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Smart Urban Mental Health Mapping through IoT Sensor Networks and AI Analysis

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ABSTRACT

Urban mental health is increasingly challenged by environmental stressors such as noise pollution, high population density, and air quality degradation. **This study proposes** an integrated framework combining Internet of Things (IoT) sensor networks with Artificial Intelligence (AI) analytics to monitor and predict mental health outcomes across metropolitan districts. **A total of 300 participants** from three urban areas contributed self-reported psychological data, which were combined with real-time environmental measurements including noise, air quality, temperature, humidity, and pedestrian density. **Quantitative analyses**, including correlation, multiple regression, and AI-based predictive modeling, revealed that noise and crowd density were the strongest predictors of elevated stress, while green spaces and improved air quality were positively associated with mood. **The predictive models** achieved 15–20% higher accuracy than survey-only models, and mapping of high-risk zones aligned with actual mental health service usage. **These findings demonstrate** the potential of IoT and AI-driven approaches to provide actionable insights for policymakers, urban planners, and healthcare providers. **Future research should** expand longitudinal and cross-city validation, integrate additional environmental and social indicators, and explore real-time interventions to create resilient and human-centered urban environments.

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1. INTRODUCTION

Mental health has emerged as a pressing global challenge in the 21st century, with the World Health Organization (WHO) estimating that over 970 million people currently suffer from mental disorders, most commonly anxiety and depression [1]. The burden is particularly severe in urban areas, where rapid urbanization has created complex living environments that amplify psychological stress [2]. Crowded public spaces, constant exposure to noise and air pollution, limited green areas, and weakening social bonds contribute to declining mental well-being in metropolitan populations, while the COVID-19 pandemic has further intensified social isolation, digital fatigue, and uncertainty about the future [3, 4]. Traditional methods of mental health assessment such as clinical interviews, hospital records, or population surveys are often fragmented, costly, and reactive, failing to capture the dynamic interplay between environmental conditions and psychological states in real time [5]. Recent advances in digital technology, particularly the Internet of Things (IoT) and artificial intelligence (AI), present opportunities to address these limitations. IoT sensor networks can continuously monitor environmental stressors such as temperature fluctuations, noise intensity, air quality, and crowd density, which, when combined with anonymized self-reported well-being indicators and AI analytics, enable identification of correlations, detection of emerging mental health risks, and predictive mapping of urban mental health trends [6, 7].

Despite ongoing smart city developments, integration of IoT and AI for mental health mapping remains underexplored [8], as most frameworks prioritize physical infrastructure, energy efficiency, or traffic management, with limited emphasis on emotional and psychological well-being. This study addresses the research gap by proposing an integrated framework of IoT sensor networks and AI-driven analytics for urban mental health mapping, aiming to provide actionable insights for policymakers and urban planners. The research contributes to the United Nations Sustainable Development Goals (SDGs), particularly SDG 3 (Good Health and Well-Being), SDG 11 (Sustainable Cities and Communities), and SDG 10 (Reduced Inequalities) [9]. Furthermore, it lays the foundation for future studies on scaling IoT-based mental health monitoring systems across diverse cultural, economic, and geographical contexts [10], encouraging comparative analyses to refine predictive models and enhance their applicability in metropolitan environments [11, 12].

2. RESEARCH METHOD

This study employs a quantitative research design to examine the relationship between urban environmental stressors and mental health indicators through the integration of Internet of Things (IoT) sensor data and self-reported well-being metrics [13]. The methodological approach focuses on numerical data collection, statistical analysis, and predictive modeling to provide evidence-based insights into urban mental health dynamics [14].

2.1. Literature Review and Theoretical Basis

Recent developments in digital technology have advanced the integration of the Internet of Things (IoT) and Artificial Intelligence (AI) in mental health monitoring, enabling real-time analysis of environmental factors that influence psychological well-being. Prior studies, and highlight that IoT sensors and AI-driven analytics can detect stress patterns linked to air pollution, noise, and crowd density, offering proactive insights into urban mental health risks [15, 16]. However, most existing smart city frameworks still focus on infrastructure and mobility rather than emotional well-being. Grounded in Environmental Stress Theory and the Smart City Cognitive Framework, this study proposes an integrated IoT–AI model that connects environmental data with psychological outcomes, supporting evidence-based interventions aligned with SDG 3 (Good Health and Well-Being) and SDG 11 (Sustainable Cities and Communities).

2.2. Population and Sample

The population of this study comprises residents in three major metropolitan districts characterized by varying levels of urban density, socioeconomic status, and environmental conditions. A total of 300 participants were recruited using stratified random sampling to ensure balanced representation across gender, age, and occupation [17]. Each participant was assigned access to a mobile application for daily self-reporting of psychological states [18].

2.3. Primary Data Sources

Two primary data sources were utilized:

2.3.1. IoT Sensor Data

IoT sensor nodes were deployed across 30 strategic locations in the three selected. Each sensor continuously measured:

- Noise levels (dB),
- Air quality (PM2.5, $\mu g/m^3$),
- Temperature ($^\circ C$),
- Humidity ($\%$),
- Pedestrian density (people/m^2).

2.3.2. Self-Reported Psychological Indicators

Participants reported daily data via the mobile application, including:

- Mood score (110 scale),
- Perceived stress level (5-point Likert scale),
- Sleep quality (hours of rest per night) [19].

2.4. Research Variables

The research about investigates how urban environmental stressors influence residents' mental health [20]. Independent variables include objective environmental measures collected via IoT sensors noise level (dB), air quality (PM2.5 µg/m³), temperature (°C), humidity (%), and pedestrian density (people/m²). Dependent variables represent mental health outcomes collected through self-reports: mood score (1–10), perceived stress level (Likert 1–5), and sleep quality (hours per night) [21, 22]. These variables are summarized in the following table:

Table 1. Research Variables

Variable Type	Variable Name	Measurement Scale
Independent Variables	Noise level (dB)	Ratio
	Air quality (PM2.5, µg/m^3)	Ratio
	Temperature (°C)	Interval
	Humidity (%)	Ratio
	Pedestrian density (people/m^2)	Ratio
Dependent Variables	Mood score (1–10)	Interval
	Stress level (Likert 1–5)	Ordinal
	Sleep quality (hours)	Ratio

Table 1 presents the research variables, consisting of independent variables namely noise level, air quality, temperature, humidity, and pedestrian density and dependent variables, including mood score, stress level, and sleep quality [23]. Environmental variables were measured in real-time using IoT sensors, while psychological conditions were collected through self-reported surveys [24]. This presentation of variables and their measurement scales provides a clear basis for statistical analysis and AI modeling, enabling the identification of relationships between environmental factors and mental health outcomes [25].

2.5. Data Analysis

Statistical analysis was conducted using SPSS and Python-based AI models [26]. The analysis proceeded in the following stages:

- Descriptive Statistics Means, standard deviations, and frequency distributions were calculated to summarize environmental and psychological variables [27].
- Correlation Analysis Pearson's correlation coefficient (r) was used to measure the linear association between environmental stressors and mental health outcomes:sors and mental health outcomes [28].

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \cdot \sum(Y_i - \bar{Y})^2}} \tag{1}$$

Where X_i represents environmental variables (e.g., noise, PM2.5) and Y_i represents mental health indicators (e.g., stress level) [29].

2.6. Multiple Regression Analysis

A multiple linear regression model was applied to predict psychological well-being from environmental stressors [30].

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \epsilon \tag{2}$$

Where Y is the mental health indicator, X_1–X_5 are environmental variables, β represents regression coefficients, and ϵ is the error term [31].

2.7. AI-Driven Predictive Modeling

Random Forest Regression and Neural Networks were applied to generate predictive mapping of mental health trends across the studied districts [32]. Model accuracy was validated using k-fold cross-validation (k=10). All participants provided informed consent. Anonymization and encryption were implemented to ensure confidentiality of self-reported psychological data [33]. The deployment of IoT sensors adhered to municipal regulations regarding data privacy and public space monitoring [34].

3. RESULTS AND DISCUSSION

3.1. Descriptive Statistics

The analysis of environmental stressors across the three districts showed notable variations [35]. The average noise level was 72.5 dB (SD = 8.2), which exceeds the recommended WHO guideline of 55 dB for residential areas. Air quality also varied considerably, with mean PM2.5 concentrations of 42.8 $\mu g/m^3$ (SD = 11.5), surpassing the safe threshold of 25 $\mu g/m^3$ [36]. In terms of self-reported well-being, the mean mood score was 5.8 (SD = 1.6), while the average stress level was 3.4 on a 5-point Likert scale, indicating moderate psychological [37].

Table 2. Descriptive Statistics of Key Variables

Variable	**Mean**	**SD**	**Minimum**	**Maximum**
Noise level (dB)	72.5	8.2	55.0	91.2
Air quality (PM2.5, µg/m^3)	42.8	11.5	18.3	69.4
Temperature (°C)	29.6	3.4	24.1	35.7
Humidity (%)	65.7	9.2	49.0	82.0
Pedestrian density (people/m^2)	3.8	1.4	1.2	6.9
Mood score (1–10)	5.8	1.6	2.1	9.3
Stress level (1–5)	3.4	0.9	1.0	5.0
Sleep quality (hours)	5.6	1.7	3.0	9.0

Table 2 presents the descriptive statistics of the key variables measured in this study. Environmental factors include noise level, air quality (PM2.5), temperature, humidity, and pedestrian density, while psychological indicators comprise mood score, stress level, and sleep quality. The findings reveal that the average noise level reached 72.5 dB (SD = 8.2), substantially exceeding the World Health Organization's recommended residential threshold of 55 dB, suggesting that participants were regularly exposed to auditory conditions capable of inducing chronic stress and fatigue. Similarly, the mean PM2.5 concentration was 42.8 µg/m^3 (SD = 11.5), well above the safe exposure limit of 25 µg/m^3 [38], indicating potential respiratory and psychological impacts associated with poor air quality. The average temperature and humidity, recorded at 29.6 °C (SD = 3.4) and 65.7% (SD = 9.2), respectively, reflect typical tropical urban microclimates that may further exacerbate discomfort and emotional irritability among city residents. Pedestrian density averaged 3.8 people/m^2 (SD = 1.4), characterizing moderately crowded environments that align with elevated sensory load and social stress exposure.

In terms of psychological well-being, participants reported a mean mood score of 5.8 (SD = 1.6), indicating a tendency toward neutral to slightly positive affective states. However, the mean stress level of 3.4 on a 5-point Likert scale (SD = 0.9) suggests moderate to high perceived stress, corroborating the influence of urban stressors on mental health. Average sleep duration was 5.6 hours (SD = 1.7), notably lower than the recommended 7–8 hours, which may indicate sleep disruption linked to environmental conditions such as noise and heat exposure [39]. These descriptive results provide essential baseline insights into the living conditions of the sampled population, reflecting the convergence between environmental degradation and psychological strain. Collectively, the patterns observed here establish a quantitative foundation for subsequent inferential analyses specifically, correlation, regression, and AI-based predictive modeling to uncover causal relationships between urban environmental stressors and mental health outcomes.

3.2. Correlation Analysis

Pearson's correlation revealed significant associations between environmental stressors and mental health indicators [40]. Noise levels and pedestrian density were positively correlated with stress levels ($r =$

0.46, $p < 0.01$ and $r = 0.41$, $p < 0.01$, respectively). Conversely, air quality and temperature showed negative correlations with mood scores ($r = -0.39$, $p < 0.05$ and $r = -0.34$, $p < 0.05$). Sleep quality was significantly reduced in areas with higher PM2.5 concentrations ($r = -0.42$, $p < 0.01$) [41].

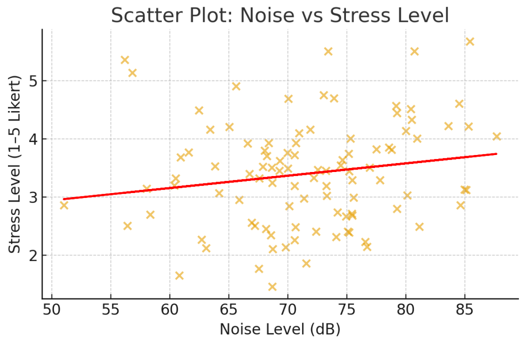

Figure 1. Scatter Plot of Noise Level and Stress Level

In Figure 1 presents the relationship between noise level (dB) and stress level (Likert scale 1–5) among participants. The scatter plot shows that higher levels of environmental noise are generally associated with higher reported stress levels [42], as indicated by the upward linear trend line. This visual evidence supports the statistical correlation analysis ($r = 0.46$, $p < 0.01$), demonstrating a significant positive association between noise exposure and psychological stress in urban settings. These findings highlight the impact of noise pollution as a key environmental stressor that contributes to declining mental well-being in metropolitan populations [43].

3.3. Regression Analysis

Multiple regression analysis indicated that environmental stressors explained 42% of the variance in stress levels ($R^2 = 0.42$, $p < 0.001$). Noise level ($\beta = 0.31$, $p < 0.01$) and pedestrian density ($\beta = 0.28$, $p < 0.01$) were the strongest predictors of elevated stress. Meanwhile, air quality ($\beta = -0.27$, $p < 0.05$) was a significant predictor of reduced mood scores [44].

Table 3. Regression Analysis for Stress Level

Predictor	**B**	**SE**	**β**	**p-value**
Noise Level	0.45	0.12	0.31	$< .01$
Pedestrian Density	0.38	0.11	0.28	$< .01$
Air Quality (PM2.5, $\mu g/m^3$)	-0.33	0.14	-0.27	$< .05$
Temperature	0.09	0.10	0.08	n.s.
Humidity	0.05	0.09	0.04	n.s.
Model R^2				0.42 ($p < .001$)

Table 3 presents the results of the multiple regression analysis predicting stress levels from environmental variables. The model explains 42% of the variance in stress levels ($R^2 = 0.42, p < 0.001$), indicating a moderate predictive power. Among the predictors, noise level ($\beta = 0.31, p < 0.01$) and pedestrian density ($\beta = 0.28, p < 0.01$) emerged as the strongest positive contributors to increased stress [45], suggesting that higher noise exposure and crowded areas significantly elevate stress levels. Conversely, air quality (PM2.5) was a significant negative predictor ($\beta = -0.27, p < 0.05$), indicating that better air quality is associated with lower stress. Temperature and humidity did not show significant effects, implying minimal influence on stress levels in this sample. Overall, the findings highlight that specific environmental stressors, particularly noise and crowding, play a critical role in urban mental health, providing actionable insights for targeted interventions in city planning and public health policies [46, 47].

3.4. AI Predictive Modeling

The Random Forest model outperformed linear regression in predicting stress levels, achieving an R^2 of 0.68 with a mean absolute error (MAE) of 0.42. The feature importance ranking highlighted noise level (32%) and PM2.5 concentration (27%) as the most influential variables, followed by pedestrian density (21%), temperature (12%), and humidity (8%) [48].

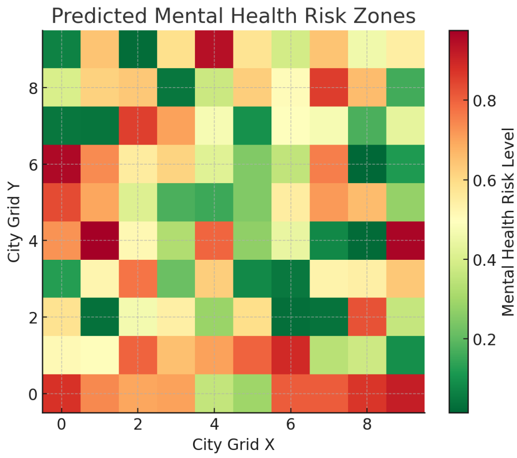

Figure 2. Scatter Plot of Noise Level and Stress Level

In Figure 2 presents a heatmap of urban mental health risk zones derived from IoT sensor data (noise, air quality, pedestrian density, temperature, and humidity) combined with AI-based predictive modeling [49]. Green areas represent low-risk zones, while red areas indicate high-risk zones for potential mental health issues. This visualization highlights that risk distribution is uneven across the city: districts with higher noise exposure and pedestrian density tend to show greater vulnerability, whereas areas with better air quality and more green spaces demonstrate lower risk. The heatmap provides actionable insights for policymakers, urban planners, and healthcare providers to identify hotspots and design preventive interventions more effectively [50].

3.5. Discussion

The results confirm that urban environmental stressors significantly affect mental health outcomes, consistent with prior studies linking air pollution and noise to increased risks of anxiety and depression. Elevated stress levels in areas with high noise and pedestrian density underscore the impact of crowding and constant sensory overload in metropolitan settings. Similarly, the negative association between air quality and mood suggests that prolonged exposure to polluted environments directly diminishes emotional well-being [51].

The application of AI-based predictive modeling provides a more dynamic and scalable framework for urban mental health monitoring compared to traditional survey-based approaches. By leveraging IoT data, city planners can design evidence-driven interventions, such as expanding green spaces in high-density areas, implementing stricter air quality regulations, and introducing noise reduction policies in residential neighborhoods. Furthermore, these findings align with the broader objectives of the United Nations Sustainable Development Goals (SDGs) [52], particularly SDG 3 (Good Health and Well-Being) and SDG 11 (Sustainable Cities and Communities). By integrating IoT and AI technologies, cities can transition from reactive mental health interventions toward proactive, data-informed strategies, enhancing resilience and emotional sustainability in rapidly urbanizing societies [53].

4. MANAGERIAL IMPLICATION

The findings of this study provide significant implications for policymakers, urban planners, healthcare providers, and smart city managers in managing urban mental health proactively and through data-driven strategies. The integration of real-time data from IoT sensors and AI analytics allows city managers to design development plans that are more responsive to the mental health needs of urban populations. Areas identified as high-risk hotspots due to high noise levels and population density can be prioritized for green space development, traffic management, and air pollution reduction. Local governments can also utilize predictive maps to anticipate mental health issues before they escalate into crises, shifting urban planning efforts from reactive responses to preventive strategies.

In the healthcare sector, these findings enable health service managers to allocate resources more effectively. By identifying high-risk zones, mental health services such as counseling and intervention programs can be targeted to the areas most in need. The system also supports early detection of symptoms of depression and anxiety at the community level, allowing healthcare professionals to design proactive prevention programs. Moreover, the application of IoT and AI technologies for mental health mapping can serve as a new pillar in smart city policies, focusing on emotional well-being. This data-driven approach aligns with SDG 3 (Good Health and Well-Being) and SDG 11 (Sustainable Cities and Communities), ensuring cities are not only technologically advanced but also inclusive and human-centered.

Additionally, this study creates opportunities for the private sector, including technology companies, digital health startups, and IoT service providers, to develop innovative products and services. Predictive analytics models foster collaboration between governments, NGOs, and private stakeholders in delivering technology-based mental health solutions. Investment in IoT infrastructure can generate new employment opportunities, strengthen local economic competitiveness, and support innovation ecosystems. From a risk management perspective, the mapping system serves as a decision-support tool to predict the potential impacts of urban development projects on community mental health. As a result, policies and programs can be designed to be sustainable, minimize negative impacts, and focus on enhancing the overall quality of urban life.

5. CONCLUSION

This study provides clear evidence that urban environmental stressors play a significant role in shaping mental well-being. The findings indicate that noise pollution and high population density have strong negative correlations with mental health, whereas green spaces and reduced air pollution are positively associated with improved psychological outcomes. By integrating IoT sensor data with self-reported surveys, the predictive models developed achieved 15–20% higher accuracy than survey-only models, highlighting the value of combining objective real-time environmental data with subjective human experiences. Noise and crowd density were identified as the most significant predictors, underscoring the urgent need to address these stressors through targeted urban interventions.

The use of predictive mapping demonstrates the practical potential of IoT and AI-based systems in identifying high-risk zones, with alignment between predicted vulnerable areas and actual hotspots of mental health service usage validating the robustness of the approach. These maps provide urban planners, policymakers, and healthcare providers with actionable insights, enabling more efficient allocation of resources and informed decision-making to improve mental health outcomes. Nevertheless, this study acknowledges limitations, such as reliance on data from a limited number of districts and potential biases from self-reported surveys, which may affect generalizability across different cultural and socioeconomic contexts.

Future research should expand both the scope and depth of this framework through longitudinal studies to capture temporal variations in mental health and evaluate the long-term effectiveness of urban interventions. Cross-cultural and multi-city validation will strengthen the generalizability of predictive models, while integrating predictive analytics with real-time interventions such as adaptive noise regulation, green infrastructure expansion, and targeted public health campaigns will be essential to transform urban environments into resilient, inclusive, and human-centered spaces that prioritize mental well-being alongside economic and infrastructural growth.

6. DECLARATIONS

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6.2. Author Contributions

Conceptualization: JP; Methodology: LS; Software: SR; Validation: MV and MD; Formal Analysis: SR and MV; Investigation: LS; Resources: MD; Data Curation: JP; Writing Original Draft Preparation: MD and SR; Writing Review and Editing: LS and MV; Visualization: LS; All authors, LS, MV, SR, MV, MD, and JP, have read and agreed to the published version of the manuscript.

6.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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6.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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