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Effect of natural and artificial surroundings on perceived restorativeness and affective states: Evidence from a satellite image segmentation-based method

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ABSTRACT

This study introduces an integrative methodology combining satellite image segmentation and psychometric modeling to investigate how near-home environments influence psychological restoration and affective experiences. Using an ad-hoc clustering procedure on satellite imagery, we quantified environmental features (green spaces, gray areas, roofs, shadows) surrounding the home of 917 Italian university students. These objective features were then linked to self-reported perceptions of restorativeness and emotional states (pleasure, arousal, dominance). University and nature restorativeness were included as negative-control outcomes to test context-specificity; objective features were extracted only around home. Results revealed that gray spaces negatively predicted restorativeness, particularly diminishing psychological distancing ("being-away"), attentional engagement ("fascination"), and spatial openness ("scope"). Structural Equation Models (SEM) confirmed that these components significantly mediated the relationship between gray space and affective outcomes. Specifically, gray spaces indirectly reduced emotional states of pleasure and arousal through diminished restorativeness, while also exerting a positive association with emotions of dominance, possibly reflecting feelings of environmental control or adaptation in urban contexts. Our approach advances previous research by isolating the psychological pathways linking built environments to emotional well-being, and by demonstrating the value of combining environmental segmentation with latent variable modeling. The findings support the development of urban planning strategies aimed at reducing gray space exposure and enhancing restorative features in residential areas, thereby promoting emotional resilience and well-being.

1. Introduction

Understanding the relationship between the environment and human experience is a cornerstone of environmental psychology. Among a variety of environmental factors, the presence of and access to natural spaces have been shown to improve physical and mental health (Wells & Evans, 2003), cognitive functioning (Bratman et al., 2015), overall life satisfaction (Hartig et al., 2014; Kaplan, 1995), social interactions (Lee et al., 2015), and restorative psychological states (Hadavi, 2017; Kaplan & Kaplan, 1989; Rapheal & Paul, 2015; Ulrich, 1984), as well as to reduce stress, anxiety and depression (Astell-Burt et al., 2013; Maas et al., 2006; White et al., 2013), and the impact of chronic diseases (Dadvand & Nieuwenhuijsen, 2018; Kingsley, 2019). Subjective experiences are essential to capture how individuals perceive and interact with their environments. Self-report surveys address this gap by assessing the perceived restorative quality of an environment (e.g., Berman, Jonides, & Kaplan, 2008; Hartig et al., 1997; Pasini et al., 2014), as well as estimating its potential for psychological recovery (Staats, 2012). Specifically, individuals are asked to evaluate the restorative qualities of a given environment (Menardo et al., 2021), based on the assumption that their metacognitive abilities enable them to understand their cognitive processes and assess how these are

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influenced by different environmental contexts (Pearson & Craig, 2014). However, despite providing significant insights, the traditional methodologies employed in this research face substantial limitations that hinder a comprehensive understanding of the intricate interplay between environmental features and human well-being.

Firstly, while observational and self-report measures are useful for direct assessments of behavior and experiences, they do not efficiently integrate all the environmental and behavioral/psychometric variability needed to fully assess effect patterns (Smith & Smith, 2015; Stigsdotter et al., 2010). In fact, many studies highlight the benefits of green space experiences but also recognize the need to incorporate physical, objective measurements. Subjective interpretations of physical spaces vary among individuals (Gong et al., 2020; Wheaton et al., 2018) and may not fully match objective characteristics (Cui et al., 2022; Raudenbush & Sampson, 1999). Self-report surveys often rely on simplified responses (Larsen et al., 2011; Matthews, 2017; Eichinger et al., 2017). Moreover, these studies usually focus on limited geographic locations, restricting the generalizability of findings (Gong et al., 2020; Kaplan & Kaplan, 1989; Mitchell, 2013). Thus, it is essential to integrate self-assessed and objective physical measures to study the impacts of the environment on behavior and well-being. The advent of technological advancements offers new avenues to overcome these methodological constraints. Geospatial analysis, facilitated by satellite imagery, allows for the objective and extensive monitoring of environments, providing the possibility to extract data features that are not limited by individual perception or geographical boundaries (El Fellah et al., 2018; He et al., 2023; Karim et al., 2017; Liu et al., 2014). Such tools may be valuable in capturing the environmental variability of spaces most relevant to individuals' daily lives, including home, work, study, and public areas.

Secondly, whereas an extensive literature documents the beneficial effects of green spaces on well-being and behavior, the understanding of the psychological and affective impact of gray spaces, such as urban congestion, lack of vegetation, and exposure to built environments, can be considered equally critical. Environments are not neutral backdrops to human activity; they actively elicit affective responses that shape emotional states, cognitive function, and stress regulation (Hartig et al., 2014; Korpela et al., 2001; Ulrich et al., 1991). Research has consistently shown that green spaces can foster positive affect and restoration, whereas gray spaces are often associated with heightened stress, anxiety, and cognitive fatigue (Roe & Aspinall, 2011; Sineva et al., 2021). Beyond psychological effects, exposure to predominantly built environments has also been linked to neurobiological and epigenetic alterations, potentially modulating stress reactivity and psychiatric vulnerability (Galea et al., 2011). Notably, higher rates of psychiatric conditions have been observed in children (Engemann et al., 2019; Markevych et al., 2017) and in vulnerable populations (Lecic-Tosevski, 2019) exposed to highly urbanized environments. Despite accumulating evidence on the adverse effects of gray space on healthy development (Evans, 2003; Evans et al., 2002, pp. P381–P383), the interaction between green and gray spaces remains underexplored, often leading to research that exclusively highlights the benefits of green environments without systematically assessing the potentially detrimental effects of gray urbanization. Moreover, it is important to note that not all built environments are necessarily detrimental to psychological restoration. Certain architectural forms, such as historical or culturally meaningful features, can contribute positively to restorative experiences and perceived environmental quality (Herzog & Bryce, 2007; Nasar, 1994).

Affective responses to environments are influenced not only by the presence of natural elements but also by specific perceptual and psychological processes, such as *perceived restorativeness* (Kaplan & Kaplan, 1989; Korpela et al., 2018). This concept refers to how individuals perceive an environment's capacity to promote psychological recovery from stress and mental fatigue. In this study, it is considered in line with Attention Restoration Theory (ART, Kaplan & Kaplan, 1989), as an individual's cognitive and experiential appraisal of an environment's capacity to promote recovery from mental fatigue. It is typically assessed using the Perceived Restorativeness Scale (Hartig et al., 1997, 2014), which assesses four core dimensions: Fascination, the extent to which the environment effortlessly captures attention; Being-Away, the sense of escape from everyday routines; Extent, the sense that the environment offers enough space, variety, and depth to allow sustained engagement and exploration, creating a coherent setting in which one can feel fully absorbed; and Compatibility, the fit between the environment and the individual's purposes and inclinations. An environment's ability to support restoration—or conversely, to trigger stress and cognitive overload—plays a crucial role in shaping affective experiences (Van den Berg et al., 2007; Meagher, 2022). Yet, despite these theoretical advances, the absence of integrated analytical tools limits our understanding of how different urban features interact to influence emotional well-being. Most current studies analyze green and gray spaces in isolation, without considering their combined and interactive effects.

In this study, we focus on three core dimensions of affective experience consistent with the Pleasure–Arousal–Dominance (PAD) model (Bakker et al., 2014; Mehrabian & Russell, 1974). Pleasure reflects the degree of positive affect or happiness, arousal captures the level of activation and alertness, and dominance indicates perceived control over one's environment and feelings. By assessing affective responses alongside perceived restorativeness, we can evaluate not only whether environments are perceived as restorative, but also how these perceptions translate into concrete emotional experiences. This conceptual distinction informs our mediation model, where perceived restorativeness functions as a cognitive–experiential filter through which objective environmental features influence affective states.

The primary aim of our study is to develop a novel method to objectively measure environmental features and to examine how these features relate to the subjective experience of perceived restorativeness and affective states. In this context, 'features' refer to latent, dimensional characteristics of the environment that are not directly observable but can be inferred through computational analysis—such as the proportion of green areas, the extent of urban surfaces, or the distribution of shadow patterns. These features are derived from the analysis of environmental color compositions, which serve as proxies for broader spatial and structural attributes.

By testing how these latent features relate to psychological variables, such as perceived restorativeness and affective states, we aim to deepen our understanding of the complex interactions between environmental contexts and psychological outcomes. In our framework, perceived restorativeness is conceptualized as a mediator in our model, translating objective environmental features – such as proportion of green areas, urban surfaces, or shadow patterns – into a set of subjective appraisals that, in turn, influence affective outcomes. Unlike affective responses (such as pleasure or arousal, which reflect emotional reactions), restorativeness refers to the individual's cognitive and experiential assessment of the environment's capacity to reduce mental fatigue, provide an opportunity for psychological escape, and engage attention. As such, restorativeness is positioned in the model as a perceptual filter through which the physical environment shapes affective states.

Our study specifically focuses on university students, building on previous research suggesting that they are particularly sensitive to environmental influences due to their unique stressors and reliance on restorative spaces (Holt et al., 2019; Ribeiro, 2024). For example, Ribeiro (2024) highlighted how green campus spaces are associated with improved well-being, and Holt and colleagues (2019) emphasized the restorative benefits of escaping academic stressors through interactions with nature. University students also represent an ideal target population for a first implementation of environmental psychometric approaches: they are relatively homogeneous in life stage and routines, yet accessible across a wide range of geographically diverse areas. Moreover, the complexity of their daily environments—typically including home, campus, and commuting spaces—makes them a suitable group for investigating the psychological interplay between subjective and objective environmental factors (Hipp et al., 2016; Si, 2024)

A widely used approach in environmental psychology and epidemiology involves the Normalized Difference Vegetation Index (NDVI), which provides an objective quantification of greenery based on satellite-derived vegetation indices (Engemann et al., 2019; Kriegler et al., 1969, pp. 97–131; Markevych et al., 2017). While NDVI-based methods offer high-resolution, scalable tools to assess green spaces, they may not fully capture other relevant environmental dimensions, such as gray spaces (built-up areas), spatial fragmentation, or subjective perceptions of the environment (Gibson et al., 2022). To enhance interpretability and reduce data complexity, we employed statistical techniques based on satellite image segmentation and latent feature extraction that allow for a multidimensional representation of environmental variability, rather than relying solely on vegetation indices. This approach leverages advanced image preprocessing and clustering techniques to quantify and categorize physical environmental characteristics at a granular level across diverse geographies. Specifically, we utilize the image-specific k-means clustering method, optimized for color images, which partitions image pixels into distinct clusters based on their color values and spatial characteristics. This allows precise identification of various environmental features, from lush green spaces to densely built urban areas.

Our pipeline subsequently merges the obtained satellite imagery data with psychometric data using a dual approach that follows a multiverse analysis logic (Steegen et al., 2016) to assess direct associations and explore complex interactions between environmental and psychological variables. The methodological advance lies in the simultaneous analysis of the effects of multiple environment types (e.g., green spaces, gray spaces) on human psychology and in the application of a multiscale approach to analyze the near-home environment in concentric, progressively far windows (from 75 to 600 m from participants' homes).

We integrate objective satellite-derived environmental data with subjective psychological assessments to investigate how physical features of the near-home environment relate to perceived restorativeness and affective states. While perceived restorativeness was assessed across three contexts – home, university, and natural leisure environments – this design allowed us to verify the context-specific nature of associations between environmental features and restorativeness, ensuring that observed effects for the home environment are not generalized across control settings (i.e., university and natural leisure environments). Affective states (Pleasure, Arousal, Dominance) were measured only for the home environment, allowing us to test whether home-based perceived restorativeness mediates the relationship between objective environmental features and emotional responses.

Based on this framework and previous research, we formulated the following hypotheses.

H1. Objective latent features of the near-home environment will predict perceived restorativeness at home. Furthermore, we expect this prediction to be context-specific: green/gray spaces will be positively/negatively associated with home restorativeness, while the same near-home features will show no associations with perceived restorativeness in control environments (university and natural leisure environments).

H2a. Green spaces and shadows will be positively associated, and gray spaces negatively associated, with perceived restorativeness at home.

H2b. The associations between environmental features and perceived restorativeness at home will be moderated by spatial scale (i.e., the neighborhood buffer radius), such that effects may increase or decrease with distance from the participant's home.

H3. Perceived restorativeness at home will mediate the relationship between objective environmental features and affective states (Pleasure, Arousal, Dominance).

The scalability and replicability of this methodological framework offer a systematic approach for assessing the health-promoting and stress-inducing potential of built and natural environments (De Vries et al., 2003; Hartig et al., 2014). This, in turn, may provide evidence-based insights for urban development and public health initiatives aimed at optimizing the balance between natural and built environments in human-centered urban planning (Gong et al., 2016; Lee et al., 2015; Sineva et al., 2021; White et al., 2013).

2. Methods

2.1. Participants and procedure

The study sample comprised an initial pool of 1386 participants recruited among Italian university students (average age = 22.6 ± 4.5 years; 57% female). Inclusion criteria were to be a university student and aged between 18 and 30 years. This population was chosen for its relative homogeneity in terms of life stage, routines, and exposure to shared campus environments, which enhances internal validity by reducing contextual confounds. Additionally, university students represent a population that is both accessible across a wide and diverse territory and particularly suitable for a first large-scale implementation of the proposed methodology. While this choice may limit generalizability to other populations, it ensures a robust testing ground for modeling perceptual and affective responses to environmental variation.

The participants were enrolled on a voluntary basis among students of the participating institutions (University of Chieti-Pescara and University of Verona) and among students in other cities (Naples, Padova, Brescia, Milan, Trento, Bologna, Vicenza, Modena, Roma, Ferrara, Pavia, Venezia, Ancona, Torino, Udine, Bari, Alessandria, Macerata, Reggio Emilia, Frosinone) that expressed their willingness to cooperate by responding by e-mail. The inclusion of students from a total of twenty-two universities in cities distributed across Italy, with substantial differences in landscape and geology, was considered to increase the generalizability of the findings across the Italian territory and potentially to other Mediterranean and Southern European contexts, given the wide variability in climate, landscape, and urban morphology. The data collection was carried out via online surveys hosted on the LimeSurvey platform. To ensure a high response rate and minimize potential attrition, we engaged students through both virtual and in-person meetings. During these sessions, the students were introduced to the study objectives and completed the surveys on their smartphones, guided and supervised by our research team. These measures helped to maintain participant motivation and ensure the quality of data collection. Participants provided informed consent prior to survey administration, were assured of the anonymous treatment of their responses, and the data were handled after a de-identification procedure. The study was conducted in accordance with the Declaration of Helsinki and received approval from the local Ethical Committee (code 2023_08, approval date December 17, 2024).

For self-reported geographic location, we recorded the home addresses of participants, which represent the primary residence where they spend most of their time during the past two weeks. This information was crucial for retrieving satellite images of the surrounding areas near each participant's home, which we further analyze in the subsequent sections (see section 2.2). To ensure the quality and completeness of our data, we employed a rigorous data acquisition process ensuring that all the responses from each successful participant would be recorded (implying limited missing data). Furthermore, we excluded survey responses that lacked the specification of the home address. This stringent criterion was necessary to maintain the integrity of our environmental analysis and led to a refined sample of 917 participants. The demographic characteristics of the sample are reported in Table 1.

We conducted a priori power assessments combining study-specific simulations and SEM-oriented benchmarks to evaluate sample adequacy for the analyses reported here. Using MATLAB R2023b, we ran 1000-iteration simulations per candidate sample size under a linear regression framework with normally distributed predictors and

Table 1
Characteristics of the sample (total N = 917).

Variable	Values
Age	Median = 21 Mean = 22.3 St. Dev = 3.9 Range = [19 57]
Gender	Females = 525 (57.3%) Males = 390 (42.5%) Non-Binary = 2 (.2%)
Geographic Area	Major city = 24 (2.6%) City = 92(10.0%) Town = 165 (18.0%) Small Town = 244 (26.6%) Hamlet = 356 (38.8%) Isolated dwelling = 36 (4.9%)
Degree Program	Psychology = 373 (40.7%) Education Sciences = 136 (14.8%) Healthcare = 104 (11.3%) Engineering = 66 (7.2%) Social Sciences = 46 (5.0%) Economic Studies = 38 (4.1%) Humanities = 24 (2.6%) Computer Science = 23 (2.5%) Other = 107 (11.7%)

outcomes plus additive noise, targeting small-to-moderate standardized effects ($\beta \approx .20$) and testing the predictor via ordinary least squares at $\alpha = .05$; these simulations indicated that approximately $N \approx 394$ participants would yield 80% power to detect $\beta = .20$. In parallel, given that the core analytic framework includes a latent mediation model estimated via Structural Equation Modeling, we verified that our sample size aligns with commonly cited SEM power benchmarks, whereby detecting standardized path coefficients in the ∼.20–.30 range in a latent mediation model of comparable complexity typically requires ∼400–500 participants to achieve ≥.80 power (Kline, 2015; Wolf et al., 2013). The final sample used in this study comfortably exceeds both thresholds, supporting adequate power for the regression- and SEM-based models presented.

All variables included in the models were checked for normality, homoscedasticity, and linearity of residuals, and no violations of model assumptions were observed. In addition, to ensure interpretability and comparability of effects across variables, all continuous variables were Box-Cox transformed and z-scored prior to modeling. This preprocessing step minimized the influence of distributional artifacts and facilitated the interpretation of model coefficients as standardized effects.

2.2. Environmental data

2.2.1. Environmental data acquisition and preprocessing

Data acquisition and preprocessing steps were implemented using MATLAB (The MathWorks, Inc.). First, one satellite image was acquired for each participant. All satellite images were acquired by the same researcher, using the same screen resolution (1920 x 1080) and a standardized procedure for consistency. Each image was acquired using a screenshot after centering Google Earth on the participant's home coordinates. To standardize the images before the analysis, each image was cropped to a fixed size of 400 × 400 pixels, corresponding to approximately 600 × 600 m, around the center (i.e., the participant's home). The cropping process involved calculating the center coordinates of each image and extracting a square region around this center. The selected spatial buffer was designed to represent the immediate visual and experiential environment around each participant's residence. This choice reflects both perceptual proximity and environmental psychology frameworks, suggesting that nearby green coverage exerts the strongest influence on restorativeness and well-being (Konijnendijk, 2021). Objective environmental features were not extracted for university/natural locations because these outcomes were not intended as primary geo-behavior links, but as specificity checks.

The optimal number of clusters for the k-means image clustering was a critical decision influenced by the need for a balance between model simplicity and the granularity of environmental segmentation. Initially, we evaluated a range of potential clusters, specifically from 2 to 12, assessing each model's performance using the Bayesian Information Criterion (BIC) and Dunn's index. BIC is derived from the likelihood function and is designed to avoid overfitting by incorporating a penalty term for the number of parameters in the model. This characteristic makes BIC a robust choice for determining the number of clusters, as it can effectively discern between models that may fit the data well but are overly complex (Kryszczuk & Hurley, 2010; Schwarz, 1978). Dunn's index, on the other hand, measures the compactness and separation of clusters being defined as the ratio of the minimum inter-cluster distance to the maximum intra-cluster distance, so that higher values indicate well-separated and compact clusters (Dunn, 1974; Maududie & Wibowo, 2019). These indices are particularly effective in determining the clustering structure that best captures inherent groupings in the data without succumbing to overfitting. After a thorough evaluation, the k value of 4 was selected. This choice offers a reasonable number of clusters that are both compact and well-separated while also maintaining a model simplicity. This approach is coherent with guidelines and recommendations (Sugar & James, 2003) emphasizing the importance of ensuring the analytical robustness necessary for k-means clustering.

2.2.2. Environmental data clustering

The primary analytical technique used in our study was the image-specific k-means clustering, implemented via MATLAB's *imsegkmeans* function. This method is particularly suited for image data, as it efficiently handles multi-dimensional data and is optimized for color images. The distance metric for the clustering was set to Euclidean distance, and the number of replicates was set to 1000 to avoid suboptimal solutions. The segmentation process was enhanced by converting the RGB images to the YIQ color space prior to the clustering, which separates luminance from color information, making it more suitable for processing color variations (Szeliski, 2010). The *imsegkmeans* algorithm's strength lies in its ability to integrate color and texture features seamlessly while maintaining spatial integrity, making it ideal for environmental studies where such characteristics are crucial. Two alternative clustering procedures were applied (a spatially enhanced clustering incorporating texture features obtained from Gabor filtering alongside color information and an alternative color coding using the CIELAB color space), but the resulting image segmentations that did not efficiently capture color variations and were consequently disregarded.

After clustering, the "Neighborhood size" was modulated between 50 and 400 pixels with increments of 50 pixels ($P = [50\ 100\ 150\ 200\ 250\ 300\ 350\ 400]$), whereas 50 pixels covered approximately 75 m (real sizes covered by the Neighborhood sizes indicated by the parameter P, in meters: [75 150 225 300 375 450 525 600]), always centered on the participant's home address. This modulation allowed us to investigate concurrently both the *immediate* near-home and *far* near-home environment and ensured consistency across analyses in the same cycle. To note, although participants lived in urban and rural areas, the 'near-home environment' refers to micro-scale exposures within daily walking distance, which have been shown to affect mood and attention restoration independently of macro-scale urbanicity (e.g., Gidlow et al., 2016; Roe et al., 2013). Each resulting image was analyzed to calculate the percentage coverage of each cluster, which represents different environmental characteristics. These measurements were normalized and transformed for statistical analysis using a Box-Cox transformation followed by z-score normalization. Finally, satellite image data were integrated with psychometric measurements (see below).

2.3. Psychological measures

Psychological constructs were assessed with validated scales targeting two domains: (a) perceived restorativeness and (b) affective experiences (pleasure, arousal, dominance). Demographic details such as age, gender, occupation, and the type of university degree were collected.

2.3.1. Perceived restorativeness

Restorativeness at university and in natural leisure environments was assessed as negative-control outcomes to test whether objective near-home features predict perceived restorativeness only in the home context.

For natural setting during leisure time, we used the Perceived Restorativeness Scale – 11-item version (PRS-11; Pasini et al., 2014), a widely validated and cross-culturally adopted instrument. It includes 11 items assessing four core dimensions of environmental restorativeness: fascination (3 items), being-away (3 items), coherence (3 items), and scope (2 items). Participants were instructed: "*Thinking about the natural environment where you spent most of your free time over the past week, carefully read each of the following statements and then rate, on a scale from 0 (not at all) to 10 (very much), how much each statement matches your experience in that place.*" An example item is: *"Places like these are a refuge from the demands of everyday life*".

For university environments, we adopted the Rest@U scale (Menardo et al., 2024), which retains the same four dimensions with a slightly rebalanced item structure (3 items per dimension, except for coherence with 4 items) and was specifically developed to assess restorativeness in educational contexts. Instructions for participants were as follows: "*Thinking about the university setting you attended most over the past week, carefully read each of the following statements and then rate, on a scale from 0 to 10, how much each statement matches your experience in that place*". An example item is: "*This place is structured so that if I need to, I can stay focused, or if I want, I can let my mind wander, for example by looking out of the window*".

To evaluate the home environment, we adapted the Rest@U scale to this context, rewording each item to explicitly refer to participants' homes. The corresponding instructions read: "*Thinking about your home, carefully read each of the following statements and then rate, on a scale from 0 to 10, how much each statement matches your experience in that place.*" An example item is: *"The place where I live is also designed to allow you to take a short break to think or do something enjoyable"*.

Restorativeness scales demonstrated satisfactory internal consistency, with Cronbach's alpha and McDonald's omega coefficients reported below (95% confidence intervals in brackets): restorativeness in the home environment: $\alpha = .828$ [.814, .841] and $\omega = .828$ [.814, .841]; restorativeness in the university environment $\alpha = .892$ [.883, .900] $\omega = .896$ [.888, .905]; restorativeness in natural environments: $\alpha = .914$ [.907, .920] and $\omega = .919$ [.913, .926].

2.3.2. Affective experiences

Affective states were assessed with the Pleasure–Arousal–Dominance (PAD) scale (Bakker et al., 2014; Mehrabian & Russell, 1974). The PAD model distinguishes three dimensions: Pleasure, the degree of positive affect experienced; Arousal, the level of physical and mental activation; and Dominance, perceived control over the situation or one's feelings. The scale includes 12 items (4 per dimension) presented as semantic differentials on a 10-point scale (1 = left adjective, 10 = right adjective). Instructions were the following: "*Please read the following list of word pairs and, for each pair, choose where you would place yourself based on how you have felt over the past week in the place where you live.* An example item is "Sad – Happy", where 1 corresponds to Sad and 10 to Happy. Each instrument was scored following the established procedures outlined in the foundational research papers for these tools. Descriptive statistics for restorativeness and affective experiences scales are reported in Table 2.

PAD scales also demonstrated satisfactory internal consistency: Pleasure at home: $\alpha = .868$ [.857, .878] and $\omega = .873$ [.863, .883]; Arousal at home: $\alpha = .676$ [.646, .705] and $\omega = .693$ [.696, .721]; Dominance at home: $\alpha = .699$ [.671, .726] and $\omega = .709$ [.682, .735].

Table 2
Descriptive statistics for perceived restorativeness and affective experiences across environmental contexts.

Questionnaire	Scale	Median	Mean	SD	Min	Max
Home - Restorativeness	Coherence	7.08	6.96	1.54	1.83	10
	Fascination	5.75	5.64	1.89	0	10
	Being-Away	6.75	6.57	1.65	.5	10
	Scope	6	6.06	1.88	.33	10
Home - Affective experiences	Pleasure	6.25	6.22	2.01	.75	9.75
	Arousal	5	5.07	1.69	.5	9.5
	Dominance	6.38	6.22	1.73	.5	9.25
University - Restorativeness	Coherence	6.5	6.29	1.86	0	10
	Fascination	4.67	4.76	2.54	0	10
	Being-Away	5.33	5.21	2.32	0	10
	Scope	5.67	5.55	2.17	0	10
Nature - Restorativeness	Coherence	6.33	6.4	1.95	0	10
	Fascination	6.67	6.41	2.25	0	10
	Being-Away	7	6.46	2.62	0	10
	Scope	7.5	6.94	2.22	0	10

2.4. Data analysis

To test H1 and H2a/b, we employed two primary analytical methods: Simple Linear Regression (SLR) and mixed effects modeling (N = 917). Primary analyses tested associations with home restorativeness; the same models were then repeated using university and nature restorativeness as negative-control outcomes (expected to be null) to evaluate specificity. The combined use of simple and multilevel regression techniques enriches our understanding, providing a dual perspective on the data that leverages both direct and integrated effects, and avoiding the problem of multicollinearity (Belsley et al., 1980).

SLR was applied to assess direct associations between each geographic variable and restorativeness. The dependent variables were the psychometric scores (i.e., Coherence, Fascination, Being-Away, and Scope) in the three environments (home, university, nature), while the independent variables were the proportions of environmental features (e.g., percentage of green space). This approach allowed for a straightforward interpretation of how single environmental features might influence psychological metrics. Standardized beta coefficients were estimated for each predictor, along with their corresponding p-values, indicating the strength of the relationships and their statistical significance, respectively. To account for multiple comparisons, *p*-values were adjusted using both the False Discovery Rate (FDR) and Bonferroni correction (Benjamini & Hochberg, 1995, pp. 289–300).

Regression analyses were stratified using concentric segmentation of satellite images around participants' homes, with the radius ranging from 75 to 600 m, as shown in Fig. 2. This approach allowed us to assess the scale-dependent effects of environmental features on psychometric variables by varying the neighborhood size. For each neighborhood scale, proportions of environmental features (e.g., green spaces, gray spaces, shadows, roofs) were computed, and statistically significant relationships with psychometric scores (perceived restorativeness) were identified. Mixed-effects modeling was employed to explore these relationships, specifying psychometric scores as dependent variables and including environmental feature proportions, neighborhood size, and their interaction terms as predictors. Participants were included as random groupings. Effect sizes were extracted to assess shifts in the strength of associations as the neighborhood size increased. This multiscale approach enables a detailed understanding of how one's environmental context influences psychometric outcomes of restorativeness.

To assess H3, we implemented a series of mediation models testing perceived restorativeness as a mediator between environmental features and affective responses (PAD). Specifically, the percentage of gray space around the home was included as the predictor, the three PAD dimensions (Pleasure, Arousal, Dominance) as outcome variables, and perceived restorativeness as a potential mediator.

In a first step, we tested a comprehensive multiple-mediator path model including the four restorativeness subdimensions (Coherence, Scope, Fascination, and Being-Away) as parallel, non-latent mediators. While this model yielded several significant indirect effects, overall fit indices were unsatisfactory, likely due to the high intercorrelation among the subscales and the rigidity of the model structure. To address these issues, we adopted a twofold analytic strategy. First, we specified a measurement model in which Restorativeness was modeled as a single latent factor reflecting the shared variance across its four theoretically grounded subdimensions. This latent construct was then used as a unified mediator in a new Structural Equation Model (SEM), which showed improved and acceptable fit indices. Second, to disambiguate the contribution of each subdimension, we estimated a set of four separate mediation models, each including one restorativeness subscale as a single latent mediator. These simpler models allowed us to examine the specific indirect effects of Scope, Fascination, Being-Away, and Coherence independently, without the confounding influence of shared variance among mediators. Note that fit indices are only reported for the full and latent-factor models. The four single-mediator models were just-identified, resulting in perfect fit (perfect fit, zero error; Kline, 2015; MacCallum & Austin, 2000); therefore, their fit indices are not informative and are not reported. The model was implemented as a path analysis given the absence of latent measurement models in the current implementation. All models were estimated using the JASP software using R package *lavaan* with maximum likelihood estimation and robust standard errors. Fit indices, standardized path coefficients, and indirect effects (with confidence intervals) were reported to assess model adequacy and mediation significance.

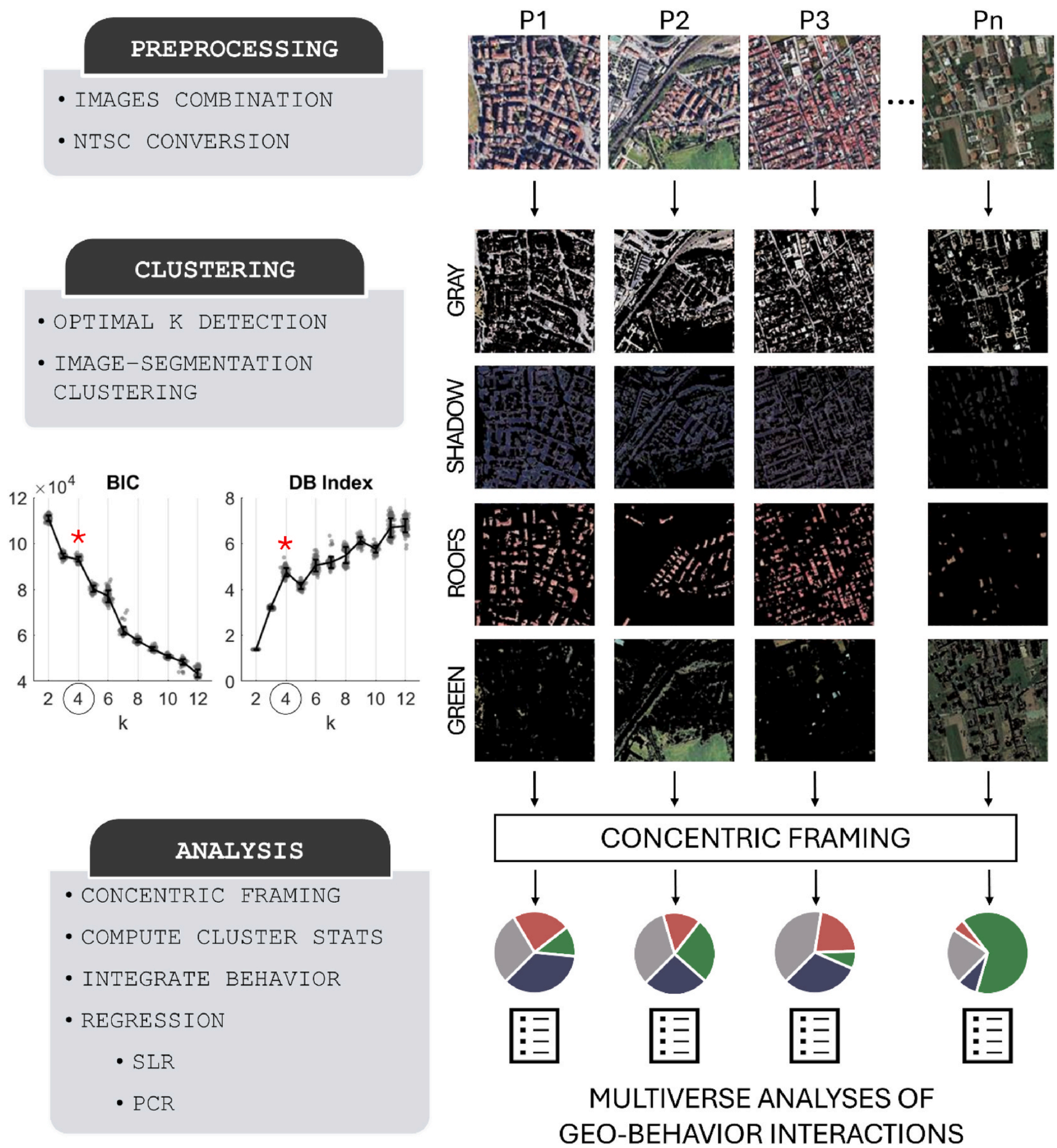

Fig. 1. Overview of the experimental procedure and cluster topographies. The figure illustrates the workflow for satellite image preprocessing, clustering, and analysis. Images were converted to the YIQ color space and segmented using k-means clustering with $k = 4$ clusters, determined as optimal through Bayesian Information Criterion (BIC) and Dunn's Index. Example cluster masks for gray spaces, shadows, roofs, and green spaces are shown for four participants. Concentric framing was applied to quantify cluster proportions across distances (75–600 m), enabling multiverse analyses of geo-behavior interactions. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

3. Results

3.1. Cluster results and topographies

Fig. 1 provides an overview of the experimental procedure, highlighting the preprocessing steps and the clustering process, where four distinct environmental clusters were identified: gray spaces (e.g., roads, urban infrastructure), urban shadows, roofs, and green spaces. Cluster masks generated for each participant in Fig. 1 visually demonstrate the segmentation across individuals, showcasing consistency in the content of each cluster and variability in cluster proportions. The concentric framing approach, illustrated for a sample participant in Fig. 2, enabled the quantification of cluster proportions across progressively larger neighborhood sizes, ranging from 75 to 600 m from participants' home coordinates.

Fig. 3 displays the distribution of cluster proportions across concentric frames. Clusters related to urbanization (gray spaces, urban shadows, roofs) exhibit a consistent presence across all neighborhood sizes, with slight variations in density at increasing radii. Green spaces, on the other hand, show slightly more variability, with an increase in coverage at larger radii, reflecting the expected transition from urban cores to more peripheral areas. Shadows and roofs demonstrate more localized patterns, primarily concentrated within smaller radii. These distributions underscore the heterogeneity of near-home environments and the importance of scale in environmental analysis.

In summary, the clustering and framing procedures provided a robust and scalable methodology for quantifying environmental features. The results reveal distinct patterns in cluster distributions across participants and neighborhood sizes, setting the stage for further analysis of their associations with psychometric outcomes.

3.2. Environment-behavior associations

We examined the associations between the proportion of environmental clusters related to the students' residence (green, roofs, shadow, and gray) and the four dimensions of perceived restorativeness of their home setting (Fascination, Being-Away, Scope, and Coherence). In line with our hypothesis, we conducted specificity checks/negative-control analyses on perceived restorativeness of university and natural leisure settings. Regression models were performed separately for each restorativeness dimension, cluster type, and neighborhood size (ranging from 75 to 600 m).

The simple linear regression models revealed significant effects of near-home environmental clusters on restorativeness measures primarily in the Home setting. Fig. 4 summarizes these findings, with positive effects indicated in red and negative effects in blue. Green spaces consistently showed positive associations with all four restorativeness subscales at Home. Conversely, gray spaces were negatively associated with restorativeness dimensions, with the strongest effects observed for Fascination and Scope. The effects of roofs and shadows varied, but their overall contribution was less pronounced compared to green and gray spaces. In the university and nature settings, no consistent patterns emerged across neighborhood sizes, with only sporadic significant associations. This reinforces the context-specific nature of environmental influences on restorativeness, particularly in near-home environments (H1).

Second-order models incorporating interaction terms between cluster proportions and neighborhood size (cluster × neighborhood) identified two significant interactions in the Home setting. Firstly, with respect to Fascination, gray spaces showed a significant interaction with neighborhood size ($\beta = -1.78e\text{-}4$, $p = .008$), indicating that the negative effect of gray space on Fascination further decreased with increasing neighborhood size (i.e., distance from participants' house; Fig. 4, top-left panel). Secondly, with relation to Scope a similar interaction was

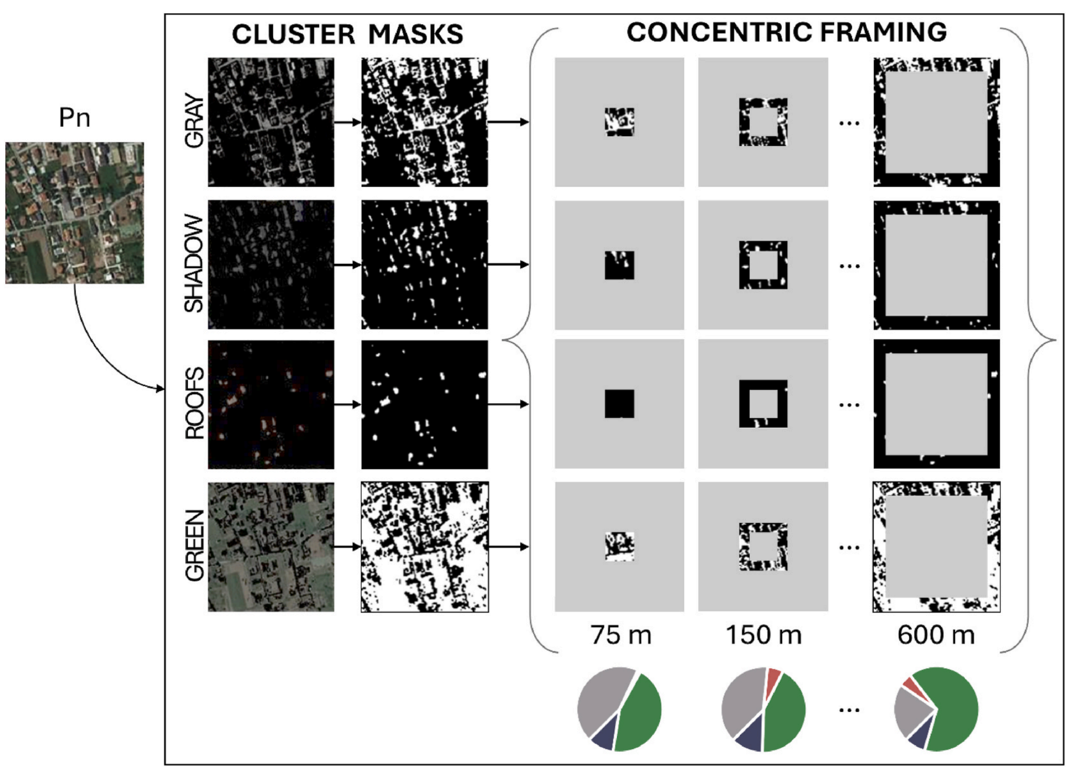

Fig. 2. Concentric framing and cluster masks. The figure illustrates the process of concentric framing applied to satellite images to extract cluster proportions. Cluster masks for gray spaces, shadows, roofs, and green spaces are shown for an example participant. Concentric frames were applied at progressively larger radii (75–600 m) around the participant's home to capture the spatial distribution of environmental features. This approach enabled a multi-scale analysis of environmental influences on restorativeness. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

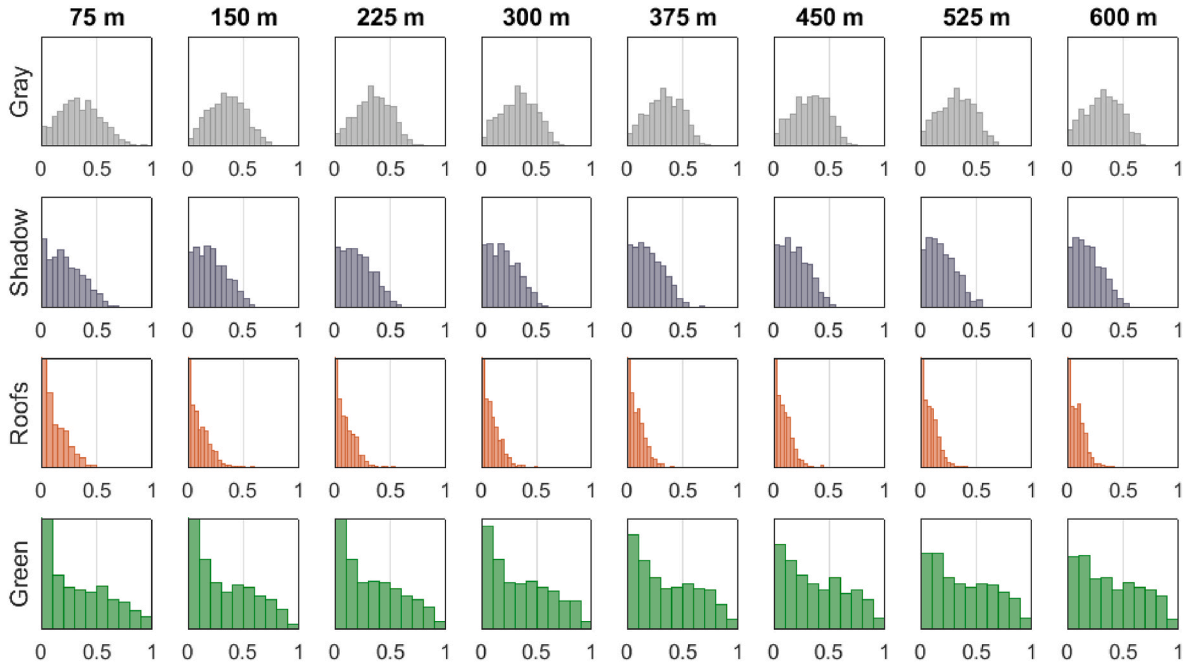

Fig. 3. Distributions of cluster proportions across concentric framings. The figure presents the distributions of proportions for each environmental cluster (Grays, Shadow, Roofs, Green) across progressively larger concentric ranges (75–600 m) around participants' homes. Each row corresponds to a specific cluster, and each column represents a concentric range. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

observed for gray spaces (β = −1.91e-4, p = .003), where the detrimental effect on Scope further decreased at larger neighborhood sizes (Fig. 4, middle-left panel). While these effect sizes might seem small at first glance, they are meaningful in practical terms. Specifically, these interactions describe how the environmental impact changes with each additional 1 m of neighborhood size. For instance, the interaction effect on Fascination (β = −1.78e-4) means that, moving from 75 to 600 m from the participants' house, the predicted negative effect of gray spaces increases by .093 units (more than doubles). This change represents a substantial portion of the overall effect. Significant interactions are highlighted with thick rectangular borders in Fig. 4 and suggest a scale-dependent relationship between gray spaces and perceived restorativeness, where proximity intensifies the negative impact of urbanized environments.

These results emphasize the predominant role of near-home environments in shaping perceptions of restorativeness. Green spaces positively influence all restorativeness dimensions at Home (H2a), whereas gray spaces exert stronger detrimental effects that are moderated by distance (H2b). These findings underline the importance of spatial scale in evaluating environment-behavior associations and support the integration of neighborhood size in future environmental psychology research.

3.3. *Structural equation modeling results*

To test the hypothesis H3, we first estimated a structural equation model (SEM). The model in which *Restorativeness* was specified as a latent construct (indicated by *Scope*, *Fascination*, *Being-Away*, and *Coherence*) showed acceptable fit based on conventional thresholds, with a Comparative Fit Index (CFI) of .924, a chi-squared (X^2) of 187.9 (df = 14), a Root Mean Square Error of Approximation (RMSEA) of .116 (90% upper and lower bounds: [.102, .131]), and a Standardized Root Mean Square Residual (SRMR) of .061. Although the RMSEA value was relatively high (≈.11), this should not be interpreted as clear evidence of poor model fit because RMSEA is known to be overly sensitive in models with low degrees of freedom, as in this case, often producing inflated values even when the model is correctly specified (Kenny et al., 2015).

The latent variable Restorativeness was significantly defined by all four indicators. Standardized factor loadings were high for Scope (.771), Fascination (.786), and Being-Away (.676), while the loading for Coherence was lower (.435) but still meaningful, suggesting that the first three dimensions contributed more strongly to the common restorativeness factor. The model accounted for substantial variance in the affective outcomes: the R-squared was .259 for Pleasure, .131 for Arousal, and .134 for Dominance.

Regarding the structural paths, the percentage of gray space was negatively associated with Restorativeness (β = −.238, p < .001), indicating that higher exposure to gray space predicted lower levels of perceived psychological restoration at home. In turn, Restorativeness was positively associated with all three affective dimensions: Pleasure (β = .521, p < .001), Arousal (β = .373, p < .001), and Dominance (β = .371, p < .001). Direct effects of gray space on affective outcomes were also observed and reached significance for all three PAD dimensions but were most pronounced for Dominance (β = .151, p < .001), while were lower for Pleasure (β = .065, p = .034) and Arousal (β = .080, p = .020). Importantly, all indirect effects of gray space on affective responses through Restorativeness were statistically significant and negative. Specifically, the indirect effect on Pleasure was β = −.124 (p < .001), on Arousal was β = −.089 (p < .001), and on Dominance was β = −.088 (p < .001). These findings support the hypothesis that Restorativeness functions as a key mediating mechanism through which environmental exposure to gray space influences affective experience.

To further disentangle the specific contributions of each restorativeness subdimension, we estimated four separate simple mediation models, each including one subdimension as a single latent mediator of the relationship between gray space and affective outcomes. Results showed that Being-Away, Fascination, and Scope all significantly mediated the effects of gray space on the three PAD dimensions. For Being-Away, gray space negatively predicted the mediator (β = −.197, p < .001), which in turn was positively associated with Pleasure (β = .309, p < .001), Arousal (β = .228, p < .001), and Dominance (β = .281, p < .001). The indirect effects were all significant, with β = −.047 (p < .001) for Pleasure, β = −.035 (p < .001) for Arousal, and β = −.043 (p < .001) for Dominance. The pattern was similar for Fascination, which was

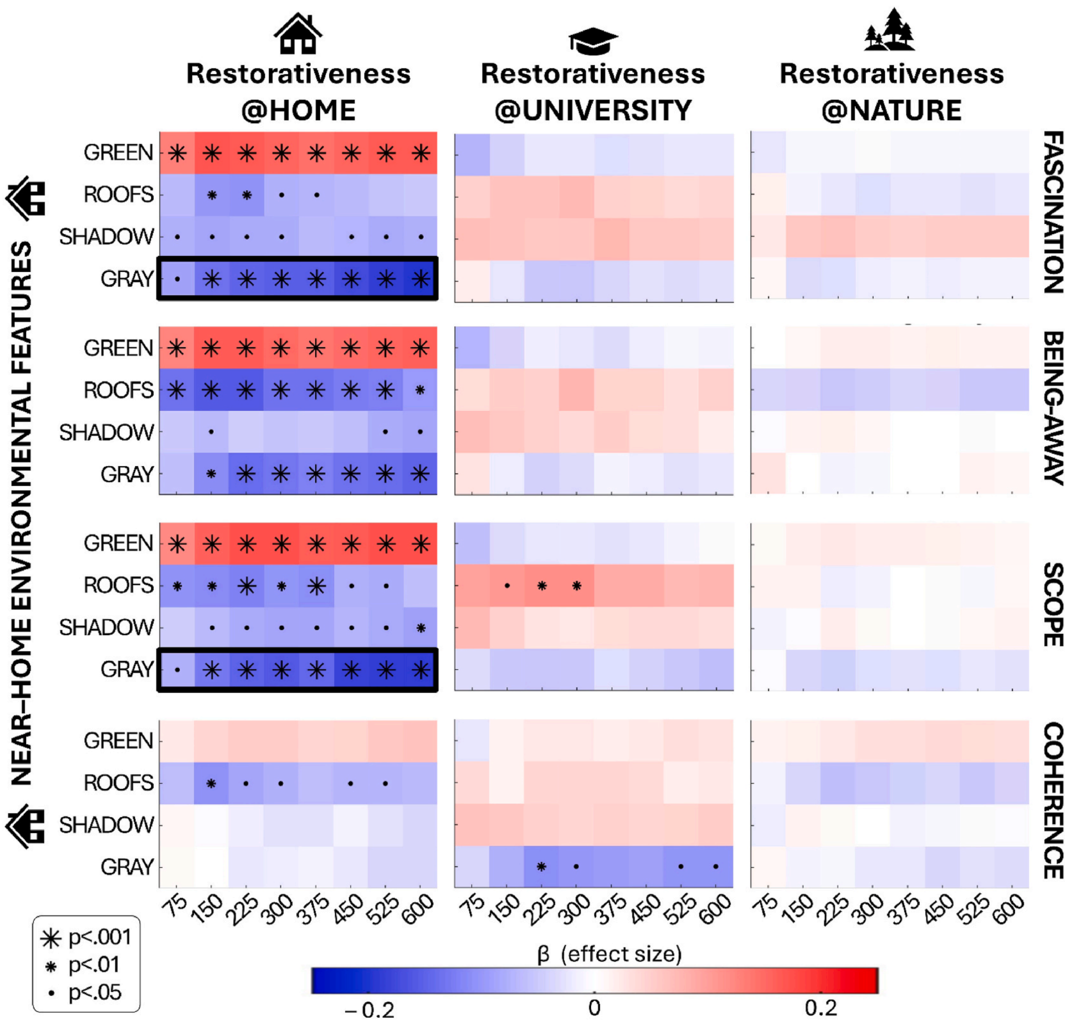

Fig. 4. Results from simple linear regressions and mixed-effect models. The heatmaps illustrate the associations between near-home cluster proportions, calculated around participants' home environment (Green, Roofs, Shadow, Gray), and restorativeness dimensions (Fascination, Being-Away, Scope, Coherence) across different settings (Home, University, Nature) and neighborhood sizes (75–600 m). University and Nature panels represent negative-control outcomes to test context-specificity (expected null associations). Red indicates positive effects, while blue indicates negative effects, with significance levels marked by symbols (small circle: $p < .05$; small asterisk: $p < .01$; large asterisk: $p < .001$). Significant interaction effects (cluster × neighborhood) are highlighted by thick rectangular borders, observed for Gray spaces influencing Fascination and Scope at Home. The figure underscores the context- and scale-dependent nature of environment-behavior associations. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

negatively associated with gray space ($\beta = -.198$, $p < .001$) and significantly predicted all three affective dimensions. The indirect effects were again significant: $\beta = -.073$ ($p < .001$) for Pleasure, $\beta = -.055$ ($p < .001$) for Arousal, and $\beta = -.042$ ($p < .001$) for Dominance. Scope also functioned as a significant mediator, with an effect of gray space on the mediator ($\beta = -.197$, $p < .001$), followed by strong

Table 3
Standardized regression coefficients (β) and p-values for each path in the mediation models: from gray space to the mediator (X → M), from gray space to the outcome (X → Y), from the mediator to the outcome (M → Y), and the computed indirect effect (X → M → Y).

X	M	Y	X → M		X → Y		M → Y		X → M → Y	
			β	p	β	p	β	p	β	p
Gray	B-A	Pleasure	−.197	<.001	−.012	.70	.309	<.001	−.047	<.001
		Arousal			.025	.43	.228	<.001	−.035	<.001
		Dominance			.105	<.001	.281	<.001	−.043	<.001
Gray	COH	Pleasure	−.037	.26	−.043	.15	.429	<.001	−.016	.26
		Arousal			.002	.94	.309	<.001	−.012	.26
		Dominance			.078	<.001	.403	<.001	−.015	.26
Gray	FAS	Pleasure	−.198	<.001	.014	.65	.369	<.001	−.073	<.001
		Arousal			.046	.16	.276	<.001	−.055	<.001
		Dominance			.105	<.001	.212	<.001	−.042	<.001
Gray	SCO	Pleasure	−.197	<.001	.017	.58	.388	<.001	−.076	<.001
		Arousal			.042	.20	.259	<.001	−.051	<.001
		Dominance			.114	<.001	.262	<.001	−.052	<.001

associations with Pleasure (β = .388, p < .001), Arousal (β = .259, p < .001), and Dominance (β = .262, p < .001). The indirect effects for Scope were β = −.076 (p < .001), β = −.051 (p < .001), and β = −.052 (p < .001), respectively. In contrast, the Coherence subdimension did not emerge as a significant mediator. Its association with gray space was not significant (β = −.037, p = .26), and although it was positively associated with affective outcomes (e.g., β = .429, p < .001 for Pleasure), the indirect effects were not statistically significant (all p-values >.25).

These results are schematized in Table 3. The SEM and mediation models are represented in Fig. 5. The conceptual model elaborated from these results is illustrated in Fig. 6.

4. Discussion

The findings of this study offer novel insights into the complex relationship between the physical environment and psychological experiences. Notably, we explore a critical aspect that is often overlooked in the literature: in studies analyzing green spaces and their positive effects on psychological restoration (Bratman et al., 2015; Hartig et al., 2014; Kaplan & Kaplan, 1989), the potentially negative impacts of gray spaces remain underexplored (Evans et al., 2002, pp. P381–P383; Ming & Fu, 2019). In the following paragraphs, we discuss the main results in relation to the three hypotheses tested.

4.1. Distinct effect of near-home environments on restorativeness

Consistent with H1, we found that the latent near-home environmental dimensions extracted from satellite data significantly predicted perceived restorativeness at home, with important differences in how these clusters influenced specific dimensions of restorativeness (Fascination, Being-Away, Scope, Coherence).

Our findings generally supported H2a, with gray spaces emerging consistently as the strongest negative predictor of restorativeness across the dimensions of *Fascination*, *Being-Away*, and *Scope*. Interestingly, these negative effects varied by distance. H2b was also partially supported, with a distance-dependent effect found only for gray spaces, but not for green spaces. Specifically, the detrimental effects of gray spaces on Fascination and Scope were most pronounced at intermediate distances (300–600 m).

This pattern suggests that urban density and infrastructure in the near-home environment reduce the availability of stimuli that naturally and involuntarily draw attention (Fascination), while also limiting the perceived openness and potential for exploration (Scope). These results align with findings that urban environments often evoke stress and reduce cognitive restoration (Malekinezhad et al., 2020; Ming & Fu, 2019). Additionally, higher proportions of gray spaces in proximity to the home environment diminished participants' ability to mentally disconnect from their surroundings (Being-Away). This might reflect a

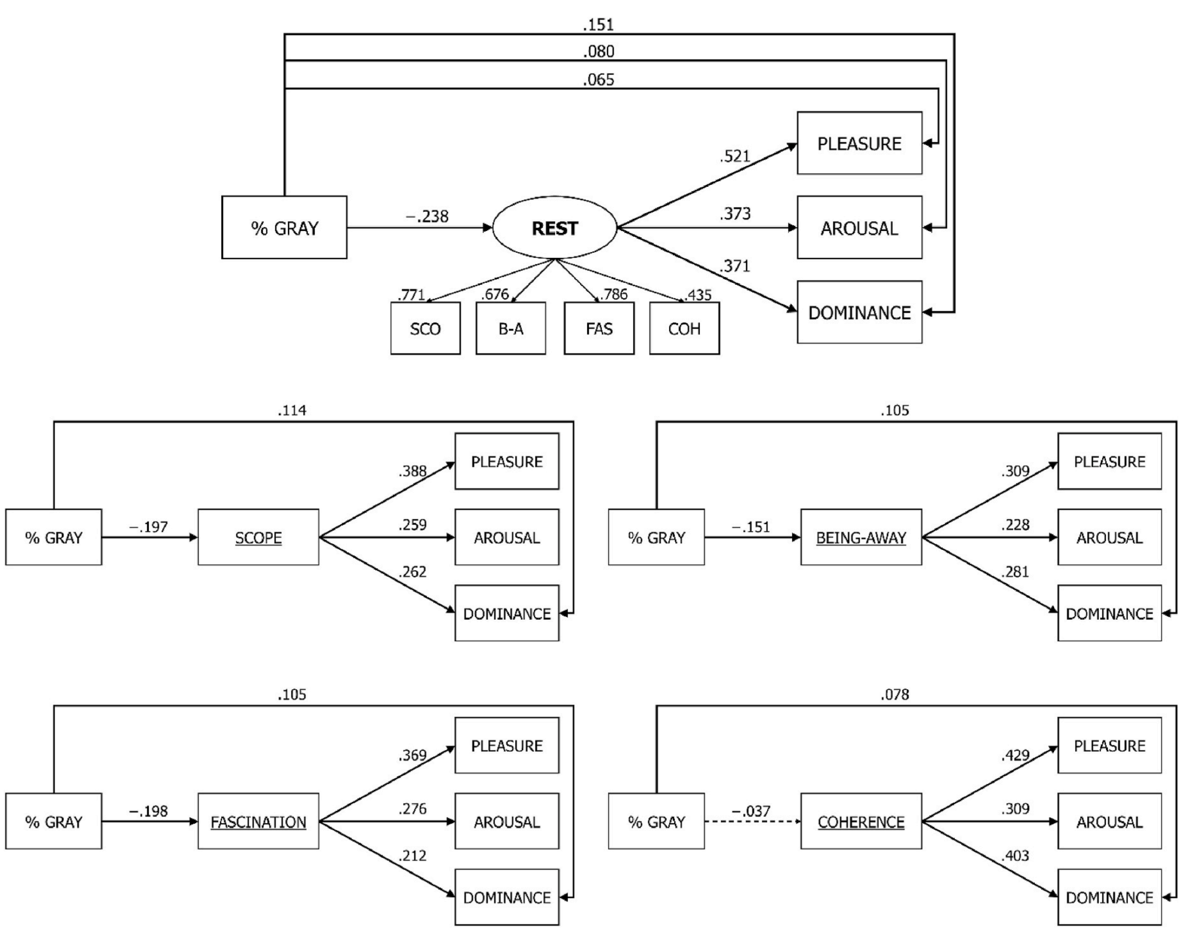

Fig. 5. Structural equation model (top) and specific mediation models (bottom) linking gray space exposure, perceived restorativeness, and affective outcomes. The top panel depicts the global SEM in which Restorativeness is modeled as a latent construct defined by four subdimensions: Scope (SCO), Being-Away (B-A), Fascination (FAS), and Coherence (COH). Restorativeness significantly mediates the effect of gray space (% GRAY) on all three affective dimensions from the PAD model: Pleasure, Arousal, and Dominance. Standardized path coefficients are reported.
The bottom panel presents four separate simple mediation models, each with a single subdimension of restorativeness as a mediator. Significant pathways are represented with solid arrows; non-significant paths are shown as dashed lines. Coherence did not significantly mediate the relationship between gray space and affective outcomes.

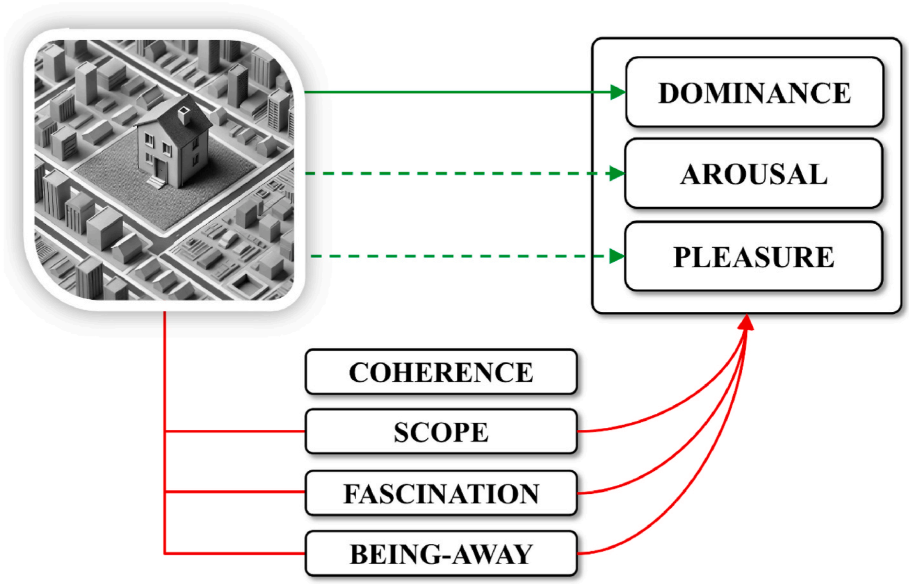

Fig. 6. Conceptual model summarizing the effects of gray space exposure on affective experience, based on structural equation modeling results. The model illustrates the direct and indirect pathways linking the percentage of gray space near the home (left) to affective outcomes—Pleasure, Arousal, and Dominance (right)—as mediated by the four subdimensions of perceived restorativeness: Coherence, Scope, Fascination, and Being Away (bottom center).
Solid red paths represent significant predictive effects from gray space to restorativeness subdimensions (except for Coherence, which was not significantly predicted). Curved red arrows indicate significant mediation effects from Scope, Fascination, and Being Away to all three PAD dimensions, while Coherence did not significantly mediate any outcome. Green arrows represent direct effects of gray space on affective outcomes. The solid green arrow (Dominance) indicates a robust and consistent direct effect across models, while dashed green arrows (Arousal, Pleasure) represent smaller direct effects that were significant only in the full SEM but not in single-mediator models. This structure highlights the multidimensional and partially mediated nature of the relationship between environmental features and emotional experience. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

psychological tendency to reinterpret familiar environments more positively to preserve a sense of place identity, while distant spaces are appraised with less emotional filtering.

Green spaces consistently showed positive associations, but slightly weaker than gray spaces, with *Fascination*, *Being-Away*, and *Scope* across all spatial scales, from 75 to 600 m. This suggests that natural environments near home contribute broadly to these dimensions of restorativeness, regardless of proximity. Green spaces may capture attention effortlessly, offering visually stimulating and dynamic environments (*Fascination*) that promote psychological engagement. This aligns with Kaplan's Attention Restoration Theory (Kaplan & Kaplan, 1989), emphasizing the role of nature in reducing mental fatigue (Kaplan & Berman, 2010; Sun et al., 2022). Furthermore, the presence of green spaces may help to mentally "escape" from daily stressors (*Being-Away*) by providing a sense of separation from academic pressures (Holt et al., 2019; Ribeiro, 2024), and to enhance perceptions of environmental openness and possibility of exploration (*Scope*). These findings reinforce the restorative potential of green spaces, highlighting their ability to shape how individuals perceive and experience multiple dimensions of restorativeness.

Roofs and shadows exhibited weaker but still noteworthy associations with restorativeness dimensions. Although not directly visible to individuals, roofs may act as indicators of urban density and built environments. Their most substantial associations were observed with *Scope*, where higher roof coverage reduced perceptions of openness. This suggests that building density indirectly constrains the restorative potential of the surrounding space. On the other hand, the effects of shadows were more subtle. Shadows may represent obstructive urban features (e.g., buildings blocking sunlight), but also beneficial natural elements (e.g., shaded areas in parks). These competing influences likely account for the weaker associations with restorativeness scales.

It is worth noting that, unlike other restorativeness dimensions, *Coherence* (i.e., the perception of environmental order and structure) showed minimal associations with most environmental clusters. The only notable relationship was an unstable negative association with roofs, suggesting that densely packed built environments may reduce perceptions of visual order. However, this dimension appears less sensitive to environmental variability overall, indicating that it may be influenced by broader contextual or personal factors.

The observed associations were mostly specific to the near-home environment's influence on perceived restorativeness at home (PRS at Home). Nevertheless, we found that roofs within 150–300 m near home covaried positively with PRS *Scope* in the university context. Conversely, gray spaces within 525–600 m near home were associated with less PRS *Coherence* at the university (see Fig. 4). In contrast, no significant associations emerged between near-home environmental features and restorativeness perceived during leisure in nature. These isolated significant effects were not consistent across buffers/dimensions and are interpreted as non-robust under extensive multiverse testing; overall, control outcomes supported specificity.

The overall pattern of findings clearly distinguishes the contributions of the four environmental clusters: Gray spaces exhibit strong negative effects, particularly on *Fascination*, *Being-Away*, and *Scope*, with variations in these effects depending on proximity; Green spaces consistently enhance restorativeness across multiple dimensions and spatial scales, underscoring their restorative potential in near-home environments; Roofs and Shadows play more subtle roles, acting as proxies for urban density and environmental structure, with limited but meaningful influences on specific dimensions. These results emphasize the importance of analyzing environmental features comprehensively, including the negative impact of certain elements, rather than focusing exclusively on green spaces.

4.2. *Direct and indirect effects of gray spaces on affective experiences*

Our primary SEM model, in which Restorativeness was modeled as a latent construct composed of four subdimensions, revealed significant indirect effects on Pleasure, Arousal, and Dominance, suggesting that gray space negatively influences affective well-being via reduced opportunities for psychological restoration at home. Four separate mediation models, each considering one restorativeness subdimension in isolation, revealed that Being-Away, Fascination, and Scope significantly mediated the relationship between gray space and all three PAD dimensions, whereas Coherence did not function as a significant mediator.

The pattern of indirect effects across these models revealed a consistent and differentiated structure. Among the four subdimensions, the indirect effects of gray space on Pleasure, Arousal, and Dominance through Scope and Fascination were the largest in magnitude, indicating that reductions in perceived environmental vastness and (passive) sensory stimulation are a particularly impactful pathway through which gray space exposure undermines affective well-being. The subdimension *Being-Away* yielded slightly smaller but still significant indirect effects, pointing to the importance of psychological distancing and mental escape in buffering the emotional toll of dense built environments. By contrast, although *Coherence* was positively associated with Pleasure, Arousal, and Dominance, its path from gray space was not significant, and all indirect effects were small and non-significant, suggesting that perceptions of environmental legibility or order are not substantially influenced by urban form in this context.

These findings partially support H3 and refine and extend prior research on the psychological costs of built environments. While earlier studies have shown that urban density and lack of natural elements reduce cognitive restoration and elevate stress (Malekinezhad et al., 2020; Ming & Fu, 2019), our results pinpoint *which* psychological mechanisms are most affected. The strongest indirect effects were observed through *Scope*, suggesting that spatial restriction and perceptual enclosure may represent key environmental constraints on affective vitality. This complements existing work showing that limited spatial openness impairs mental restoration (Roe & Aspinall, 2011) and may induce chronic strain (Evans et al., 2002, pp. P381–P383). The mediation pathway through Fascination suggests that gray spaces fail to provide the kind of involuntary attention and sensory richness needed to evoke positive arousal and pleasure (Gidlöf-Gunnarsson & Öhrström, 2007). Our findings further align with theories of restorative environments (Kaplan, 1995) by confirming that monotonous or visually impoverished settings reduce the environment's capacity to attract involuntary attention, which in turn affects emotional tone. The role of *Being-Away* as a mediator suggests that proximity to gray space limits the possibility of psychological distancing within the home environment, consistent with research showing that contrast from routine is essential to restoration and autonomy (Downey & Willigen, 2005).

Beyond the indirect effects mediated by restorativeness, our results also revealed significant direct effects of gray space exposure on affective outcomes. In the full SEM with Restorativeness as a latent mediator, gray space showed small but significant direct associations with all three PAD dimensions. Notably, the strongest direct effect was observed for Dominance, suggesting that gray space may evoke a sense of control or territorial familiarity in densely built environments, independent of perceived restoration. This finding aligns with previous work on adaptation to urban settings and perceived environmental mastery (Evans et al., 2002, pp. P381–P383) as well as with earlier environmental psychology literature highlighting how urban design can promote a sense of control and predictability (Nasar, 1988; Kaplan & Kaplan, 1989). This finding does not contradict the restorative benefits of green spaces but rather suggests that built environments may support different affective components, such as cognitive control or environmental mastery.

Interestingly, the direct effects of gray space on Pleasure and Arousal were only detectable in the full model and disappeared in the single-mediator models, indicating that these effects are more likely to be fully mediated by the components of restorativeness. In contrast, the persistence of the direct effect on Dominance across all models suggests the presence of additional, non-restorative mechanisms, such as routine, predictability, or spatial familiarity, which may reinforce feelings of agency (dominance) in urban home environments. This may reflect a deeper phenomenological relationship with built environments, which are human-made and thus inherently more controllable and familiar, thus contrasting with the more unpredictable and awe-inducing qualities of natural settings (Bachelard, 1994; Heidegger, 1971). This divergence highlights the value of combining global and specific mediation models to reveal both common and unique pathways linking environmental features to emotional experience.

Altogether, these results underscore the importance of incorporating multi-dimensional psychological constructs into environmental research. Rather than treating restorativeness as a global or undifferentiated variable, our findings show that only certain components—Scope, Fascination, and Being-Away—mediate the emotional burden associated with gray urban structures. This has concrete implications for urban planning: interventions that increase perceptual openness, visual richness, and opportunities for psychological escape may offer targeted pathways to buffer the affective consequences of gray space exposure, fostering resilience and well-being in dense residential areas.

4.3. Implications for well-being and urban planning

Our findings underscore the dual impact of green and gray spaces on psychological outcomes, showing both their interdependence and their distinct effects. The innate negative correlation between green and gray spaces complicates the disambiguation of their individual contributions, yet our results provide valuable insights. Specifically, gray spaces exert stronger (and distance-dependent) negative effects, and their association with reduced Pleasure and Arousal was most pronounced. In contrast, green spaces showed broader and more consistent positive effects across multiple dimensions of restorativeness and spatial scales. The interplay between green and gray spaces suggests that the absence of gray spaces likely amplifies the restorative qualities of green environments, supporting prior research on the benefits of natural settings (Astell-Burt et al., 2013; Bratman et al., 2015; Hartig et al., 2014; Kaplan, 1995; Trecartin & Cummings, 2018). However, our study extends this understanding by emphasizing that reducing gray spaces may be as critical as increasing green spaces for enhancing psychological restoration. Future studies should aim to further isolate these effects, potentially through experimental designs that manipulate environmental features independently or by leveraging longitudinal data to track changes over time.

Several studies have highlighted the interplay between environmental factors and mental health, emphasizing how exposure to different types of settings (e.g., urban vs. rural) can shape affective states, perceived restorativeness, and overall psychological well-being. For instance, Roe and Aspinall (2011) found restorative benefits in rural over urban walking experiences, yet their dichotomy "urban vs. rural" oversimplified the complexity of near-home environments. Similarly, other studies reviewed urban environmental determinants such as noise and air quality, revealing their broad impacts but not detailing novel environmental types or psychometric measures (Sineva et al., 2021). Other works (e.g., Evans, 2003; Evans et al., 2002, pp. P381–P383) corroborated the importance of built-environment quality, particularly for vulnerable populations, but tended to focus on indoor housing conditions without fully addressing the diverse outdoor spaces that surround residential areas. While large-scale epidemiological studies (Engemann et al., 2019; Markevych et al., 2017) underscored the long-term advantages of green exposure, their reliance on aggregate measures (e.g., NDVI) limited consideration of psychological processes such as perceived restorativeness. Other studies offered macro-level perspectives on urban living and mental disorders, primarily highlighting socio-environmental stressors without capturing multiple, concentric layers of environmental variability (Galea et al., 2011; Lecic-Tosevski, 2019).

The present study introduces a state-of-the-art concentric clustering approach to examine a variety of near-home settings—ranging from gray and green spaces to urban shadows—and systematically links these environmental typologies to psychometric measures of affective states and perceived restorativeness in multiple environments. By moving beyond the common binary distinctions (e.g., urban/rural) and incorporating multidimensional psychometric tools, this research captures subtle psychological responses to different environmental categories. Moreover, the study's concentric clustering design enables a finer-grained analysis of how distance and gradient shifts in environmental features correspond to variations in affective and restorative experiences. This multifaceted methodology addresses previous over-simplifications by considering an array of built and natural factors in tandem, thus providing a comprehensive account of environmental impacts on mental health and advancing both theoretical and methodological frontiers in the field.

The practical implications of our findings are particularly significant for urban planning and public health. Whereas much of the existing literature has focused on the addition of green spaces, there could be an equally important need to address gray space prevalence, especially in relation to their proximity to residential areas (Gong et al., 2016; Guite et al., 2006; Phillips et al., 2005; White et al., 2013). By quantifying environmental features and their psychological impacts across spatial scales, this methodology equips urban planners and policymakers with evidence-based tools to design healthier urban environments. Our multiscale and multi-environment analysis suggests that in-home emotional well-being may be improved when a house is surrounded by natural (green) spaces at varying distances, has minimal nearby housing density (roofs), and includes infrastructures providing services and accessibility (gray) only within close proximity (Dadvand & Nieuwenhuijsen, 2018; Russo & Cirella, 2018). The hypothesized optimal urban model emerging from these findings is a balanced, modular environment that prioritizes abundant greenery and natural elements, allows circumscribed residential clustering, and strategically places necessary services and infrastructures close to residential areas to provide convenience without dominating the natural elements.

4.4. Limitations and future directions

Despite its strengths, our study is not without limitations. First, the correlational nature of the data precludes definitive causal inferences, limiting our ability to disentangle the temporal relationships between environmental features and psychological outcomes. Second, while our SEM models identified key mediating pathways, our study could not fully isolate the independent effects of green and gray spaces due to their interdependence. Third, our methodological approach did not rely on traditional geospatial segmentation techniques, such as NDVI or infrared satellite imaging, which are commonly used to estimate vegetation cover. While these methods provide objective and high-resolution environmental data, they often require advanced technical expertise and may not be readily applicable to large-scale psychological research. In contrast, our approach offers a more accessible and adaptable alternative, capable of capturing meaningful environmental variability beyond simple vegetation indices.

Fourth, our study considered gray spaces as a homogeneous category, without differentiating between distinct architectural features that may evoke different psychological responses. While our satellite-based operationalization quantifies built surfaces, it does not account for architectural aesthetics, historical value, or urban symbolism, which have been shown to influence perceived restorativeness (Herzog & Bryce, 2007; Nasar, 1994). Future studies may explicitly differentiate between gray spaces with high architectural value and those characterized by urban monotony or deterioration.

A further limitation is the lack of control for recent individual exposure to green or built environments, which may influence perceived restorativeness. However, our study purposefully avoided subjective self-report measures of environmental exposure, to isolate the effect of objectively assessed environmental features. Future research could integrate our latent environmental metrics with behavioral data (e.g., GPS tracking, ecological momentary assessment) to better capture the dynamic interaction between actual environmental contact and perceptual processes.

A methodological consideration concerns the categorization of environmental features through satellite image clustering. While urban and natural landscapes are inherently heterogeneous, we opted for a 4-cluster solution based on data-driven evaluation of clustering stability across iterations. This choice balanced interpretability and robustness, avoiding over-fragmentation that would compromise both statistical power and theoretical clarity. However, we acknowledge that more granular distinctions may offer further insights in future studies, particularly when larger sample sizes and refined classification algorithms can be employed.

Finally, our study focused exclusively on near-home environments, which may not fully capture the range of participants' daily environmental exposures across multiple settings such as university campuses, commuting spaces, or workplaces. Similarly, the sample consisted solely of university students, which may limit the generalizability of the results to the broader population. However, students were recruited from different cities across Italy, encompassing diverse landscapes and urban forms, thereby enhancing the external validity of our findings. Future work should extract objective features around multiple contexts to more directly examine how environmental variation across settings (e.g., home vs. campus) interacts with affective outcomes and restoration processes.

4.5. Conclusions

Building on these findings, future research should aim to address these limitations and expand the scope of inquiry. One promising avenue is the use of experimental and longitudinal designs to establish causal links between environmental features and psychological outcomes, particularly by accounting for temporal variability in environmental interactions. Additionally, further exploration of other environmental features, such as blue spaces, sensory experiences (auditory, visual, olfactory, temperature, luminosity), biodiversity, spatial distributions, and aesthetic qualities of both green and gray spaces, could contribute to a more comprehensive understanding of the broader urban ecosystem. Finally, integrating neurophysiological measures, including brain imaging and stress biomarkers, alongside psychometric assessments, may provide deeper insights into the mechanisms through which environmental factors impact psychological well-being.

In conclusion, this study highlights the critical influence of near-home environmental features on perceived restorativeness and consequential affective experiences, with distinct and partially spatially dependent effects of green and urban spaces. These insights not only advance theoretical frameworks in environmental psychology but also offer actionable recommendations for urban planning, emphasizing the importance of balancing natural and built elements to create healthier, more restorative living spaces.

CRediT authorship contribution statement

Simone Di Plinio: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Elisa Menardo:** Writing – review & editing, Methodology. **Claudia Greco:** Writing – review & editing, Investigation, Data curation. **Daniela Cardone:** Writing – review & editing, Software, Data curation. **David Perpetuini:** Data curation. **Arcangelo Merla:** Writing – review & editing. **Margherita Brondino:** Writing – review & editing, Supervision, Methodology, Funding acquisition. **Margherita Pasini:** Writing – review & editing, Supervision, Methodology. **Sjoerd Ebisch:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Formal analysis, Conceptualization.

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