

From Spatial to Platial Decision Support: A Methodological Digital Framework for Urban Experience

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Abstract

Urban planning increasingly seeks to account for how urban spaces are experienced and interpreted by city dwellers and visitors, yet experiential dimensions remain only weakly integrated into planning decision support. This article presents a proof-of-concept implementation of a platial decision support system (PDSS) that structures diverse forms of in situ, human-generated evidence into a planning-oriented analytical framework. The PDSS operationalises these observations through four analytical levels of increasing resolution. An environmental context layer, together with aggregated self-reported appraisals, establishes a structural baseline for identifying locations that warrant deeper investigation. Level 1 documents salient sensory cues through visual and acoustic observations, while Level 2 interprets these cues through individual and group-specific sense-making, transforming multimodal observations into shared empirical

evidence of experiential conflicts, affordances, and planning-relevant priorities. A conceptual Level 3 situates this evidence within planning deliberation, where it can inform stakeholder negotiation and the implementation of planning measures. The framework is demonstrated using a case study in Würzburg, Germany. Results show that locations with comparable environmental characteristics and aggregated appraisal can nevertheless differ substantially in how they are perceived, interpreted, and prioritised by different user groups. Rather than prescribing planning solutions, the PDSS provides a transparent and scalable workflow that translates multimodal urban observations into shared empirical evidence, complementing established spatial analyses and supporting planning deliberation through structured, context-sensitive, and evidence-informed urban planning.

Keywords

decision support system; experience; interdisciplinary; methodological framework; place-person interaction

1. Introduction

In times of a global polycrisis (Lawrence et al., 2024) relating to climate change, inequalities in participation, etc., cities face the challenge of intensifying reorganisation and transformation. However, because capital is tied up in cities' socio-physical materiality, necessary adaptations are expensive. Thus, careful consideration is increasingly required to make sustainable and well-accepted governance decisions. Traditional urban planning (Kostof, 1991) and, unfortunately, current planning concepts, such as the 15-minute city (Moreno, 2024), often follow a one-size-fits-all approach, neglecting that individuals experience and interact with urban environments in highly variable ways (Pozoukidou & Chatziyiannaki, 2021). This problem intensifies as global crises demand adaptations of the built environment (Borgstedt & Calmbach, 2023). While traditional planning focuses on functional aspects, such as land use, traffic flows, or infrastructure, it is crucial to acknowledge the emotional and experiential dimensions of city spaces (Tonkiss, 2013) and to develop personalised and adaptive planning strategies (Kyttä et al., 2015).

To create truly inclusive cities that address the needs of diverse target groups in a changing environment, we must move beyond static and simplified planning paradigms. This means embracing planning support systems (Harris & Batty, 1993), which support and accompany planning processes, or spatial decision support systems (Geertman et al., 2015), which help structure and inform decision-making. Both enable us to integrate as much relevant information as possible before finalising decisions and policies. Sources for synthesised data range from (a) urban sensor networks (Cuff et al., 2008), (b) innovative (smart-)city applications (Murgante & Borruso, 2014), and (c) earth observation technologies (Taubenböck et al., 2015) to (d) human-centred sensing approaches (Campbell et al., 2006). Qualitative assessment of their integration (Kanning et al., 2023) into planning processes is becoming imperative. However, a key question behind human-centred approaches remains: How are specific places in urban environments experienced by individuals regarding their preferences, needs, and ways of sense-making?

Current urban and environmental planning practices rely predominantly on objective, spatial datasets, such as satellite imagery, sensor signals, and GIS layers. While these provide the “structural skeleton” of urban environments, they offer limited insight into how people actually experience, evaluate, and use these in their

daily lives. This disconnect between physical infrastructure and subjective experience creates a critical gap in the planning process, often hindering the development of truly human-centred urban interventions.

To bridge this gap, we propose the platial decision support system (PDSS)—a multi-layered methodological framework designed not as a finalised software tool, but as a conceptual “microscope” for urban analysis. We follow Tuan (1975) and Cresswell (2011) in defining place as constructed through the meaningful interaction between people and their physical environment, rather than as a purely spatial location. The PDSS structures the analytical and decision-making process through four interrelated levels, moving from a broad, resource-efficient screening of the environment and appraisals (ENV and L0) toward a high-resolution, interpretive analysis of sensory cues and sense-making (L1 and L2), and finally into governance and implementation (L3). By systematically “zooming in” from structural baselines to context-sensitive human experiences, the PDSS enables the identification of subtle tipping points and individual divergences that remain invisible in aggregated data.

The feasibility and operational value of this multi-layered approach (Figure 1) are demonstrated here through a case study in Würzburg, Germany. Würzburg was chosen for reasons of accessibility to all involved researchers and serves as a “supertestsites” to validate the framework’s performance and its capacity to integrate diverse data streams, rather than as a basis for statistically generalisable results on urban experience.

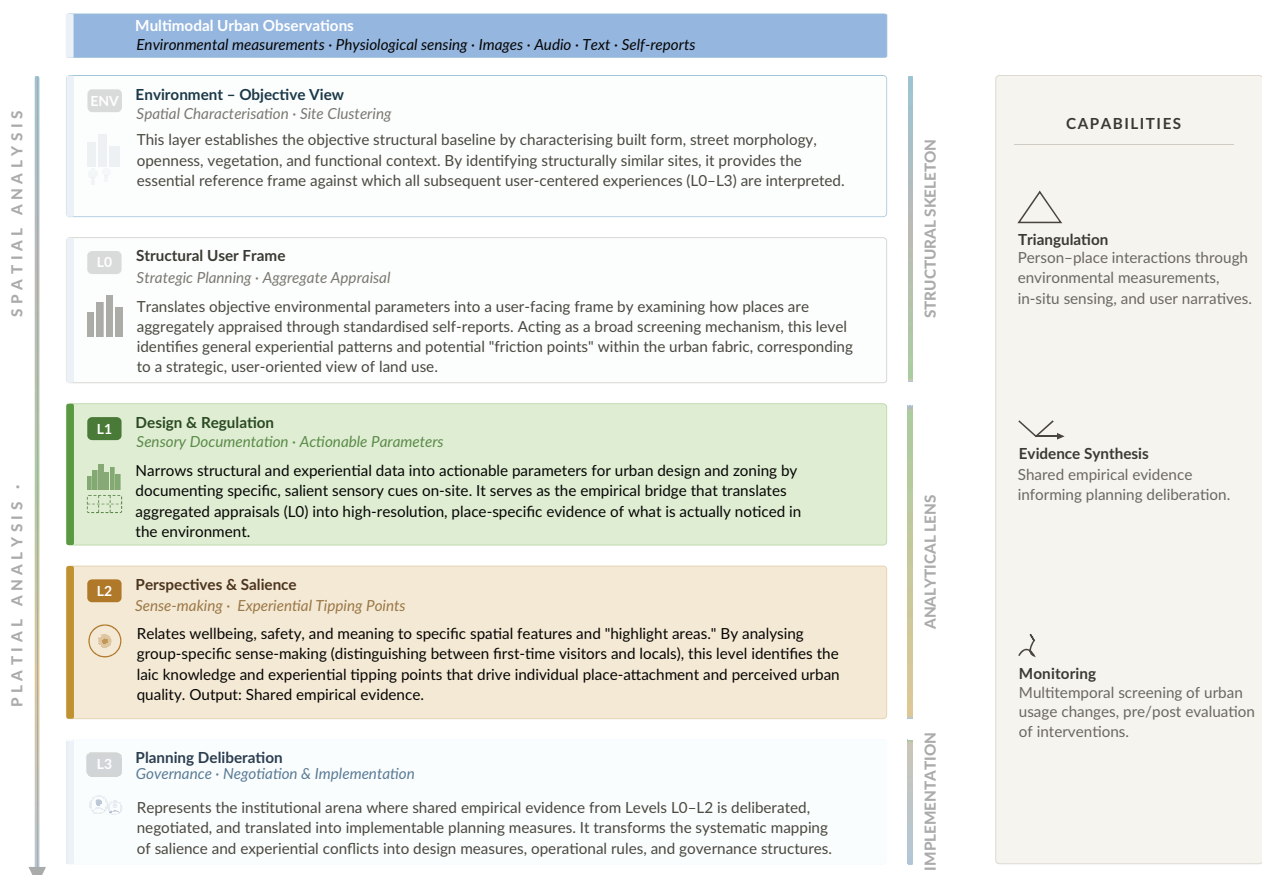


Figure 1. Framework for PDSS.

2. Conceptual Approach and Theoretical Framing

Planning support systems provide a vital platform for collecting and analysing data from multiple sources. Urban sensor technology enables real-time monitoring, e.g., of noise levels, air quality, pedestrian dynamics, and public space use, providing valuable ground for deeper analysis of how different target groups experience urban environments. Complementary to this, earth observation sensor data provide a broader view, e.g., of urban structure, land-use changes, climate impacts, and environmental risks, informing long-term planning and the build-up of resilience (Smith et al., 2007). An interplay of various interdependent sources on different scales has always characterised spatial planning (Kostof, 1991). Weighing factors that describe the environment and how people are affected, and processing them “simply and transparently” in spatial analysis, with all its caveats or “wicked problems” (Rittel & Webber, 1973), are the key challenges for later decision-making.

Recent research on this, such as the urban comfort index by Lei et al. (2025), shows the added value of assessing the dynamic quality of urban life according to the ongoing interaction between people and their environment. While previous approaches often focused solely on measuring spatio-temporal (and merely behavioural) phenomena, Lei et al. (2025) offer a multidimensional system for evaluating urban experiences. Another approach to enrich planning support systems is provided by research on Urban Emotions (Zeile et al., 2015; see also Kremer et al., 2025). Early multimodal sensing concepts demonstrated how combining biosensors, contextual self-reporting, and emotion extraction based on volunteered geographic information (VGI) benefits urban planning support (Resch et al., 2015). The experience of a place gathered from social media analysis (Lemoine-Rodríguez et al., 2024; Mast et al., 2025) or participatory mapping, contrasted with biometric sensors like smartwatches, helps uncover how individuals respond in specific urban settings. This enables planners to move from abstract, one-purpose top-down designs to human-centred urban environments that cater to diverse needs (Zeile et al., 2015). Only urban planning built on needs analyses can take the contingency of multi-perspective, i.e., partially contradictory practices of usage, into account when investigating innovative designs of future cities (D’Ignazio & Klein, 2025).

When measuring individual place-related assessments, the perspectives of social studies provide suitable means for the “deep inspection” of specific edge cases, complementing statistical analyses of multidimensional parameters. Implementing social studies in a methodological framework requires careful epistemological consideration of their background in social theory. In essence, the concept of place in geography (Agnew, 1987; Cresswell, 2011; Tuan, 1975) signifies spatially vague and sometimes even distorted or fragmented areas of human attention, acting both as a stage and a resource for activity on different scales (Vasardani & Winter, 2016). Places’ scales can range from individual landmarks, e.g., trees or houses, to extended features, e.g., waterfronts and parks, or even the uniform notion of districts, entire cities, or landscapes. In related methodologies (Schatzki, 2002), there is no “objective” measurement, but only practices of sensing (mediated by technological means) and sense-making (mediated by expectations, needs, beliefs and emotions) that have to be scrutinised in their specific socio-technological context (Rose, 2001).

Important examples of integrative methodologies strongly rely on mixed methods that draw on a broad range of quantitative and qualitative social research practices (Münderlein, 2021). Place-related methods of data collection include (a) go-along interviews or walking voices, (b) auto-photography, photo-voice, or

photoelicitation anchoring individual experience in specific places, and (c) elicitation of self-reported human experiences. Our study substantially extends these by arranging the extraction of place-based in situ media on four planning-oriented levels (L0–L3), introducing salience mapping and multi-level decision support as core components of a PDSS (for a schematic overview see Figure 1). We argue that neither focusing on the objective assessment of the environment (from the perspective of spatial sciences) nor on self-reported individual practices of sense-making (from the social studies perspective) alone is suitable to provide urban planning with empirical evidence anchored in reality. While the deep look of social studies does not react quickly enough or provide regular and repetitive screening of urban environments, quantitative approaches cannot explain specific individual needs. In our framework, we highlight the added value of triangulation: scaling the findings from deep inspection by calibrating qualitative findings within multidimensional observation parameters.

To capture the polyvalence and complexity of urban environments according to individual needs and expectations, we specifically rely on the concept of person-place-relations. Accessing these for thorough analysis in the field of urban planning requires an interdisciplinary view on the level of theory (e.g., determining which variables should be focused on), assessment methods (e.g., combination of time-varying objective and subjective measures), as well as data analysis and interpretation (Baer et al., 2024; Kanning et al., 2023). When collecting and analysing place-related information, we rely on the approaches and methods developed in the field of place-based GIS (Gao, 2022; Purves et al., 2019; Westerholt et al., 2020) to join different, multimodal data streams.

In this regard, we clearly diverge from the concept of the Smart City since corresponding approaches are often driven by industry-led agendas focused on efficiency, automation, and data economies (Greenfield, 2013). While they promise solutions, they risk reinforcing technocratic control, surveillance, and social exclusion (Bauriedl & Strüver, 2018; Rosol et al., 2018). In contrast, we align with the concept of the “digital city,” emphasising participatory, context-sensitive, and human-centred urban transformation (Humann et al., 2022; Rezende, 2023; Yasuoka & Ishida, 2023). Rather than a top-down technological fix, it offers a bottom-up, pluralistic approach to urban futures fostering inclusion, transparency, and local resilience. Beyond (digitally assisted) participatory methods like experience walk-alongs, we aim to provide insights into urban needs long before developing concrete ideas about (re-)design.

Likewise, our approach differs from Citizen Science or VGI, which emphasise collaborative collection of data according to pre-standardised categories. Instead, we follow a participant-driven empirical approach recording the unmodified logics of individual sense-makings, where participants act as situated interpreters rather than data contributors. However, in contrast to complete ethnographic immersion, which requires long-term observation, our method foregrounds immediate, multimodal place experience, enabling a fine-grained perspective on the sense-making of an urban environment in real time.

Our resulting framework operates as a methodological microscope, integrating multimodal evidence beyond disciplinary boundaries to expose the nuanced layers of person-place interactions. Rather than a static model, the PDSS is conceived as a first increment in a design-based research process; it focuses on the feasibility of a multi-level integration and the generation of actionable information, rather than on the statistical generalisation of effects.

The framework is structured as a sequence of analytical resolutions, designed to move from broad structural baselines to high-resolution, situated insights:

1. The structural skeleton (Environment & Level 0): This foundation captures the objective morphology, greenness, and openness of the urban fabric, confronting these parameters with aggregated self-reports. We recognise these as established methods within the field of GIS and spatial statistics that are highly efficient for broad screening. However, in the context of the PDSS, they function as a standardised baseline to identify where experiential patterns diverge without explaining why. Thus, the structural skeleton provides potential “friction points” that warrant deeper investigation.
2. The analytical lens (Level 1 & Level 2): This is the core of the “microscopic” approach, focusing on identifying salience in human-centred experience and sense-making. While L0 identifies that a difference exists, L1 and L2 reveal what humans notice and value. Working with documented specific sensory cues (L1), the framework identifies the most salient features of the environment as those that capture the user’s attention and shape their experience. These cues are then interpreted through the lens of individual sense-making (L2) to reveal individual practices of knowledge generation and experiential tipping points. This allows for a multi-perspective analysis that captures the “platial” nature of experience: distinguishing, for example, between the readability of a place for first-time visitors and the channelled design intentions of residents. Here, the focus shifts from statistical representativeness to the richness of diverse human perspectives.
3. The implementation layer (Level 3): This level represents the transition from shared empirical evidence to planning deliberation. It is the arena where the systematic mapping of salience and identified experiential conflicts are negotiated and translated into implementable design measures, operational rules, and governance structures.

Through this tiered logic, the PDSS enables a triangulated synthesis of environmental measurements, in situ sensing, and user narratives. By systematically zooming in from the structural skeleton (ENV/L0) through the analytical lens (L1/L2) and finally to planning deliberation (L3), the framework provides a scalable way to monitor urban usage over time and evaluate the impact of interventions with a continuous feedback loop of screening and profound analyses.

Using the app SpaceLog (Kremer et al., 2025), we collect audio messages recorded by the participants describing and evaluating the place of observation along with imagery and sounds documenting the experienced environment. These data are the core of the analytical lens, revealing information about experiences and needs on site, which is intentionally non-exhaustive and may not optimally represent each domain. This constraint is methodological, as our aim is not to provide definitive feature catalogues but to demonstrate how heterogeneous data streams can be integrated into a coherent, cross-layer workflow to identify and inspect potential planning controversies. The multilayer architecture is diagnostic as it highlights which sites warrant deeper investigation. While the present implementation prioritises transparency, reproducibility, and cross-level comparability over completeness, its modular design allows for additional indicators or modalities to be incorporated in future applications.

Rather than prescribing fixed solutions, the PDSS enables planners to interpret heterogeneous data in situ and to make decisions that reflect lived experience in specific urban spaces. We provide a middle ground, bridging computational spatial analysis and extensive participatory formats, explicitly acknowledging the indispensable importance of a comprehensive understanding of the situated platial experience. In terms of

critical data studies (Iliadis & Russo, 2016), a framework like this can provide the means to highlight underrepresented and marginalised needs in debates on urban transformations, thus fostering a more inclusive and differentiated view on the needs of target groups. Given that adaptations in the built environment are expensive and temporarily immutable, this framework contributes to a customised evaluation and the continuous monitoring of human needs in urban environments. As part of a larger interdisciplinary consortium (Figure 2), the human-centred data can later be easily combined with

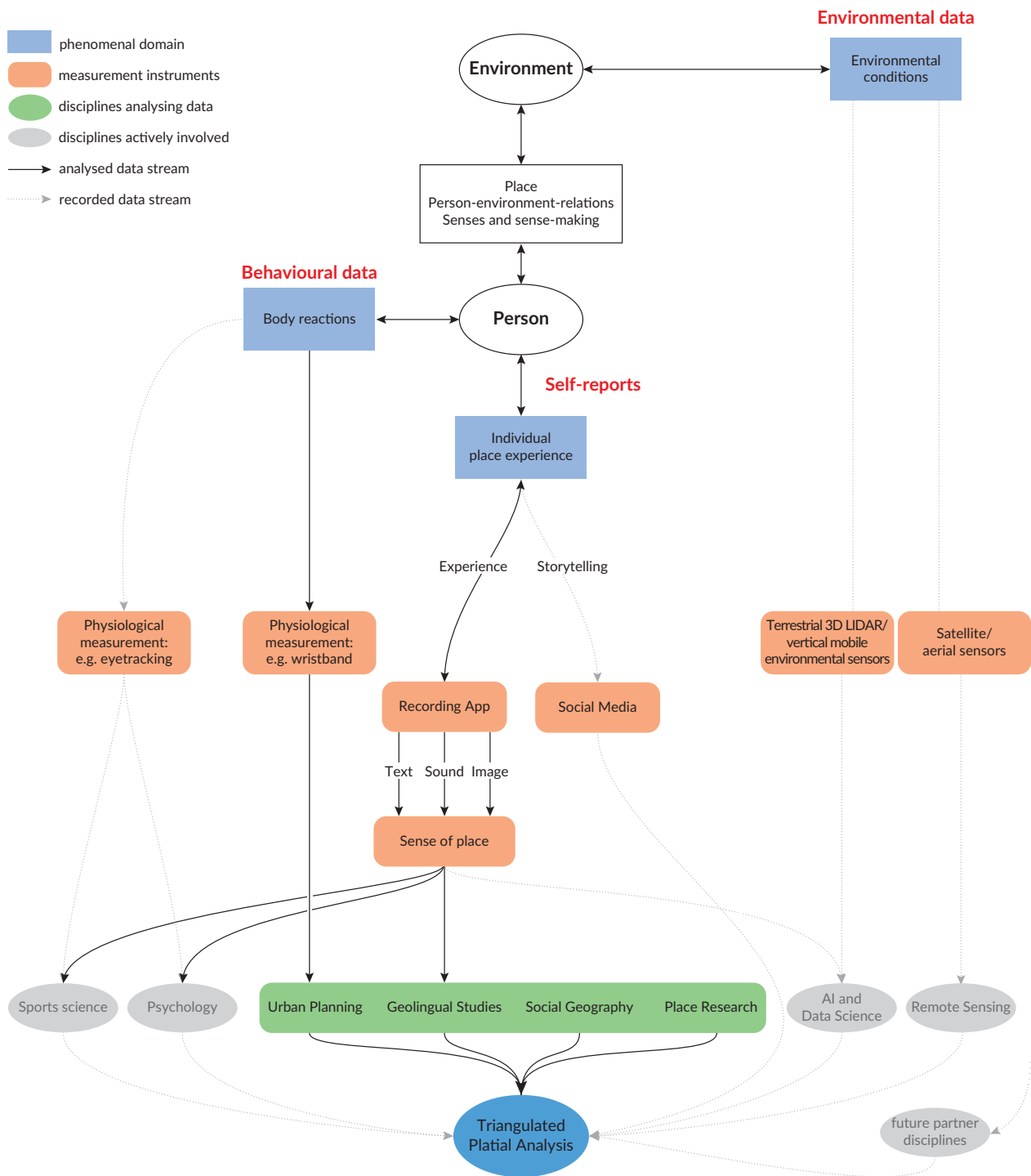


Figure 2. General setup for interdisciplinary platial analysis.

physiological measurements at the person level, as well as with terrestrial and aerial LIDAR measurements. As a proof of concept, we integrated four disciplinary perspectives in this study: (a) urban planning, translating multimodal, in situ evidence when balancing planning processes, (b) place research, highlighting the role of self-reporting when collecting data on place-based human experiences, (c) social geography, anchoring multimodal sensory data in the lived social organisation of urban spaces, and (d) geolinguistic studies, investigating the construction of place identity through language, including place-based sentiment and discursive assessments.

3. Study Sites and Data Collection

The data collection process aimed to develop a proof of concept for our framework, providing insights into the experiences of individuals in the old town and urban centre of Würzburg, Germany. The study location reflects the typical structure of a Central European city with just over 100,000 inhabitants, with a dense pedestrian area in the old town and surrounding urban green spaces at the site of former fortifications. Study sites were chosen to represent inner-city places with similar yet varying spatial profiles along two alternative routes (Figure 4). Route 1 consists of five predefined places, and Route 2 of three predefined places. Both routes intersected at Herzogenstraße (HER), resulting in observations for seven different places.

For the collection of experiential data, a total of 42 participants were recruited by convenience sampling. Using SpaceLog (Kremer et al., 2025), basic socio-demographic information on participants was collected in a short questionnaire (see the Supplementary File, Part A). The sample is not representative of a specific social group but serves as a basis for exploring affordances and challenges of the data collection and analysis process. At each location, participants were asked to perform four subtasks using the app's menu (Figure 3):

1. Record an audio of the sounds in your surroundings!
2. Describe the place! Record a voice message!
3. How do you feel at this place? What are the reasons for this? Record a voice message!
4. Take three pictures of views in your surroundings that you find interesting!

According to the specific language skills, the study yielded both English and German responses. Each piece of media was uploaded with a geocoordinate of the location where the observation was recorded. In addition, participants were asked to provide a general assessment of each place on three Likert scales (see Level 0 for details). In our framework, one observation corresponds to the multimodal information recorded by a participant at a single surveying site.

The resulting place-specific data streams consisted of:

- socio-economic data
- item data on the Likert scales
- ambient 5-second noise recording
- up to three images per place
- voice recordings of place description and experiential place assessment



Figure 3. Main interface of the app SpaceLog (Kremer et al., 2025): study profile (wue01), visualisation of the study task, and main menu to type, record, upload, and review media.

As preprocessing steps, we cleaned, standardised, and integrated the heterogeneous data types. Observations located within 80 m of a predefined location were assigned the corresponding site label (Figure 4). In comparison, those located more than 80 m from any predefined surveying location or separated from them by physical barriers were labelled as “unassigned.”

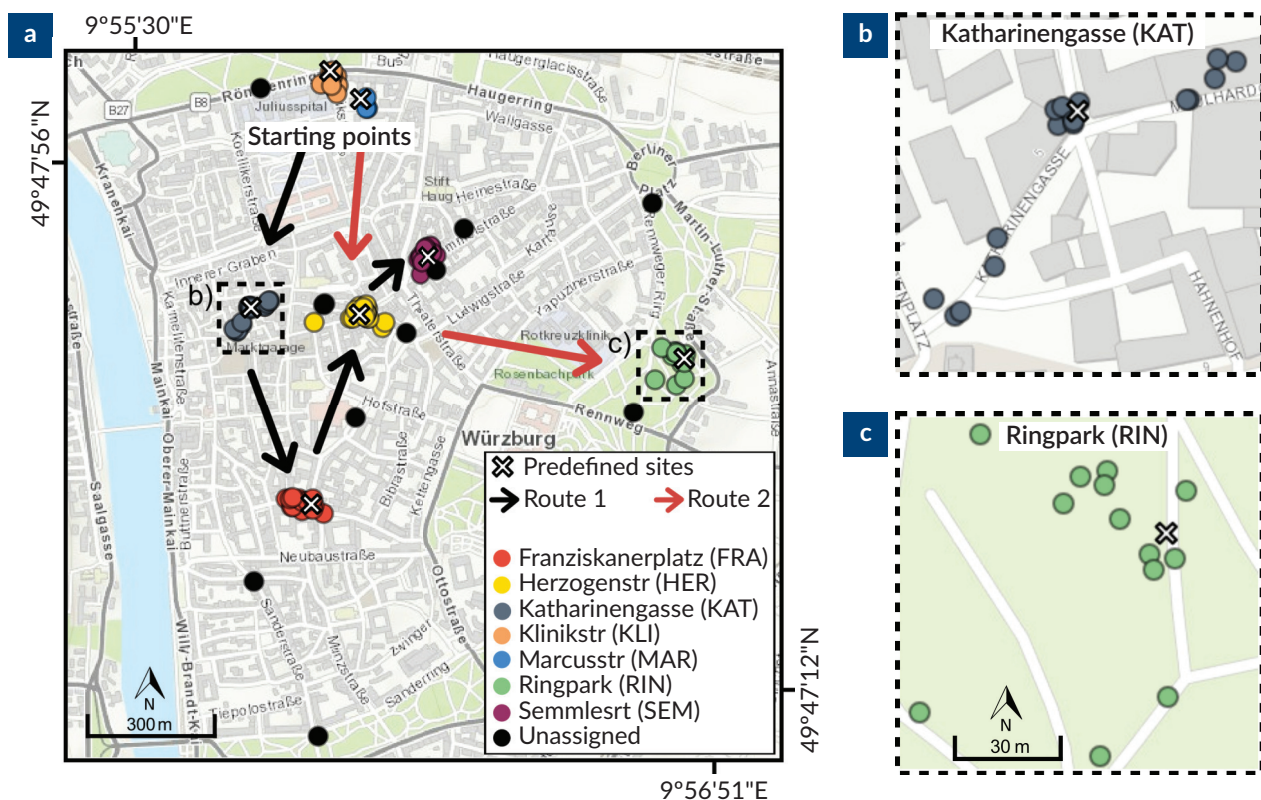


Figure 4. Sites included in the survey campaign (panel a); panels b and c provide close-up views of two survey sites, highlighting the spatial distribution of the first recorded piece of media of participants at each location. Note: Abbreviations for site labels will be used throughout the article.

After mapping the recorded information, we observed varying spatial distributions of the locations where observations were made. For observations with assigned survey sites, we identified distinct spatial patterns, including high-density clusters as well as scattered, isolated observations (Figure 4, panels b and c).

Structural place profiles were created to provide an urban morphology-based baseline using a harmonised geospatial workflow applied around the predefined sites in Würzburg (see the Supplementary File, Part B). We included the following features as a benchmark:

- building density, computed from building footprints
- building height and height variability, computed from Level-of-Detail-2 building models
- street width, computed using distances between façades and lanes
- urban openness, computed by Sky View Factor
- normalised Difference Vegetation Index (NDVI), based on Sentinel-2 images
- functional context, retrieved from OpenStreetMap point-of-interest data

4. Multilayered Analysis: From Structural Skeleton to Analytical Lens

This section illustrates the empirical application of the proposed multi-level framework. It demonstrates how different types of insights are obtained by incrementally adding resolution across the levels to derive actionable results for urban planning. We explicitly aimed to provide a mixed-method approach, augmenting and thus overcoming traditional essentialist spatial analyses by including rich data on individual experiences of place in urban contexts, building on the methodology of urban walks, photo-based research, and capturing emotions (Münderlein, 2021) to be used for a deep analysis of everyday urban practices (Schatzki, 2002). To ensure methodological transparency, the analysis is structured along the levels of the PDSS framework introduced in Section 2. Specifically, this section uses the Würzburg case study to validate the transition from broad structural screening (ENV and L0) to in-depth experiential analysis (L1 and L2), culminating in the translation of these insights into planning-relevant discourses (L3).

4.1. Environment (ENV): Objective View

The environmental baseline was established using a suite of standardised geospatial indicators (see the Supplementary File, Part B, for full technical details), resulting in three structural clusters (Figure 5). The classifications at the site level show that the study design encompasses both strong structural contrasts (e.g., open/green versus dense/compact) and a group of structurally similar sites. Of particular interest is the intermediate central configuration (Cluster 2), characterised by mixed morphological features and greater vertical heterogeneity, including FRA, HER, MAR, and SEM. Crucially, the question arises whether similar environments are also used and experienced in similar ways, which motivates the transition to Level 0, in which aggregated user ratings of the sites are examined.

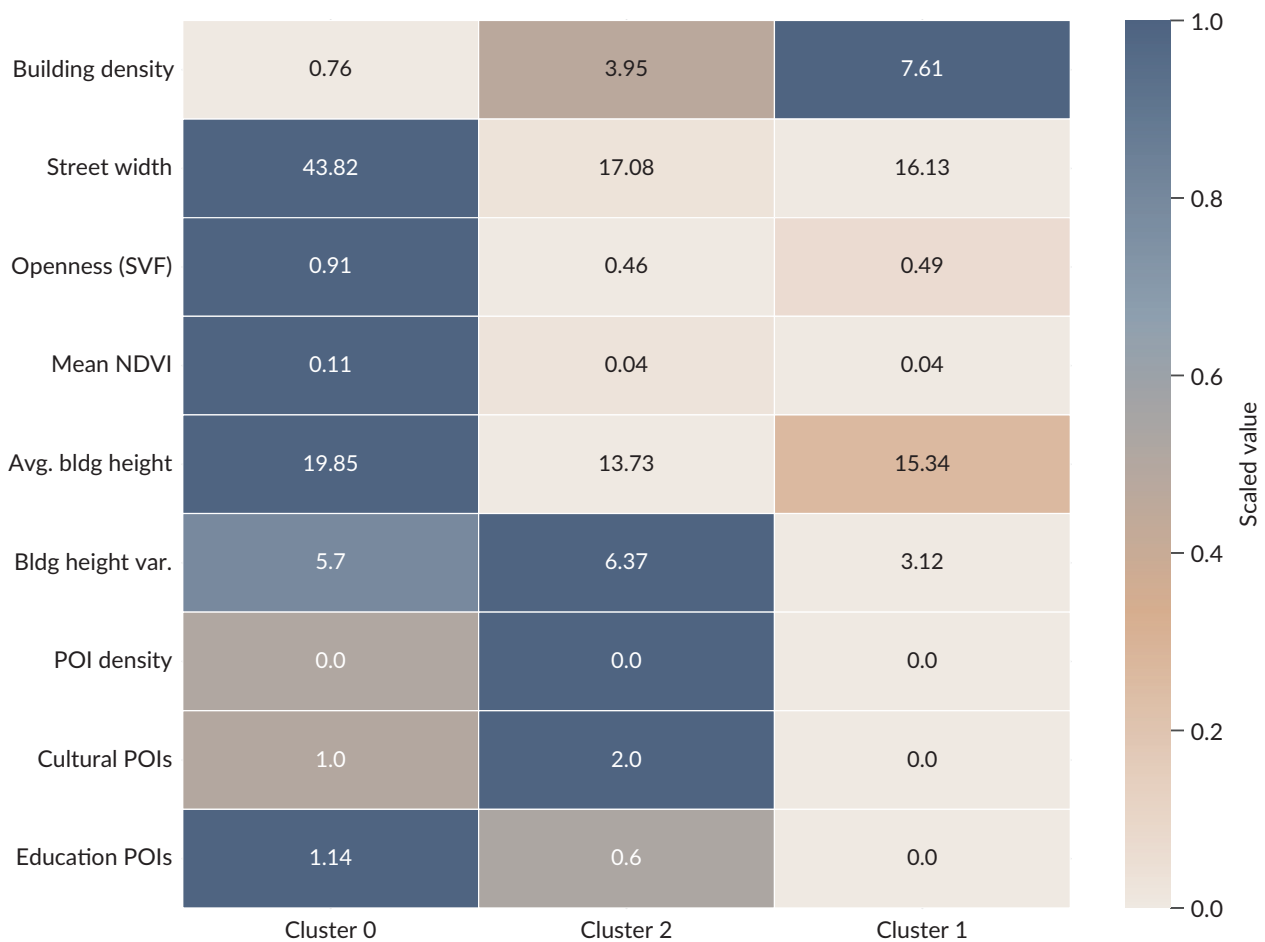


Figure 5. Cluster centroid heatmap for selected environment variables. Notes: Cell shading represents min-max scaled values for each variable across clusters; annotations report unscaled cluster centroids in the original units.

4.2. Level 0: Structural User Frame

L0 serves as a diagnostic screening layer, where the objective structural baseline is confronted with aggregated user appraisals. Using standardised self-reports across three experiential domains, i.e., acoustic atmosphere, personal wellbeing, and spatial context (see the Supplementary File, Part C, for detailed metrics), this level identifies whether structurally similar sites are also experienced similarly.

The results show convergent appraisal for structurally similar central sites and divergent appraisal when comparing a park and a downtown location (Table 1; see also Figure 6).

The domain split suggests that this contrast is not driven by a single experiential dimension, meaning that structurally similar locations can receive highly similar ratings, while still leaving room for latent differences that are not resolved at this level. Accordingly, L0 indicates where experiential similarity can be assumed and where further investigation is required, but it does not explain which environmental cues shape these judgements. This motivates progression to Level 1, where attention to specific visual and acoustic elements is examined.

Table 1. Intersection-over-Union (IoU) overlap of interval-based rating profiles for structurally similar sites (FRA and SEM; both Cluster 2) and structurally contrasting sites (FRA and RIN; Cluster 2 and Cluster 0).

Site pair	Acoustic atmosphere appraisal	Personal wellbeing state	Perceived spatial context
Franziskanerplatz and Semmelstraße (FRA and SEM)	0.708	0.560	0.661
Franziskanerplatz and Ringpark (FRA and RIN)	0.250	0.017	0.161

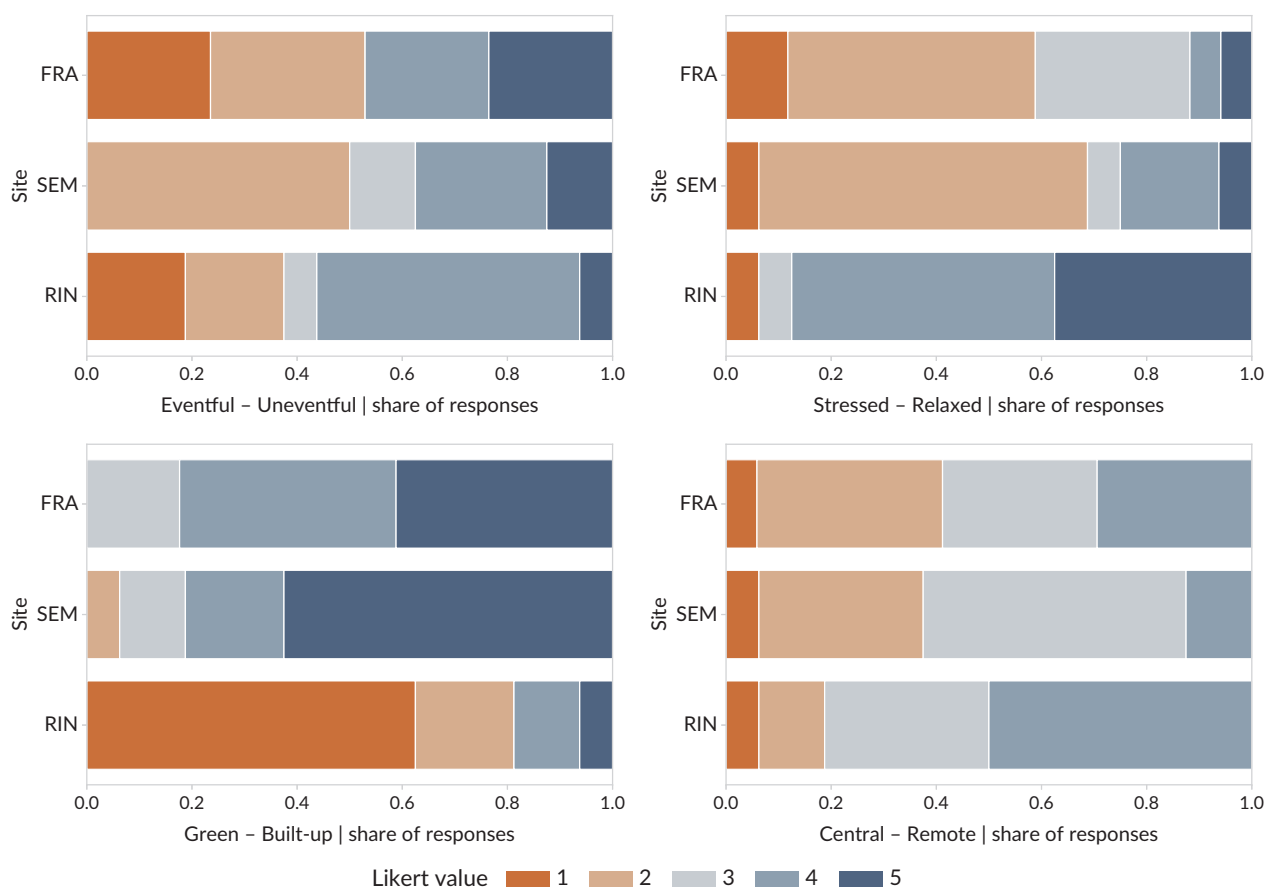


Figure 6. Likert composition plots (stacked response shares) for selected key items comparing FRA, SEM, and RIN. Note: Each panel shows the distribution of responses across the 5-point scale (1 = left pole, 5 = right pole), enabling direct comparison of response concentration and divergence between sites.

4.3. Level 1: Design and Regulation

Building on potential friction points identified in L0, L1 was employed to isolate sensory cues that drive divergent experiences. This shift from aggregated ratings to documenting salience allows us to identify observable indicators that informants actively attend to at structurally similar locations and that can serve as starting points for urban design and land-use planning. Details for the acoustic analysis are provided in the Supplementary File, Part D1 (summary indicators are listed in Table 2).

Table 2. Median values of selected acoustic descriptors computed from participant-recorded clips. Metrics are reported as medians across clips per site.

Site	LAeq	Loudness	Fluctuation strength	Sharpness	Roughness	Tonality	RelApproach
RIN	42.43	67.79	25.53	1176.81	0.12	0.0180	0.4997
FRA	56.06	74.14	115.13	1164.71	0.55	0.0185	0.5260
SEM	50.47	71.66	54.62	1082.49	0.26	0.0185	0.5063

The analysis shows that the acoustic composition distinguishes the open/green context from the central sites (Figure 7). FRA and SEM both exhibit anthropophony dominance, whereas RIN shows a comparatively higher biophony-geophony contribution. At the same time, the micro-level composition reveals that the central sites

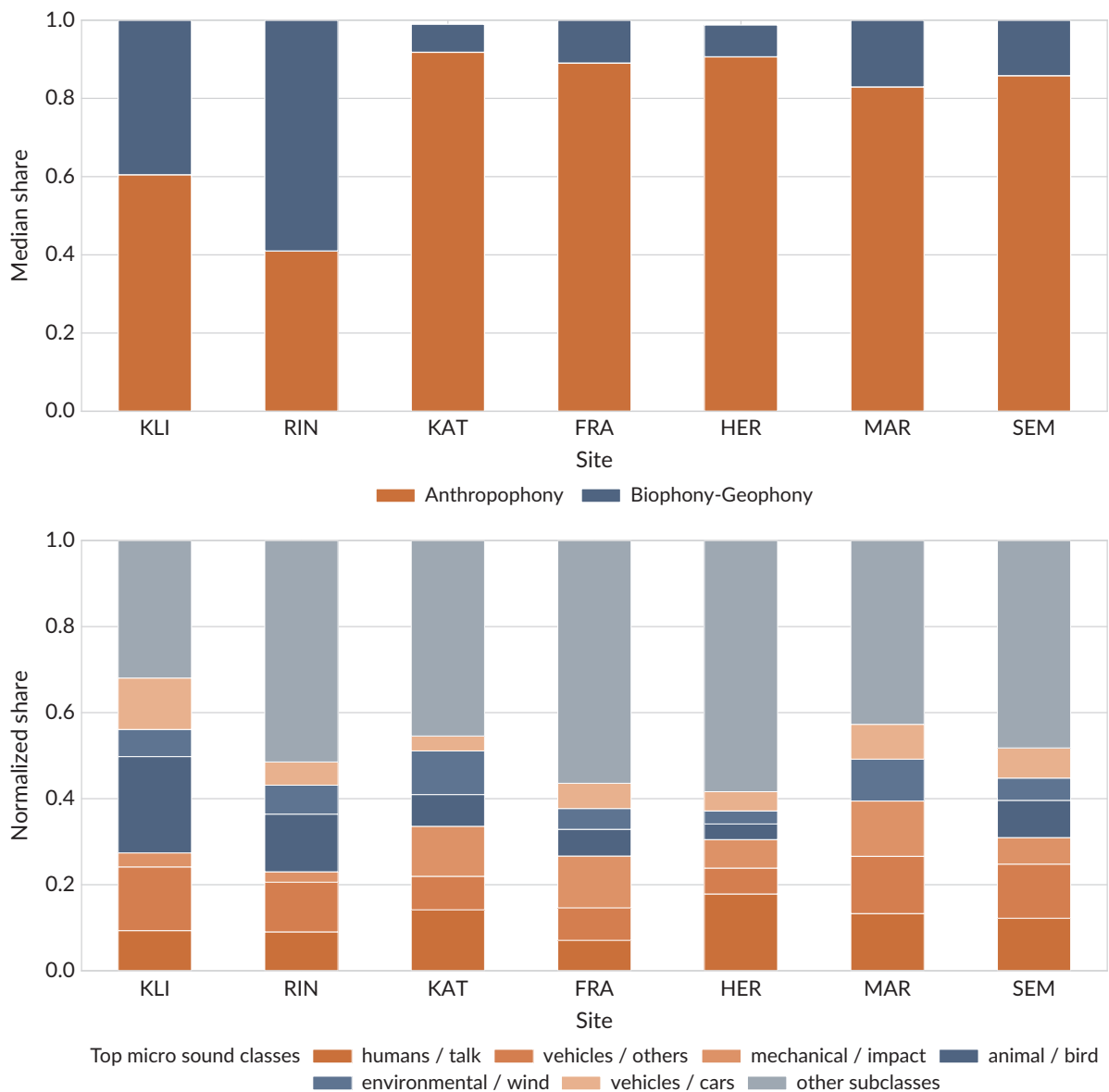


Figure 7. Acoustic source composition by site, showing macro source shares (top) and the distribution of dominant micro subclasses (bottom).

are not acoustically identical. SEM shows relatively stronger contributions from birds, wind, human voices, and vehicles, whereas FRA contains comparatively more mechanical sounds and a larger share of residual other subclasses. Acoustic patterns indicate that locations with similar environmental structures and aggregated ratings can nevertheless differ in salient sound characteristics, supporting the assumption that differences in experience arise at the level of attention rather than overall ratings.

Visual attention patterns confirm this finding by showing that structurally similar central locations, while exhibiting broad visual similarities, display subtle differences at the level of stimuli relevant to design and regulation. Conceptual and methodological details regarding the interpretation of acoustic and image-based attention within the framework of a soundscape and visual perception model are provided in the Supplementary File, Part D.

While Level 1 identifies salient elements that capture attention, it does not explain how these cues are weighted or interpreted by individuals. To illustrate the transition from experience to meaning, the analysis proceeds to Level 2, where sensory inputs are embedded in individual sense-making.

4.4. Level 2: Perspective and Salience

Level 2 focuses on the transformation of documented observations into a deeper understanding of place-related meaning. While L1 identifies what is noticed, L2 examines how these elements are weighted and appraised by different user groups, thereby making them relevant for planning decisions. This can, for instance, reveal contrasts between residents' experiences and the gradual appropriation of the space by first-time visitors.

To analyse sense-making practices at inner-city locations, we adopt a geolinguistic approach (Biewer et al., 2026) that combines (semi-)automated language processing with interpretive discourse analysis. This step moves beyond descriptive appraisal and investigates how participants articulate their experiences, construct relevance, and implicitly negotiate evaluations of place. Details on transcription, topic modelling, and sentiment analysis used at Level 2 are provided in the Supplementary File, Part E.

Across all sites, participants' accounts reveal a consistent salience of visual, auditory, and social experience in place-related sense-making. At the same time, the distribution and framing of topics vary between locations. In denser inner-city settings (Cluster 1), participants refer more frequently to built form, services, and motorised traffic. In contrast, references to tranquillity, nature, and calmness dominate in green and open environments (Cluster 0). Variation in topic ranking confirms the relevance of POIs for places in the intermediate Cluster 2. Occasionally, topics reflecting the built environment, e.g., "churches," occur only in the discourses for some places even though they are present and visible at different places. Such discursive choices may relate to an underlying temporal effect at inner-city sites and the occurrence—or absence of—an auditory experience, such as bell ringing.

Sentiment analysis provides an additional perspective on the valence of the participants' experience. While several sites exhibit a higher share of negative sentiment across topics, qualitative inspection shows that negative polarity does not always correspond to negative experience. In particular, tranquillity and emptiness are sometimes algorithmically classified as negative, despite participants framing them positively

and associating the marked absence of activity in the usually experienced co-existence of biophony and anthrophony in the city (Chesnokova et al., 2019, pp. 2440–2441) with calmness and recovery, as in the example below, in which bold print highlights expressions of appraisal (affect, appreciation, or judgement); force of evaluation is underlined, and italics indicate targets of appraisal:

well here I definitely feel **calmer**, eh because there is nothing really going on here. The only thing I can hear are some cars and a *blackbird* in the bushes. (RIN; author translation from German)

This highlights the limits of polarity-based sentiment analysis and underlines the added value of discursive interpretation.

Comparing FRA and SEM, participant accounts indicate that both sites are primarily characterised by their built environments (Figure 8). However, specific topics differ in frequency and framing. At FRA, references to a church and a construction site are more prominent. At the same time, accounts of SEM emphasise points of interest, such as restaurants and shops, as well as traffic-related elements, thus reflecting the rating of FRA as slightly more remote than SEM (see Figure 6). Sentiments diverge, with some informants experiencing FRA as relatively quiet and calm, especially in comparison to the nearby pedestrian area, and others feeling stressed by the moving cars and the infrastructure. Similarly, participants experience SEM as busy and thus partially stressful but at the same time describe the design as pleasant and appreciate options for going out, which aligns with the interpretation of the anthrophony-dominated profile on L1.



Figure 8. Examples of image and place description recorded at FRA (left) and SEM (right).

4.5. Level 3: Deliberation

Level 3 represents the transition from shared empirical evidence to urban planning action. Thus, L3 prepares the institutional setting in which the evidence generated across Levels 0–2 is deliberated, negotiated, and translated into planning practice. While the preceding levels establish structural and experiential evidence, Level 3 focuses on transforming this multi-perspective understanding into actionable planning measures. By systematically documenting relevance as a shared empirical evidence base, the PDSS supports more targeted planning deliberation that reconciles stakeholder perspectives, planning regulations, and administrative requirements. This enables the development of compromise matrices and planning processes that move beyond technical feasibility by being socially embedded and responsive to lived urban experiences—dimensions that cannot be derived from quantitative data alone.

5. Overall Insights and Discussion

Urban transformation requires evidence that captures not only the physical and functional city but also its lived, felt, and interpreted dimensions. Our results demonstrate that while sensor- and remote-sensing layers reveal macro-structural conditions (e.g., thermal exposure, openness, connectivity; ENV) whose general assessment (L1) can be translated into rules for form and function, such approaches remain incomplete without an intermediate level that anchors salient group-specific experience in concrete places. Our framework (Figure 1) therefore positions L1 and L2 as the levels that integrate situated sense-making with concrete salient design features because such a lens allows for the digitally supported analysis of multi-perspective social data with the potential to reveal how different groups experience, use, and value urban environments.

From a planning perspective, L1 and L2 are an integral part of planning processes. They augment current one-dimensional approaches with structured inputs that convert individual experiences (sensory cues and in situ narratives) into actionable salience maps and compromise matrices that highlight where quick wins (affordances) are likely and where conflicts require deeper inspection involving participatory processes (L3). Crucially, once implemented, the workflow can be applied iteratively through semi-automated analyses, retrospective evaluations, and multi-temporal observations. This makes planning not only data-rich, but also responsive: structural decisions and design interventions can be continuously evaluated and refined. L3 marks the transition from empirical analysis to planning action. While not implemented here, it defines the institutional arena in which evidence from Levels 0–2 is transferred to negotiation, compromise, and policy. While each layer produces meaningful insights on its own, their combination reveals where structural similarity conceals experiential differences.

5.1. *Money for Value!*

While study costs increase with each analytical level, additional analyses are only needed for places that cannot be explained by the preceding level. In general, we recommend complementing environmental analysis (ENV) with aggregated ratings (LO), where structural screening alone is insufficient to predict place appraisal. If places with similar environmental conditions show clusters of diverging rating behaviour, integrating multimodal evidence (images, sound recordings, and self-reports) can inform the planning of balancing practices across different needs and demands regarding an urban environment (L1 and L2). Of course, involving people directly seems straightforward, but a quick poll on a few selected places highlighted by our workflow will cost much less than a fully-fledged, broad participation process.

Thus, our approach provides high-temporal change monitoring of urban places once the workflow has been established. When requirements of public spaces shift quickly in times of polycrisis, measuring tools have to keep pace to quickly inform urban planners, e.g., in the context of climate resilience. Given the standardised general framework, studies can be repeated across time and cities, evaluating local success criteria. Moreover, the PDSS may help identify perspectives from marginalised groups that are often underrepresented in conventional participatory processes due to self-selection effects.

5.2. Collaborate!

One main advantage of our approach is that richer situational knowledge is gained from multidisciplinary perspectives. In other words, diverse analyses feed into the proposed PDSS, allowing urban planners to review specific places through an analytical lens in which different disciplinary perspectives converge on the same place without repeating data collection. This dramatically reduces the effort required for complementary studies in complex locations.

By drawing together expertise, methods that are already used interdisciplinarily, e.g., discourse analysis in geography, can be applied in a more (linguistically) informed and detailed way. In addition, referring to the same data facilitates communication and feedback loops with public discourse: Interview data, multimodal observations, and general sentiment can always be tied back to the specific situation experienced by individual participants on specific days. This also reveals the time-geographic context of specific experiences that can be missed in studies conducted at isolated points in time. Based on the generic screening and data structure, the same evidence base can be revisited by different disciplines, allowing in-depth analyses according to planners' information needs.

5.3. From Digital Screening Frameworks to Real Tools: The Road Ahead

At this point, the presented implementation of the framework is subject to several limitations across all analytical levels. As a proof-of-concept, the study is based on a limited, partly unbalanced sample, and the resulting observations are not balanced across sites and data modalities; the findings should therefore be interpreted as exploratory rather than representative. Recruitment and the smartphone-based workflow may introduce demographic bias, and all data collected are prone to information bias, i.e., pre-existing information on a place presented to participants intentionally or unintentionally will guide the individual experiences on site as immediate triggers beyond basic socio-cultural contexts. While this limits statistical generalisation beyond the study context, it does not impair the successful identification of place-specific experiential patterns that complement structural planning evidence.

Across all analytical levels, the framework is shaped by temporal and situational environmental factors, including time of day, weather, and participants' positions while making their observations, which limits generalisability but also highlights the framework's potential for detecting short-term changes when such contextual factors are recorded and studied systematically. Environmental descriptors such as SVF, NDVI, POI density, and related variables provide reproducible contextual baselines, yet remain proxies that cannot fully capture complex conditions, such as shade quality, microclimatic conditions, or experienced safety. In addition, external data sources, such as OSM, may vary in completeness and tagging consistency.

Within the structural skeleton (ENV+LO), environmental descriptors and appraisal measures necessarily reduce complex spatial and experiential conditions to operational indicators. Similarity estimates based on ordinal rating data, including the interval-based IoU measure used here, remain sensitive to sample size, the spread and overlap of response distributions, and aggregation choices. Consequently, these levels constitute a robust screening approach that identifies divergence of experiential patterns, rather than explaining why it occurs.

Within the analytical lens (L1+L2), the analysis of participant-generated photographs, audio recordings and discourse provides increasingly rich insights into salient place experiences but also introduces successive sources of uncertainty related to acquisition quality, preprocessing, language processing, and coding decisions. At the same time, these methods help identify where additional analyses of subsamples are worthwhile, while allowing findings to be related back to broader patterns identified at previous levels. Cross-level alignment should therefore be understood as a triangulated convergence of evidence rather than as proof of causal mechanisms. The added value of the framework lies in integrating multiple data streams into shared empirical evidence, although the heuristic thresholds used to identify targets for deeper analysis still require validation across seasons, times, and urban contexts.

The framework enables multiple disciplinary perspectives to review the same empirical evidence, providing a shared base for complementary analyses based on established methods. However, the PDSS remains a tool for digital screening, triangulation and hypothesis generation, and should not be used in isolation to justify political decisions or specific design measures. Instead, it contributes empirically grounded insights that inform planning deliberation by complementing established planning evidence and participatory processes.

Future studies should focus on robust sample design by adopting diverse communication channels and incentives to different target groups. Equally important is the systematic integration of the framework into planning processes, using guided interviews and other participatory methods to further investigate places identified through the screening process and contextualise the empirical evidence.

To turn our approach into real decision support, we will have to add a software component (like a dashboard) to the end of our pipeline, acting as a “reading machine” that allows the analyst to engage with exploratory tools and plots on the dataset. Another crucial point is defining a suitable standardised format to provide the data collected in a FAIR manner (Wilkinson et al., 2016) and enable comparative follow-up studies.

6. Conclusion

This article introduced a PDSS that complements spatially oriented decision support by systematically integrating person–place interactions into urban planning. By organising multimodal, in situ observations within a multilevel analytical framework, the PDSS provides shared empirical evidence for analysing interactions while remaining fully compatible with established spatial analyses.

Using a proof-of-concept study in Würzburg, we demonstrated how increasing analytical depth progressively transforms contextual information into planning-relevant evidence: from user-based screening (L0), through rule-bound design cues (L1), to group-specific salience and sense-making (L2). At L2, experiential evidence becomes interpretable for planning by revealing conflicts, latent affordances, and priority areas for intervention. L3, conceptualised but not implemented here, marks the transition from evidence to planning deliberation, where professional judgement, stakeholder dialogue, and governance shape planning decisions.

For urban planning, the key contribution lies not in prescribing solutions but in informing planning deliberation. The PDSS enables planners to distinguish between situations that reveal design-oriented opportunities and those that indicate conflicts. In doing so, the framework helps identify where limited spatial interventions may be sufficient and where broader participation, coordination, or negotiation is needed, supporting context-sensitive and proportionate planning responses.

Importantly, the PDSS does not aim to optimise outcomes or automate planning decisions. Instead, it repositions digital technologies from Smart City optimisation towards a Digital City approach in which multimodal observations are analysed from multiple perspectives. As a modular, scalable, and transferable screening framework, the PDSS remains compatible with established planning practices and decision-support approaches. Rather than calling for more data, this article argues for better-placed data that regards person–place interaction in ways that strengthen equitable, context-sensitive, and evidence-informed urban transformation.

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Conflict of Interests

The authors declare no conflict of interests. In this article, editorial decisions were undertaken by Gamze Dane (Eindhoven University of Technology) and Bernd Resch (Interdisciplinary Transformation University Austria).

Data Availability

The data underlying this study cannot be made publicly available because they contain potentially identifiable private information and are subject to applicable data protection and privacy regulations.

LLMs Disclosure

The authors used an AI-based language model (ChatGPT, OpenAI) to assist with English language editing, phrasing, and concision of the manuscript. The model was used solely to improve clarity and readability and was not involved in generating scientific content, interpretations, or conclusions. All outputs were critically reviewed and discussed by the author team, who take full responsibility for the final manuscript.

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