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Posted Date: 5 February 2026

doi: 10.20944/preprints202602.0312.v1

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A Spatial Analysis of Perceived Wellbeing During Large Urban Infrastructure Construction: The Case of the Flyover in Thessaloniki, Greece

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Abstract

Large-scale urban infrastructure projects are essential, yet they often introduce prolonged disruptions that affect residents' perceived wellbeing. Existing research has demonstrated temporary declines in wellbeing during construction periods, but often relies on aggregate indicators, longitudinal averages, or proximity-based measures, providing limited insight into neighbourhood-level spatial inequalities. This study addresses this gap by developing a Perceived Wellbeing Indicator (PWI) and applying a place-based, spatially explicit framework to examine perceived wellbeing patterns associated with the Thessaloniki Flyover project. A questionnaire survey captured residents' experiences of stress, accessibility, and perceived air and noise pollution. Indicator weights were derived using a hybrid approach combining Principal Component Analysis and the Analytic Hierarchy Process. Exploratory Spatial Data Analysis techniques were applied to identify clusters, spatial outliers, and neighbourhood typologies of perceived wellbeing, which were further compared with income levels and child dependency ratios. Results reveal pronounced spatial heterogeneity in perceived wellbeing. Low-wellbeing clusters are concentrated in Evosmos, Sykies, and Ano Toumpa, while higher wellbeing is observed in Efkarpia, Kato Toumpa, and Thermi. Lower PWI values are more frequent near the Flyover axis, suggesting localized construction-related effects, although similar patterns also appear in districts distant from the project. Overall, the findings demonstrate that perceived wellbeing is shaped by a combination of local environmental, socio-economic and neighborhood conditions, rather than infrastructure proximity alone.

Keywords: perceived wellbeing indicator; PPGIS; citizen science; geolocated perceptions; urban infrastructure impacts; Thessaloniki Flyover

1. Introduction

Large-scale infrastructure projects are widely recognized as vital components of urban development and economic growth. However, they also entail extended construction periods that can negatively affect residents' everyday lives. Several studies document that perceived wellbeing often declines during major transport construction phases due to disruptions, noise, environmental changes, traffic congestion and altered daily routines [1–3]. Perceived environmental exposures have been linked to higher levels of stress among urban residents and are recognized as a significant environmental health risk, contributing to annoyance, sleep disturbance, and other stress-related effects that can be detrimental to the wellbeing [4,5]. Empirical studies also indicate that perceived air and noise pollution often shape satisfaction with the living environment more strongly than objective measures, suggesting that residents' subjective experience of environmental exposures is an important determinant of perceived wellbeing [1]. These findings highlight that disruptions, environmental exposures, and altered daily routines associated with infrastructure constructions can influence both objective and perceived wellbeing of residents.

Wellbeing is a multidimensional concept encompassing both objective and perceived (subjective) components. Objective wellbeing refers to externally measurable conditions of life, such as income, employment, housing quality, accessibility, environmental exposures, and health outcomes, and is commonly assessed using administrative, environmental, or economic data [6,7]. By contrast, perceived wellbeing captures individuals' personal evaluations of their lives and experiences, including life satisfaction, emotional affect, perceived stress, and quality of daily life [8,9]. While objective indicators provide essential context for living conditions, they do not fully reflect how these conditions are experienced, interpreted, and valued by residents. Research shows that people exposed to similar objective conditions can report different levels of wellbeing depending on personal expectations, social context, and subjective perceptions of environmental exposures and daily routines [10]. In urban and infrastructure research, perceived wellbeing is particularly important because disruptions such as construction noise, altered mobility, and changes in environmental exposure are mediated through residents' experiences and perceptions rather than through measurable exposures [11]. Incorporating subjective wellbeing thus allows for a more citizen-science approach assessment, capturing dimensions of everyday life that objective measures alone cannot fully represent.

In previous work, researchers assessing perceived wellbeing during large-scale urban infrastructure construction have primarily relied on longitudinal, mixed-methods, and qualitative approaches tailored to capture subjective experiences while construction is ongoing. In longitudinal survey designs, researchers have exploited panel or repeated cross-sectional household surveys to track changes in residents' satisfaction with their neighbourhoods and wellbeing indicators over time, with comparison across periods before, during, and after project implementation; for example, data from the nationally representative Household Income and Labour Dynamics in Australia (HILDA) survey were used to model residents' satisfaction with neighborhoods using random-effects ordered logit models, explicitly distinguishing the construction phase as an exposure period while controlling for sociodemographic attributes and life events [1]. Natural experimental designs also employ multiple waves of postal or community surveys, conducted in cohort and repeated cross-sectional formats, to measure wellbeing using validated instruments such as the SF-8 Mental Component Summary and the short Warwick-Edinburgh Mental Well-being Scale (SWEMWBS), with individual exposure defined by spatial proximity to active motorway construction [12]. Large mixed-methods protocols, such as the Wellbeing Impact Study of High-Speed 2 (WISH2), combine longitudinal and repeated cross-sectional surveys with planned semi-structured interviews and focus groups, along with administrative data linkage (e.g., medical records aggregated at the primary care level) to comprehensively assess mental health and wellbeing across phases of the infrastructure project [13]. Qualitative and inductive methods, grounded in grounded theory, use structured observations, expert consultations, and open-ended resident questionnaires to develop explanatory frameworks of how construction activities relate to perceived quality of life, systematically organising themes that emerge from residents' descriptions of their lived experience during active construction [3,14]. In addition to standalone instruments, Social Impact Assessment (SIA) frameworks are applied to integrate these diverse methods, such as surveys, interviews, and participatory engagements, into a structured evaluation of psychosocial wellbeing impacts during construction, enabling systematic documentation and comparison of subjective indicators across different stakeholder groups [15,16].

Despite the rich repertoire of research examining perceived wellbeing during large urban infrastructure construction, several important gaps remain. Existing studies predominantly rely on longitudinal, mixed-methods, or qualitative designs that examine temporal changes in wellbeing before, during, and after construction. While these approaches are well-suited to capturing dynamics over time, they typically treat space in a limited or instrumental manner, most often operationalising exposure as distance-based proximity or binary categories (construction/non-construction). As a result, they provide relatively little insight into how perceived wellbeing is spatially structured across neighbourhoods or how local wellbeing patterns relate to broader urban contexts. Moreover, many

 doi:10.20944/preprints202602.0312.v1

studies assess wellbeing at the individual level without systematically aggregating perceptions to reveal spatial patterns at the neighbourhood level. This limits their capacity to identify spatial inequalities or to inform place-based mitigation strategies during infrastructure development. In addition, while subjective wellbeing is widely measured using validated psychometric scales (i.e., SF-8), these indicators are often analysed without accounting for spatial statistical techniques that could reveal non-random spatial configurations and "hidden" local effects. Similarly, environmental stressors such as noise and air pollution are frequently treated as objective exposure measures or background variables, with less attention paid to their perceived, place-specific role in shaping wellbeing within the construction context.

Consequently, there is a lack of empirical studies that integrate subjective wellbeing assessment, spatial analysis, and neighbourhood-level contextualization into a unified framework capable of capturing spatial heterogeneity during large urban infrastructure construction. To address these gaps, the current study introduces a Perceived Wellbeing Indicator (PWI) designed to capture the multidimensional and spatially heterogeneous nature of residents' lived experience during large urban infrastructure construction. The proposed PWI integrates multiple thematic pillars (stress and wellbeing, accessibility and mobility, noise, and air pollution) into a single, interpretable metric, enabling systematic spatial comparison across neighbourhoods. Importantly, the PWI is designed for spatial aggregation and analysis, enabling examination of perceived wellbeing at the neighbourhood scale through Exploratory Spatial Data Analysis (ESDA) techniques. Rather than replacing validated wellbeing instruments, the indicator complements them by translating individual perceptions into a place-based framework that supports spatial interpretation, comparative assessment, and targeted urban mitigation strategies within the context of large-scale infrastructure interventions.

The proposed PWI is implemented in Thessaloniki, Greece, where a major urban transport construction project, the Flyover, is underway in a dense urban context that directly affects residential neighbourhoods over an extended construction period. Its scale, spatial extent, and proximity to urban life make it a suitable case for examining neighbourhood-level variability in perceived wellbeing and for testing a place-based, spatially explicit wellbeing assessment framework.

2. Materials and Methods

2.1. The Flyover Project in Thessaloniki

Thessaloniki is the second-largest city in Greece, with 1 million inhabitants [17]. Mobility is one of the most pressing environmental and urban challenges in Thessaloniki, where the limited availability of diverse travel options and transport modes has led to overreliance on private vehicles, resulting in deteriorating air quality and a diminished overall quality of life [18]. Thus, the Flyover project was adopted as a solution and is among Greece's most significant ongoing road infrastructure redevelopment projects. This elevated expressway, located along the eastern section of the Thessaloniki Ring Road, is intended to improve overall urban traffic flow and alleviate congestion within the existing network. The initiative is expected to benefit daily commuters by improving quality of life, road safety, and regional accessibility [19]. The Flyover will be 13 km in total, with 4 km of the route elevated. Key design elements include elevating nine bridges, opening three tunnels, constructing six grade-separated interchanges, and 15 km of auxiliary roads flanking the main axis. It is estimated to serve 10.000 vehicles per hour in each direction. The Greek Ministry of Infrastructure and Transport officially launched the project in autumn 2022, and it is anticipated to be delivered in spring 2027 [19]. Simulated renderings of the Flyover and the exact location of the infrastructure are presented in Figure 1. Despite the expected advantages of this large-scale infrastructure project, notable concerns persist. Construction phases have disrupted local traffic, generating noise and dust, and drivers experience multiple daily delays across the whole city. Land-use changes and encroachments affect certain neighbourhoods, while environmental impacts are significant, particularly the partial destruction of the Seich Sou peri-urban forest. The project entails clearing 82,000 m^2 of forested land for road elements and supporting infrastructure. This loss threatens air quality and living conditions citywide, extending beyond adjacent communities.

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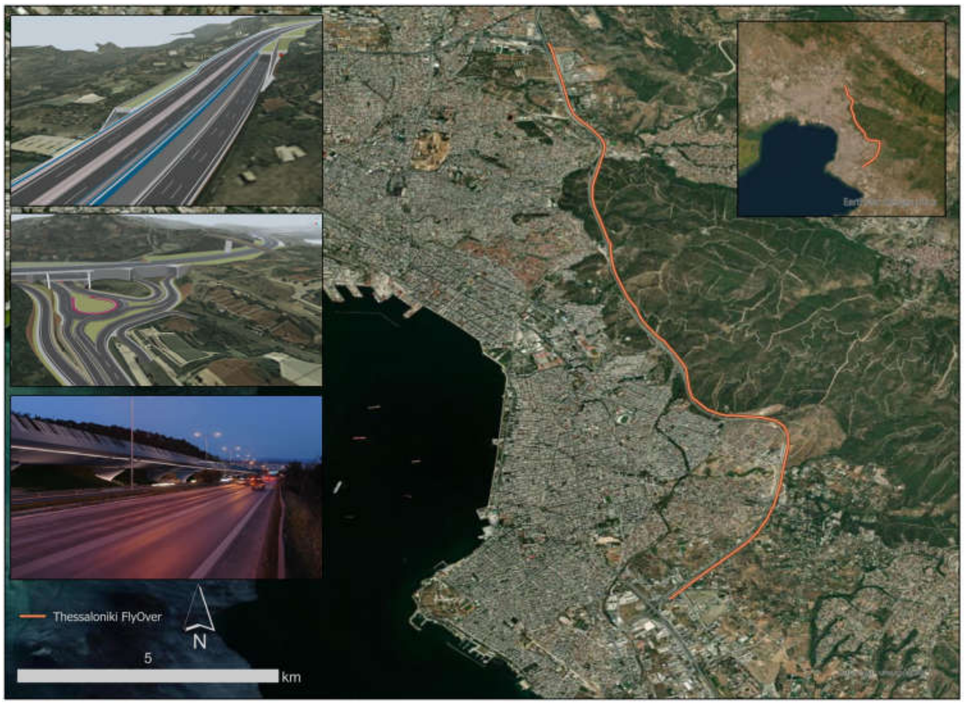

Figure 1. Simulated Renderings and Location of the Thessaloniki Flyover.

2.2. Study Participants and Ethics

The eligibility criteria for participants were that they were adult volunteers who lived in the city of Thessaloniki. In total, 341 participants completed the questionnaire via social media and word of mouth. Participants were provided with detailed information about the study’s aims, methods, and data collection and management. Ethical approval was granted by the Committee on Ethics and Research Ethics of Aristotle University of Thessaloniki (February 2024: 43723/2025).

2.3. Data Collection

Data were collected via a web-based questionnaire implemented on the Limesurvey platform, with responses being fully anonymised. The survey was active for 4months (May - August 2025) and comprised five sections: (1) stress and wellbeing, (2) accessibility and mobility, (3) noise annoyance, (4) air pollution and (5) participants’ demographics. More details about each section are provided in Appendix A (Table A1). There was also an integrated geospatial tool (Figure 2) in which participants were asked to place a pin at the nearest crossroad to their home and workplace on an interactive map. Thus, it was feasible to aggregate spatial data with responses without compromising individual privacy.

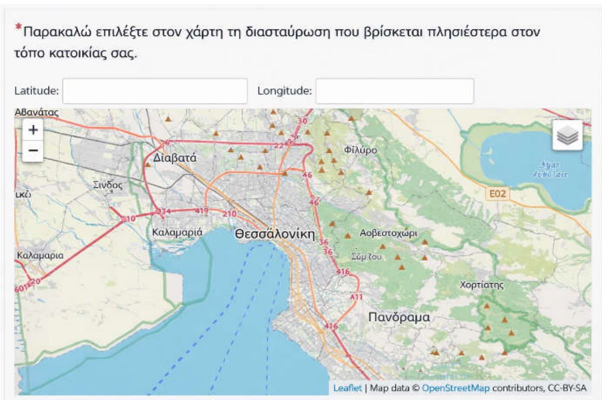

Figure 2. Interactive tool for Geolocating Home and Workplace via Nearest Crossroad.

2.4. Development of the Perceived Wellbeing Indicator (PWI)

To assess the impact of the flyover project on residents' wellbeing, a novel multidimensional indicator was developed comprising four pillars: stress and wellbeing (SW), accessibility and mobility (AM), noise (N), and air pollution (AP). Generative artificial intelligence (ChatGPT, OpenAI GPT-5) was used to assist in interpreting Principal Component Analysis (PCA) results. All methodological decisions, analyses, and final interpretations were performed and verified by the authors. The use of AI did not influence data collection, statistical analyses, or the study's conclusions.

Questionnaire Reliability and Structural Analysis for Indicator Development

To assess the internal consistency of the questionnaire items within each thematic pillar, Cronbach's alpha was calculated. This statistic assesses the degree to which items within a scale measure the same underlying construct, ensuring that the thematic pillars reliably capture their intended dimensions (e.g., Stress, Accessibility, Noise, Air Pollution). Items that did not contribute to internal consistency were excluded to improve reliability. High Cronbach's alpha values indicate that the items within each pillar are coherent and suitable for further analysis [20,21]. To further examine the underlying structure of the questionnaire and the conceptual relationships among items, Principal Component Analysis (PCA) with Varimax rotation was applied. PCA reduces data dimensionality and identifies latent components that account for the maximum variance in the dataset. This method helps confirm whether items cluster according to the theoretically defined thematic pillars, providing evidence of structural validity. Components with eigenvalues greater than 1 were retained, and their factor loadings were interpreted to determine which items contribute to each dimension [22]. Last, to assess the degree of association between the thematic pillars and examine whether related constructs co-occur while remaining distinct, both Pearson and Spearman correlation coefficients were computed:

- Pearson correlations were applied to the mean scores of the pillars to quantify linear relationships between continuous variables.
- Spearman's rho was used due to the ordinal nature of the underlying Likert-scale items, capturing monotonic relationships without assuming normality [23,24].

Significant positive correlations indicate convergent validity, confirming that related dimensions of stress, mobility disruption, and environmental impacts tend to co-occur. Strong but imperfect correlations support discriminant validity, indicating that the pillars measure conceptually distinct aspects of the urban experience.

Pillars Weighting

Weights for each pillar of the proposed indicator framework were derived through two independent procedures: Principal Component Analysis (PCA) and the Analytic Hierarchy Process (AHP). Pillar weights were derived via Principal Component Analysis (PCA) using SPSS software [25]. Originally formulated by Hotelling [26], PCA is a dimensionality-reduction technique that identifies principal components that maximise the variance explained in the dataset, producing objective weights based on factor loadings. The approach generates orthogonal components and explains variance proportions, computed via eigenvalue decomposition of the covariance matrix: the principal eigenvectors yield component loadings (weights), and the corresponding eigenvalues quantify the variance captured [27]. Weights reflected the dataset's underlying structure from participant responses.

Pillar weights were also calculated using the Analytic Hierarchy Process (AHP) with the AHP Priority Calculator (bpmsg.com/ahp/ahp-calc.php). Originally developed by Thomas L. Saaty, the AHP facilitates multi-criteria decision-making by deriving ratio scales from pairwise comparisons of criteria and accommodating minor inconsistencies in judgments. The approach generates priority weights and a consistency ratio (CR), which are computed by solving an eigenvalue problem: pairwise comparisons are represented as a matrix whose principal normalised right eigenvector yields the weights, with the corresponding eigenvalue indicating consistency [28,29]. Expert judgments from the research team informed the assessment.

Thus, PCA objectively derived pillar weights based on the variance explained in the dataset, whereas AHP elicited subjective weights through structured pairwise comparisons conducted by the research team. A hybrid approach was subsequently developed by averaging the PCA objective weights with the AHP expert judgments to determine the most suitable weighting scheme for the indicator. Sensitivity analysis was performed using Pearson and Spearman correlation coefficients computed between composite indicators derived from PCA-based, AHP-based, and hybrid (averaged) weighting schemes. This approach evaluated the robustness, stability, and consistency across the different weighting methods to determine the most appropriate scheme for the final indicator.

2.5. Exploratory Spatial Data Analysis of Perceived Wellbeing

Because participants were distributed across Thessaloniki, including its outskirts, hexagonal aggregation units with a 300 m radius were employed to produce a spatially coherent representation of the composite indicator. This radius was selected to capture local sensitivity and aggregation stability [30]. These hexagons provided a regular tessellation that avoided boundary effects common in administrative units, enabling consistent spatial analysis. Mean indicator values were subsequently calculated for each hexagon based on the aggregated participant scores within its boundaries, facilitating visualisation of spatial patterns in urban environmental perceptions.

2.5.1. Hotspot Analysis (Getis-Ord G_i^*)

The first stage utilized the Getis-Ord G_i^* statistic to identify the presence of broad regional clusters. This method is particularly effective for identifying the "spatial reach" of the Flyover's impact on community wellbeing. The G_i^* statistic identifies locations where high or low PWI values are surrounded by similar values, resulting in statistically significant Hotspots and Cold Spots [31]. In the context of this study, this tool was prioritised to visualise the general "wellbeing landscape" and to determine if the Flyover route intersects with large-scale clusters of low perceived wellbeing.

2.5.2. Cluster and Outlier Analysis (Anselin Local Moran's I)

In the second stage, Anselin's Local Moran's I (LISA) was employed to refine the analysis by identifying spatial outliers. Unlike the Hotspot analysis, which focuses on similarity, LISA identifies locations that are significantly different from their neighbours [32]. This was a critical step for "unmasking" socio-demographic disparities that might be hidden within broader regional trends [33].

2.5.3. Hotspot Comparison with Socio-Economic Indicators

To examine the spatial relationship between perceived wellbeing and socio-economic conditions, hotspots of PWI were compared with area-level income and child dependency ratios. Both socioeconomic variables were aggregated to the same hexagonal grid used for the PWI, and Getis-Ord Gi* statistics were applied to identify significant hotspots and Cold Spots. Hexagons were then classified based on the co-location of PWI and socio-economic significance (e.g., Hot-Hot, Cold-Cold, Hot-Not Significant, Cold-Not Significant), thereby enabling identification of neighbourhoods in which wellbeing aligns with or diverges from the local economic and demographic context. These co-location patterns informed the exploratory typology of Thessaloniki neighbourhoods.

3. Results

3.1. Participants' Demographics

A total of 341 participants completed the survey. However, not all respondents completed the questionnaire in full, prompting the establishment of a completeness threshold. Specifically,

 doi:10.20944/preprints202602.0312.v1

responses from participants who completed fewer than 50% of the items were excluded from the analysis. Consequently, data from 236 participants were retained for subsequent analysis. Table 1 presents the participants' demographic characteristics. To assess the campaign's representativeness, national demographic data for the Greek population were used for comparison [34,35].

Table 1. Participants' demographics.

	Characteristics	**N**	**%**	**Greece (2021)**
No. of participants		236		10482487
Age	18-29	98	41.5	17
	30-44	55	23.3	21
	45-59	57	24.2	23
	60-74	17	7.2	19
	>75	3	1.3	20
	I do not wish to answer	6	2.5	-
Sex	Male	85	40.3	52
	Female	121	57.3	51.8
	Other	1	0.5	-
	I do not wish to answer	4	1.9	-
Marital status	Male	85	40.3	52
	Female	121	57.3	51.8
	Other	1	0.5	-
	I do not wish to answer	4	1.9	-
Employment status	Full-time employment	159	75.4	38
	Student/trainee / unpaid worker gaining experience	33	15.6	17
	Retired	15	7.11	22.4
	Unemployed	1	0.5	6.3
	I do not wish to answer	1	0.5	-
	Another type of economically inactive person	2	1	6.1
Educational attainment	Primary school	1	0.5	18.7
	High school graduate	22	10.4	27.1
	Short-cycle tertiary education	16	7.6	13
	University/Technical college graduate/Master's degree/ Doctorate	170	80	21
Income	1st Quantile	122	57.7	6.8
	2nd Quantile	26	12.3	13.1
	3rd Quantile	14	6.6	17.7
	4th Quantile	13	6.1	23.2
	5th Quantile	3	1.5	39.3
	I do not wish to answer	33	15.6	-

Females were overrepresented in the campaign. Most participants were employed, with a smaller proportion unemployed or otherwise economically inactive. Individuals with higher education levels and higher incomes were also overrepresented. Compared with national demographic data, it was clear that the campaign did not fully represent either population. Participants aged 18–29 were overrepresented. Participants were asked to indicate their home and workplace locations on an interactive map within the questionnaire. The Spatial Distribution of Participant Locations (Figure 3) shows a dispersed pattern across Thessaloniki, including its outskirts. Workplaces situated outside Thessaloniki or Greece were excluded from the analysis.

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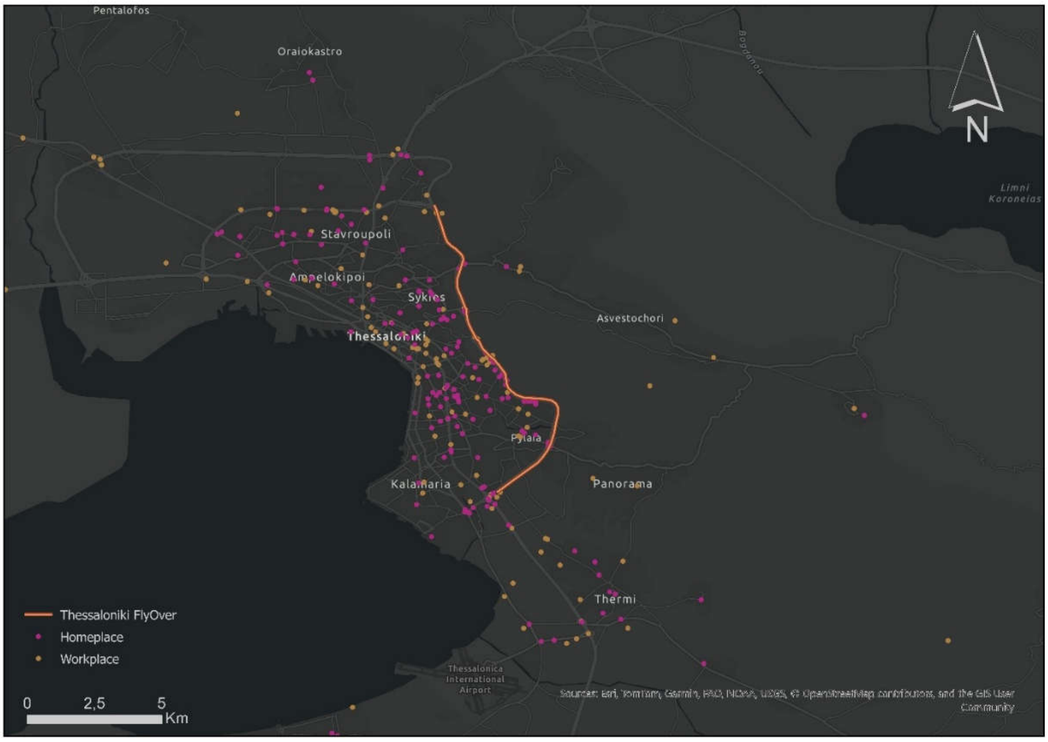

Figure 3. Spatial Distribution of Participant Locations.

3.2. Perceived Wellbeing Indicator (PWI)

3.2.1. Questionnaire Reliability and Structural Analysis for Indicator Development

The Stress thematic pillar, comprising items related to emotional strain, psychological burden, and perceived quality-of-life impacts, demonstrated excellent internal consistency (Cronbach's α = 0.947). This high coefficient indicates strong coherence among the included items and suggests that they reliably capture a common underlying construct associated with the emotional and psychological impacts of commuting and construction-related disruptions. Items that did not contribute to internal consistency were excluded to enhance the scale's reliability. The Accessibility pillar, which includes items addressing commuting time, delays, parking availability, access to services, and restrictions on daily activities, also exhibited very high reliability (Cronbach's α = 0.903). This result confirms that the selected questions consistently measure the perceived impacts of construction works on urban mobility and accessibility. The Noise pillar, comprising items measuring perceived noise pollution at both the workplace and the place of residence, demonstrated good internal consistency (Cronbach's α = 0.815). This indicates that the items reliably measure a single construct of environmental disturbance related to noise exposure. Finally, the Air Pollution pillar, based on items assessing perceived atmospheric pollution at the workplace and at the place of residence, demonstrated acceptable internal consistency (Cronbach's α = 0.701). Although lower than the other pillars, this value remains above commonly accepted thresholds for exploratory research, indicating that the scale is suitable for inclusion in further analyses.

Table 2 summarises the thematic pillars derived from the questionnaire, the items retained within each pillar following reliability analysis, the underlying constructs measured, and the corresponding Cronbach's alpha values. The reliability coefficients demonstrate strong internal consistency for the Stress and Accessibility pillars and satisfactory reliability for the environmental disturbance pillars (Noise and Air Pollution). The questions are provided in Table A1 of Appendix A. Overall, the Cronbach's alpha results support the reliability and construct validity of the thematic pillars developed.

Table 2. Thematic pillars, questionnaire items, measured constructs, and reliability coefficients (Cronbach's alpha).

Pillar	Questions	Cronbach's Alpha
Stress	Q10, Q17, Q20, Q22, Q25, Q29, Q30, Q39, Q41	0.947
Accessibility	Q11, Q12, Q13, Q14, Q34, Q35, Q36, Q37, Q38, Q40	0.903
Noise	Q23, Q33	0.815
Air pollution	Q32, Q21	0.701

The PCA extraction yielded six components with eigenvalues greater than 1, indicating a multidimensional structure of the dataset. The first two components together accounted for approximately 59% of the total variance, with Component 1 accounting for 49.5% and Component 2 for 9.3%. Given their substantial explanatory power, these components were considered the most relevant for interpretation. Following Varimax rotation, a clear and interpretable loading pattern emerged. Items related to the Stress and Wellbeing, Accessibility and Mobility, and Noise pillars loaded predominantly on Component 1, with factor loadings ranging from 0.61 to 0.91. This pattern suggests that these domains share a common underlying dimension, reflecting a broader construct associated with psychosocial strain and daily mobility disruption resulting from construction-related traffic conditions. In contrast, items measuring Air Pollution (Q21, Q32) loaded strongly on Component 2, with high loadings (0.82–0.83), indicating that perceived air pollution constitutes a distinct and separable dimension. This finding supports the conceptual distinction between environmental air quality impacts and the broader psychosocial and mobility-related effects captured by Component 1. Although additional components (components 3, 4, 5, and 6) were statistically extracted (see Table B1 in the Appendix B), their explanatory contribution was limited, and their loading patterns were less theoretically coherent. Therefore, the analytical focus was placed on the first two components, which provide the most meaningful representation of the underlying construct structure. Overall, the PCA results provide strong evidence of structural validity for the proposed index. The clear clustering of items within conceptually meaningful components, combined with high loadings and consistency with the predefined thematic pillars, confirms that the instrument captures distinct yet related dimensions of stress, mobility disruption, and environmental impacts associated with the Ring Road construction project.

To further examine the relationships between the four thematic pillars, Pearson and Spearman correlation analyses were conducted. Pearson correlations were computed on the mean scores of each pillar, while Spearman's rho was applied, given the ordinal nature of the underlying Likert-scale items. Pearson correlation results (Table 3) indicated statistically significant positive associations across all pillars, with coefficients ranging from $r = 0.595$ (Stress and Air Pollution) to $r = 0.887$ (Stress and Accessibility; $p < 0.01$). The strongest correlation was observed between the Stress and Accessibility pillars, suggesting that perceived emotional and psychological strain is closely related to perceived disruptions in mobility and access. Lower, yet significant, correlations between Stress and Air Pollution confirm that the pillars represent distinct constructs while remaining related aspects of the urban experience. Similarly, Spearman correlation analysis yielded strong positive associations across all pillars ($\rho = 0.768$–0.876, $p < 0.001$), with the highest correlation between Noise and Air Pollution ($\rho = 0.876$). This further indicates that perceived environmental disturbances tend to co-occur, while remaining conceptually distinguishable from psychosocial impacts. Together, these correlation results provide evidence for convergent validity, confirming that the thematic pillars measure related aspects of the impacts of construction and urban mobility conditions, while maintaining discriminant validity, as the correlations are strong but do not approach unity. These findings complement the PCA results, which identified a shared underlying dimension for Stress, Accessibility, and Noise, and a separate dimension for Air Pollution, reinforcing the conceptual structure of the index.

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Table 3. Pearson and Spearman correlations between thematic pillars (above and below, respectively).

	Stress	Accessibility	Noise	Air pollution
Stress	1	0.887*	0.733*	0.595*
Accessibility	0.887*	1	0.816*	0.698*
Noise	0.733*	0.816*	1	0.846*
Air pollution	0.595*	0.698*	0.846*	1
	Stress	**Accessibility**	**Noise**	**Air pollution**
Stress	1	0.859*	0.817*	0.768*
Accessibility	0.859*	1	0.874*	0.837*
Noise	0.817*	0.874*	1	0.876*
Air pollution	0.768*	0.837*	0.876*	1

* $p < 0.01$ (2-tailed).

These results reinforce that the proposed index captures interrelated yet conceptually distinct dimensions of psychosocial strain, mobility disruption, and environmental impacts, supporting its use as a robust tool for assessing the multifaceted effects of urban construction projects.

3.2.2. Pillars Weighting

PCA-Derived Weights

Principal Component Analysis (PCA) identified four principal components from the questionnaire items, which together explain key dimensions of urban environmental perception. Component 1, labelled "Stress," exhibited the highest mean loading (0.809), with loadings ranging from 0.664 (Q10) to 0.906 (Q41), indicating a robust association with stress and wellbeing factors. Component 1 also captured "Accessibility and mobility", though with moderate mean loading (0.590) and variability (e.g., low Q11 at –0.094 vs. high Q38 at 0.825), suggesting nuanced accessibility perceptions. Component 2 ("Noise") included Q23 (0.722) and Q33 (0.693), with a solid mean loading of 0.708, highlighting auditory environmental stressors. Component 3 ("Air Pollution") comprised Q21 (0.827) and Q32 (0.382), yielding a mean loading of 0.605 and reflecting air quality concerns, although Q32 contributed less. These components demonstrate a clear factorial structure, with Component 1 accounting for most of the variance through high-loading stress and accessibility items, supporting their use in subsequent weighting for the composite indicator. The mean loadings were then normalised to sum to 1, and the final PCA-derived weights are presented in Table 4.

AHP-Derived Weights

After applying the Analytic Hierarchy Process, the following weights (Figure 4) for the objective and subjective factors were obtained, with a consistency ratio of 9.5%.

Cat		Priority	Rank	(+)	(-)
1	Stress	61.6%	1	26.5%	26.5%
2	Accessibility	16.8%	3	6.7%	6.7%
3	Noise	16.9%	2	3.2%	3.2%
4	Air Pollution	4.6%	4	2.5%	2.5%

Figure 4. Derived weights from AHP.

Hybrid Weights

The hybrid weights were calculated as the mean of the PCA-derived objective weights and the AHP-derived authors' judgment weights, integrating both data-driven variance patterns and expert assessment to produce a balanced weighting scheme for the indicator. The results of all implemented methods are presented in Table 4.

Table 4. Derived weights per method.

	PCA	AHP	Hybrid
Stress and Wellbeing (SW)	0.298	0.616	0.457
Accessibility and Mobility (AM)	0.217	0.168	0.192
Noise (N)	0.261	0.169	0.215
Air Pollution (AP)	0.223	0.046	0.134

Sensitivity Analysis Results

Sensitivity analysis compared pillar rankings and composite indicator scores across PCA, AHP, and hybrid weighting schemes, revealing high consistency among methods. Pillar ranking correlations showed a strong positive association between PCA and AHP (r = 0.800) and between PCA and hybrid (r = 0.800), and a perfect correlation between AHP and hybrid (r = 1.000), indicating nearly identical priority structures. Pearson correlations between composite indicators further confirmed robustness: PCA vs. AHP (r = 0.930, p < 0.001), PCA vs. hybrid (r = 0.994, p < 0.001), and AHP vs. hybrid (r = 0.965, p < 0.001), all based on n = 234 cases. Spearman rho correlations yielded similarly strong results: PCA vs. AHP (ρ = 0.930, p < 0.001), PCA vs. hybrid (ρ = 0.992, p < 0.001), and AHP vs. hybrid (ρ = 0.966, p < 0.001). These inter-method correlations validated the selection of the hybrid weighting scheme, demonstrating its stability while balancing objective data patterns with the authors' judgment. So, the proposed indicator is shaped as follows:

$$\text{PWI} = 0.606 * SW + 0.301 * AM + 0.345 * AM + 0.246 * AP, \quad (1)$$

3.3. Geospatial Assessment of Perceived Wellbeing

Following the initial data collection, raw point values were aggregated into a hexagonal grid to normalise for varying response densities and to mitigate the Modifiable Areal Unit Problem (MAUP). Figure 5 displays the mean PWI score per hexagon, providing a clearer visualisation of the city's wellbeing gradient. The hexagonal map clearly illustrates a broad geographic disparity in wellbeing. The lowest values are identified in Evosmos (northwestern), in the city centre and Ano Toumpa (north-eastern), representing lower mean PWI values (2.01 – 4.49). By contrast, the Southeastern peri-urban areas (Thermi), Kato Toumpa, and Ampelokipoi show a high concentration of dark-green hexagons, indicating significantly higher average well-being (5.14–7.10). The map highlights specific areas of concern where the Flyover route intersects with residential zones. Notably, in the Ano Toumba and Sykies regions, hexagons directly adjacent to the construction areas often exhibit lower mean scores than their immediate neighbours farther from the axis. This suggests that the aggregation process has successfully captured a localised "infrastructure shadow" where wellbeing is depressed. Figure 6 depicts the spatial variation in PWI with buffer zones of 500m and 1000m, respectively, enabling a proximity-based assessment of potential construction-related impacts. Hexagons intersected by the 500m buffer zone tend to exhibit lower PWI values than more distant areas, suggesting a potential proximity effect associated with the construction. Intermediate patterns observed within the 1000m buffer indicate a gradual attenuation of this effect with distance.

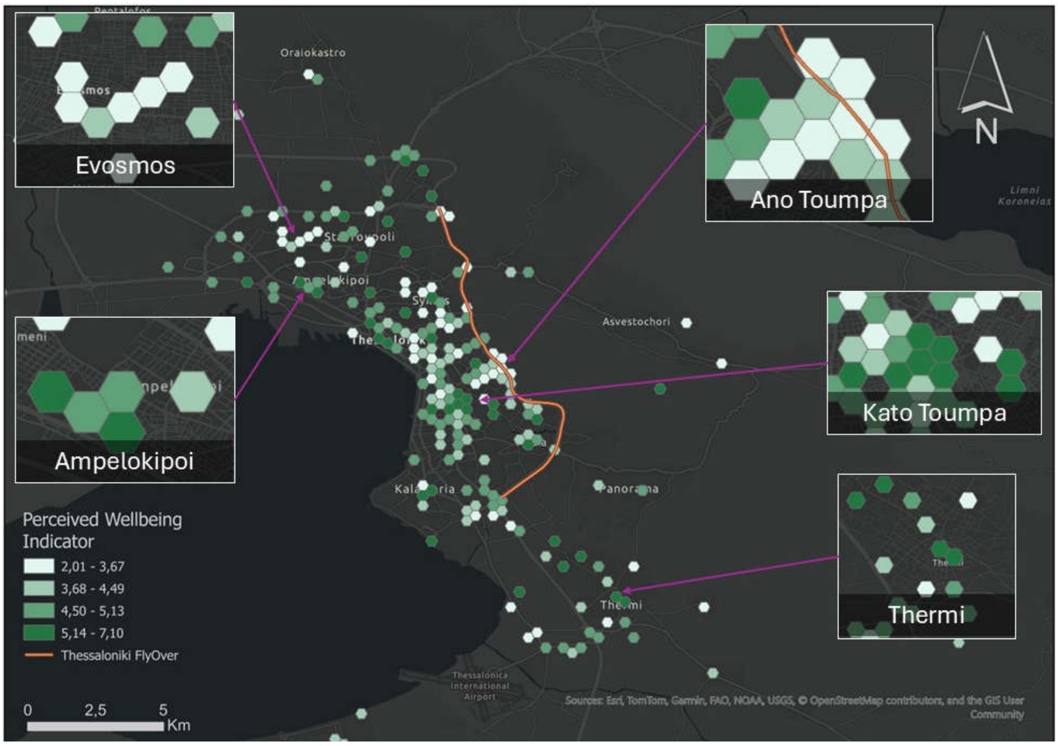


Figure 5. Spatial distribution of the Perceived wellbeing Indicator.

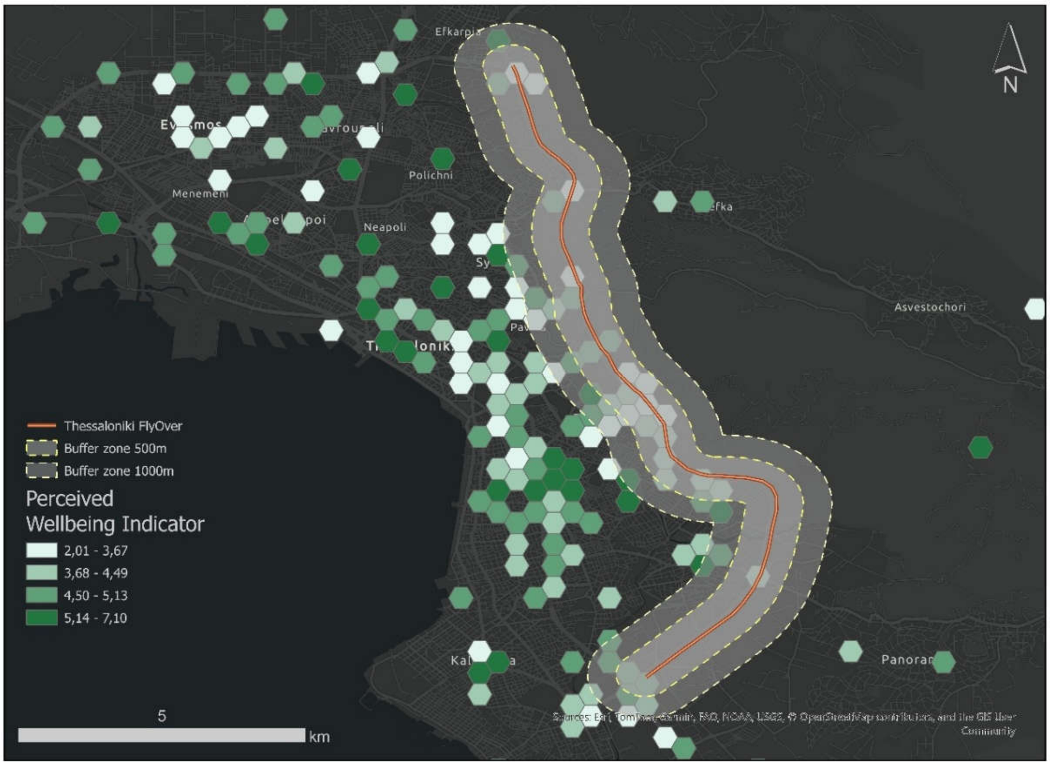
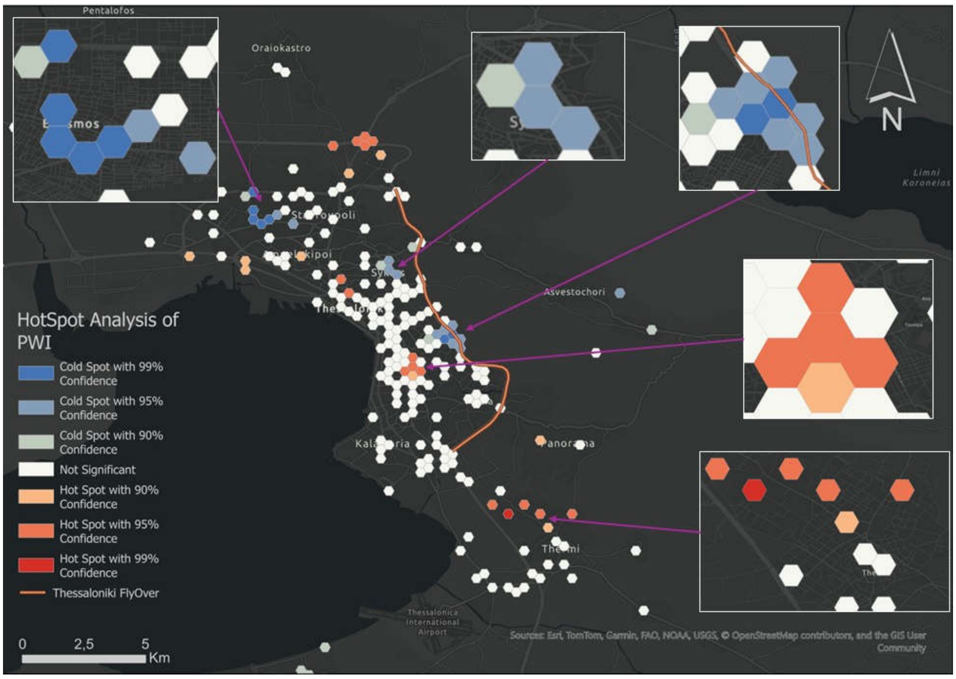


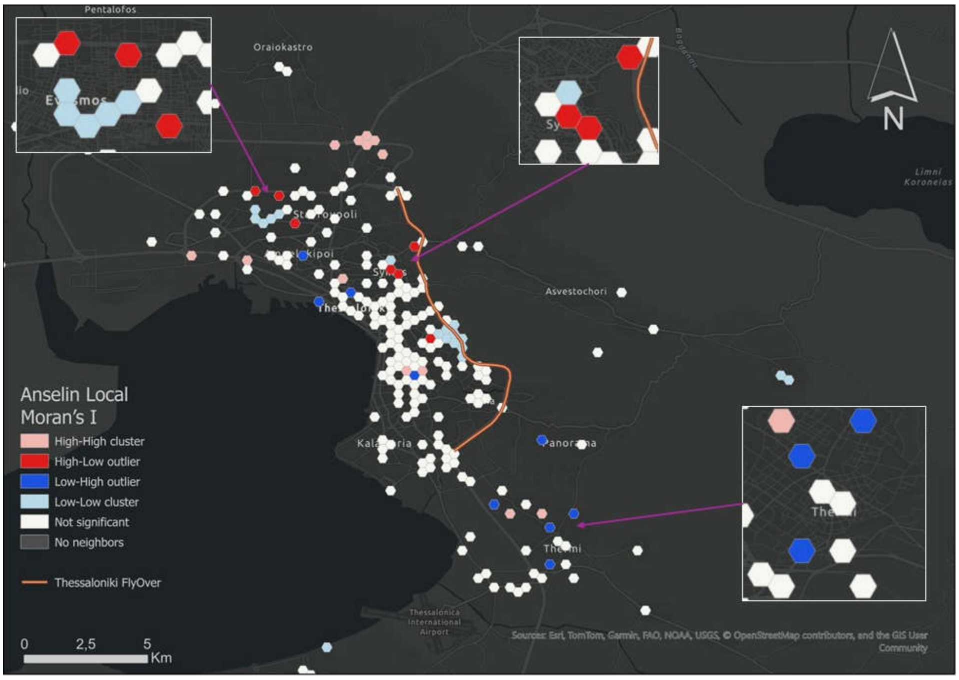
Figure 6. Spatial distribution of the Perceived wellbeing Indicator in relation to the construction area.

The Getis-Ord (G_i^*) Hotspot Analysis (Figure 7a) reveals a marked spatial polarisation of Perceived Wellbeing Indicator (PWI) across the study area. A statistically significant Cold spot (at a confidence level > 95%) is identified northeast (Ano Toumpa), an area where Flyover intersects the district directly. Beyond the intersection at Ano Toumba, other significant Cold spots were identified in Evosmos and Sykies, indicating a concentration of residents with lower perceived wellbeing, even though the flyover does not physically intersect these areas, suggesting that wellbeing perceptions are influenced by broader district-level characteristics rather than immediate proximity to the infrastructure axis alone. Conversely, a robust Hotspot of high perceived wellbeing (at a confidence level > 95%) is in the southeastern peri-urban zone (Thermi), in Efkarpia (northwestern), and in Kato Toumpa. Rest areas intersected by the flyover project are predominantly statistically non-significant.

Figure 7b further refines these findings by identifying specific outliers. Notably, High-Low (HL) outliers were detected in Sykies, representing areas of high wellbeing within a statistically significant low-wellbeing environment. On the contrary, the presence of Low-High (LH) outliers in the southeastern sector (Thermi) highlights localised "Pockets of Vulnerability" where residents report significantly lower wellbeing than their immediate neighbours.



(a)



(b)

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Figure 7. a) Hot spot analysis of Perceived wellbeing Indicator, b) Local Moran's I of Perceived wellbeing Indicator.

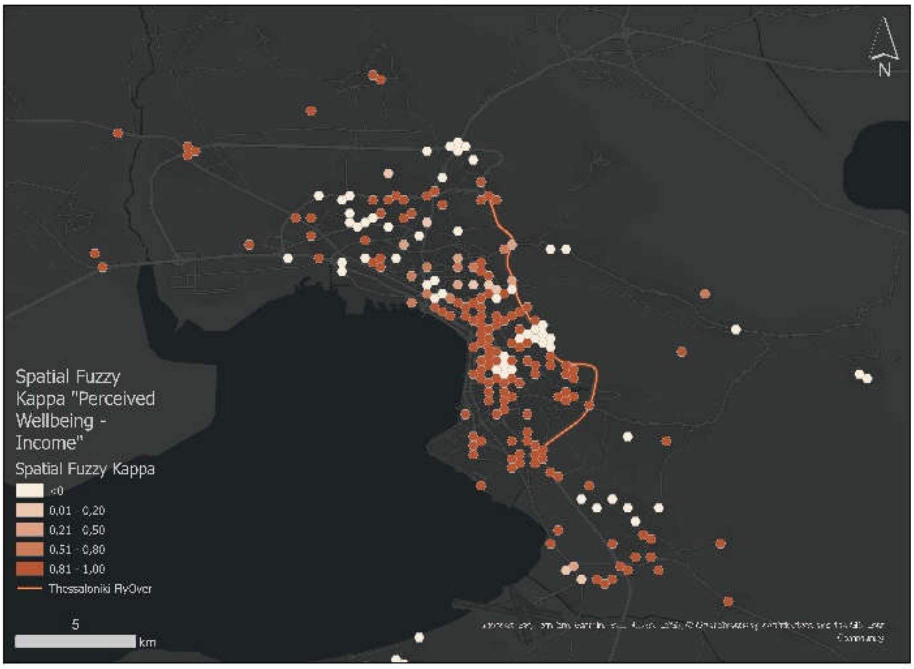
Figure 8a presents the spatial distribution of local spatial fuzzy kappa values between perceived wellbeing and income, calculated at the hexagonal grid level. Darker shades indicate higher kappa values, reflecting more pronounced spatial heterogeneity in the relationship between economic prosperity and perceived wellbeing. These high kappa values (0.81–1.00) dominate the central urban area of Thessaloniki and adjacent corridors, indicating very strong to near-perfect spatial agreement, suggesting that income levels closely align with perceived wellbeing in these locations. Conversely, lower kappa values in peripheral zones highlight areas where wellbeing appears to be influenced by additional contextual factors. Overall, the results demonstrate that while economic prosperity is a key determinant of wellbeing across much of the study area, its influence is not spatially uniform. Figure 8b depicts the spatial distribution of statistically significant local combinations between perceived wellbeing and income, revealing a typology of areas:

A. Cold to hot areas (dark red) denote areas where income is a cold spot (significantly low) but perceived well-being is a hot spot (significantly high). These areas are only notified in Efkarpia and a few in the city centre, implying that, despite economic hardship, the population reports high perceived wellbeing.

B. Not Significant to Hot areas (red) like in Kato Toumpa and Thermi, denote areas where income is not significant (average/random), but Wellbeing is a Hot Spot. In these areas, wellbeing is "over-performing" relative to wealth, so the high wellbeing is likely driven by Non-Economic Factors. This could be due to the physical environment (e.g., parks or proximity to nature) or to specific demographics (e.g., a high concentration of retirees or a particular gender balance).

C. Not Significant to Cold (light blue) areas, such as in Ano Toumpa and Evosmos. In this case, income is not significant (average/random), but Wellbeing is significantly low. These are areas where wellbeing is "under-performing." Even though these people aren't technically in an "income cold spot," they feel significantly worse than their neighbours. These are "At-Risk" areas. They may not qualify for economic aid solely on the basis of salary, but they are clearly struggling.

D. Cold to not sig areas (blue hash) denote areas where the perceived wellbeing is low, but the relationship between wellbeing and income is not significant. People in these areas (i.e., the western part of the city centre) report lower wellbeing, but income differences are not evident in the data.



(a)

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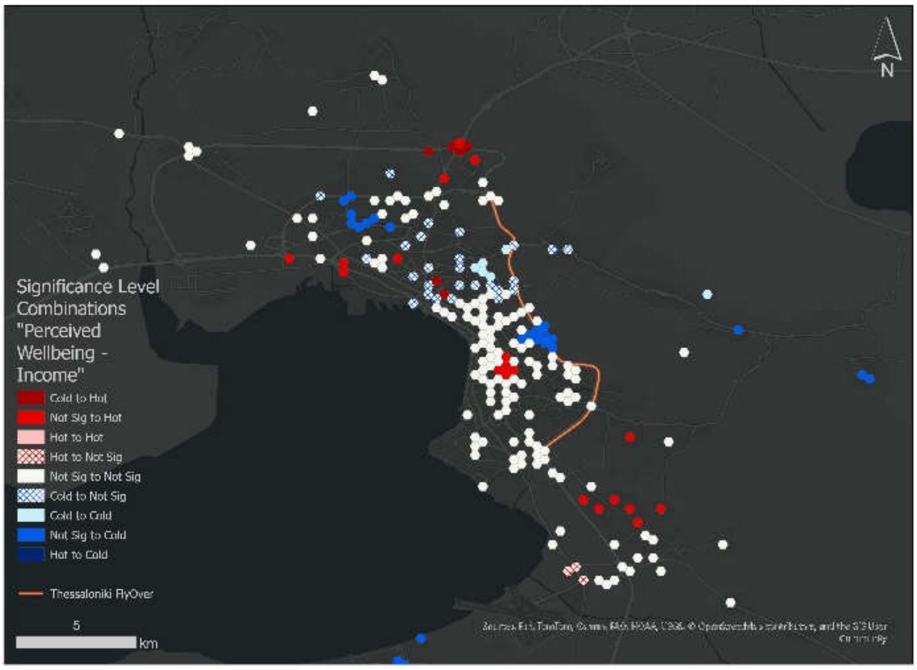

(b)

Figure 8. Spatial dependency between: (a) economic prosperity and perceived wellbeing, (b) dependency (children under 18 years old) and perceived wellbeing.

Following the completion of the spatial analyses, the results were synthesised to develop an exploratory typology of neighbourhoods within the city of Thessaloniki. The typology was constructed by jointly considering absolute levels of perceived wellbeing (PWI), their spatial configuration, and their relationship with surrounding socio-economic conditions. Specifically, local wellbeing intensity, spatial embeddedness, and co-location with income patterns were used to characterise distinct spatial wellbeing profiles across the study area.

To enrich the interpretation of these spatial patterns, additional contextual information was incorporated. Socioeconomic context was represented by the child dependency ratio, while environmental conditions were captured by residents' perceptions of annoyance from air and noise pollution. These variables were not treated as spatially analysed indicators but were included to provide complementary insight into neighbourhood conditions. Environmental stress indicators were calculated as area-level ratios based on survey responses and subsequently classified into qualitative frequency categories (e.g., rare, often, very often). No spatial statistical analysis was applied to these variables. Their role in the analysis is therefore descriptive and interpretative, supporting the contextual understanding of the identified wellbeing patterns rather than contributing to their spatial delineation. The resulting typology combines absolute perceived wellbeing levels, their spatial embeddedness, and their co-location with socio-economic conditions. It is intended as an exploratory, place-based framework that supports the interpretation of spatial heterogeneity in perceived wellbeing across Thessaloniki, rather than as a basis for causal inference.

Table 5 summarises neighbourhood typologies by combining absolute perceived wellbeing levels, their spatial embeddedness, and their co-location with socio-economic conditions.

Table 5. Neighbourhood Profiles Combining Wellbeing, Socio-Economic, and Environmental Indicators.

Area	**Spatial wellbeing patterns**			**Contextual characteristics**		
	Absolute local PWI	Spatial embeddedness	Co-location (or lack thereof)	Child Dependency Ratio	Frequency of air	Frequency of Perceived noise

	(PWI hot spot)	(PWI Morans' I)	between perceived wellbeing hotspots and economic prosperity hotspots. (Hotspots comparison: PWI - Income)	(children <18y)	pollution annoyance	pollution annoyance
Evosmos	Low PWI	Persistent low wellbeing (Low PWI in low PWI environment)	Not sig income – Low PWI	Low	Very often	Very often
Ano Toumpa	Low PWI	Persistent low wellbeing (Low PWI in low PWI environment)	Not sig income – Low PWI	Low	Very often	Very often
Sykies	Low PWI	Local resilience (High PWI in low PWI environment)	Low income – Low PWI	No	Often	Rare
Efkarpia	High PWI	Cumulative high wellbeing (High PWI in high PWI environment)	High income – High PWI	High	Often	Rare
Kato Toumpa	High PWI	Not sig	Not sig income – High PWI	No	Rare	Rare
Thermi	High PWI	Local vulnerability (Low PWI in high PWI environment)	Not sig income – High PWI	Moderate	Often	Rare

Figure 9 illustrates the exploratory typology of neighbourhoods derived from the Perceived Wellbeing Indicator (PWI), spatial configuration, and co-location with socio-economic and environmental factors. Typologies are classified as:

- Type 1: Persistent low wellbeing & environmentally stressed (Evosmos, Ano Toumpa): Low wellbeing in these areas appears more closely associated with perceived environmental stress than with economic deprivation.
- Type 2: Socio-economic stress but environmental relief (Sykies): Low wellbeing appears more closely aligned with socio-economic conditions than with perceived environmental stress.
- Type 3: Cumulative high wellbeing (Efkarpia): These areas exhibit cumulative advantage across socio-economic and perceived environmental dimensions.
- Type 4: Localised wellbeing pockets (Kato Toumpa, Thermi): High perceived wellbeing despite mixed contextual signals, suggesting the influence of localised place-based qualities or social factors.

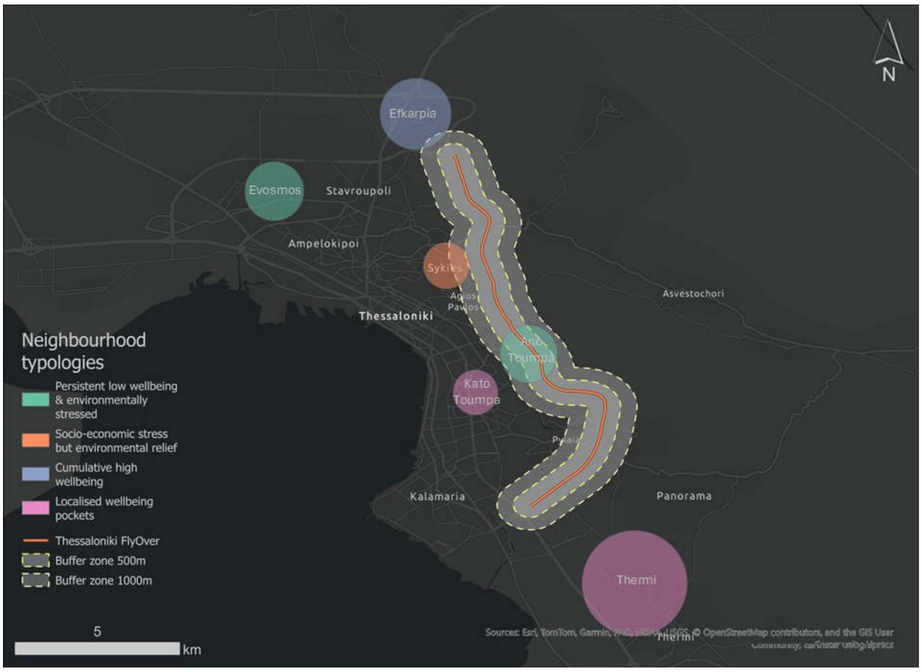

Figure 9. Spatial Distribution of Neighbourhood Profiles in Thessaloniki.

4. Discussion

While previous longitudinal studies demonstrate temporal declines in satisfaction and wellbeing during transport construction, they typically do not explicitly measure spatial proximity [1]. The findings of this study confirm that perceived wellbeing in Thessaloniki is highly heterogeneous and spatially structured, rather than uniformly distributed across the urban fabric. The hotspot analyses reveal clear geographic contrasts, with clusters of low perceived wellbeing concentrated Evosmos, Sykies and Ano Toumpa, while higher wellbeing is predominantly observed in Efkarpia, Kato Toumpa and Thermi. These patterns suggest that residents' perceived wellbeing is shaped by a combination of local conditions and broader neighbourhood contexts, rather than by proximity to infrastructure works alone. The identification of lower PWI values in areas intersecting or adjacent to the Flyover axis, particularly in Ano Toumpa and parts of Sykies, points to a potential localised effect associated with proximity to major infrastructure works, where construction-related disruption may exacerbate existing pressures on daily life. At the same time, the presence of cold spots in areas not directly intersected by the Flyover, such as Evosmos, indicates that perceived wellbeing is influenced by district-level characteristics that extend beyond immediate construction exposure.

A key contribution of this study lies in the combined use of hotspot analysis and local spatial autocorrelation to move beyond simple identification of high- and low-wellbeing areas. While Getis–Ord Gi* highlights broader regional patterns, the Local Indicators of Spatial Association (LISA) analysis reveals more nuanced spatial configurations, including localised pockets of resilience and vulnerability embedded within contrasting neighbourhood environments. The detection of High–Low outliers in Sykies, where relatively high perceived wellbeing occurs within a low-wellbeing spatial context, suggests the presence of local buffering factors that mitigate wider district-level pressures. Conversely, Low–High outliers identified in Thermi point to areas where residents experience lower wellbeing despite being surrounded by generally high-wellbeing environments. These findings support previous work highlighting the risk of "masking effects" in hotspot analyses [32], in which localised vulnerabilities can be obscured by global spatial statistics. By explicitly addressing these outliers, the analysis provides a more fine-grained understanding of urban wellbeing inequalities.

The spatial comparison between perceived wellbeing and income in Thessaloniki aligns with evidence from previous studies showing that socioeconomic conditions at the local level are significant correlates of perceived wellbeing. For example, research using longitudinal and multilevel data indicates that individuals residing in more deprived neighbourhoods tend to report lower perceived wellbeing compared to those in less deprived areas, even after controlling for individual characteristics [36,37]. Moreover, analyses of neighbourhood income distributions suggest that relative income-rank effects within neighbourhoods are associated with perceived wellbeing, highlighting the importance of local socioeconomic context. At the same time, other studies find that income inequality at the neighbourhood level does not always exert a uniform effect on wellbeing, as observed in analyses of elderly populations where absolute income differences, rather than income inequality per se, were more predictive of wellbeing outcomes [38,39]. These findings support our finding that while economic prosperity is an important factor in shaping perceived wellbeing across Thessaloniki, its influence varies across neighbourhoods and interacts with other place-based and social factors. In particular, neighbourhoods classified as "Not significant income – High PWI", such as Kato Toumpa and Thermi, indicate that favourable wellbeing outcomes can emerge even in the absence of strong economic signals. These areas may benefit from non-economic attributes, such as environmental quality, urban form, access to green space, or specific demographic compositions. Conversely, areas where wellbeing is significantly low despite non-significant income patterns, such as Ano Toumpa and Evosmos, indicate that factors beyond economic prosperity contribute to residents' perceived wellbeing.

Regarding the role of environmental stress perceptions, although perceived air and noise pollution were not subjected to spatial statistical analysis, their inclusion as contextual indicators provides important interpretative depth. Studies have shown that perceptions of air and noise pollution are significantly associated with perceived wellbeing, highlighting that environmental annoyance can meaningfully shape residents' lived experience and quality of life [40]. Moreover, research comparing subjective and objective environmental measures suggests that perceptions capture dimensions of environmental quality that objective indicators alone may miss, reinforcing the value of integrating subjective environmental indicators into wellbeing assessments. Other work demonstrates that noise exposure influences mental health through pathways such as environmental annoyance and diminished restorative quality, which may help explain why frequent perceived pollution may co-occur with lower perceived wellbeing in neighbourhoods [41]. In the current study, the typology reveals that neighbourhoods with persistently low perceived wellbeing, such as Evosmos and Ano Toumpa, are also characterised by frequent reports of environmental annoyance. This alignment suggests that environmental stress perceptions may amplify wellbeing challenges, particularly in areas where economic disadvantage is not the dominant factor. By contrast, areas with high perceived wellbeing consistently report low levels of noise and air pollution annoyance, reinforcing the idea that environmental quality is a meaningful component of residents' lived experience. While causal relationships cannot be inferred, the findings underline the value of integrating subjective environmental indicators into wellbeing assessments, especially in the context of large-scale infrastructure projects that alter everyday urban conditions.

The exploratory typology of Thessaloniki neighbourhoods provides additional nuance to the spatial patterns of perceived wellbeing revealed by the hotspot and LISA analyses. Type 1 neighbourhoods (Evosmos, Ano Toumpa) exhibit persistently low wellbeing, closely aligned with frequent reports of environmental annoyance, suggesting that environmental stress may be a primary driver of wellbeing deficits even in the absence of strong economic deprivation. Type 2 areas (Sykies) exhibit low wellbeing, which appears more strongly influenced by socioeconomic pressures than by environmental factors, indicating that interventions targeting social and economic support may be particularly relevant. In contrast, Type 3 neighbourhoods (Efkarpia) demonstrate cumulative high wellbeing across both socio-economic and environmental dimensions, highlighting the synergistic benefits of favourable conditions. Finally, Type 4 areas (Kato Toumpa, Thermi) represent localised pockets of high wellbeing despite mixed contextual signals, suggesting that place-based factors such as urban form, access to green space, or social cohesion can buffer residents against broader neighbourhood pressures. Collectively, this typology underscores that low or high perceived wellbeing arises through multiple pathways, emphasising the need for tailored, place-sensitive urban planning and mitigation strategies rather than uniform interventions.

Several limitations should be acknowledged. The survey sample was relatively small and not fully representative of the Thessaloniki population, with younger, higher-educated, and higher-income participants overrepresented. While the spatial dispersion of respondents supports the robustness of the spatial analysis, the results should be interpreted as reflecting perceived, rather than objective, conditions. Additionally, environmental stress indicators were derived from self-reported perceptions and analysed descriptively. Future research could strengthen this framework by integrating objective environmental measurements, longitudinal survey data, or participatory approaches to further explore how perceptions evolve over time in response to infrastructure interventions.

Despite these limitations, the proposed framework can inform urban planning and infrastructure decision-making by providing a spatially nuanced understanding of perceived wellbeing at the neighbourhood level. The proposed indicator and typology enable planners and policymakers to distinguish between areas in which low wellbeing is primarily associated with perceptions of environmental stress and those in which it is more closely associated with socioeconomic conditions. This differentiation can support the design of more targeted, place-based interventions, such as prioritising environmental mitigation measures in environmentally stressed neighbourhoods or complementing infrastructure projects with social and community-focused actions in areas experiencing socio-economic pressure. In the context of large-scale transport infrastructure, such as the Thessaloniki Flyover, the framework can be used as an ex ante or ex post evaluation tool to identify neighbourhoods that may be more sensitive to construction-related disruption or long-term environmental change. More broadly, the approach offers a transferable method for integrating subjective wellbeing indicators into spatial planning processes, supporting people-centred assessments of urban quality of life alongside conventional technical and economic criteria.

5. Conclusions

This study endeavours to examine how perceived wellbeing is distributed across Thessaloniki during the construction of a large-scale infrastructure project, moving beyond temporal assessments of construction impacts to consider their spatial patterns. The findings demonstrate that perceived wellbeing is neither uniform nor randomly distributed across the city. Instead, it exhibits clear spatial patterns and neighborhood-level differentiation. Clusters of low perceived wellbeing are concentrated in specific districts, notably Evosmos, Sykies, and Ano Toumpa, while higher wellbeing is consistently observed in Efkarpia, Kato Toumpa, and Thermi. These patterns confirm that residents' perceived wellbeing is shaped by a combination of local conditions and broader neighbourhood contexts, rather than by proximity to infrastructure works alone. At the same time, the identification of lower perceived wellbeing values in areas intersecting or adjacent to the Flyover axis, particularly in Ano Toumpa and parts of Sykies, suggests that construction-related disruption may intensify existing pressures on everyday life in certain neighborhoods. Importantly, the presence of low-wellbeing clusters in areas not directly affected by the Flyover, such as Evosmos, indicates that district-level characteristics and environmental or social conditions play a critical role in shaping perceived wellbeing. In conclusion, the findings of the presented research in this paper highlight the need to interpret infrastructure impacts within their wider urban context, recognizing that large projects interact with pre-existing spatial inequalities rather than producing uniform effects across the urban fabric.

Several open challenges will be addressed in future research. These include the implementation of a larger survey campaign with a more diverse and representative sample of participants, the systematic incorporation of experts' knowledge to formulate the PWI and the integration of objective environmental exposures and stress moments of participants through wearable sensors, complemented by machine learning algorithms.

Author Contributions: Conceptualization, K.K. and A.P.; methodology, K.K. and A.M.; validation, K.K., and K.L.; formal analysis, K.K.; investigation, K.K.; resources, A.M.; data curation, K.K. and A.M.; writing—original draft preparation, K.K.; writing—review and editing, K.K.; visualization, K.K.; supervision, K.K. and K.L.; project administration, K.K.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Ethical approval was granted by the Committee on Ethics and Research Ethics of Aristotle University of Thessaloniki (February 2024: 43723/2025).

Informed Consent Statement: Written informed consent was obtained from all participants prior to data collection via questionnaires.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data is not publicly available due to ethical considerations and the confidentiality of survey respondents.

Acknowledgments: The authors thank all participants who completed the questionnaire and made this study possible.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

PWI	Perceived Wellbeing Indicator
PCA	Principal Component Analysis
AHP	Analytic Hierarchical Process

Appendix A

Table A1. Data collected via an online questionnaire.

Domain	Question Code	Variable	Description
Personal information	Q1	Sex	Respondent's self-reported gender
	Q2	Age group	Respondent's age category
	Q3	Marital status	Respondent's marital status
	Q4	Educational attainment	Highest level of education completed
	Q5	Employment status	Current employment status or occupation

	Q6	Monthly income after taxes	Monthly net income category
	Q7	Children	Presence of children under 18 in the household
	Q8	Nearest crossroad to home address	Closest major intersection to the place of residence
	Q9	Years of living in the neighbourhood	Length of time (in years) the residence lives in the current neighbourhood
	Q18	Years of working in the current work	Length of time (in years) the respondent has been employed in their current job
	Q16	Nearest crossroad to work address	Closest major intersection to workplace location
Stress & Wellbeing	Q10	Commuting-related stress (workplace)	Level of stress experienced during or after commuting to the workplace due to Ring Road construction works
	Q17	Workplace calmness disturbance	Perceived impact of construction works on the sense of calm and environmental quality (e.g., noise, traffic) at the workplace
	Q20	Commuting irritation	Frequency of feelings of anger or irritation during commuting to work due to traffic congestion and delays
		Work productivity impact	The extent to which commuting delays negatively affects work productivity and concentration
	Q22	Mental health impact	Perceived impact of construction-related commuting conditions on overall mental health (anxiety, tension, fatigue)
	Q24	Work punctuality impact	The frequency with which commuting conditions affect the ability to meet schedules or arrive at work on time
	Q25	Mental health impact (commuting)	Perceived impact of daily commuting due to Ring Road construction works on overall mental health (e.g., anxiety, tension, fatigue)
	Q29	Sleep quality impact	Impact of commuting-related traffic changes on sleep quality
	Q31	Residential calmness disturbance	The extent to which the sense of calm at home (e.g., noise, traffic) is affected by construction works near the place of residence
	Q30	Commuting-related stress (residence)	Level of stress experienced during or after travel to the place of residence due to Ring Road construction works
	Q39	Residential safety perception	Perceived impact of increased traffic and construction works on the sense of safety at the place of residence
	Q41	Overall quality of life impact	Perceived overall impact of the project on quality of life
	Q43	Cost–benefit perception	Perceived balance between the problems and impacts of the construction works and the expected benefits of the project
	Q44	Institutional responsiveness	The degree to which authorities are perceived to seriously consider residents' concerns regarding quality-of-life impacts

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	Q11	Commuting time impact	Impact of Ring Road construction on commuting time between home and workplace
	Q12	Public transport delays	Perceived frequency of public transport delays caused by increased traffic due to Ring Road construction works
	Q13	Route changes (workplace)	Whether construction works have forced changes in the usual commuting routes to the workplace
	Q14	Workplace parking availability	Impact of traffic congestion caused by construction works on parking availability at the workplace (private vehicle users)
	Q15	Teleworking preference	Preference for working from home in order to avoid traffic congestion caused by flyover construction works
Accessibility & Urban Mobility	Q34	Access to everyday services	Frequency of difficulties in accessing everyday services near the place of residence due to traffic conditions
	Q35	Leisure activity limitation	Impact of traffic congestion on participation in recreational and leisure activities
	Q36	Social life restriction	The extent to which commuting conditions and construction impacts restrict social life
	Q37	Residential parking availability	Impact of traffic congestion on parking availability near the place of residence
	Q38	Access to healthcare services	Perceived difficulty of accessing healthcare services due to construction-related traffic impacts near the place of residence
	Q40	Route changes (residence)	Whether construction works have forced changes in the usual travel routes to the place of residence
	Q42	Perceived positive outcomes	Perceived presence of positive effects from the construction works, such as improved mobility or local infrastructure
Noise	Q33	Perceived noise pollution at homeplace	Frequency of increased noise pollution at the place of residence
	Q23	Perceived noise pollution at the workplace	Frequency of increased noise pollution at the place of work
Air Pollution	Q32	Perceived air pollution at homeplace	Observed an increase in atmospheric pollution at the place of residence
	Q21	Perceived air pollution at the workplace	Observed an increase in atmospheric pollution at the place of work

Appendix B

Table 1. Component Matrix[a].

	Component					
	1	2	3	4	5	6
Q11	-.094	.623	.471	-.244	-.030	.335
Q12	.612	-.133	.114	.545	.330	-.132
Q13	.155	.279	.545	-.198	-.450	-.117
Q14	.802	-.085	.121	-.073	-.182	.153

doi:10.20944/preprints202602.0312.v1

Q20	.776	-.001	-.020	-.275	.102	.202
Q15	-.767	.069	.149	.157	.112	.163
Q22	.763	.291	.139	-.125	.233	-.109
Q24	.842	.078	.189	-.125	.015	-.201
Q17	.753	.276	-.221	-.290	.019	.033
Q21	.342	.827	.094	.164	-.068	-.179
Q10	.664	.174	-.037	-.418	.236	.257
Q23	.722	.525	.162	.145	-.176	-.228
Q31	.853	-.097	-.095	.043	.206	.213
Q32	.815	.382	-.136	.222	-.064	.068
Q33	.693	.197	-.319	.377	-.171	-.030
Q29	.871	-.077	-.249	-.019	-.127	-.056
Q34	.780	.046	-.019	.422	-.158	.248
Q38	.825	.214	-.271	.178	-.071	.174
Q35	.823	-.112	-.246	.119	-.057	-.063
Q36	.777	-.193	-.061	.112	.165	-.130
Q39	.768	-.383	.120	-.046	.027	.140
Q30	.880	-.118	-.086	-.332	-.053	-.108
Q37	.512	-.505	.390	-.046	-.168	.288
Q40	.712	-.210	.249	.048	-.355	-.168
Q25	.897	-.015	-.116	-.188	.081	.040
Q41	.906	-.207	-.053	-.257	.039	.014
Q42	.670	-.219	.410	.186	.258	-.105
Q43	-.195	.492	.001	.165	.425	.368
Q44	.432	-.068	.525	.051	.523	-.272
Q18	.203	-.217	.354	.421	-.234	.380

Extraction Method: Principal Component Analysis.

a. 6 components extracted.

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