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Micro urban spaces and mental well-being: Measuring the exposure to urban landscapes along daily mobility paths and their effects on momentary depressive symptomatology among older population

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ABSTRACT

The urban environment plays an important role for the mental health of residents. Researchers mainly focus on residential neighbourhoods as exposure context, leaving aside the effects of non-residential environments. In order to consider the daily experience of urban spaces, a people-based approach focused on mobility paths is needed. Applying this approach, (1) this study investigated whether individuals' momentary mental well-being is related to the exposure to micro-urban spaces along the daily mobility paths within the two previous hours; (2) it explored whether these associations differ when environmental exposures are defined considering all location points or only outdoor location points; and (3) it examined the associations between the types of activity and mobility and momentary depressive symptomatology. Using a geographically-explicit ecological momentary assessment approach (GEMA), momentary depressive symptomatology of 216 older adults living in the Ile-de-France region was assessed using smartphone surveys, while participants were tracked with a GPS receiver and an accelerometer for seven days. Exposure to multiple elements of the streetscape was computed within a street network buffer of 25 m of each GPS point over the two hours prior to the questionnaire. Mobility and activity type were documented from a GPS-based mobility survey. We estimated Bayesian generalized mixed effect models with random effects at the individual and day levels and took into account time autocorrelation. We also estimated fixed effects. A better momentary mental wellbeing was observed when residents performed leisure activities or were involved in active mobility and when they were exposed to walkable areas (pedestrian dedicated paths, open spaces, parks and green areas), water elements, and commerce, leisure and cultural attractors over the previous two hours. These relationships were stronger when exposures were defined based only on outdoor location points rather than all location points, and when we considered within-individual differences compared to between-individual differences.

1. Introduction

More than one in six people in Europe suffered from mental health problems in 2016 (OECD and EU, 2018), causing disabilities and death risk. This is reflected in the economic cost of mental illness that corresponded to 4% of European GDP in 2015, including not only costs for the health care system but also for social security and the negative impacts on labour market. Based on OECD studies (OECD and EU, 2018), France ranks third country in Europe with highest prevalence of mental health disorders, affecting 18.5 percent of the population, depression and anxiety being the most prevalent. Mental health problems increase steadily with age and are particularly prevalent in middle age and old age (Eurostat, 2020). Healthy ageing is becoming one of the policy priorities in Europe (OECD and EU, 2018), with more than 18 percent of

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people in Europe aged 65 and over and an expected increase in this population from 90.5 million at the start of 2019 to 129.8 million by 2050 (Eurostat, 2020).

According to a large body of literature (Buttazzoni et al., 2021; Gong et al., 2016; Park et al., 2021), individual factors and urban environments play an important role for psychological well-being, depression and stress. However, how the daily experienced urban environment is related to mental well-being, and especially to momentary well-being and depressive symptomatology, remains an open question. The exposure to urban environments with stressors (lack of safety, physical hazards, air pollution, etc.) or pleasant elements (walkable environments, blue and green elements, etc.) may harm or support mental health of people (Burton and Mitchell, 2006; Curtis, 2010).

Most of the literature examining associations between urban environments and mental health relies only on residential neighbourhoods (Park et al., 2021) to define exposure contexts. Multiple socioeconomic and environmental factors of residential neighbourhoods are recognized as determinants of mental health (Barnett et al., 2017; Gong et al., 2016; Park et al., 2021). For example, depression was found to be more common for those living in neighbourhoods with recent buildings, predominant deck access, few private gardens and lack of shared recreational spaces (Weich et al., 2002). Lower degrees of depression and anxiety were associated with having a green area within a one kilometre distance from residence (Maas et al., 2009) and with canopy cover and perceived usage quality of green spaces (Zhang et al., 2018). Low walkability, land use mix and retail availability in residential neighbourhoods were associated with greater odds of depression for old people in the USA (Saarlos et al., 2011). Traffic volume and residential exposure to extreme levels of transport noise (Klompmaker et al., 2019; Zhang et al., 2018) and to air pollution (Braithwaite et al., 2019; Klompmaker et al., 2019) were associated with psychological distress, mental illness, depression and risk of suicide. The exposure to urban disorder (physical and social conditions in urban areas that create a sense of disorder or instability, such as litter, graffities, abandoned buildings, and social disorder) was associated with momentary spikes of pain and fatigue in a study by York Cornwell & Goldman (2020).

However, considering only the residential neighbourhood environment gives a truncated picture of the exposure on a daily basis. In Paris region, it has been shown that living in deprived neighbourhoods was less strongly associated with depression among people whose daily travels extended beyond their residential neighbourhood than among people whose activity space was limited to it (Vallée et al., 2011). Considering only the residential neighbourhood environment as a health-relevant exposure context could lead to falsely attribute non-residential effects to the residential effect and therefore to give a biased estimation of residential context effects (Chaix et al., 2017; Duncan et al., 2021). Moreover, it is possible that the residential neighbourhood exposure context accounts only for longer-term effects on mental health, disregarding the influence that the daily environment of activity can exert on momentary depressive symptomatology and momentary mental well-being.

During daily activities people are surrounded by the micro urban environment of street landscapes that visually affect their feelings and mood, thus influencing their momentary mental well-being (Rautio et al., 2018). Besides providing access to activities, streets are places to be in and where to experience the space with its urban design qualities and landscape and environmental elements. Familiarity, legibility (Lynch, 1981), accessibility, comfort and safety of streetscapes are helpful for older population to positively experience urban spaces and improve their mental well-being (Barnett et al., 2017; Burton and Mitchell, 2006; Rautio et al., 2018). Preliminary support of the importance of everyday experiences in urban space for mental well-being comes from studies which found streetscape greenery and blue spaces to be predictive of better momentary depressive symptomatology (Bakolis et al., 2018; Bergou et al., 2022; Roberts et al., 2019; Roberts and Helbich, 2021). Yet, there is a dearth of studies analysing the restorative effects of other urban design qualities and landscape elements on momentary mental well-being (Bornioli et al., 2018; Hartig et al., 1997; Lindal and Hartig, 2013; Mavros et al., 2022; Zhao et al., 2019). Multiple characteristics of streetscape influence momentary mental well-being, such as walkable environments, proximity to commerce leisure and cultural attractors (Van Cauwenberg et al., 2018), enclosure and spaciousness (Stamps and Smith, 2002), architectural variation (Lindal and Hartig, 2013), presence of historical monuments and landmarks, low noise and traffic (Bornioli et al., 2018). The environmental features of the built environment exert visual stimuli and mental restoration and could have an influence on momentary depressive symptomatology even when people are located indoor, looking at the window or being in a terrace. Despite these first efforts, these studies have limitations. Various studies have used simulated environments using photos or virtual scenarios (Buttazzoni et al., 2021); however, very few studies have assessed the impact of urban environments on momentary mental well-being with in-situ ecological measures (ecological momentary assessment, i.e., EMA) and consideration of the spatial mobility or spatial behaviour of people in space.

In order to consider individuals' everyday experience of urban spaces, an approach focused on daily mobility paths is needed (Chaix, 2018; Duncan et al., 2021). Different methods are used to collect mobility and activity data. Activity surveys and diaries on visited locations are among the most commonly used to study activity spaces (Chaix et al., 2012; Golledge and Stimson, 1997; York Cornwell and Goldman, 2020). However, these methods are time consuming for participants, and prone to recall bias as participants may find it hard to remind their activities as well as the details about locations. In recent years, innovative devices and approaches using multiple sensors, smartphones, and geographic information systems allowed researchers to collect spatio-temporal data, measure accurate environmental exposures, and study their association with individual behaviours and momentary mental well-being. For example, geographically explicit ecological momentary assessment (GEMA) (Chaix, 2020; Fernandes et al., 2021) combines EMA smartphone questionnaires with GPS tracking in order to monitor participants over consecutive days in space and time. EMA is a research method that involves collecting data from individuals in their natural environment by asking individuals to report on their thoughts, feelings, behaviours, and experiences in real-time using electronic devices such as smartphones or wearable sensors (Shiffman et al., 2008). Despite their promising results and possibilities of implementation with additional sensors (Chaix, 2018), GEMA methods have been used by only few studies (Chaix, 2020; Kondo et al., 2020; Li et al., 2018; York Cornwell & Goldman, 2020).

Some efforts to apply GEMA methods and geographic information system (GIS) processing to explore the links between urban spaces and depressive symptomatology or momentary mental well-being have been made by Li et al. (2018), York Cornwell & Goldman (2020), Kondo et al. (2020), Kamalyan et al. (2021), Tao et al. (2020), Bollenbach et al. (2022) and Jacobson & Bhattacharya (2022). Li et al. (2018) observed the association between exposure to varying concentrations of nature and adolescents' mood by using GPS receivers and a profile of mood states questionnaire for four consecutive days. The concentration of nature participants were exposed to was measured by assessing the Google Street View images at the locations they visited throughout each day. However, as the authors only had a single mental well-being outcome for each day, they had to summarize and aggregate the spatial exposure data at the day level, losing intra-day variations both in the outcome and in environmental exposures as offered by the GPS data. York Cornwell & Goldman (2020) conducted a GEMA study aimed at analysing whether socioeconomic disadvantage and disorder in the residential neighbourhood and activity spaces were associated with momentary stress and strain. They measured self-reported negative environmental stressors with EMA questionnaires. Nevertheless, this method is prone to reverse causality, because depressed people may declare more urban problems, not enabling to assess the causal effect of

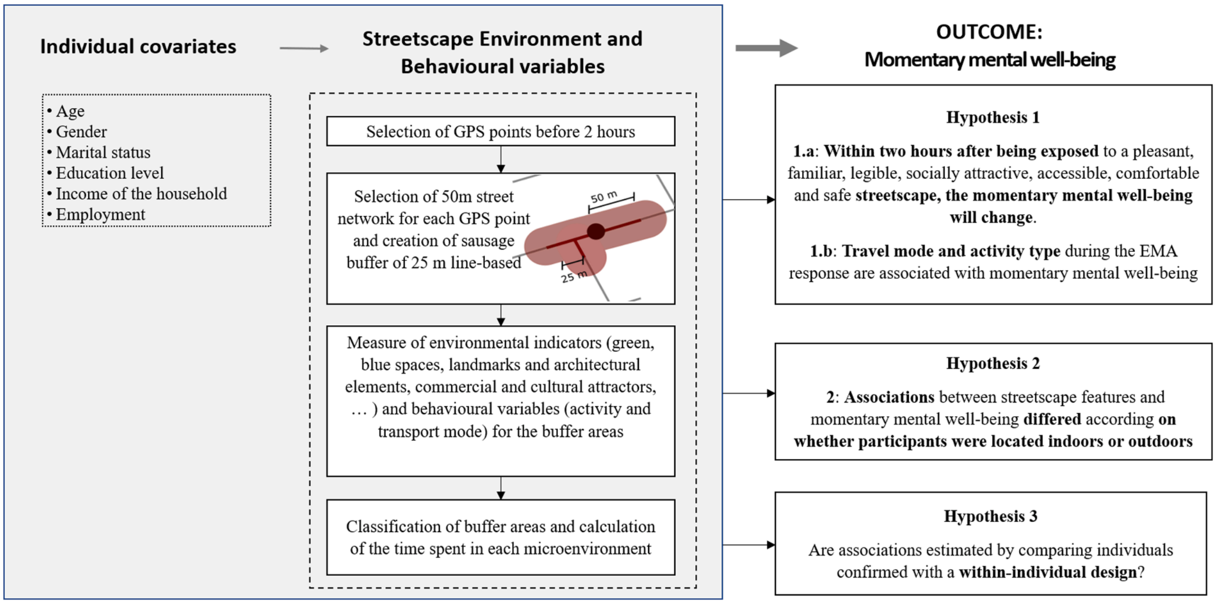

Fig. 1. Data analysis process and main hypotheses.

objective urban stressors on depressive symptomatology. Kondo et al. (2020) used GEMA to examine the association between exposure to green spaces within 10 and 30 min prior to participants' completing the EMA and depressive mood. They found positive associations between exposure to green spaces over 10 min and people's positive mood (be happy and restored); however, as they focused only on one environmental feature, they could not assess interactions with other features in the urban space. Bakolis et al. (2018) and Bergou et al. (2022) developed and used the URBAN MIND app (Bakolis et al., 2018) to explore mental health benefits of self-reported environmental features and found positive associations between visits to canals and rivers, seeing trees, seeing the sky, or being outdoor and momentary mental well-being. However, a weakness of this method relates to the self-reported environmental features, which for example makes it vulnerable to reverse causality. In conclusion, despite the use of GEMA methods on this topic, only few studies have used GIS to objectively measure environmental features or to document time-varying effects of these components of environmental exposures (Bollenbach et al., 2022; Jacobson and Bhattacharya, 2022; Tao et al., 2020).

In the present study, we expanded the above body of work by collecting individual-level spatiotemporal location data and repeated measures of momentary depressive symptomatology with GEMA. Mobility paths (based on continuous timestamped and geolocated individual positions) were then used to objectively measure the time spent in different streetscape microenvironments over the two hours prior to participants completing EMA questionnaires. Our main hypothesis is that being exposed to a pleasant, familiar, legible, socially attractive, accessible, comfortable and safe streetscape environment over two hours will affect the momentary depressive symptomatology. Specifically, we hypothesize that being exposed over two hours to streetscapes characterised by the presence of green and water elements, historical monuments, landmarks and architectural variation, commerce leisure and cultural attractors, openness, walkable paths, low noise and low traffic environments will positively affect momentary mental well-being by decreasing the momentary depressive symptomatology. We assumed that momentary depressive symptomatology could also be influenced by the travel mode or activity type at the time of the EMA survey. Moreover, we explored whether the associations between streetscape features and momentary depressive symptomatology differed when exposures were defined based on all location points or only on outdoor location points and on time spent outdoor. Finally, we focused on both between- and within-individual differences in momentary depressive symptomatology, as within-individual associations cannot be biased by individual-level variables such as individual preferences.

2. Method

2.1. Study participants and data collection

This study included a sample of 216 adults aged 60 years and over from the RECORD Cohort (Chaix et al., 2011), selected for the HANC (Healthy Aging and Networks in Cities) and MINDMAP sub-studies (Fernandes et al., 2021). The study integrated traditional computer-based surveys, a web-based mapping application (VERITAS) questionnaire (Chaix et al., 2011; Naud et al., 2020), mobile sensing tools and a GPS-based web mobility survey (Chaix et al., 2019). Data were collected in the Paris region (France) from July 2019 to July 2021. Before the observation period, participants filled in a questionnaire assessing their health and socioeconomic profile. During their daily activities, participants wore a GPS receiver (BT-Q1000XT, QStarz, Taipei, Taiwan, with a 3-meter accuracy) and an accelerometer (tri-axial, wGT3X+, Actigraph, Pensacola, FL) on the waist on the right side and were provided a smartphone for 7 days. Participants completed a paper-based travel diary on the places visited, as supporting information for the mobility survey conducted after the observation period. An EMA smartphone questionnaire was administered four times a day (at random time within the following slots: 9:00 am-12:00 am, 12:00 am-2:00 pm, 2:00 pm-4:00 pm, 4:00 pm-6:00 pm) to survey depressive momentary mood through the Eco Emo Tracker application developed for the study (Fernandes et al., 2021). Eco Emo Tracker is a smartphone application that allowed us to survey environmental perceptions and momentary mental mood states in real-time throughout EMA questionnaires. After the 7 days, GPS data were uploaded in the TripBuilder Web mapping application; visited places, trips, and transport modes were automatically identified with algorithms; and a web-based mobility survey was conducted on the phone to confirm or correct these visited places and transport modes, while considering the travel diary filled by the participants (Chaix et al., 2019).

2.2. Outcome: Momentary depressive symptomatology

The EMA smartphone questionnaire on momentary depressive symptomatology was an adapted version of the short version of the CES-D questionnaire (Radloff, 1977), modified to inquire with 8 items (Karim et al., 2015) about momentary depressive mood. It contained the same eight items, but they were framed with the prefix 'At the moment, I …'. Items included 'be bothered by things that usually do not bother'; 'feel depressed'; 'feel that everything done is an effort'; 'feel happy'; 'feel lonely'; 'enjoy life'; 'feel sad'; 'feel unmotivated or uninspired'. The 4 response options ranged from 'no, not at all' to 'yes, absolutely'. Each of the 8 items of the CES-D questionnaire were asked only once per day over 4 successive EMA questionnaires (in 4 time slots indicated above): 2 of the items were asked in the first time slot, 2 in the second time slot, 2 in the third time slot, and 2 in the last one (the items were asked in a different order on each day; this is because we assessed other dimensions in these surveys). In order to focus on momentary mental well-being, the negative item scores were reverse-coded by using the scale 0–3, with 3 meaning 'momentarily not depressed' and 0 'momentarily depressed'.

2.3. Streetscape micro urban environment and activity variables

We quantified the time spent in microscale urban environments to which people were exposed over two hours prior to responding to each smartphone EMA questionnaire (see Fig. 1 for the whole process).

We used the database of location points created by the research assistants during the mobility survey with the TripBuilder application (see above). This database was created by merging GPS points (collected each 5 s), points related to Google directions API (shortest street network trips generated with the TripBuilder software when there were no GPS data at all collected for a trip), and points related to trips manually drawn by the research assistant during the mobility survey when Google directions API could not be used (e.g., for a trip through a park without street network). For Google directions and manually drawn trips, we generated points (every 10 m) and corresponding imputed times along the tracks (with ArcMap Desktop 10.1 and R 4.0 software). Then, we selected the points corresponding to tracks and places visited over the two hours before answering each EMA questionnaire. All the points located outside the Ile-de-France region were removed from this selection. In total, the final database was composed of 1,333,759 (93%) GPS points, 1,929 (0.1%) points manually drawn and 98,305 (6.9%) points from Google direction API.

We classified all GPS points as being outdoor or indoor based on the number of visible satellites. Our aim was to explore whether the association between streetscape elements and momentary mental well-being was stronger when environmental exposure was defined only on the basis of outdoor GPS points. Literature on this subject proposes detailed classification of GPS points (indoor, semi-indoor, semi-outdoor, outdoor) with complexes algorithms (Bui et al., 2020; Chen and Tan, 2017; Kim et al., 2012; Zhu et al., 2019) considering the number of satellites in view and several other indicators (accuracy, speed, temperature, etc.). Following Chen & Tan (2017) and Kim et al. (2012), we classified GPS points as outdoor when there were at least nine visible satellites.

Streetscape micro-urban areas of exposure were created for each selected point separately by drawing a street-network line-based buffer (Forsyth et al., 2012; Frank et al., 2017). Doing the exposure assessment at the point level (and not at the level of all points within 2 h prior to answering) provides a way to measure durations of exposures. To identify the potentially accessible street network from the point, we first created a buffer area, i.e. an area that encompasses the accessible street network within a 50-meter street network radius, then we used the corresponding selected street network inside this buffer area (we cropped the street network with the buffer) in order to draw a line buffer (a crow-fly buffer around the selected street network) of 25 m of radius (ArcMap Desktop 10.1). Following Frank et al. (2017), we choose a 25-meter radius because it allowed considering variability in road and sidewalk width and to collect only features accessible and visible from the road network. Overall, this approach aimed to assess exposures from the perspective of the street viewpoint.

Table 1
Streetscape environment variables and thresholds used for classification of micro-urban buffer areas.

Attribute	Indicator	Buffer area classification thresholds****
Natural elements		
Green and open spaces	Green and open spaces (m^2)	*>30%*
Water elements	Water element (m^2)	*>30%*
Building elements		
Landmarks and architectural elements	Historical monuments and river heritage (bridges) (m^2)	*>30%*
Commerce, leisure and cultural attractors*	Number of commerce, leisure and cultural attractors*	n > *5*
Openness	Ratio between green, open space and street space width and the mean height of the buildings	*>3*
Walkable path	Ratio between pedestrian spaces** and driveway space (in case the driveway space was null, it was set to a value of 1 m^2 to avoid division by 0)	*>0.4*
Noise Pollution	Average concentration of route noise pollution (db, Lden)***	*<50 Lden*
Traffic (security)	Average maximum speed permitted for cars in the streets (km/h)	*<30 km/h*
Social environment		
Population density	Population density (inhabitants/ km^2)	*>2000 inhabitants/ km^2*
Elderly ratio	Ageing index (people > 65 / people < 14)	*>0.70*
Income	Income per capita (€)	*>30.000 €/ household*

* **Food services and restaurants; commerce and services; well-being and health services; leisure and cultural services.**
** **Pedestrian paths (street area minus road area accessible to vehicles), green and open spaces.**
*** **Limit values adopted by France for transport noise in application of the European Directive 2002/49/EC.**
**** For cut-off definition see Appendix A.

A set of spatial attributes describing the landscape and streetscape environment was calculated for each of these micro-urban areas of exposure (Table 1, Fig. 2). Streetscape built environment attributes and sociodemographic characteristics were measured by geoprocessing data obtained from the National Institute of Statistics Economic Studies (i.e. census data, the FiLoSoFi database, the Permanent equipment database), the Regional Institute of Paris [i.e. street and road network, urban tissue data (TUF), and land use data (MOS)] and the Bruitparif centre (2017 LDEN - Day-evening-night level - strategic noise pollution map for road, railroad and airborne traffic, 5-meter resolution, using the NMPB 2008European method (SETRA, 2009)). Aspects of the pleasantness of the environment were measured by the percentage of space covered by green and blue spaces. Distinctiveness and attractiveness were measured by the percentage of space covered by landmarks and architectural elements and by the presence of commercial, leisure and cultural attractors. Accessibility to walkable paths was measured by the percentage of the street area represented by pedestrian and green and open spaces. Visual permeability and sense of relaxation were measured by the layout of an urban area that promotes a sense of openness and accessibility. Openness was measured by considering the ratio between the distance between buildings and the mean height of the buildings. Comfort and safety of the environment were measured by traffic noise pollution and traffic maximum speed. The sociodemographic and economic environment were analysed through indicators of population density, the elderly ratio, and the mean income level of the area.

The area of exposure associated with each GPS or location point was

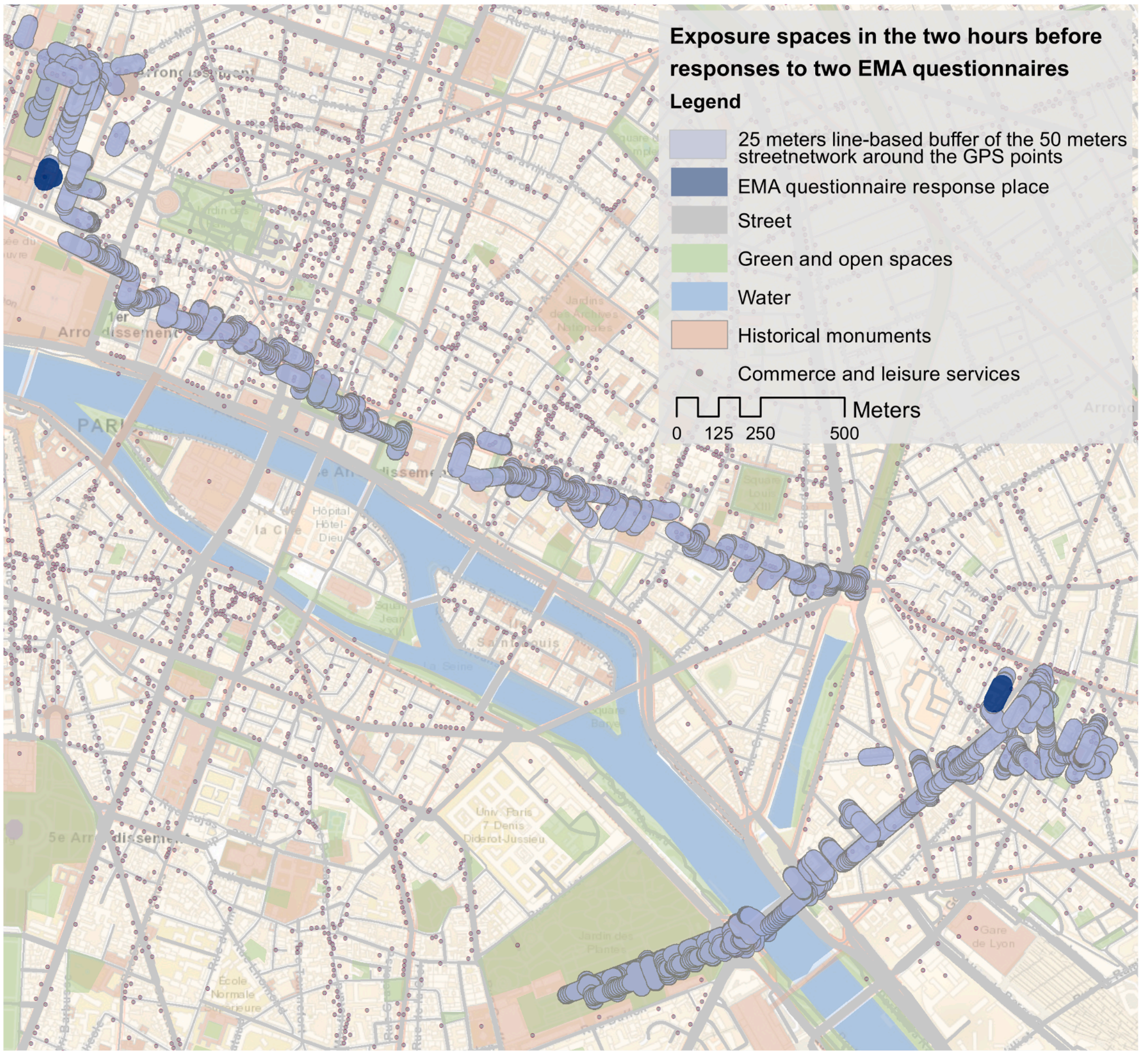

Fig. 2. 25 m radius sausage buffers of the street network around each GPS or location point and example of geoprocessing of streetscape variables for two paths. Elaborated by the authors, base https://openstreetmap.org, urban tissue data (TUF), and land use data (MOS).

classified considering the percentage cover of each environmental variable (Table 1). For example, we classified the location point as ‘green and open’ if the corresponding area of exposure was covered by at least 30% of green and open spaces. Then, we calculated the total time spent in that specific category of space over the two-hour period (one GPS or location point corresponding to 5 s). Thresholds for streetscape environmental variables were defined considering our own hypothesis and the literature on the specific indicator.

Moreover, we explored whether behavioural and situational elements at the exact time of the EMA questionnaire were related to momentary mental well-being. We analysed the type of activity performed (travel mode or type of visited place known from the mobility survey) and we examined whether the individual was located indoor or outdoor (considering both the activity type known from the mobility survey and the number of satellites in view) when responding to the questionnaire.

2.4. Sociodemographic covariates

We included information on participants’ age (60–70; 71–80; >80 years), gender (male, female), marital status (in couple; divorced/widowed/unmarried), education level [low-medium education (from none to the completion of high school); high education (high school + 2 to 4 years); very high education (high school + 5 years and over)]; household income per consumption unit (<2000; 2000–4000; >4000), and employment status [employed, retired, other (i.e., housewife, handicapped people and one unique unemployed participant)]. These variables were included as covariates in the regression model. To account for the effects of the pre and post Covid-19 pandemic periods, we incorporated a binary variable into our analysis.

3. Statistical analysis

After calculating descriptive statistics, considering the nested nature of our data, we fitted Bayesian linear mixed effect models with Monte Carlo Chain using the Stan modelling language (Carpenter et al., 2017) and the brms R package (R Core Team, 2014) (Bürkner, 2019). Based on the item response theory (Embretson & Reise, 2013; Gibbons et al., 2008), we modelled the data at the item levels (items are nested within questionnaires, nested within days, nested within participants). The fundamental premise of the item response theory is that every response to an item provides some inclination about the individual’s level of the latent trait or ability, here the CES-D 8 score. To distinguish between the items, we controlled for indicator variables corresponding to each item, allowing to assess the so-called severity of the items in their ability to discriminate between individuals with different levels of momentary depression symptomatology. While the outcome could take values between 0 and 3, we applied a linear model. The issue that the model could predict values out of the 0–3 range is compensated by the fact that only the linear model permits a straightforward decomposition of variance based on the random coefficients and offers an easier interpretation of fixed effect coefficients. As a result of the latter aspect, multiplying by 8 the predicted outcome yields the predicted CES-D 8 score.

We tested whether the participant, the day, and the questionnaire (comprising several successive questions) should be treated as random-effect variables and we chose the best model based on the Widely Applicable Information Criterion (WAIC) and on the leave-one-out cross validation (LOO) indices. These tests favoured models fitted with random effects at the day level (7 groups within each participant) and at the participant level (216 groups) for 9689 answers to momentary mental well-being items (7361 items with exposures based on outdoor points). A first-order auto-regression function of day-time (within participants) level was also specified for all the models (Bürkner, 2019) to control for temporal autocorrelation. Non-informative priors were used for the coefficients of explanatory variables and for the random effects, while the Student's t-distribution was used for the temporal autoregression coefficient. Models converged with 4 sampling chains and 100,000 iterations.

To test our fist hypothesis, we estimated a model with random effects at the day level and participant level, controlling for potential confounders by adjusting for age, sex, education level, employment, marital status, household income, and Covid-19 pandemic period (pre-post pandemic). A variable considering previous momentary mental well-being status was added to the model for controlling for reverse causality. This variable was a weighted average of the 2 momentary mental well-being items answered in the previous time slot, weighted by the severity of the corresponding items estimated from the model. We also controlled for the total amount of time spent outside in the previous two hours. However, we did not find any relationship between this variable and the outcome (5.03e-04, 95% CI: 0.00, 0.00 for one additional hour spent outside) and we decided to not control for it in the reported analyses (the same was found in the within-individual fixed-effect mode). The model estimated linear associations between each additional hour spent in the different streetscape environments (over the previous two hours) and the momentary well-being outcome. The final models were the result of a careful manual stepwise selection process. In addition to the control variables, only the behavioural and streetscape environment variables that were associated with the outcome were retained in the final model.

To test our second hypothesis, a first analysis was made considering exposures (over two hours) defined on the basis of all the GPS points (Model 1 and Model 2) and then with the subset of points collected in outdoor environments (Model 3 and Model 4). Finally, we tested our third hypothesis by estimating a model considering individuals as fixed effects in order to estimate associations only on the basis of within-individual differences. The fixed effect model specifies for each individual a fixed intercept or effect by adding k-1 dummy variables for the k individuals (Schempf and Kaufman, 2012). This approach permits to neutralize all individual-level confounders.

We set credible intervals at 95% and we verified for correlation of posterior distribution. As indices of effect existence, we computed the probability of direction (PD), ranging from 50% to 100%, representing the certainty with which an effect goes in a particular direction (objective existence of an effect corresponding to PD > 95%) and the percentage of the a posteriori distribution in the region of practical equivalence (ROPE, the region corresponding to the null hypothesis) (effect existence corresponding to percentage in ROPE < 5%) (Makowski et al., 2019).

Finally, we estimated the total momentary well-being score by combining the predicted value for each of the items according to their severity level for different streetscape environmental elements favourably associated with momentary mental well-being. The momentary well-being score reflects the sum of the predicted values for each of the items depending on the environmental characteristics.

Table 2
Descriptive characteristics of study participants.

Characteristics	Individuals **(N = 216)**	%
Age, n (%)		
60–70	106	49%
71–80	93	44%
>80	17	7%
Gender, n (%)		
Female	77	36%
Male	139	64%
Marital status, n (%)		
In couple	145	67%
Divorced/widowed/single	71	33%
Education level, n (%)		
Low-medium education	65	30%
High education	70	32%
Very high education	81	38%
Household income per consumption unit, n (%)		
<2000	32	15%
2000–4000	128	59%
>4000	56	26%
Employment, n (%)		
Employed	29	13%
Retired	183	85%
Unemployed	1	0.5%
Other	3	1.5%

Table 3
Descriptive analysis (mean and standard deviation) of the streetscape environment in the spaces visited by individuals during two hours prior to the EMA questionnaire (n = 4830).

Attribute	*Mean (SD)*
Natural elements	
Green and open spaces (m^2)	8.85 (14.67)
Water elements (m^2)	0.56 (3.85)
Building elements	
Landmarks and architectural elements (m^2)	1.03 (5.46)
Commerce, leisure and cultural attractors (n)	0.51 (1.11)
Openness	31.87 (126.50)
Walkable path	4.8 (11.4)
Noise pollution (db, Lden)	48.20 (12.62)
Traffic (security) (km/h)	30.99 (13.55)
Social environment	
Population density (inhabitants/km^2)	2,913.75 (2,142.34)
Elderly ratio	0.43 (0.56)
Income per capita (€)	30,770.18 (9,426.18)

4. Results

We collected data from a sample of 216 people aged 60 years and older. Participants were more often males (64%), living in couple (67%) and retired (85%). The sample was distorted towards high education levels (Table 2).

Participants responded to 4830 EMA depression questionnaires corresponding to 9689 questions (i.e., momentary depressive symptomatology items). More than one million (1,082,047) points in space were available to measure relations people have with the built environment over time. Each individual answered an average of 22.3 questionnaires and 48.6 questions over a week. Overall, participants responded to 84% of the a priori planned questionnaires. For each of the 8 depression items, we collected on average 1211 responses, while each item was answered 5.7 times during the week by the same individual.

Individuals responded on average 14 min after the prompt (notification on the smartphone) when they were indoors and after 43 min when they were outdoors. The percentage of response was not affected by the day of the survey, and we observed a uniform distribution of responses during the week.

Participants spent the two hours before the responses (Table 3) in micro-areas around location points with on average 8% (*SD* = 14.7) of

Table 4
Number of minutes spent in each category of exposure during the two hours prior to the EMA questionnaire.

Attribute	*All point exposure areas(n questionnaires = 4830)*	*Outdoor point exposure areas(n questionnaires = 3650)*
	Mean (SD) ***minutes***	**Mean (SD)** ***minutes***
Natural elements		
Green and open spaces (*>30%*)	4.3 (14.4)	2.2 (9.0)
Water elements (*>30%*)	0.4 (4.7)	0.1 (0.6)
Building elements		
Landmarks and architectural elements (*>30%*)	0.4 (4.1)	0.32 (3.5)
Commerce, leisure and cultural attractors (n *> 5*)	2.5 (11.6)	0.94 (5.7)
Openness (*>3*)	103.8 (29.6)	31.81 (32.4)
Walkable path (*>0.4)*	0.03 (1.9)	6.03 (15.3)
Noise pollution (*<50 Lden)*	39.3 (41.)	11.3 (21.6)
Traffic (security) (*<30 km/h)*	22.7 (34.5)	9.4 (38.8)
Social environment		
Population density (*>2000 inhabitants/ km²)*	61.7 (52.6)	6.4 (18.8)
Elderly ratio (*>0.70)*	34.7(49.6)	8.5 (19.1)
Income per capita (*>30.000 €/ household)*	66.4 (52.9)	19.5 (28.4)
Behavioural variables (at the time of the response)		
Visited places and mobility	***n questionnaires (%)***	***n questionnaires (%)***
Food, commerce and services	239 (4.9%)	215 (5.9%)
Leisure, cultural and social activity	405 (8.4%)	357 (9.8%)
Residence	3685 (76.3%)	2628 (72%)
Work	183 (3.8%)	91 (2.5%)
Private transport	72 (1.5%)	73 (2.0%)
Public transport	57 (1.2%)	58 (1.6%)
Active mobility	189 (3.9%)	226 (6.2%)
Indoor/outdoor activity		
n. satellites ≥ 9 or outdoor activity	821 (17%)	693 (19%)

green spaces, 0.5% (*SD* = 3.9) of water elements, 1% (*SD* = 5.5) of historical monuments and 0.5 (*SD* = 1.1) commerce, leisure and cultural attractors. Micro-urban spaces visited were open (*M* = 31.8, *SD* = 126.5), had a low proportion of pedestrian paths (*M* = 0.4, *SD* = 11.4) and an average concentration of route noise pollution of 48 Lden (near the standard limit of 55 Lden for street noise, *SD* = 12.6). Demographic and socioeconomic attributes showed densely populated microspaces (*M* = 2,913.8 inhabitants per km^2, *SD* = 2,142.3) with an income per capita in line with the average of the Ile-de-France region (M = 30,770 €, SD = 9,426).

Table 4 summarizes the time spent in each category of space during the two hours before the EMA questionnaire, differentiating between exposure micro-spaces based on all location points and only on outdoor points. When considering exposures based on all location points, within two hours before answering a questionnaire, participants spent on average 4 min in green areas and 0.42 min in spaces with water elements, 0.42 min in spaces with landmarks, and 2.5 min near commerce, leisure or cultural services. Most of the time, people were in spaces with a high openness (103 min). They also spent significant time in micro-spaces with low levels of traffic noise pollution (39 min) and low average traffic speed (22 min). Behavioural variables indicated that the majority of the EMA questionnaires were answered indoor at the residence; only 24% of responses were given while performing an activity outside of home (food, shopping, other services, leisure, cultural and social activities, work) or when commuting.

Table 5 and Table 6 report the results of the multilevel Bayesian models for the associations of environmental variables (expressed in one-hour unit) and behavioural variables with momentary well-being. Momentary well-being outcomes were temporally autocorrelated with a coefficient of 0.07, meaning that responses close to each other in time were more correlated than responses further apart in time. The reverse coded question #2 (‘At the moment, I don’t feel depressed’) and question #7 (‘At the moment, I don’t feel sad’) were the items with the highest severity, i.e., differences in these items were associated with the largest difference in the underlying momentary well-being score.

4.1. *Interindividual variability*

In Table 5 we summarise the models assessing the associations between durations of environmental exposures (based on all location points and outdoor points only) and interindividual variability in momentary well-being. The model considering exposure spaces based on all location points (adjusted for all environmental variables and covariates) estimated that spending one hour in urban areas near commerce, leisure and cultural attractors or water elements was associated with a better momentary mental well-being (respectively for each item, +0.06, 95% CI:0.01, 0.13 and +0.20, 95% CI: 0.02, 0.32) (Fig. 3).

When focusing on exposures based on outdoor location points (Table 5), we found stronger associations compared to when exposures were defined based on all location points. The strongest association was observed between the time spent in walkable spaces and momentary well-being, with an average 3.32 (95% CI: 1.05, 7.69) better mental well-being score for each additional hour of exposure (Fig. 3). It must be considered that for this environmental element the model estimated a large confidence interval, suggesting that there was a substantial heterogeneity in the sample in the corresponding effect and/or lack of data to support the estimation. Spending one hour in urban spaces near water elements and commerce, leisure and cultural attractors and in low traffic noise areas was associated with a better momentary mental well-being score, by respectively +0.88 (95% CI: 0.17, 1.89), +0.20 (95% CI: 0.04, 0.36) and +0.03 (95% CI: 0.01, 0.07) (over a range of the outcome from 0 to 3). Moreover, being involved in active mobility or leisure and cultural activities (respectively +0.07, 95% CI: 0.01, 0.13 and +0.13, 95% CI: 0.10, 0.17) when answering EMA questionnaires was associated with a better momentary mental well-being.

4.2. *Intraindividual variability*

In Table 6 we summarise the models assessing the associations between the duration of environmental exposures (based on all location points and outdoor points only) and within-individual variations in momentary depressive symptomatology. When defining exposures based on all location points (Model 2, Table 6), momentary well-being was associated with the presence of water elements and walkable spaces near the participant. All within-individual associations became stronger when exposures accounted for outdoor points only (Model 4, Table 6). Spending one hour in outdoor spaces (i.e., outdoor points) with commerce, leisure and cultural attractors, water elements and walkable areas was associated with a 0.20 (95% CI: 0.04, 0.36), 0.88 (95% CI: 0.17, 1.89), and 3.32 (95% CI: 1.05, 7.69) better momentary mental well-being (over a range from 0 to 3) (Fig. 4). Active mobility or leisure and cultural activities performed when answering the EMA questionnaires were also associated with a better momentary mental well-being.

5. Discussion and conclusions

This study investigated how momentary depressive symptomatology is associated with the environment to which aged people are exposed during their daily activities. Our main finding is that momentary mental

Table 5
Associations of streetscape environment and behavioural variables with momentary mental well-being. Between individual models for environmental exposures defined based on all location points or only outdoor points.

	Model 1 - all pointsSeparate models(95% CI)	**Model 2 - all pointsFull model**(95% CI)	**Model 3 - outdoor pointsSeparate models**(95% CI)	**Model 4 - outdoor pointsFull model**(95% CI)
Intercept	2.15 (1.96, 2.34)*	2.14 (1.95, 2.33)*	2.18 (2.02, 2.34)*	2.16 (2.01, 2.34)
Item1 – feel bothered	0.32 (0.28, 0.36)*	0.32 (0.28, 0.36)*	0.32 (0.29, 0.36)*	0.32 (0.29, 0.37)
Item2 – feel depressed	0.46 (0.42, 0.50)*	0.46 (0.42, 0.50)*	0.45 (0.41, 0.49)*	0.45 (0.42, 0.49)
Item3 – feel that everything is an effort	0.15 (0.11, 0.19)*	0.15 (0.11, 0.19)*	0.14 (0.10, 0.17)*	0.13 (0.10, 0.17)
Item4 – feel happy	*ref*	*ref*	*ref*	*ref*
Item5 – feel lonely	0.30 (0.26, 0.33)*	0.30 (0.26, 0.34)*	0.30 (0.26, 0.33)*	0.30 (0.26, 0.34)
Item6 – enjoy life	0.00 (−0.03, 0.05)	0.00 (−0.03, 0.05)	0.00 (−0.03, 0.04)	0.00 (−0.03, 0.04)
Item7 – feel sad	0.40 (0.36, 0.44)*	0.40 (0.36, 0.44)*	0.39 (0.36, 0.43)*	0.39 (0.36, 0.43)
Item8 – feel could not get going	0.12 (0.08, 0.16)*	0.12 (0.08, 0.16)*	0.13 (0.10, 0.17)*	0.14 (0.9, 0.17)
Green and open spaces	0.03 (−0.02, 0.08)		0.07 (0.00, 0.15)*	
Water elements	0.18 (0.01, 0.36)*	0.20 (0.02, 0.37)*	0.96 (0.28, 2.22)*	0.88 (0.17, 1.89)*
Landmarks and architectural elements	0.06 (−0.11, 0.23)		0.03 (−0.20, 0.26)	
Commerce, leisure and cultural attractors	0.08 (0.01, 0.15)*	0.06 (0.01, 0.13)*	0.25 (0.09, 0.40)*	0.20 (0.04, 0.36)*
Openness	0.00 (−0.03, 0.03)		0.03 (0.01, 0.06)*	
Walkable path	0.24 (−0.08, 0.57)*		3.28 (1.17, 7.68)*	3.32 (1.05, 7.69)*
Noise pollution	0.00 (−0.00, 0.00)		0.04 (0.01, 0.09)*	0.03 (0.01, 0.07)*
Traffic	−0.01 (−0.04, 0.02)		−0.01 (−0.07, 0.04)	
Population density	0.00 (−0.03, 0.02)		0.00 (−0.03, 0.04)	
Elderly ratio	−0.01 (−0.04, 0.02)		0.01 (−0.03, 0.06)	
Income per capita	0.00 (−0.02, 0.02)		0.00 (−0.04, 0.04)*	
Trip purpose and mobility (at the time of response)				
Food, commerce and services	0.00 (−0.04, 0.05)	0.00 (−0.05, 0.05)	0.00 (−0.05, 0.04)	0.00 (−0.06, 0.05)
Leisure, cultural and social activities	0.13 (0.09, 0.16)*	0.13 (0.09, 0.17)*	0.13 (0.10, 0.17)*	0.13 (0.09, 0.18)*
Residence	*ref*	*ref*	*ref*	*ref*
Work	0.02 (−0.05, 0.09)	0.02 (−0.06, 0.10)	0.05 (−0.03, 0.12)	0.05 (−0.05, 0.14)
Private transport	0.04 (−0.03, 0.12)	0.05 (−0.05, 0.14)	0.05 (−0.03, 0.13)	0.04 (−0.07, 0.14)
Public transport	0.05 (−0.03, 0.13)	0.05 (−0.06, 0.14)	0.04 (−0.04, 0.13)	0.05 (−0.05, 0.15)
Active mobility	0.08 (0.04, 0.13) *	0.08 (0.02, 0.14)*	0.08 (0.03, 0.13)*	0.07 (0.01, 0.13)*
In/out (at the time of response)				
In	*ref*		*ref*	
Out	0.03 (0.00, 0.05)*		0.03 (0.00, 0.05)	
Sigma	0.49 (0.49, 0.50)*	0.49 (0.48, 0.50)*	0.49 (0.48, 0.50)*	0.49 (0.48, 0.50)*
WAIC		14451.3		14666.7
LOO		14457.5		14668.0

Hanc and Mindmap studies: 216 participants; 7 days; 4830 questionnaires in total; 3650 questionnaires with exposures based on outdoor points; 9689 momentary depressive symptomatology items; 7361 momentary depressive symptomatology items with exposures based on outdoor points. * PD > 95% or % in Rope < 5. Model 1 and Model 3: Bayesian models including a random effect at the levels of the participant and day of response and an autoregressive function that considers date-time for ordering the observations of each participant, adjusted for previous momentary mental health symptomatology, age, gender, education, household income, marital status, and employment status. In these models, each streetscape microenvironment and behavioural variable is included in a separate model. Model 2 and Model 4: Fully adjusted Bayesian model retaining in the same model all environmental and situational variables that are associated with the outcome in Model 1 or 3.

well-being assessed by the reverted scale of depressive symptomatology is affected by exposure to microscale urban environments during daily mobility paths over the previous two hours. Spending time outdoor was not sufficient to improve momentary mental well-being (being outdoor just when responding to the questionnaire was very weekly positively associated with well-being in the within-individual model, but being outdoor over the previous 2 h was not in any model). However, potential environmental influences were related to multiple streetscape environmental elements.

Associations between environmental elements of the streetscape and momentary well-being also differed according to whether environmental exposures were defined based on all location points or only those for which the participant is known to be outdoor. This is an important improvement compared to previous studies (Kondo et al., 2020; Li et al., 2018; York Cornwell and Goldman, 2020) that calculated outdoor environmental exposures based on GPS points without consideration of whether these points were outdoor or indoor. It should be mentioned that some locations points were likely classified as outdoor when people were actually indoor near a window; however, we do not think it is a major concern because in these cases, the participants were nonetheless exposed to the outdoor environment through visual contact through the window. As we expected, the relationships of interest became stronger when we defined environmental exposures only by considering locations points over the previous two hours that were outdoor, which corresponded to a true exposure to the outdoor environment.

Also, we observed that the relationships between environmental exposures and momentary well-being were stronger when we considered within-individual differences (compared to between-individual analysis). When considering within-individual variability, the results emphasized associations with environmental elements (water, commerce, leisure and cultural attractors and walkable paths) that make people feeling safe, comfortable, attracted, and autonomous.

Higher momentary mental well-being was observed after participants performed outdoor activities in spaces with pedestrian areas (pedestrian dedicated paths, open spaces, parks and green areas), water elements or with commerce, leisure and cultural attractors. These results could be explained by the sense of safety and autonomy given to elderly people by walkable spaces, as well as by their capacity to provide easy access to services and to favour sociability, as demonstrated by the large body of literature on walkability spaces (Barnett et al., 2017; Forsyth,

Table 6
Associations of streetscape environment and behavioural variables with momentary mental well-being. Within individual models for environmental exposures defined based on all location points or only outdoor points.

	Model 1 - all pointsSeparate models(95% CI)	**Model 2 - all pointsFull model**(95% CI)	**Model 3 - outdoor pointsSeparate models**(95% CI)	**Model 4 - outdoor pointsFull model**(95% CI)
Intercept	2.39 (2.19, 2.57)*	2.39 (2.19, 2.57)*	2.32 (2.12, 2.51)*	1.90 (−6.97, 26.82)
Item1 – feel bothered	0.32 (0.28, 0.36)*	0.32 (0.28, 0.36)*	0.32 (0.28, 0.37)*	0.32 (0.29, 0.35)*
Item2 – feel depressed	0.46 (0.42, 0.50)*	0.46 (0.42, 0.50)*	0.45 (0.40, 0.50)*	0.44 (0.41, 0.47)*
Item3 – feel that everything is an effort	0.16 (0.12, 0.19)*	0.16 (0.12, 0.19)*	0.14 (0.09, 0.19)*	0.13 (0.10, 0.17)
Item4 – feel happy	*ref*	*ref*	*ref*	*ref*
Item5 – feel lonely	0.30 (0.26, 0.33)*	0.30 (0.26, 0.33)*	0.30 (0.25, 0.35)*	0.29 (0.26, 0.32)*
Item6 – enjoy life	0.00 (−0.03, 0.05)	0.00 (−0.03, 0.05)	0.00 (−0.04, 0.05)	0.00 (−0.03, 0.03)
Item7 – feel sad	0.41 (0.37, 0.45)*	0.41 (0.37, 0.45)*	0.40 (0.35, 0.44)*	0.39 (0.36, 0.42)*
Item8 – feel could not get going	0.12 (0.08, 0.16)*	0.12 (0.08, 0.16)*	0.14 (0.09, 0.18)*	0.13 (0.10, 0.17)*
Green and open spaces	0.03 (−0.02, 0.09)		0.07 (−0.02, 0.16)	
Water elements	0.16 (0.02, 0.34)*	0.17 (0.01, 0.36)*	0.85 (−0.49, 2.03)*	1.12 (−0.36, 2.32)*
Landmarks and architectural elements	0.07 (−0.10, 0.24)		0.03 (−0.20, 0.26)	
Commerce, leisure and cultural attractors	0.08 (−0.02, 0.15)*	0.06 (0.00, 0.13)*	0.25 (0.10, 0.41)*	0.20 (0.07, 0.33)*
Openness	0.00 (−0.04, 0.03)		0.03 (0.03, 0.06)*	
Walkable path	0.18 (−0.11, 0.49)	0.19 (−0.09, 0.50)*	3.36 (0.67, 8.17)*	3.38 (0.25, 6.94)*
Noise pollution	0.00 (−0.03, 0.02)		0.05 (0.01, 0.08)*	
Traffic	−0.01 (−0.04, 0.01)		0.00 (−0.06, 0.05)	
Population density	0.01 (−0.04, 0.01)		0.00 (−0.03, 0.05)*	
Elderly ratio	−0.02 (−0.05, 0.01)		0.05 (0.01, 0.09)*	
Income per capita	0.00 (−0.02, 0.02)		0.03 (0.00, 0.06)*	
Trip purpose and mobility (at the time of response)				
Food, commerce and services	0.00 (−0.05, 0.06)	0.00 (−0.05, 0.06)	0.00 (−0.06, 0.05)	0.00 (−0.05, 0.04)
Leisure, cultural and social activities	0.13 (0.09, 0.17)*	0.13 (0.08, 0.17)*	0.13 (0.09, 0.18)*	0.13 (0.09, 0.17)*
Residence	*ref*	*ref*	*ref*	*ref*
Work	0.02 (−0.06, 0.10)	0.02 (−0.06, 0.09)	0.05 (−0.05, 0.14)	0.05 (−0.02, 0.12)
Private transport	0.05 (−0.04, 0.15)	0.05 (−0.03, 0.15)	0.05 (−0.05, 0.14)	0.05 (−0.03, 0.13)
Public transport	0.06 (−0.04, 0.16)	0.06 (−0.03, 0.17)	0.04 (−0.04, 0.14)	0.03 (−0.06, 0.11)
Active mobility	0.08 (0.03, 0.15)*	0.08 (0.02, 0.14)*	0.08 (0.02, 0.13)	0.07 (0.02, 0.12)*
In/out (at the time of response)				
In	*ref*	*ref*	*ref*	
Out	0.03 (0.00, 0.06)*	0.02 (−0.01, 0.04)	0.03 (0.01, 0.06)*	
Sigma	0.49 (0.49, 0.50)*	0.49 (0.49, 0.50)*	0.50 (0.50, 0.51)*	0.49 (0.49, 0.50)*
WAIC		14459.3		10910.0
LOO		14467.4		10908.4

Hanc and Mindmap studies: 216 participants; 7 days; 4830 questionnaires in total; 3650 questionnaires with exposures based on outdoor points; 9689 momentary depressive symptomatology items; 7361 momentary depressive symptomatology items with exposures based on outdoor points. * PD > 95% or % in Rope < 5. Model 1 and Model 3: Bayesian models including a fixed effect for each participant and a random effect for the day of response and an autoregressive function that considers date-time for ordering the observations of each participant, adjusted for previous momentary mental health symptomatology. In these models, each streetscape microenvironment and behavioural variable is included in a separate model. Model 2 and Model 4: Fully adjusted Bayesian model retaining in the same model all environmental and situational variables that are associated with the outcome in Model 1 or 3.

2015; Speck, 2018; Talen, 2002; Talen and Koschinsky, 2013). Moreover, spending one hour over the previous two hours in areas with water elements was associated with a better momentary mental well-being. These results confirm the mental well-being therapeutic effects (contemplation, emotional bonding, participation and physical activity) of urban blue elements, shown in the Völker & Kistemann (2015) study. The positive visual stimuli and mental restoration given by water elements is confirmed by several studies assessing the benefits of natural elements in cities (White et al., 2019). However, only few studies focused on blue elements at the city level, usually showing positive associations between home proximity to water bodies and mental well-being, general well-being and restoration (Gascon et al., 2017; White et al., 2010; White et al., 2020).

We found evidence of associations between activity and mobility-type when the questionnaire was answered and momentary well-being. Individuals performing leisure, cultural or social activities and individuals walking or biking reported a better momentary mental well-being. These results confirm the importance of social and leisure activities and of active mobility for the mental well-being of older adults. Older people are thought to obtain benefits in terms of cognition, social support, and sense of belonging when they participate to leisure activities, thus improving their mental well-being (Bone et al., 2022; Han et al., 2021; Paggi et al., 2016; Sala et al., 2019).

Contrary to other studies, we did not find associations with green elements, openness of the space, and traffic noise, except when environmental effects were analysed separately from each other. Contrary to our hypothesis, the socioeconomic level and traffic noise along the mobility paths were found to be associated with momentary well-being only when analysed separately from each other.

These results stress the importance of streetscape for momentary mental well-being of older adults (WHO, 2019). Overall, designing urban public policies that prioritize the creation of recreational and therapeutic spaces can be a cost-effective way to improve the mental health of urban residents and reduce the societal burden of depression (Sallis et al., 1998). Policies oriented towards the accessibility to commerce, leisure and cultural attractors, water elements and walkable spaces will favour active mobility, enhance social relationships and emotional well-being, thus improving mental well-being.

Our study addressed the need for innovation in the evaluation of the relationship between the exposure to the urban environment and mental

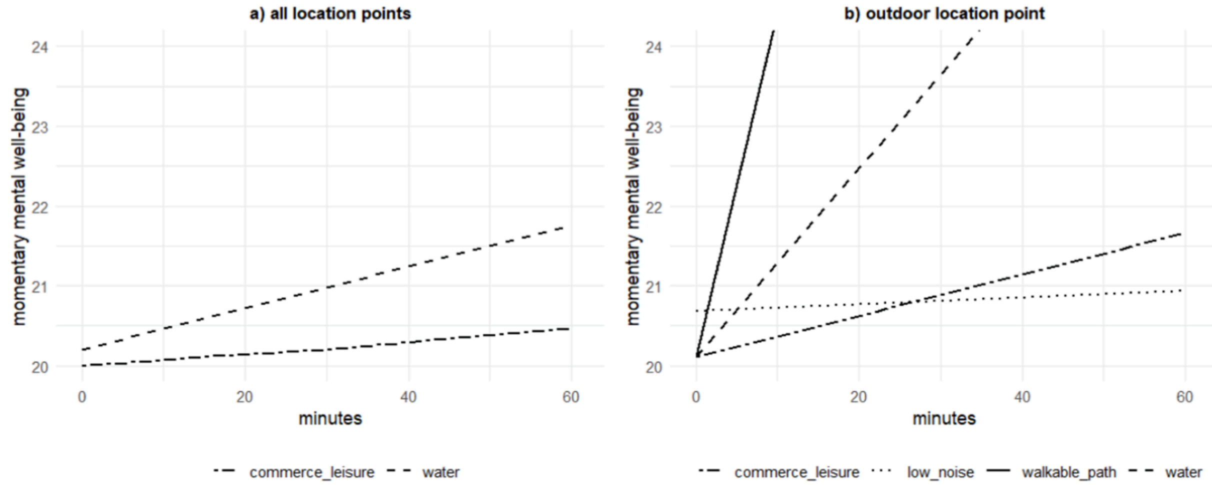

Fig. 3. Prediction of momentary mental well-being associated with exposures defined with all location points (a) and with only outdoor location points (b) (between individual model). The momentary mental well-being score here reflect the sum of the predicted values for each of the items depending on the environmental characteristics. Predictions are made separately for each individual and are then averaged over the sample.

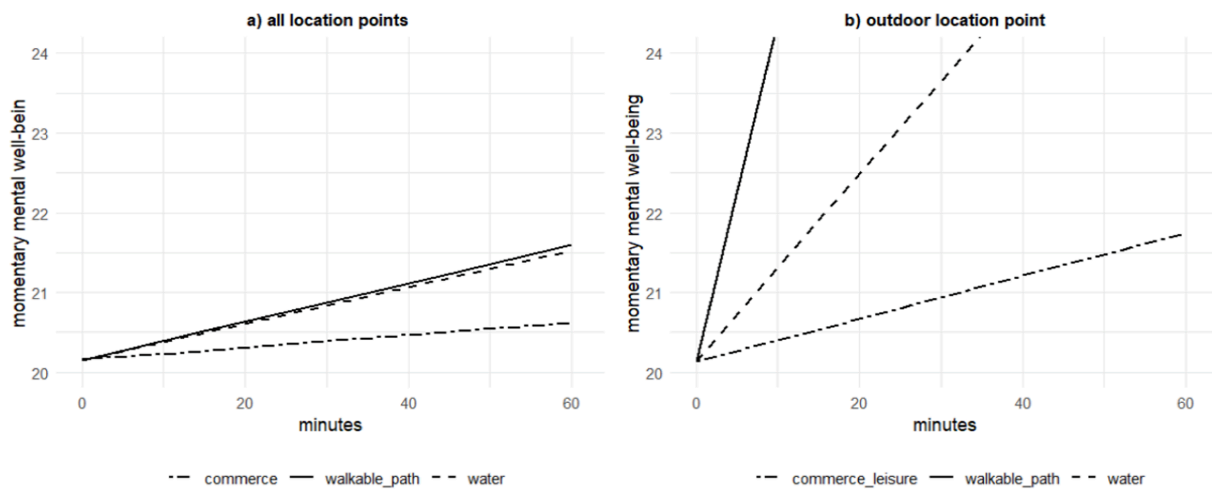

Fig. 4. Prediction of momentary mental well-being associated with exposures defined with all location points (a) and with only outdoor location points (b) (within individual model). The momentary mantal well-being score here reflect the sum of the predicted values for each of the items depending on the environmental characteristics. Predictions are made separately for each individual and are then averaged over the sample.

well-being outcomes (Park et al., 2021). We innovated in the literature by using GEMA methods (Chaix, 2020) collecting detailed GPS spatiotemporal data and repeated measures of momentary depressive symptomatology. The use of GEMA questionnaires reduced the risk of bias of retrospective surveys and allowed to model the effects of the daily exposure to environments on mental well-being over space and time. In doing so, we go beyond the analysis of the residential space as the exposure environment for mental well-being (Park et al., 2021; Vallée et al., 2011) and we proposed an approach focused on daily mobility paths (Chaix et al., 2019; Duncan et al., 2021). Moreover, detailed spatiotemporal data manipulated in a geographic information system allowed us to assess the effect of exposures to multiple urban elements (Roberts and Helbich, 2021), rather than focusing on only one feature (for example natural elements) (Beute and de Kort, 2018; Kondo et al., 2020; Li et al., 2018). An innovative aspect of our analysis is that we were able to compare environmental exposures based on all collected location points vs. only outdoor locations points, and we confirmed according to our hypothesis that the second approach was more relevant.

Some limitations to our study should be mentioned. We assumed that the effects of the duration of exposure to urban environment on momentary well-being were linear, and that the relevant time window to consider was of two hours prior to the momentary assessment. Sensitivity analyses considering nonlinear patterns of relationship (e.g., with quadratic terms for example) as well as different durations of exposure should be conducted. Another limitation is that our study did not consider social interactions during daily activities. Positive or negative social interactions prior to or at the time of the EMA questionnaire may influence the momentary mental mood of participants. Another potential limitation of this study is due to the possible spatial imprecision of GPS trackers in high density environments due to the canyoning effect. We plan to overcome this limitation in future studies by collecting GPS and location data from smartphones that use technologies that can be more accurate spatially (Goodspeed et al., 2018). Finally, our model did not evaluate whether spatially nearby residuals were similar, meaning that residual spatial patterns may be potentially still present in the data even after accounting for the spatial predictor variables, although it is unlikely.

In conclusion, this study found that momentary depressive symptomatology in older adults is influenced by the microscale urban environment to which they are exposed during their daily mobility paths. Certain environmental elements, such as water, commerce, leisure and

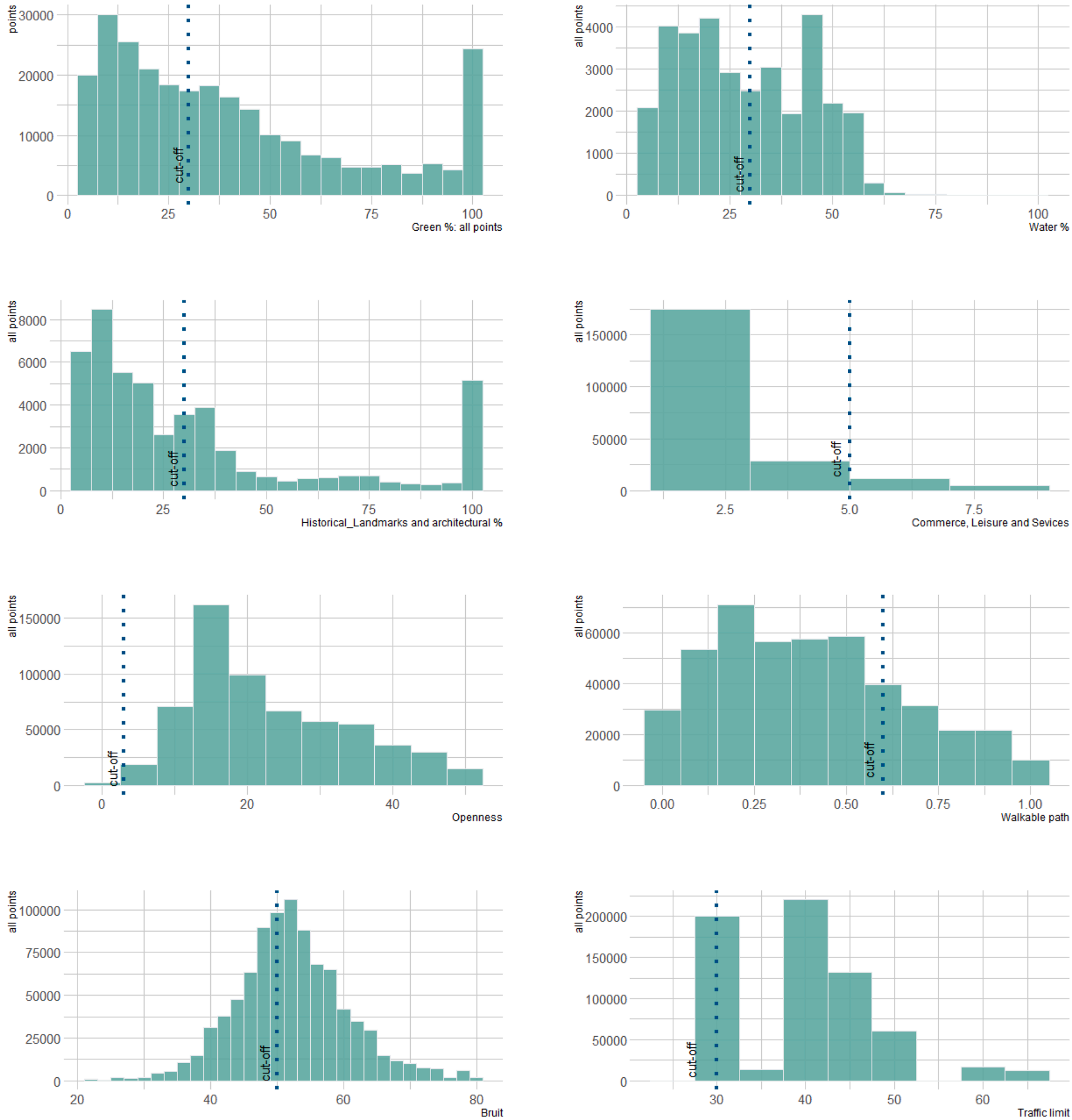

Fig. A1. Histograms and cut off for environmental variables.

cultural attractors, and walkable paths, were associated with better momentary mental well-being. Spending time in areas with water elements and walkable environments was specifically found to have a therapeutic effect on momentary mental well-being, suggesting the design of urban policies oriented to reduce the spatial print of road space and encouraging dedicated walking areas. Additionally, leisure, cultural, or social spaces, as well as engaging on walking or biking, was associated with better momentary mental well-being. A detailed assessment of microspaces together with the continuous measurement of mobility and mood in space and time in order to explore between- and within-individual differences are helpful in further understanding the relationships between exposure to urban contextual features and momentary mental well-being.

CRediT authorship contribution statement

Giovanna Fancello: Conceptualization, Formal analysis, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **Julie Vallée:** Funding acquisition, Writing – review & editing. **Cédric Sueur:** Funding acquisition, Writing – review & editing. **Frank J. van Lenthe:** Funding acquisition, Writing – review & editing. **Yan Kestens:** Funding acquisition, Writing – review & editing. **Andrea**

Table A1
Streetscape environment variables and cut-off used for classification of micro-urban buffer areas.

Attribute	Threshold	Thresholds definition method
Natural elements		
Green and open spaces	*>30%*	Based on our hypothesis and observation of data distribution
Water elements	*>30%*	Based on our hypothesis and observation of data distribution
Building elements		
Landmarks and architectural elements	*>30%*	Based on our hypothesis and observation of data distribution
Commerce, leisure and cultural attractors*	n > *5*	Based on the walkability literature and observation of data distribution
Openness	*>3*	Based on the definition of openness in literature
Walkable path	*>0.4*	Based on our hypothesis and observation of data distribution
Noise pollution	*<50 Lden*	Based on data distribution and on suggestions from the European Environment Agency literature
Traffic (security)	*<30 km/h*	Based on our hypothesis
Social environment		
Population density	*>2000 inhabitants/Km²*	Based on our hypothesis that a walkable space is positively associated with momentary mental wellbeing
Elderly ratio	*>0.70*	Based on our hypothesis that a living environment with similar class age people favours momentary mental wellbeing
Income	*>30.000 €/household*	Based on our hypothesis that a socially advantaged environment favours momentary mental wellbeing

Montanari: Visualization, Writing – review & editing. **Basile Chaix:** Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Cedric Sueur reports financial support was provided by French National Research Agency. Basile Chaix reports financial support was provided by Horizon Europe.

Data availability

Data will be made available on request.

Appendix A. Streetscape environment variables and thresholds used for classification of microscale urban buffer areas – Histograms distribution and thresholds

All the thresholds were defined considering hypotheses, data distribution and the literature on specific streetscape environment variables (See Fig. A1 and Table A1).

References

Bakolis, I., Hammoud, R., Smythe, M., Gibbons, J., Davidson, N., Tognin, S., Mechelli, A., 2018. Urban Mind: Using Smartphone Technologies to Investigate the Impact of Nature on Mental Well-Being in Real Time. Bioscience 68, 134–145. https://doi.org/10.1093/biosci/bix149.

Barnett, A., Zhang, C.J.P., Johnston, J.M., Cerin, E., 2017. Relationships between the neighborhood environment and depression in older adults: A systematic review and meta-analysis. Int. Psychogeriatrics 30, 1153–1176. https://doi.org/10.1017/S104161021700271X.

Bergou, N., Hammoud, R., Smythe, M., Gibbons, J.o., Davidson, N., Tognin, S., Reeves, G., Shepherd, J., Mechelli, A., Clarke, T.-K., 2022. The mental health benefits of visiting canals and rivers: An ecological momentary assessment study. PLoS One 17 (8), e0271306.

Beute, F., de Kort, Y.A.W., 2018. The natural context of wellbeing: Ecological momentary assessment of the influence of nature and daylight on affect and stress for individuals with depression levels varying from none to clinical. Heal. Place 49, 7–18. https://doi.org/10.1016/j.healthplace.2017.11.005.

Bollenbach, L., Schmitz, J., Niermann, C., Kanning, M., 2022. How do people feel while walking in the city? Using walking-triggered e-diaries to investigate the association of social interaction and environmental greenness during everyday life walking. Front. Psychol. 13, 6022. https://doi.org/10.3389/FPSYG.2022.970336/BIBTEX.

Bone, J.K., Bu, F., Fluharty, M.E., Paul, E., Sonke, J.K., Fancourt, D., 2022. Engagement in leisure activities and depression in older adults in the United States: Longitudinal evidence from the Health and Retirement Study. Soc. Sci. Med. 294, 114703 https://doi.org/10.1016/j.socscimed.2022.114703.

Bornioli, A., Parkhurst, G., Morgan, P.L., 2018. Psychological Wellbeing Benefits of Simulated Exposure to Five Urban Settings: an Experimental Study From the Pedestrian's Perspective. J. Transp. Heal. 9, 105–116. https://doi.org/10.1016/J.JTH.2018.02.003.

Braithwaite, I., Zhang, S., Kirkbride, J.B., Osborn, D.P.J., Hayes, J.F., 2019. Air pollution (Particulate matter) exposure and associations with depression, anxiety, bipolar, psychosis and suicide risk: A systematic review and meta-analysis. Environ. Health Perspect. 127 https://doi.org/10.1289/EHP4595.

Bui, V., Le, N.T., Vu, T.L., Nguyen, V.H., Jang, Y.M., 2020. GPS-based indoor/outdoor detection scheme using machine learning techniques. Appl. Sci. 10 (2), 500.

Bürkner, P.-C., 2019. Bayesian Item Response Modeling in R with brms and Stan.

Burton, E., Mitchell, L., 2006. Inclusive Urban Design. Streets for life, Elsevier Ltd, Oxford.

Buttazzoni, A., Parker, A., Minaker, L., 2021. Investigating the mental health implications of urban environments with neuroscientific methods and mobile technologies: A systematic literature review. Heal. Place 70, 102597. https://doi.org/10.1016/j.healthplace.2021.102597.

Carpenter, B., Gelman, A., Hoffman, M.D., Lee, D., Goodrich, B., Betancourt, M., Brubaker, M.A., Guo, J., Li, P., Riddell, A., 2017. Stan: A probabilistic programming language. J. Stat. Softw. 76 https://doi.org/10.18637/jss.v076.i01.

Chaix, B., 2018. Mobile Sensing in Environmental Health and Neighborhood Research. Annu. Rev. Public Health 39, 367–384. https://doi.org/10.1146/annurev-publhealth-040617-013731.

Chaix, B., 2020. How daily environments and situations shape behaviors and health: Momentary studies of mobile sensing and smartphone survey data. Heal. Place 61, 2019–2021. https://doi.org/10.1016/j.healthplace.2019.102241.

Chaix, B., Kestens, Y., Bean, K., Leal, C., Karusisi, N., Meghiref, K., Burban, J., Fon Sing, M., Perchoux, C., Thomas, F., Merlo, J., Pannier, B., 2011. Cohort profile: Residential and non-residential environments, individual activity spaces and cardiovascular risk factors and diseases-The RECORD cohort study. Int. J. Epidemiol. 41, 1283–1292. https://doi.org/10.1093/ije/dyr107.

Chaix, B., Kestens, Y., Perchoux, C., Karusisi, N., Merlo, J., Labadi, K., 2012. An interactive mapping tool to assess individual mobility patterns in neighborhood studies. Am. J. Prev. Med. 43, 440–450. https://doi.org/10.1016/j.amepre.2012.06.026.

Chaix, B., Duncan, D., Vallée, J., Vernez-Moudon, A., Benmarhnia, T., Kestens, Y., 2017. The "Residential" effect fallacy in neighborhood and health studies: Formal definition, empirical identification, and correction. Epidemiology 28, 789–797. https://doi.org/10.1097/EDE.0000000000000726.

Chaix, B., Benmarhnia, T., Kestens, Y., Brondeel, R., Perchoux, C., Gerber, P., Duncan, D. T., 2019. Combining sensor tracking with a GPS-based mobility survey to better measure physical activity in trips: Public transport generates walking. Int. J. Behav. Nutr. Phys. Act. 16, 1–13. https://doi.org/10.1186/s12966-019-0841-2.

Chen, K., Tan, G., 2017. SatProbe: Low-Energy and Fast Indoor/Outdoor Detection based on Raw GPS Processing. In: EEE INFOCOM 2017 - IEEE Conference on Computer Communications SatProbe.

Curtis, S., 2010. Space. Place and Mental Healt. Ashgate Publishing Ltd., Farnham, UK.

Duncan, G.E., Hurvitz, P.M., Moudon, A.V., Avery, A.R., Tsang, S., 2021. Measurement of neighborhood-based physical activity bouts. Heal. Place 70, 102595. https://doi.org/10.1016/j.healthplace.2021.102595.

Eurostat, 2020. Ageing Europe - Looking at the lives of older people in the EU, Eurostat.

Fernandes, A., Van Lenthe, F.J., Vallée, J., Sueur, C., Chaix, B., 2021. Linking physical and social environments with mental health in old age: A multisensor approach for continuous real-life ecological and emotional assessment. J. Epidemiol. Community Health. 75 (5), 477–483.

Forsyth, A., 2015. What is a walkable place? The walkability debate in urban design. Urban Des. Int. 20, 274–292. https://doi.org/10.1057/udi.2015.22.

Forsyth, A., Van Riper, D., Larson, N., Wall, M., Neumark-Sztainer, D., 2012. Creating a replicable, valid cross-platform buffering technique: The sausage network buffer for measuring food and physical activity built environments. Int. J. Health Geogr. 11, 1–9. https://doi.org/10.1186/1476-072X-11-14.

Frank, L.D., Fox, E.H., Ulmer, J.M., Chapman, J.E., Kershaw, S.E., Sallis, J.F., Conway, T. L., Cerin, E., Cain, K.L., Adams, M.A., Smith, G.R., Hinckson, E., Mavoa, S., Christiansen, L.B., Hino, A.A.F., Lopes, A.A.S., Schipperijn, J., 2017. International comparison of observation-specific spatial buffers: maximizing the ability to estimate physical activity. Int. J. Health Geogr. 16, 4. https://doi.org/10.1186/s12942-017-0077-9.

Gascon, M., Zijlema, W., Vert, C., White, M.P., Nieuwenhuijsen, M.J., 2017. Outdoor blue spaces, human health and well-being: A systematic review of quantitative studies. Int. J. Hyg. Environ. Health 220, 1207–1221. https://doi.org/10.1016/j.ijheh.2017.08.004.

Golledge, R.G., Stimson, R.J., 1997. Spatial behaviour: a geographic perspective, Spatial behaviour: a geographic perspective. 10.2307/144350.

Gong, Y., Palmer, S., Gallacher, J., Marsden, T., Fone, D., 2016. A systematic review of the relationship between objective measurements of the urban environment and psychological distress. Environ. Int. 96, 48–57. https://doi.org/10.1016/j.envint.2016.08.019.

Goodspeed, R., Yan, X., Hardy, J., Vydiswaran, V.V., Berrocal, V.J., Clarke, P., Romero, D.M., Gomez-Lopez, I.N., Veinot, T., 2018. Comparing the Data Quality of Global Positioning System Devices and Mobile Phones for Assessing Relationships Between Place, Mobility, and Health: Field Study. JMIR mHealth uHealth 6. https://doi.org/10.2196/MHEALTH.9771.

Han, A., Kim, J., Kim, J., 2021. A Study of Leisure Walking Intensity Levels on Mental Health and Health Perception of Older Adults. Gerontol. Geriatr. Med. 7 https://doi.org/10.1177/2333721421999316, 233372142199931.

Hartig, T., Korpela, K., Evans, G.W., Gärling, T., 2007. A measure of restorative quality in environments. https://doi.org/10.1080/02815739708730435 14, 175–194. 10.1080/02815739708730435.

Jacobson, N.C., Bhattacharya, S., 2022. Digital biomarkers of anxiety disorder symptom changes: Personalized deep learning models using smartphone sensors accurately predict anxiety symptoms from ecological momentary assessments. Behav. Res. Ther. 149, 104013.

Kamalyan, L., Yang, J.A., Pope, C.N., Paolillo, E.W., Campbell, L.M., Tang, B., Marquine, M.J., Depp, C.A., Moore, R.C., 2021. Increased Social Interactions Reduce the Association Between Constricted Life-Space and Lower Daily Happiness in Older Adults With and Without HIV: A GPS and Ecological Momentary Assessment Study. Am. J. Geriatr. Psychiatry 29, 867–879. https://doi.org/10.1016/J.JAGP.2020.11.005.

Karim, J., Weisz, R., Bibi, Z., ur Rehman, S., 2015. Validation of the Eight-Item Center for Epidemiologic Studies Depression Scale (CES-D) Among Older Adults. Curr. Psychol. 34, 681–692. https://doi.org/10.1007/S12144-014-9281-Y/TABLES/5.

Kim, T., Lee, K., Yang, W., Yu, S.D., 2012. A new analytical method for the classification of time-location data obtained from the global positioning system (GPS). J. Environ. Monit. 14, 2270–2274. https://doi.org/10.1039/C2EM30190C.

Klompmaker, J.O., Hoek, G., Bloemsma, L.D., Wijga, A.H., van den Brink, C., Brunekreef, B., Lebret, E., Gehring, U., Janssen, N.A.H., 2019. Associations of combined exposures to surrounding green, air pollution and traffic noise on mental health. Environ. Int. 129, 525–537. https://doi.org/10.1016/j.envint.2019.05.040.

Kondo, M.C., Triguero-Mas, M., Donaire-Gonzalez, D., Seto, E., Valentín, A., Hurst, G., Carrasco-Turigas, G., Masterson, D., Ambròs, A., Ellis, N., Swart, W., Davis, N., Maas, J., Jerrett, M., Gidlow, C.J., Nieuwenhuijsen, M.J., 2020. Momentary mood response to natural outdoor environments in four European cities. Environ. Int. 134, 105237 https://doi.org/10.1016/j.envint.2019.105237.

Li, D., Deal, B., Zhou, X., Slavenas, M., Sullivan, W.C., 2018. Moving beyond the neighborhood: Daily exposure to nature and adolescents' mood. Landsc. Urban Plan. 173, 33–43. https://doi.org/10.1016/j.landurbplan.2018.01.009.

Lindal, P.J., Hartig, T., 2013. Architectural variation, building height, and the restorative quality of urban residential streetscapes. J. Environ. Psychol. 33, 26–36. https://doi.org/10.1016/J.JENVP.2012.09.003.

Lynch, K., 1981. A theory of Good city form. The MIT Press, Cambridge Massachussets.

Maas, J., Verheij, R.A., de Vries, S., Spreeuwenberg, P., Schellevis, F.G., Groenewegen, P.P., 2009. Morbidity is related to a green living environment. J. Epidemiol. Community Heal. 63, 967–973. https://doi.org/10.1136/jech.2008.079038.

Makowski, D., Ben-Shachar, M.S., Chen, S.H.A., Lüdecke, D., 2019. Indices of Effect Existence and Significance in the Bayesian Framework. Front. Psychol. 10 https://doi.org/10.3389/FPSYG.2019.02767.

Mavros, P., J Wälti, M., Nazemi, M., Ong, C.H., Hölscher, C., 2022. A mobile EEG study on the psychophysiological effects of walking and crowding in indoor and outdoor urban environments. Sci. Rep. 12 (1) https://doi.org/10.1038/s41598-022-20649-y.

Naud, A., Sueur, C., Chaix, B., Kestens, Y., 2020. Combining social network and activity space data for health research: tools and methods. Heal. Place 66, 102454.

OECD Eu Health at a Glance: Europe 2018 2018 Europe. OECD, Paris Health at a Glance 10.1787/health_glance_eur-2018-en.

Paggi, M.E., Jopp, D., Hertzog, C., 2016. The Importance of Leisure Activities in the Relationship between Physical Health and Well-Being in a Life Span Sample. Gerontology 62, 450–458. https://doi.org/10.1159/000444415.

Park, Y.-S., McMorris, B.J., Pruinelli, L., Song, Y., Kaas, M.J., Wyman, J.F., 2021. Use of geographic information systems to explore associations between neighborhood attributes and mental health outcomes in adults: A systematic review. Int. J. Environ. Res. Public Health 18 (16), 8597.

Radloff, L.S., 1977. The CES-D Scale: A Self-Report Depression Scale for Research in the General Population. Appl. Psychol. Meas. 1 (3), 385–401.

Rautio, N., Filatova, S., Lehtiniemi, H., Miettunen, J., 2018. Living environment and its relationship to depressive mood: A systematic review. Int. J. Soc. Psychiatry 64, 92–103. https://doi.org/10.1177/0020764017744582.

Roberts, H., Helbich, M., 2021. Multiple environmental exposures along daily mobility paths and depressive symptoms: A smartphone-based tracking study. Environ. Int. 156, 106635.

Roberts, H., van Lissa, C., Hagedoorn, P., Kellar, I., Helbich, M., 2019. The effect of short-term exposure to the natural environment on depressive mood: A systematic review and meta-analysis. Environ. Res. 177, 108606.

Sala, G., Jopp, D., Gobet, F., Ogawa, M., Ishioka, Y., Masui, Y., Inagaki, H., Nakagawa, T., Yasumoto, S., Ishizaki, T., Arai, Y., Ikebe, K., Kamide, K., Gondo, Y., Ginsberg, S.D., 2019. The impact of leisure activities on older adults' cognitive function, physical function, and mental health. PLoS One 14 (11), e0225006.

Sallis, J.F., Bauman, A., Pratt, M., 1998. Environmental and policy interventions to promote physical activity. Am. J. Prev. Med. 15, 379–397. https://doi.org/10.1016/S0749-3797(98)00076-2.

Schempf, A.H., Kaufman, J.S., 2012. Accounting for context in studies of health inequalities: a review and comparison of analytic approaches. Ann. Epidemiol. 22, 683–690. https://doi.org/10.1016/j.annepidem.2012.06.105.

Setra, 2009. Prévision du bruit routier : méthode de calcul de propagation du bruit incluant les effets météorologiques (NMPB 2008). CEREMA.

Shiffman, S., Stone, A.A., Hufford, M.R., 2008. Ecological momentary assessment. Annu. Rev. Clin. Psychol. 4, 1–32. https://doi.org/10.1146/annurev.clinpsy.3.022806.091415.

Speck, J., 2018. Walkable City Rules. Walkable City Rules. https://doi.org/10.5822/978-1-61091-899-2.

Stamps, A.E., Smith, S., 2002. Environmental Enclosure in Urban Settings. Environ. Enclosure Urban Settings. 34 (6), 781–794.

Talen, E., 2002. Pedestrian Access as a Measure of Urban Quality. Plan. Pract. Res. 17, 257–278. https://doi.org/10.1080/026974502200005634.

Talen, E., Koschinsky, J., 2013. The Walkable Neighborhood: A Literature Review. Int. J. Sustain. L. Use Urban Plan. 1, 42–63.

Tao, Y., Chai, Y., Kou, L., Kwan, M.P., 2020. Understanding noise exposure, noise annoyance, and psychological stress: Incorporating individual mobility and the temporality of the exposure-effect relationship. Appl. Geogr. 125 https://doi.org/10.1016/j.apgeog.2020.102283.

Vallée, J., Cadot, E., Roustit, C., Parizot, I., Chauvin, P., 2011. The role of daily mobility in mental health inequalities: The interactive influence of activity space and neighbourhood of residence on depression. Soc. Sci. Med. 73, 1133–1144. https://doi.org/10.1016/j.socscimed.2011.08.009.

Van Cauwenberg, J., Nathan, A., Barnett, A., Barnett, D.W., Cerin, E., 2018. Relationships Between Neighbourhood Physical Environmental Attributes and Older Adults' Leisure-Time Physical Activity: A Systematic Review and Meta-Analysis. Sport. Med. 48 (7), 1635–1660.

Völker, S., Kistemann, T., 2015. Developing the urban blue: Comparative health responses to blue and green urban open spaces in Germany. Heal. Place 35, 196–205. https://doi.org/10.1016/j.healthplace.2014.10.015.

Weich, S., Blanchard, M., Prince, M., Burton, E., Erens, B., Sproston, K., 2002. Mental health and the built environment: Cross-sectional survey of individual and contextual risk factors for depression. Br. J. Psychiatry 180, 428–433. https://doi.org/10.1192/bjp.180.5.428.

White, M.P., Alcock, I., Grellier, J., Wheeler, B.W., Hartig, T., Warber, S.L., Bone, A., Depledge, M.H., Fleming, L.E., 2019. Spending at least 120 minutes a week in nature is associated with good health and wellbeing. Sci. Rep. 9, 1–11. https://doi.org/10.1038/s41598-019-44097-3.

White, M.P., Elliott, L.R., Gascon, M., Roberts, B., Fleming, L.E., 2020. Blue space, health and well-being: A narrative overview and synthesis of potential benefits. Environ. Res. 191, 110169 https://doi.org/10.1016/j.envres.2020.110169.

White, M., Smith, A., Humphryes, K., Pahl, S., Snelling, D., Depledge, M., 2010. Blue space: The importance of water for preference, affect, and restorativeness ratings of natural and built scenes. J. Environ. Psychol. 30, 482–493. https://doi.org/10.1016/j.jenvp.2010.04.004.

WHO, n.d. Mental Health: Strengthening Our Response. [WWW Document]. URL https://www.who.int/en/news-room/fact-sheets/detail/mental-health-strengthening-our-response (accessed 4.5.23).

York Cornwell, E., Goldman, A.W., 2020. Neighborhood Disorder and Distress in Real Time: Evidence from a Smartphone-Based Study of Older Adults. J. Health Soc. Behav. 61, 523–541. https://doi.org/10.1177/0022146520967660.

Zhang, C.J.P., Barnett, A., Sit, C.H.P., Lai, P.C., Johnston, J.M., Lee, R.S.Y., Cerin, E., 2018. Cross-sectional associations of objectively assessed neighbourhood attributes with depressive symptoms in older adults of an ultra-dense urban environment: The Hong Kong ALECS study. BMJ Open 8, 1–13. https://doi.org/10.1136/bmjopen-2017-020480.

Zhao, J., Wu, J., Wang, H., 2019. Characteristics of urban streets in relation to perceived restorativeness. J. Expo Sci. Environ. Epidemiol. 30 (2), 309–319.

Zhu, Y., Luo, H., Wang, Q.u., Zhao, F., Ning, B., Ke, Q., Zhang, C., 2019. A fast indoor/outdoor transition detection algorithm based on machine learning. Sensors (Switzerland) 19 (4), 786.