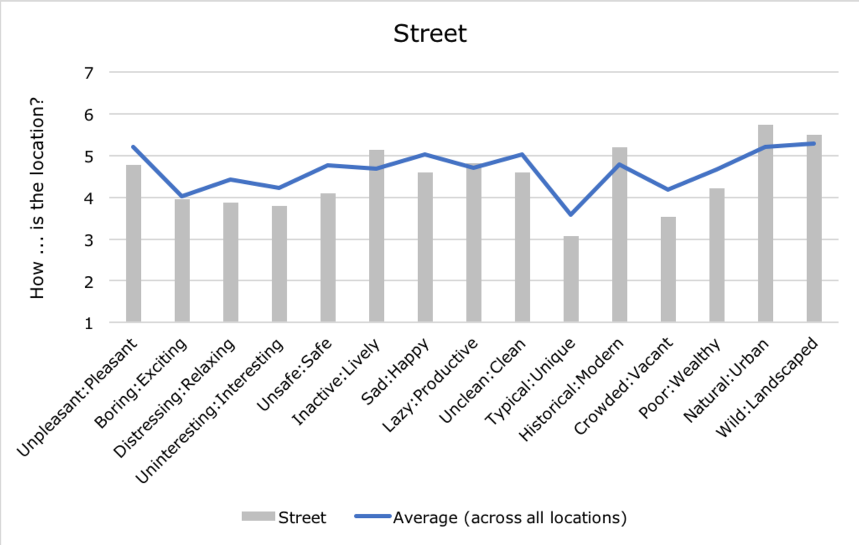

Pub/club
How ... is the location?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Pub/club
Average (across all locations)

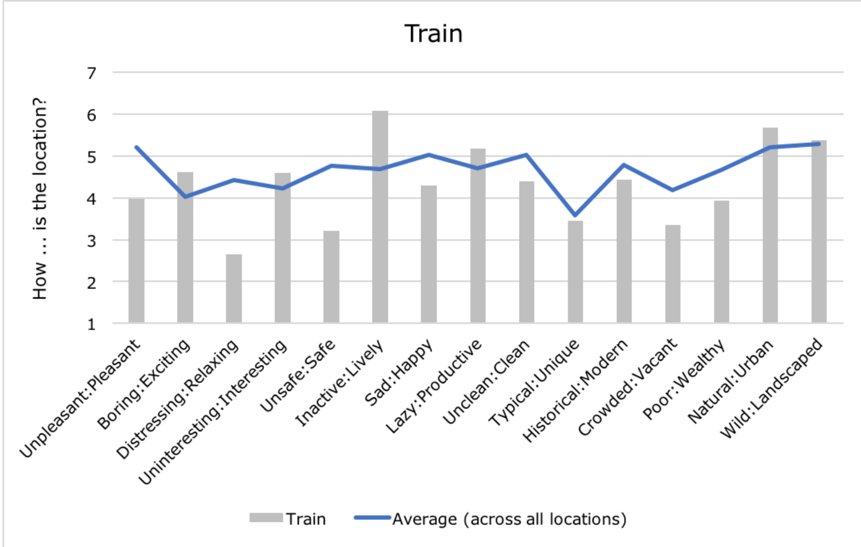

Religious building
How … is the location?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Religious building
Average (across all locations)

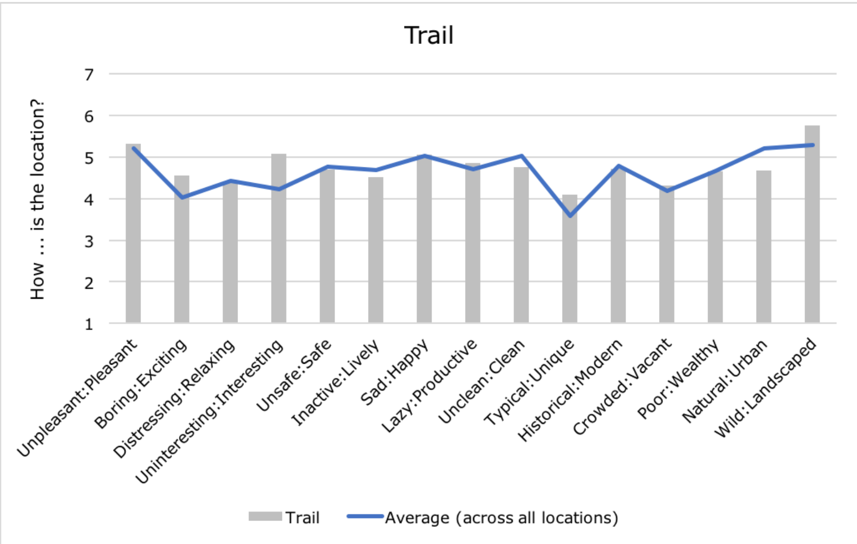

Shop
How … is the location?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Shop
Average (across all locations)

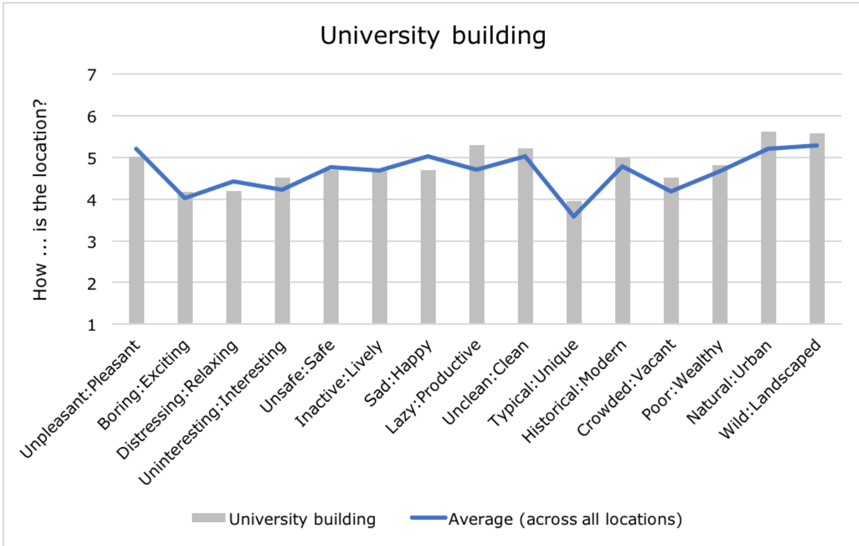

Restaurant
How … is the location?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Restaurant
Average (across all locations)

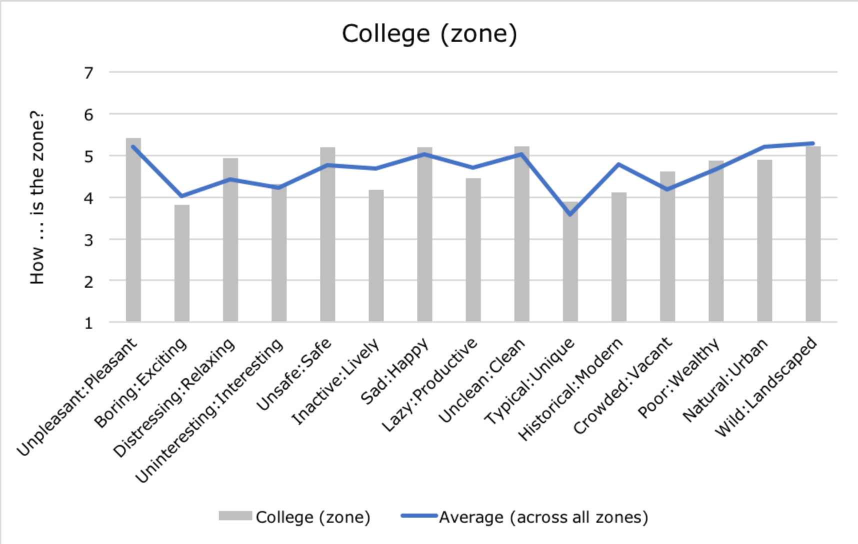

Shopping mall
How … is the location?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Shopping mall
Average (across all locations)

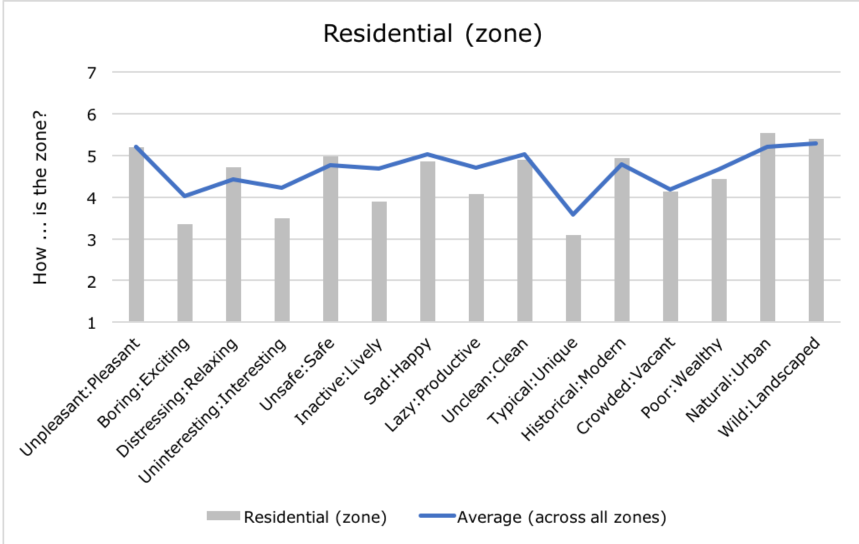

Street
How … is the location?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Street
Average (across all locations)

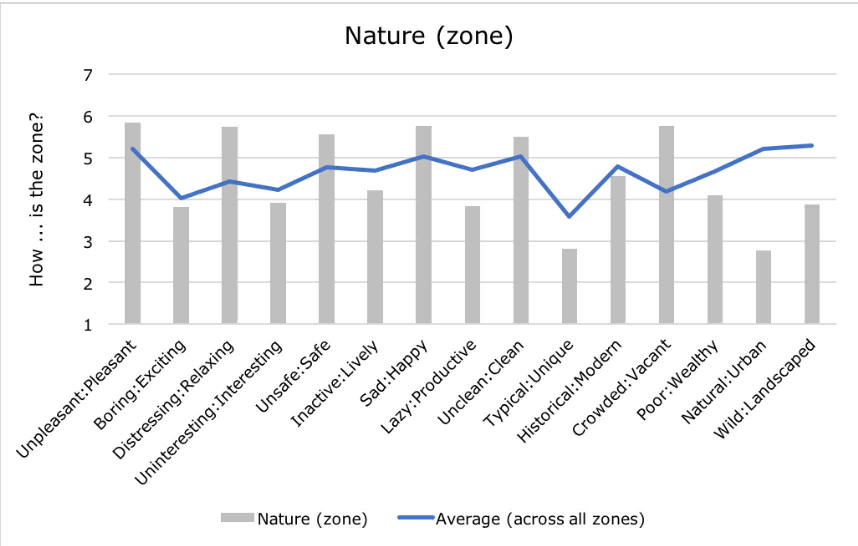

Train
How … is the location?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Train
Average (across all locations)

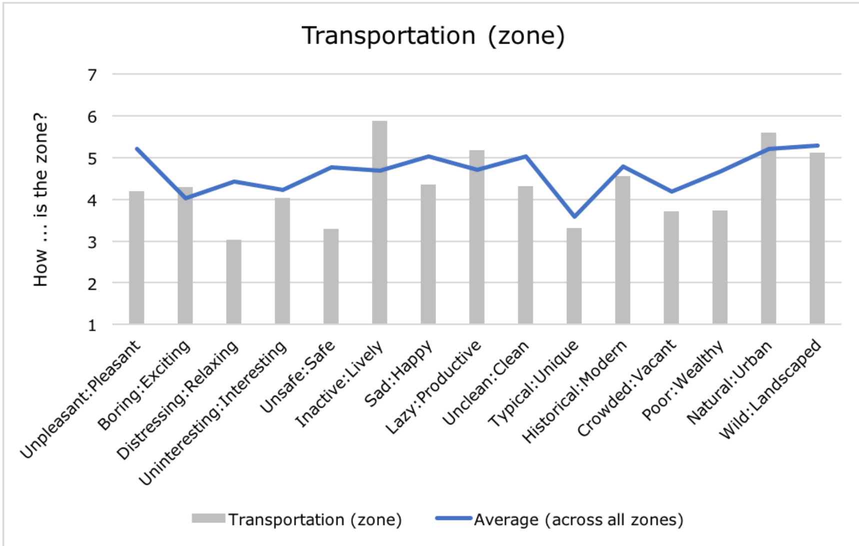

Trail
How … is the location?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Trail
Average (across all locations)

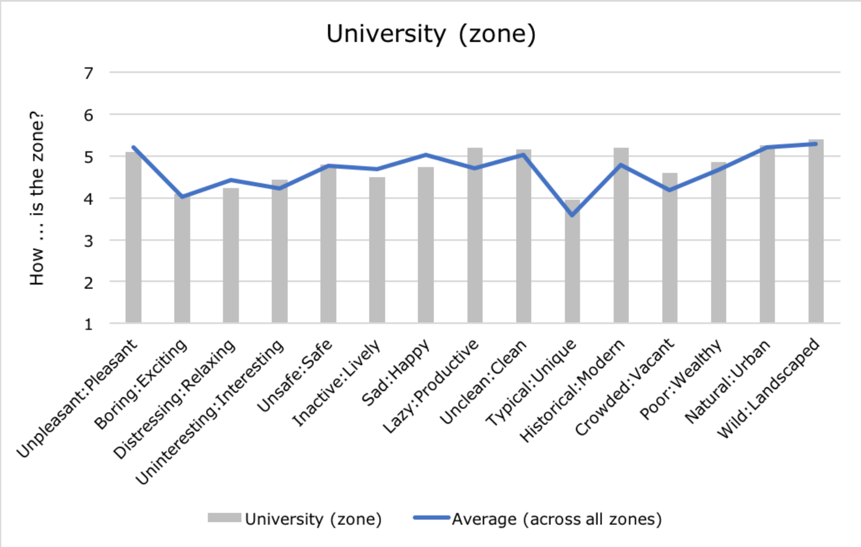

University building
How … is the location?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
University building
Average (across all locations)

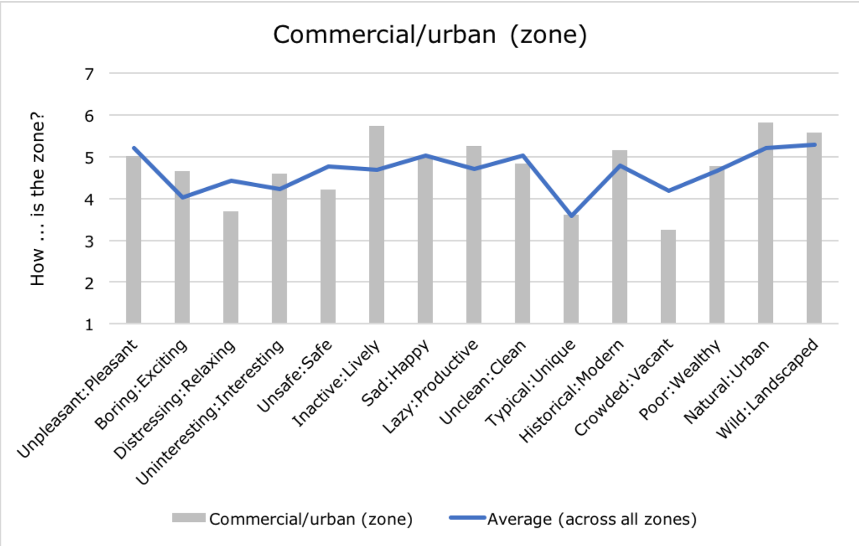

College (zone)
How ... is the zone?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
College (zone)
Average (across all zones)


Residential (zone)
How ... is the zone?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Residential (zone)
Average (across all zones)

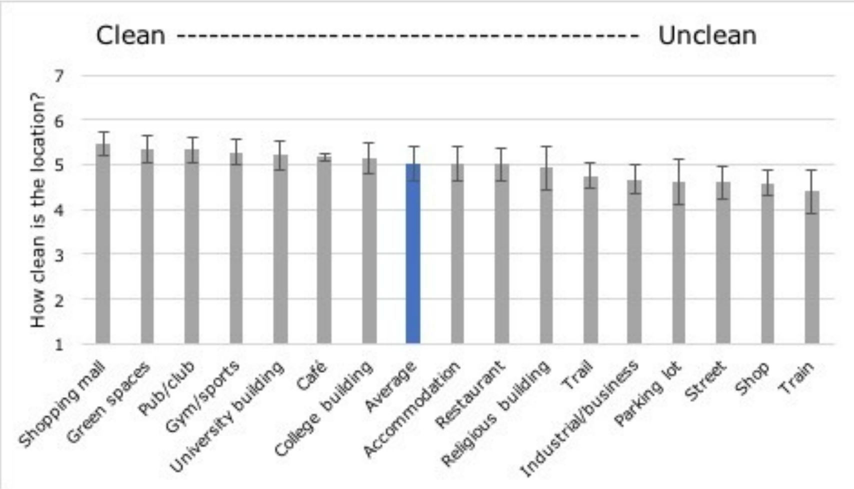

Nature (zone)
How ... is the zone?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Nature (zone)
Average (across all zones)

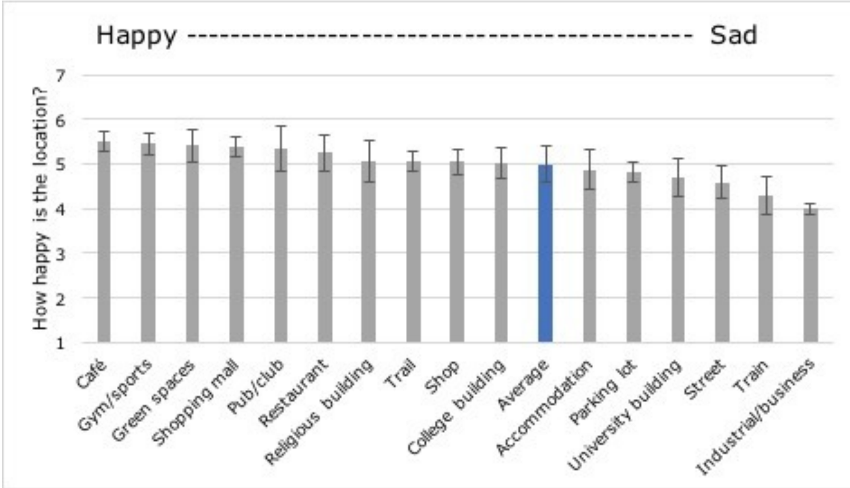

Transportation (zone)
How ... is the zone?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Transportation (zone)
Average (across all zones)

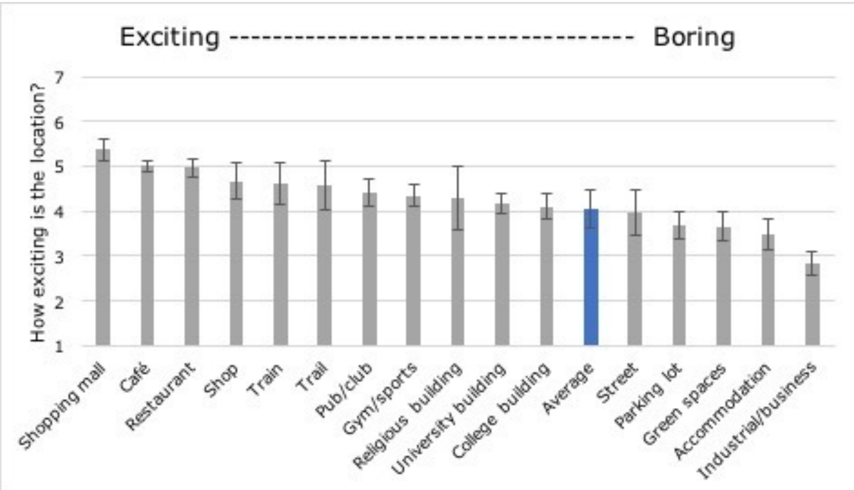

University (zone)
How ... is the zone?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
University (zone)
Average (across all zones)

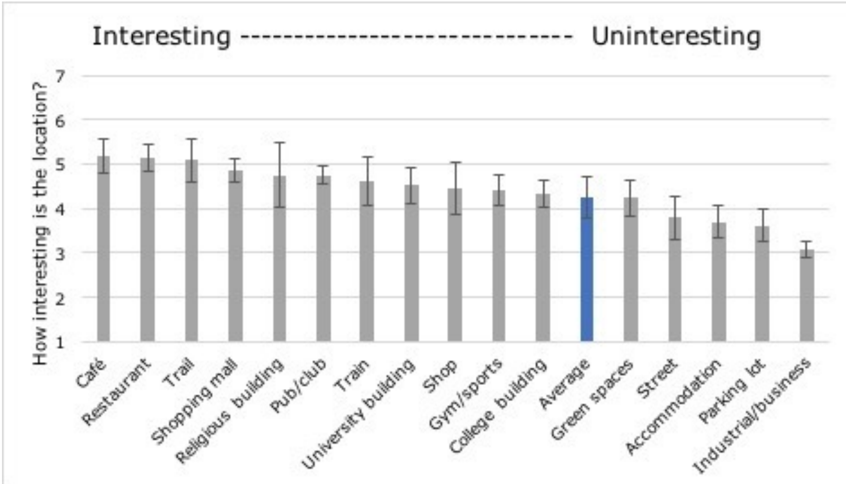

Commercial/urban (zone)
How ... is the zone?
7
6
5
4
3
2
1
Unpleasant:Pleasant
Boring:Exciting
Distressing:Relaxing
Uninteresting:Interesting
Unsafe:Safe
Inactive:Lively
Sad:Happy
Lazy:Productive
Unclean:Clean
Typical:Unique
Historical:Modern
Crowded:Vacant
Poor:Wealthy
Natural:Urban
Wild:Landscaped
Commercial/urban (zone)
Average (across all zones)

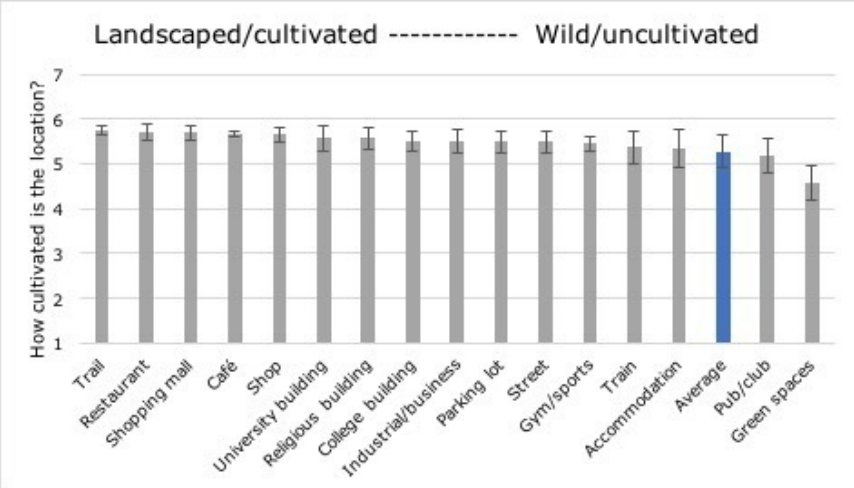
Appendix F: Comparisons of All Places and Zones on Ambience and Personality Dimensions



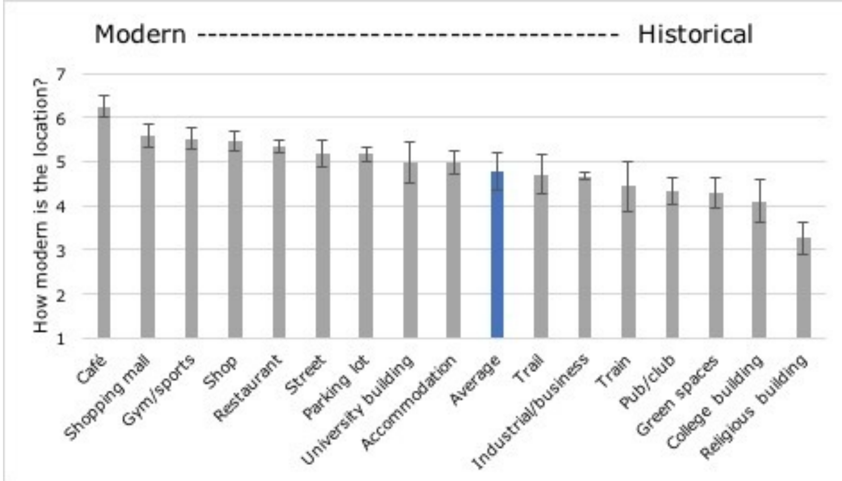




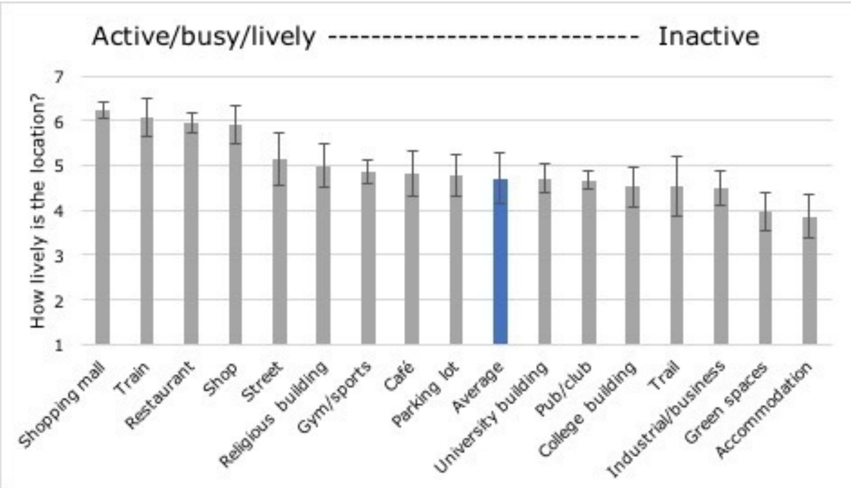




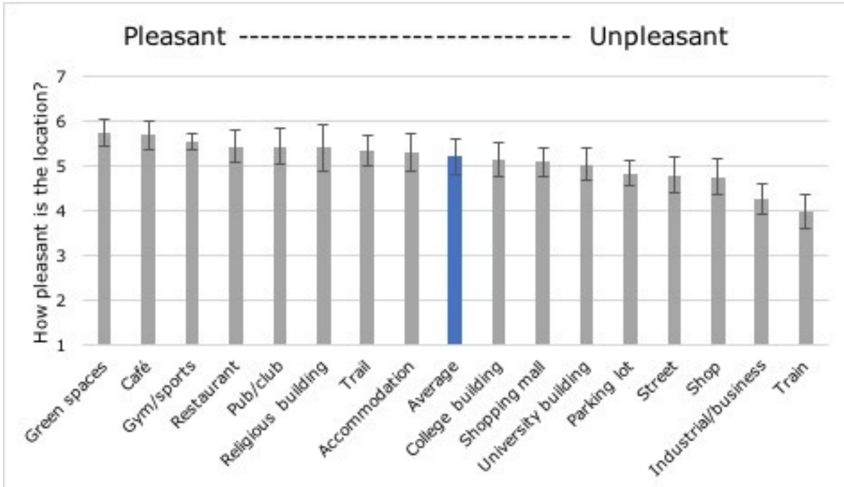
Landscaped/cultivated ------------ Wild/uncultivated
How cultivated is the location?
Trail
Restaurant
Shopping mall
Café
Shop
University building
Religious building
College building
Industrial/business
Parking lot
Street
Gym/sports
Train
Accommodation
Average
Pub/club
Green spaces



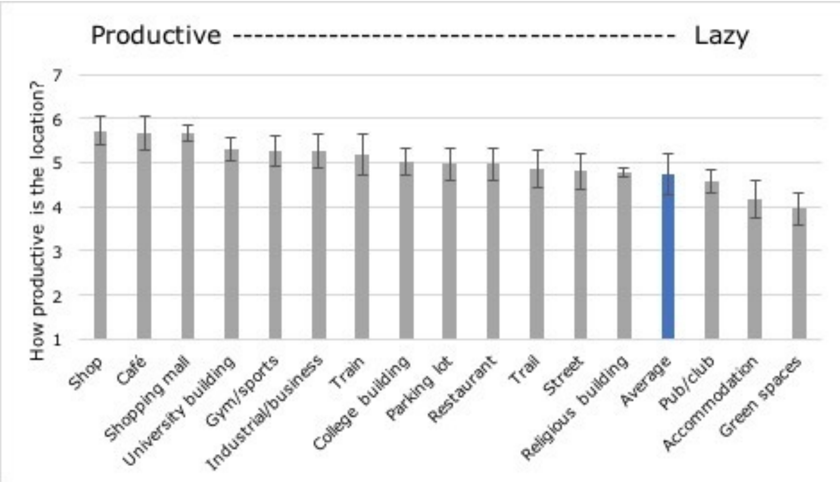
Modern ------------------------------------ Historical
How modern is the location?
Café
Shopping mall
Gym/sports
Shop
Restaurant
Street
Parking lot
University building
Accommodation
Average
Trail
Industrial/business
Train
Pub/club
Green spaces
College building
Religious building

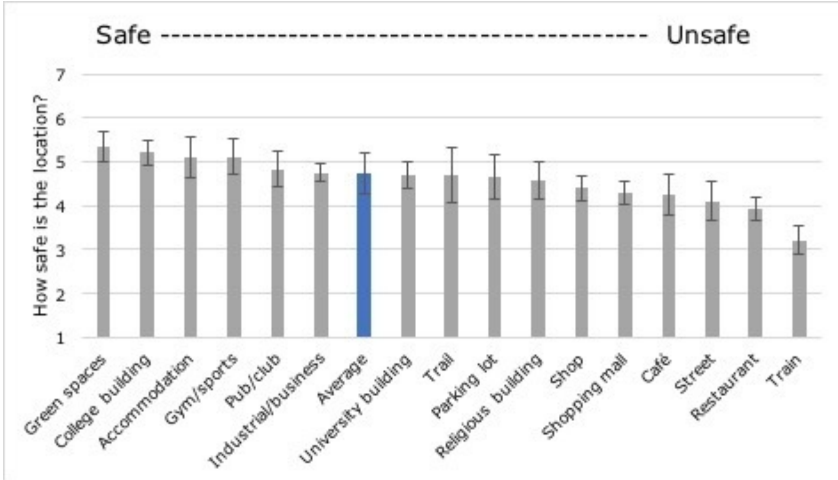


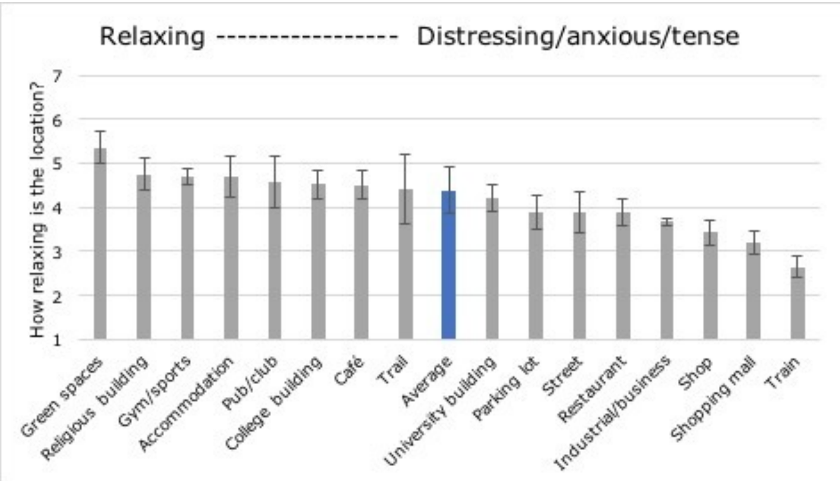
Active/busy/lively --------------------------- Inactive
How lively is the location?
Shopping mall
Train
Restaurant
Shop
Street
Religious building
Gym/sports
Café
Parking lot
Average
University building
Pub/club
College building
Trail
Industrial/business
Green spaces
Accommodation

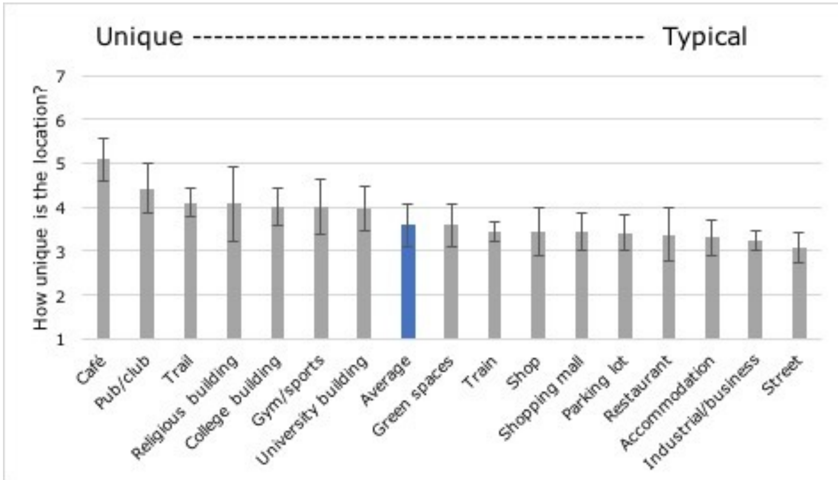


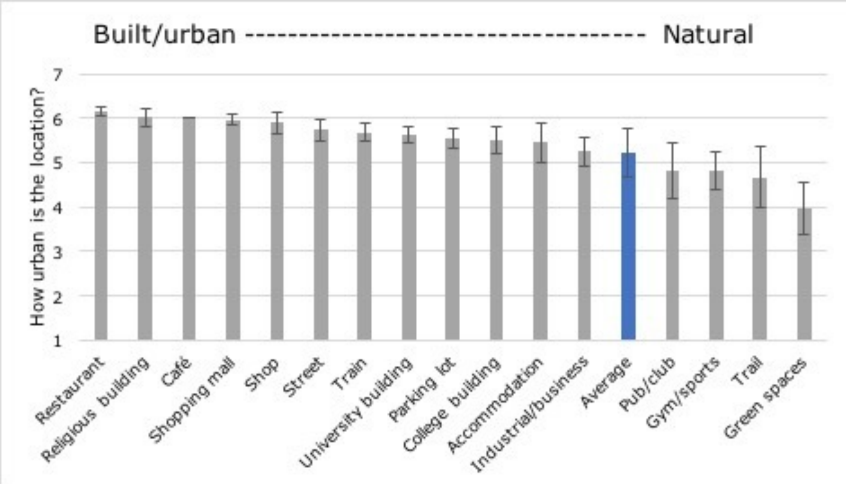
Pleasant ---------------------------- Unpleasant
How pleasant is the location?
Green spaces
Café
Gym/sports
Restaurant
Pub/club
Religious building
Trail
Accommodation
Average
College building
Shopping mall
University building
Parking lot
Street
Shop
Industrial/business
Train


Productive -- Lazy
How productive is the location?
7
6
5
4
3
2
1
Shop
Café
Shopping mall
University building
Gym/sports
Industrial/business
Train
College building
Parking lot
Restaurant
Trail
Street
Religious building
Average
Pub/club
Accommodation
Green spaces

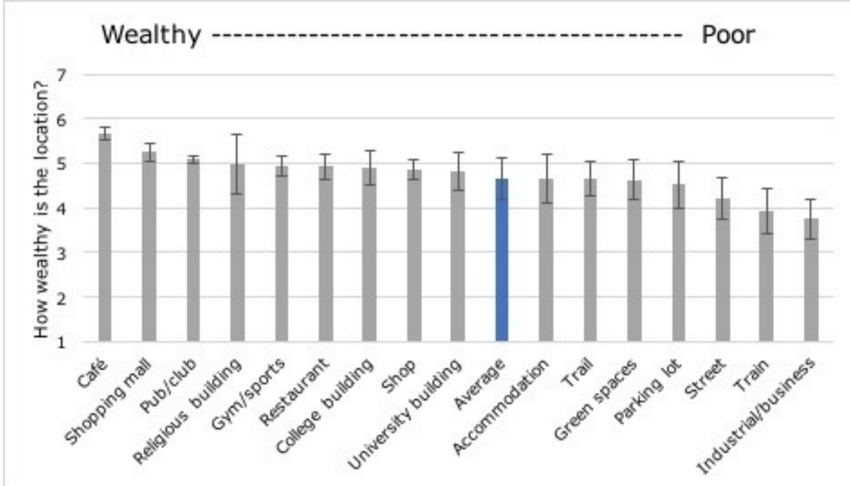

Safe --- Unsafe
How safe is the location?
7
6
5
4
3
2
1
Green spaces
College building
Accommodation
Gym/sports
Pub/club
Industrial/business
Average
University building
Trail
Parking lot
Religious building
Shop
Shopping mall
Café
Street
Restaurant
Train


Relaxing ---------------- Distressing/anxious/tense
How relaxing is the location?
7
6
5
4
3
2
1
Green spaces
Religious building
Gym/sports
Accommodation
Pub/club
College building
Café
Trail
Average
University building
Parking lot
Street
Restaurant
Industrial/business
Shop
Shopping mall
Train

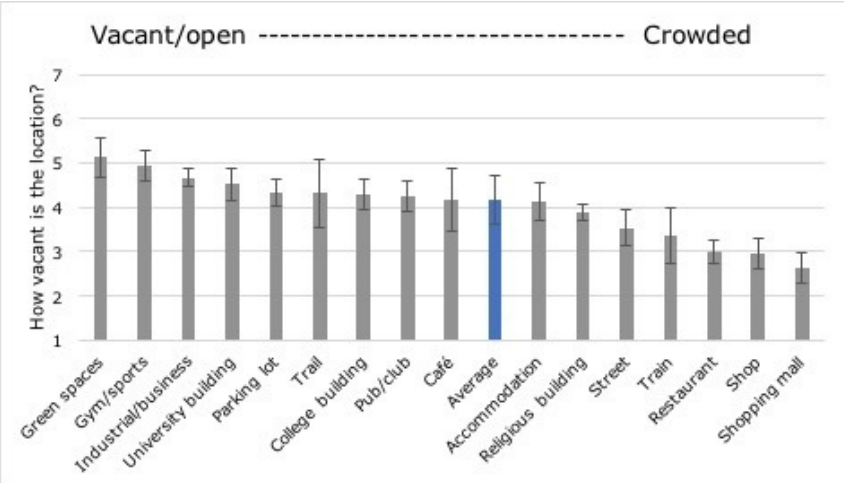

Unique -- Typical
How unique is the location?
7
6
5
4
3
2
1
Café
Pub/club
Trail
Religious building
College building
Gym/sports
University building
Average
Green spaces
Train
Shop
Shopping mall
Parking lot
Restaurant
Accommodation
Industrial/business
Street



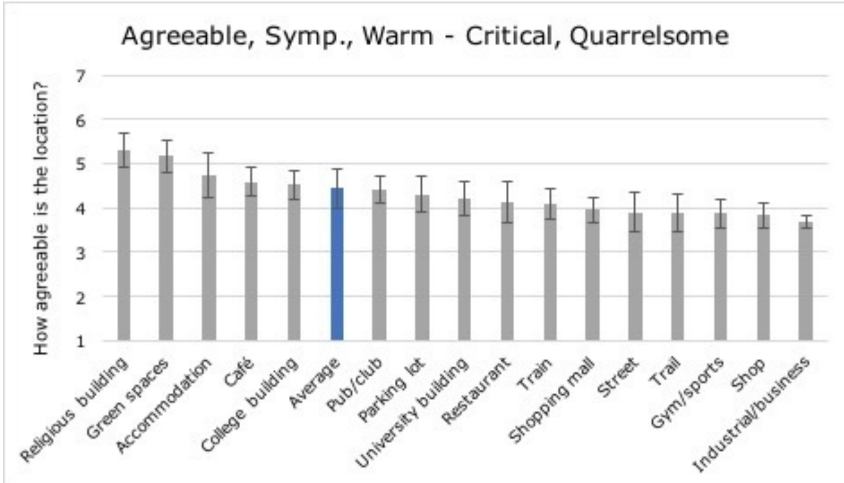
Built/urban ---------------------------------- Natural
How urban is the location?
Restaurant
Religious building
Café
Shopping mall
Shop
Street
Train
University building
Parking lot
College building
Accommodation
Industrial/business
Average
Pub/club
Gym/sports
Trail
Green spaces



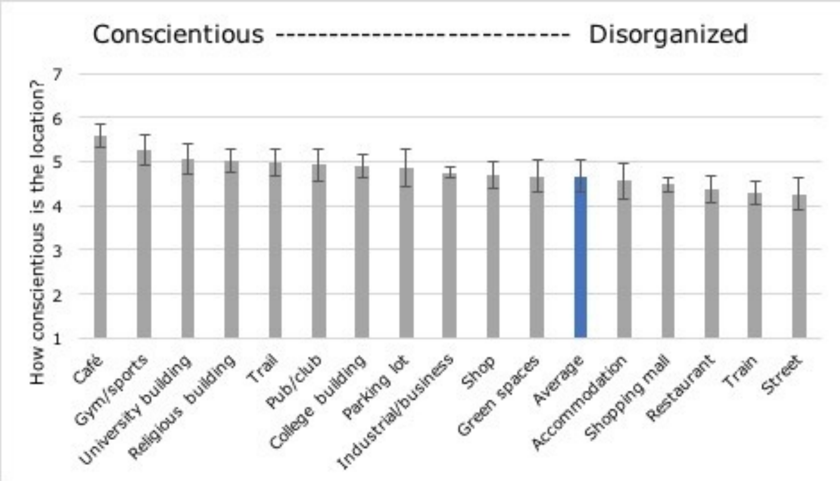
Wealthy -- Poor
How wealthy is the location?
Café
Shopping mall
Pub/club
Religious building
Gym/sports
Restaurant
College building
Shop
University building
Average
Accommodation
Trail
Green spaces
Parking lot
Street
Train
Industrial/business

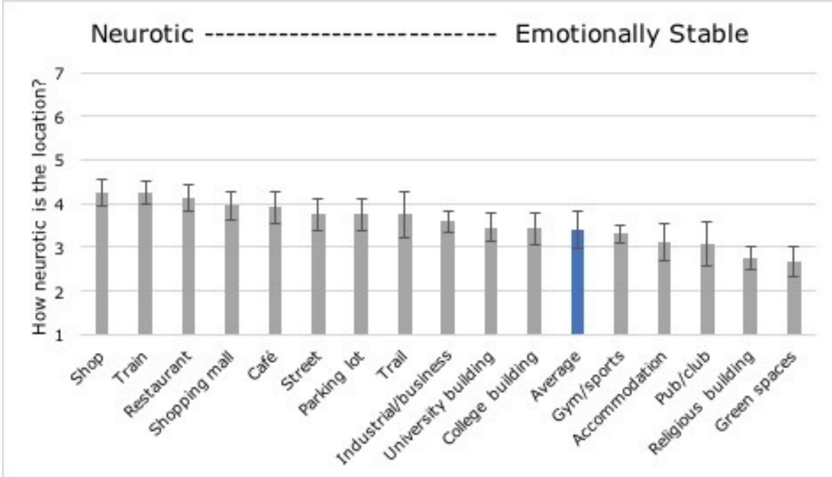


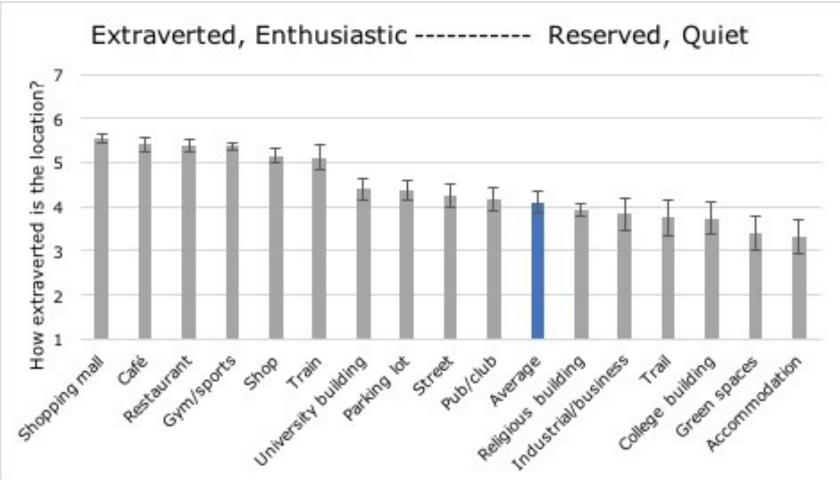
Vacant/open ------------------------------ Crowded
How vacant is the location?
Green spaces
Gym/sports
Industrial/business
University building
Parking lot
Trail
College building
Pub/club
Café
Average
Accommodation
Religious building
Street
Train
Restaurant
Shop
Shopping mall

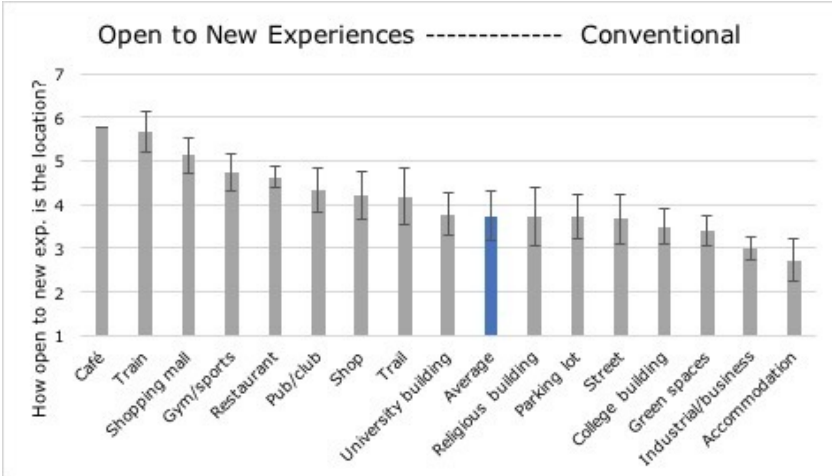


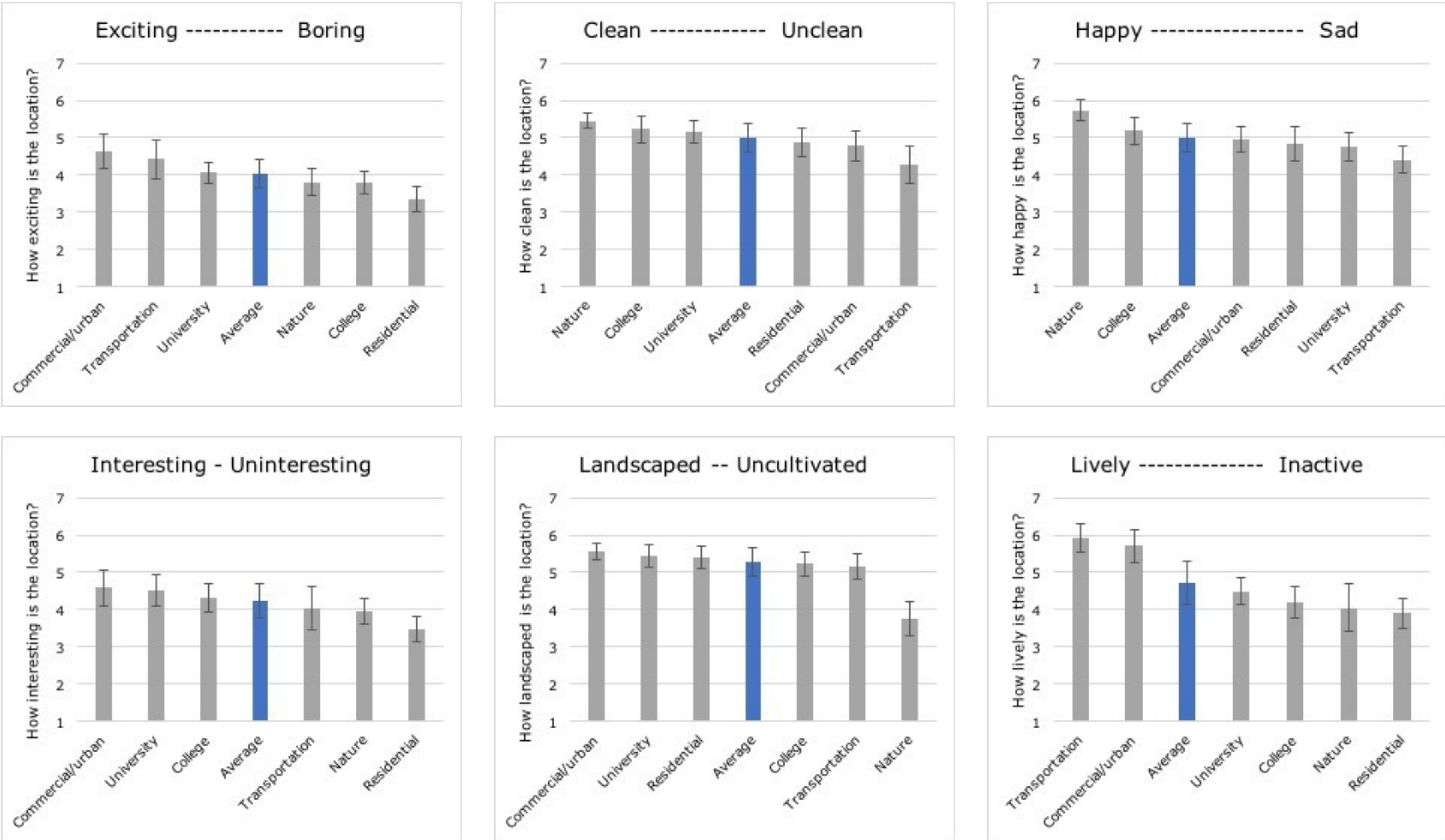
Agreeable, Symp., Warm - Critical, Quarrelsome
How agreeable is the location?
Religious building
Green spaces
Accommodation
Café
College building
Average
Pub/club
Parking lot
University building
Restaurant
Train
Shopping mall
Street
Trail
Gym/sports
Shop
Industrial/business

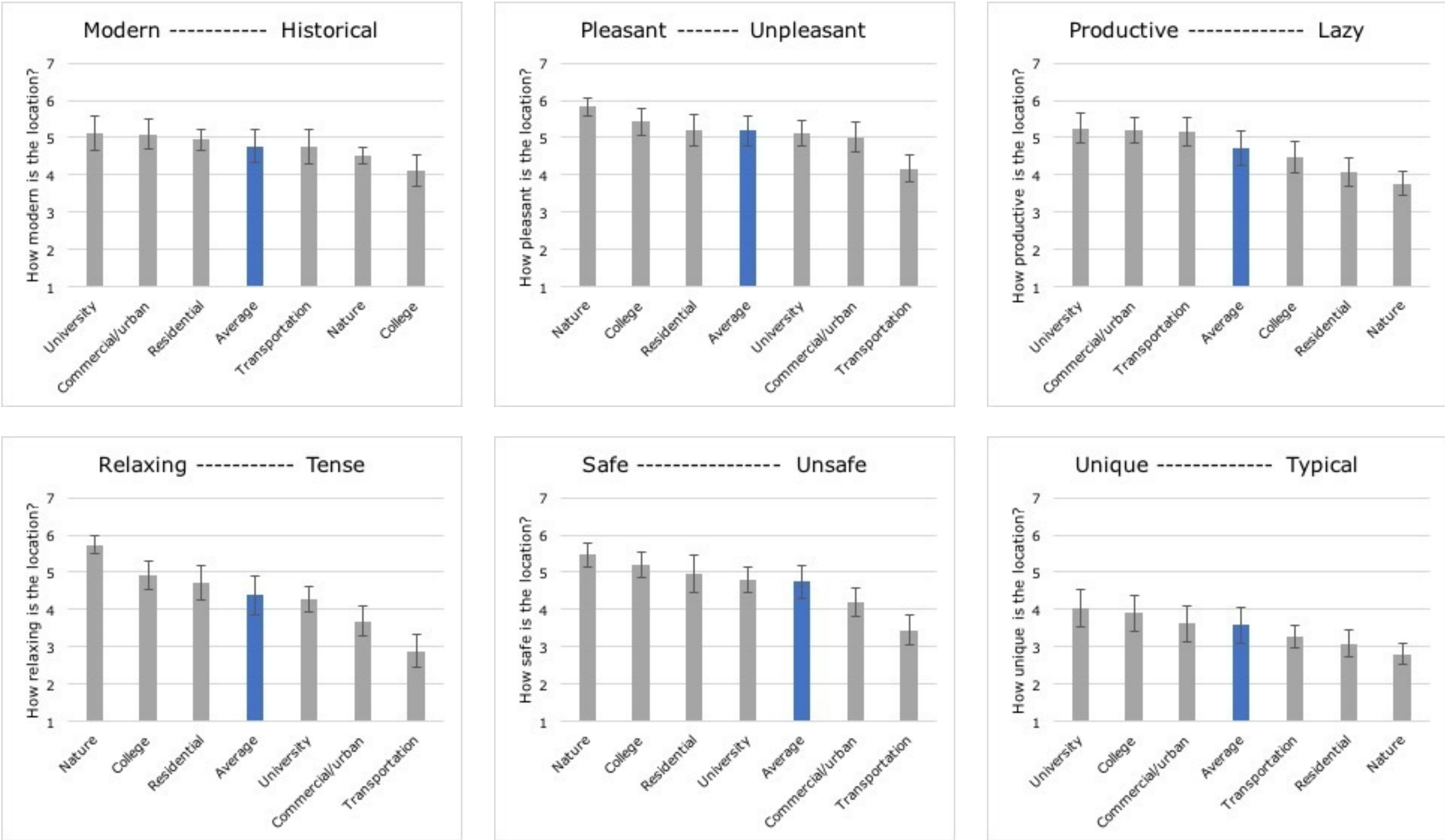

Conscientious --------------------------- Disorganized
How conscientious is the location?
1
2
3
4
5
6
7
Café
Gym/sports
University building
Religious building
Trail
Pub/club
College building
Parking lot
Industrial/business
Shop
Green spaces
Average
Accommodation
Shopping mall
Restaurant
Train
Street

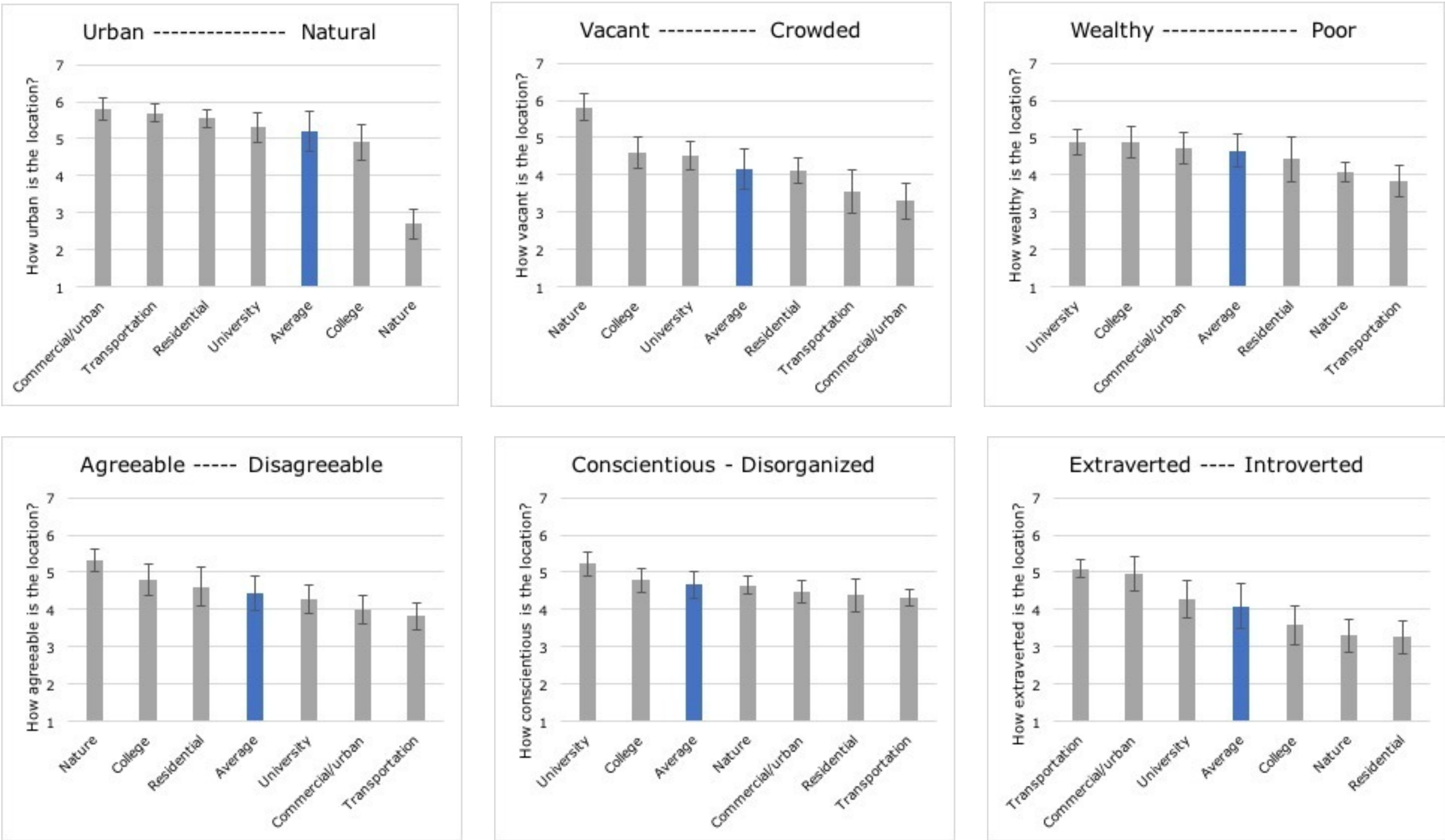

Neurotic --------------------------- Emotionally Stable
How neurotic is the location?
1
2
3
4
5
6
7
Shop
Train
Restaurant
Shopping mall
Café
Street
Parking lot
Trail
Industrial/business
University building
College building
Average
Gym/sports
Accommodation
Pub/club
Religious building
Green spaces

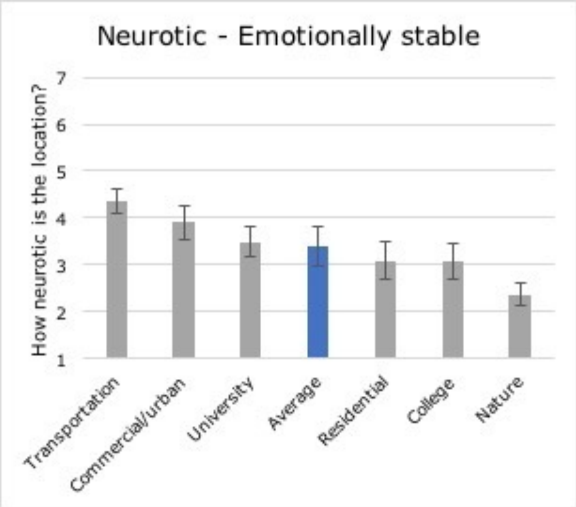

Extraverted, Enthusiastic ----------- Reserved, Quiet
How extraverted is the location?
1
2
3
4
5
6
7
Shopping mall
Café
Restaurant
Gym/sports
Shop
Train
University building
Parking lot
Street
Pub/club
Average
Religious building
Industrial/business
Trail
College building
Green spaces
Accommodation

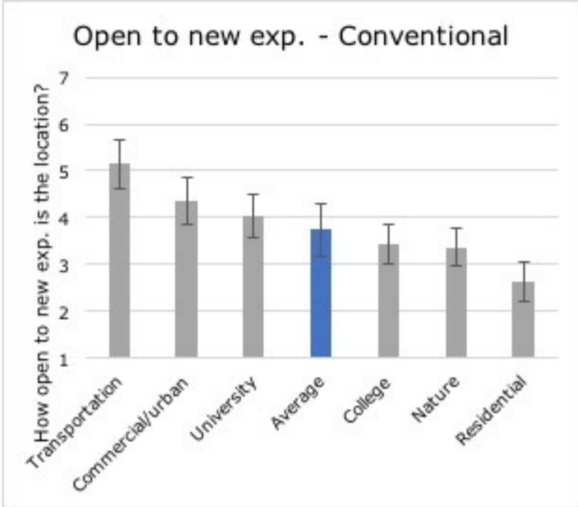

Open to New Experiences ------------- Conventional
How open to new exp. is the location?
1
2
3
4
5
6
7
Café
Train
Shopping mall
Gym/sports
Restaurant
Pub/club
Shop
Trail
University building
Average
Religious building
Parking lot
Street
College building
Green spaces
Industrial/business
Accommodation


Exciting ----------- Boring
How exciting is the location?
7
6
5
4
3
2
1
Commercial/urban
Transportation
University
Average
Nature
College
Residential
Clean ------------- Unclean
How clean is the location?
Nature
College
University
Average
Residential
Commercial/urban
Transportation
Happy ----------------- Sad
How happy is the location?
Nature
College
Average
Commercial/urban
Residential
University
Transportation
Interesting - Uninteresting
How interesting is the location?
Commercial/urban
University
College
Average
Transportation
Nature
Residential
Landscaped -- Uncultivated
How landscaped is the location?
Commercial/urban
University
Residential
Average
College
Transportation
Nature
Lively ------------- Inactive
How lively is the location?
Transportation
Commercial/urban
Average
University
College
Nature
Residential


Modern ----------- Historical
How modern is the location?
University
Commercial/urban
Residential
Average
Transportation
Nature
College
Pleasant ------- Unpleasant
How pleasant is the location?
Nature
College
Residential
Average
University
Commercial/urban
Transportation
Productive ------------ Lazy
How productive is the location?
University
Commercial/urban
Transportation
Average
College
Residential
Nature
Relaxing ----------- Tense
How relaxing is the location?
Nature
College
Residential
Average
University
Commercial/urban
Transportation
Safe --------------- Unsafe
How safe is the location?
Nature
College
Residential
University
Average
Commercial/urban
Transportation
Unique ------------ Typical
How unique is the location?
University
College
Commercial/urban
Average
Transportation
Residential
Nature

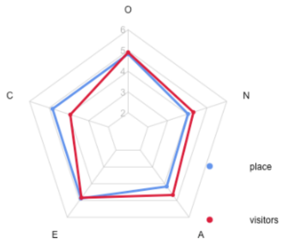

Urban --------------- Natural
How urban is the location?
1
2
3
4
5
6
7
Commercial/urban
Transportation
Residential
University
Average
College
Nature
Vacant ----------- Crowded
How vacant is the location?
Nature
College
University
Average
Residential
Transportation
Commercial/urban
Wealthy --------------- Poor
How wealthy is the location?
University
College
Commercial/urban
Average
Residential
Nature
Transportation
Agreeable ----- Disagreeable
How agreeable is the location?
Nature
College
Residential
Average
University
Commercial/urban
Transportation
Conscientious - Disorganized
How conscientious is the location?
University
College
Average
Nature
Commercial/urban
Residential
Transportation
Extraverted ---- Introverted
How extraverted is the location?
Transportation
Commercial/urban
University
Average
College
Nature
Residential


Neurotic - Emotionally stable
How neurotic is the location?
7
6
5
4
3
2
1
Transportation
Commercial/urban
University
Average
Residential
College
Nature

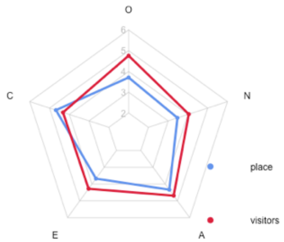

Open to new exp. - Conventional
How open to new exp. is the location?
7
6
5
4
3
2
1
Transportation
Commercial/urban
University
Average
College
Nature
Residential

Appendix G: Personality Profiles of Place / Zones Types and Visitors to Those

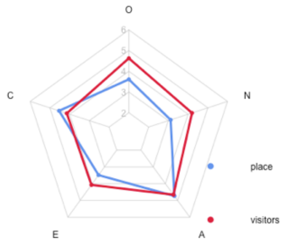
Cafe and visitors



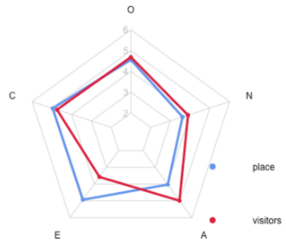
College building and visitors



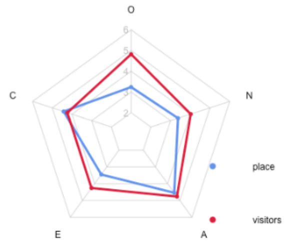
Green spaces and visitors



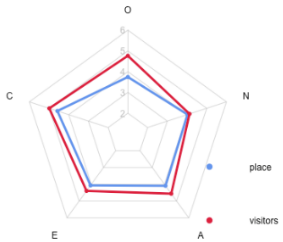
Gym & sports and visitors



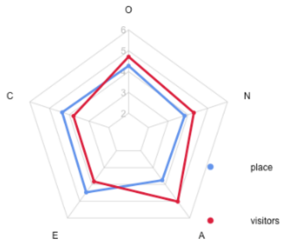
Houses and visitors



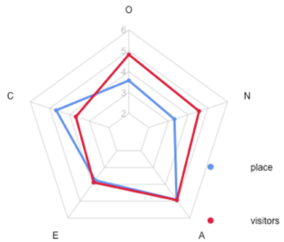
Parking lot and visitors



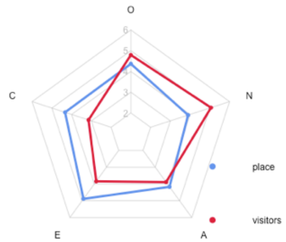
Pub & clubs and visitors



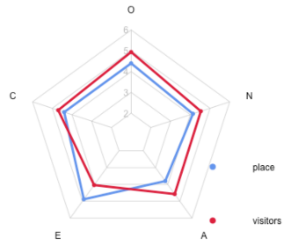
Religious organisation and visitors



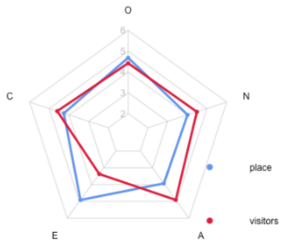
Restaurant and visitors



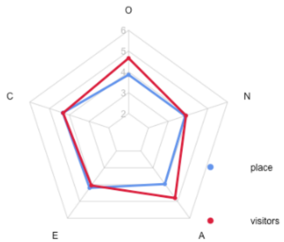
Shop (retail) and visitors



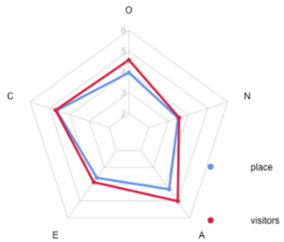
Shopping mall and visitors



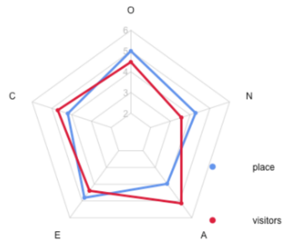
Street and visitors



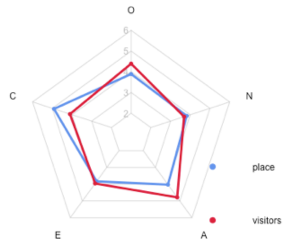
Trails and visitors

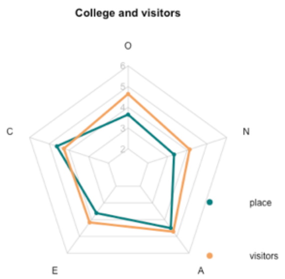


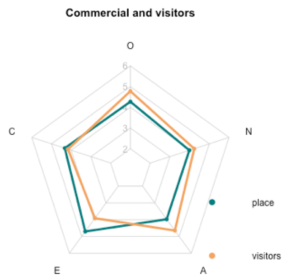
Train and visitors

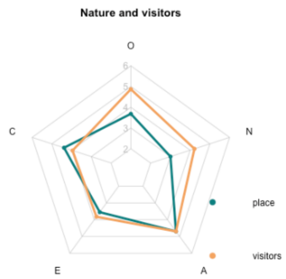


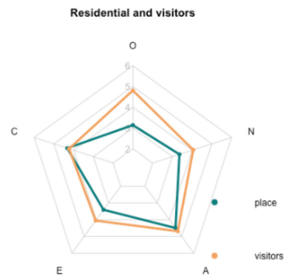
University buildings and visitors

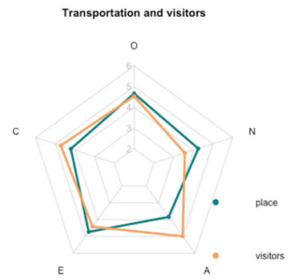


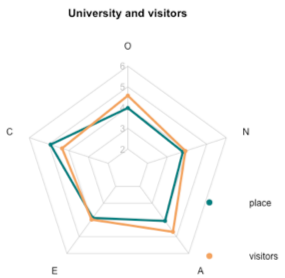

College and visitors
O
N
A
E
C
place
visitors


Commercial and visitors
O
N
A
E
C
place
visitors


Nature and visitors
O
N
A
E
C
place
visitors


Residential and visitors
O
N
A
E
C
place
visitors


Transportation and visitors
O
N
A
E
C
place
visitors


University and visitors
O
N
A
E
C
place
visitors

Appendix H: Published Papers and Book Chapter

H.1: Harari, G. M., Müller, S. R., Gosling, S. D. (2018). Naturalistic assessment of situations using mobile sensing methods. In J. F. Rauthmann, R. Sherman, D. C. Funder (Eds.), *Oxford Handbook of Psychological Situations* (pp.1-28). Oxford: Oxford University Press.

H.2: Wang, W., Harari, G. M., Wang, R., Müller, S. R., Mirjafari, S., Masaba, K., & Campbell, A. T. (2018). Sensing Behavioral Change over Time: Using Within-Person Variability Features from Mobile Sensing to Predict Personality Traits. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 2(3), 141.

H.3: Harari, G. M., Müller, S. R., Aung, H., Rentfrow, P. J. (2017). Smartphone sensing methods for studying behavior in everyday life. *Current Opinion in Behavioral Sciences, 18,* 83-90. http://doi.org/10.1016/j.cobeha.2017.07.018

H.4: Harari, G. M., Müller, S. R., Mishra, V., Wang, R., Campbell, A. T., Rentfrow, P. J., & Gosling, S. D. (2017). An evaluation of students' interest in and compliance with self-tracking methods: Recommendations for incentives based on three smartphone sensing studies. *Social Psychological and Personality Science*, *8*(5), 479-492. http://doi.org/10.1177/1948550617712033

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