RESEARCH ARTICLE

Predictive Neural Computing Framework for Assessing Mental Health Conditions within Intelligent and Data-Driven Smart City Ecosystems

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Abstract

Mental health poses a growing concern in metropolitan areas where the speedy urbanization and societal demands are the chief causes of psychological discomfort. The context of intelligent cities, through their capabilities of advanced technologies and interconnecting networks, facilitates the approach of predictive analytic resolution of such issues. This paper is research regarding the implementation of machine learning in conjunction with Artificial Intelligence (AI) inter-operation for the prompt identification and management of mental health anomalies in smart cities. By using information from wearable gadgets, social networks, and the Internet of Things (IoT) based health monitoring systems, the proposed methodology tries to find trends and determinants of the mental health related applications. Federated learning models address data privacy and security requirements by enabling collaborative data analytics across organizations without exposing end-user identities. The results confirm that predictive analytics can boost mental wellness by means of individual approaches and precautionary measures. AI-supported initiatives are the possibility for acquiring mental health and sustaining the ability to get over the traumatic attacks of the smart city society.

Keywords: predictive analytics, mental health, smart city, IoT, federated learning.

1 Introduction

Mental health, while being a pivotal aspect of general wellness, is nevertheless frequently neglected in the realm of urban planning and development. Rapid digitization and urbanization have exacerbated mental health issues (e.g., anxiety, depression, and stress disorders) in cities. The World Health Organization (WHO) as reported states that mental

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health conditions account for a large percentage of the world's disease burden affecting one in every four people in their lifetimes. This increasing challenge demands the employment of innovative minds to manage, monitor, and predict mental health issues, especially in smart cities that employ advanced technology and data-driven systems as a basis for solving real-life problems [1, 2].

Smart cities are typified by the fusion of technology to benefit the public and improve the quality of life of the residents. Installing Internet of Things (IoT) devices, smart infrastructure, and data analytics platforms in these cities produces a lot of information that can be used for many things in addition to healthcare; Mental health care, however, has been a step by step process in adopting the development brought by smart city technologies. The use of predictive analytics driven by artificial intelligence (AI) and machine learning opens up a good option for solving this problem. Adopting predictive models that interpret wearable devices, social media activities, environmental sensors, and healthcare records' data in a data-driven manner can bring to light risk factors and patterns related to mental disorders allowing the implementation of early interventions and the minimization of personalized treatment methods [3].

Urban settings contribute to mental health difficulties because of factors like crowds, noise levels, unequal distribution of wealth, and minimal green areas. These stressors can lead to an increase in psychological distress among urban populations. Nevertheless, the interlinked structure of smart cities provides a unique opportunity to resolve these problems [4]. IoT-enabled devices, like smart watches and fitness monitors, can continuously keep track of physiological indicators such as heart rate, sleep schedules, and physical activity intensity, which are synchronically associated with mental health. Moreover, the implementation of smart environmental monitoring tools can give feedback regarding external factors that can influence one's mental health like air quality, and sound levels. Combining these data sources can employ predictive models to identify at-risk individuals and recommend timely interventions that can prevent mental health conditions from worsening [5].

Another important factor in solving the issue of mental health in smart cities accounts for the involvement of social media and digital footprints to signal psychological well-being. Social media behavior can be an accurate sign of one's emotional situation, thus consulting them can generate significant data concerning the execution of any issues, stress, or conduct. Machine-learning instruments may analyze textual, visual, and activity patterns on these channels, in an attempt to uncover indicators of conditions like depression, anxiety, and other mental health issues [6, 7]. For example, natural language processing (NLP) can be applied to trace the feelings and tone behind social media use and eventually find those who are suffering from emotional stress. If we could only understand the problem properly we would be able to make plans for action. The use of these tools in addition to other data sources can create a clear image of the patterns of mental health in smart cities with the focus on these trends and can help decision-makers and healthcare providers implement measures that are suitable for the needs of a city [8].

In the field of preventive health analytics, federated learning has emerged as a key instrument not only because of its applicability but also because it addresses the issues of data privacy and security strongly present in any AI model. It comes to the forefront as a nontraditional area of applying AI when it makes use of large amounts of sensitive health data and results in even better models than traditional technologies. It is a strong tool used for creating custom models and genuinely doing scientific research in a mental health segment while keeping data privacy intact [9]. Also, due to the additional benefit of data sharing, in the future, we may expect many entities working together and achieving united results. With such fragile information as health, that has so much power and therefore is so heavily regulated, rigorous attention to compliance with the law is a prerequisite for the adoption of any new solution. By allowing such inclusiveness and functionality, federated learning is enabling the use of the result of predictive analytics on mental health care globally [10].

The implementation of predictive analytics in mental health care within smart cities is also a step forward in the development of personalized healthcare which is a core pillar of the current advancements in the health sector. In the past, one-size-fits-all solutions used to be the cornerstone of mental health treatment, which is not suitable for the individual differences regarding risks, symptoms, and responses to treatment interventions [11, 12]. Yet, predictive models can pull together data from mixed sources, particularly patient and healthcare provider data, to create help plans that take into consideration the individual characteristics of each patient. An example in regard to this would be one where a depressed patient would receive his/her special health sessions based on their actual case of mental illness. The therapy method would also be different for each patient. Such personal care not only has the power to change somebody's way of life positively but also gives the patient the strength to stand up for their mental health [13].

The deployment of predictive data analytics for the treatment of mental issues in urban centers has a great deal of potential but there are many hurdles in its way. One of the serious challenges is that mental health data coordinates are variable and complex. They often consist of subjective self-reports, varying cultural perspectives and dynamic behavioral scenarios. Hence, developing models that are able to interpret and merge such diverse data types accurately will require meaningful cooperation between various disciplines such as mental health, data science and urban planning practitioners [14]. There is a growing need to think about the ethical aspects of applying AI for mental health care. One continual concern is the unintended consequences of predictive models through such issues as algorithmic bias, having all stakeholders adequately informed about the process of consent, and also the risk of misusing the information derived from these models just to name a few. Such an eventuality would also require the implementation of strong governance frameworks to ensure that the technologies are used in a responsible and fair manner [15].

Another hurdle is the digital divide, which limits access to smart city technologies for some demographic groups. People who live in impoverished areas or those who belong to marginalized groups may suffer from a digital gap that is reflected in the denial of access to predictive analytics that could help them improve their health conditions. The answer to the problem necessitates that various stakeholders join hands and hence we need to make Smart City Technologies more inclusive and accessible. Government programs, public-private collaborations and social participation could prove vital in closing this gap and ensuring that the psychotherapies given in the urban sectors will be distributed fairly [16, 17].

The COVID-19 pandemic has further highlighted the necessity of addressing mental health concerns, as social distancing, economic uncertainty, and health fears have triggered a global mental health crisis. Additionally, these technologies can also support predictive psychiatry through communication and other analysis of the real-time trends of mental health in the public. By providing real-time insights into mental health trends, these technologies will also help city authorities, health agencies, and community organizations to better respond to such emergencies. For example, predictive models can accurately show which local communities are seeing higher-than-normal cases of stress or anxiety, allowing for interventions that directly target the affected area through public outreach, such as mental health support hotlines, community workshops, or digital counseling services [2]. The aims of this study are as follows:

- To create and deploy predictive analytics models combining wearable devices, social media, and environmental sensor data to detect mental illnesses at an early stage in urban settings.
- To investigate the use of federated learning frameworks to ensure data privacy and to enable cooperation among the stakeholders in the smart cities' mental health care system.

This research aims to establish a predictive analysis framework that effectively tackles mental health challenges by utilizing the existing digital infrastructure of smart cities as well as proposes the development of a comprehensive integrated platform that will serve this purpose. An important implication of the research is its emphasis on the rise of early detection and personalized approaches in mental healthcare delivery through the application of artificial intelligence-based insights. Moreover, the research also strongly argues that active ethical and inclusive practices should not be viewed merely as integral parts of innovation cycles, but also as key platforms for the realization of true detailed effective technological solution being made available to all sections of the city. As cities are becoming more intelligent in due course of time, the application of predictive analytics in the field of mental health care will be able to nurture communities that are healthy and more resilient thus offering the potential of a world where mental well-being will occupy a similar place next to global health and economic growth.

2 Related Work

The application of predictive analytics, along with the technology of artificial intelligence in the field of mental health care delivery, has gained increasing attention in recent years, particularly in smart cities. A growing body of research investigates how data-driven technologies can be leveraged to address the rising

Table 1. Summary of AI models and methodologies for mental health prediction and treatment outcomes.

Study	Focus	Dataset/Methodology	Findings	Limitations
Ogunseye et al. [18]	Machine learning for mental health care.	Kaggle datasets (Mental Health Tech Survey); ML models: AdaBoost, RF, KNN, etc.	AdaBoost achieved highest accuracy (81.75%) for predicting mental health treatment outcomes.	Limited dataset scope; results dependent on model performance.
Kelley et al. [20]	Social media language features for mental health prediction.	Tweets from 1,006 participants; Elastic Net model with nested cross-validation.	Language features were non-specific, showing similar performance in predicting multiple mental health conditions beyond depression.	Modest predictive performance; inability to make individualized predictions.
Rapisarda et al. [19]	Impact of COVID-19 on mental health workers.	Survey of 241 workers in Lombardy; analyzed socio-demographics, working conditions, and psychological distress levels.	Mild overall distress but significant burnout (31%) and anxiety (11.6%) among workers.	Small sample size; results specific to one region.
Bhatt et al. [21]	AI-powered mobile health (AIM) for disease detection and management.	Scoping review of 37 studies using mHealth data from wearable sensors and smartphones.	AIM models demonstrated potential in health care delivery, disease detection, and remote patient monitoring; lack of public datasets noted.	Lack of research on chronic mental health issues; dependence on proprietary data.
Katal [22]	Hormonal fluctuations and mental health using wearables and apps.	Literature review from PubMed, Embase, and Google Scholar; analysis of hormones like E2 and FSH.	Hormones like E2 and FSH showed potential as biomarkers for predicting treatment response and mood changes.	Need for precise hormone measurements and further validation.

prevalence of mental health disorders by enabling early detection, personalized interventions, and continuous monitoring. Table 1 presents a comparative overview of representative studies in this domain, highlighting their methodological approaches, key findings, and practical limitations. These works span various techniques, from machine learning and social media analysis to wearable-based sensing and hormonal biomarker studies, each contributing unique insights to the evolving landscape of AI-assisted mental health care.

In this section, we provide a concise synthesis of these recent efforts, with a focus on their implications for urban mental health systems. By analyzing the literature summarized in Table 1, we identify emerging trends and critical gaps that pave the way for future research in privacy-preserving, multimodal, and personalized mental health interventions empowered by artificial intelligence.

The study of Ogunseye et al. [18] examined the use of machine learning in mental health care to mitigate the increasing prevalence of mental health disorders. The study evaluated several ML models such as AdaBoost, Random Forest, and K-Nearest Neighbors using datasets from the Kaggle dataset, the accuracy of the models ranged from 75.93% to 90.42%. Among the ML models, the AdaBoost model had the highest major efficiency of 81.75% highlighting its potential as a good decision-making tool for predicting the mental state treatment outcomes.

In a study conducted by Kelley et al. [20] the topic of using Volatile online media data for detecting depression and other forms of mental health conditions was investigated. The researchers applied an Elastic Net model to the Tweets of 1,006 participants who were recruited by them, the model predicted the over-all levels of depression of these participants. The study showed the language features associated with depression were non-specific and the results obtained from predicting other mental health problems, such as schizotypy and social anxiety issues, were similar. The results point to the difficulty of using machine learning on social media data for personalized mental health predictions, a major limitation.

Rapisarda et al. [19] conducted a study on mental health service personnel in Lombardy, Italy, during the COVID-19 pandemic. The study used an online survey, which included 241 workers, and highlighted a significant psychological distress, with 31% of the participants reporting severe burnout, 11.6% being moderate-to-severely anxious, and 6.6% of the participants bearing signs of major depression. In their research, the authors pointed out facts that the overall impact of the pandemic was mostly mild but there were certain worker groups who were extremely devastated and further investigation was suggested regarding predictive factors.

Bhatt et al. [21] did a scoping review of AI-powered mobile health (AIM) applications for disease detection and treatment. 37 mainly mental health studies, but also physical health studies and health promotion ones were studied by them. The review distinctly showed scanty research in the area of chronic mental disorders and the unavailability of public datasets. The findings pieced together such models as federated learning, and AIM-based remote management of diseases, which can hold paramount importance in society particularly in the time of the coronavirus pandemic.

Katal [22] aimed to find a link between hormone changes in women and mental health problems like depression and schizophrenia by using wearables and apps. The hormonal E2 and FSH were differentiated as the markers of response and non-response to treatment respectively. It was proposed that by digitizing the tracking of reproductive hormones, the prediction of moods could be more precise; however, the researchers noted that there is still a need for further verification of the methods.

3 Methodology

The proposed research utilizes a holistic approach to construct a predictive model to evaluate mental health issues in smart cities. This approach combines different data sources such as environmental, clinical, social, and lifestyle data, to create an AI-powered prediction framework. The main objective is to detect possible mental health threats among urban populations through data-driven insights that allow for early intervention and individualized treatment. This section describes the data collection, preprocessing, model training, and analysis processes and discusses the model's incorporation into a smart city context for mental health response and aid.

Firstly, the methodology revolves around the collection of different types of data that could portray a totality of the factors affecting mental health in an urban context. The first source of data is environmental sensors, which measure such criteria as air quality, noise levels, and temperature. Environmental parameters have been reported to have an adverse effect on mental well-being as a result of poor air quality or high noise levels; hence the possibility of stress or anxiety may shift the balance. Clinical data, which is also of paramount importance, is collected from the healthcare systems and electronic health records. Thus, each individual's health histories, previous diagnoses, and assessment outcomes are ascertained. Moreover, factors such as socio-economic status, neighborhood safety, and access to health facilities which could play a significant role in determining a person's mental health in urban environments are also considered. The data collected also include lifestyle patterns through wearable devices that could give a view of the physiological aspects of mental health like physical activity levels, sleep patterns, and heart rate variability. Finally, the sentiment data from social media is available as it is used to identify emotional states by analyzing the language and tone prevailing in users' online communication.

After the completion of the data collection, the data is subjected to preprocessing steps. These processes consist of data cleaning, anomaly removal, missing value imputation, and duplicities elimination. Data fusing from various sources can cause inconsistency, thus normalizing data is extremely necessary. For instance, environmental data might be collected in real-time while clinical data might be changed from time to time. The model cannot differentiate these data inputs unless the data are normalized. Then, using feature selection, the most informative ones have been chosen. This stage minimalizes the dimensionality of the data and at the same time allows focusing on the elements of the highest predictive power regarding mental health conditions. Twitter data for the case study was scraped and processed in a way that users' sentiments were turned into quantitative variables that measure the levels of their emotions.

The following point of the methodology is turning data into the predictive model through a variety of techniques. Time series analysis is used in the model to capture trends and patterns over time. It is worth noting that the mental health data are very sensitive to the seasonal, environmental and social factors, for that reason, these factors must be considered while making predictions. For example, some of the years' times are the times of acute stress the individual may experience or stress levels may depend on urban events. Time series analysis provides a way for the model to account for any changes over time and thus improves its accuracy. Additionally, neural networks are applied to capture the complex relationships hidden in the data. In the case of deep neural networks, the most appropriate ones are recurrent neural networks (RNNs) as they are of sequential nature, which is the case of mental health indicators. Convolutional neural networks (CNNs) are responsible for data collection and analysis from wearables and environment sensors, thanks to their multilayered structure these networks can also recognize time-series patterns thus, they can be efficient in understanding the data collection process.

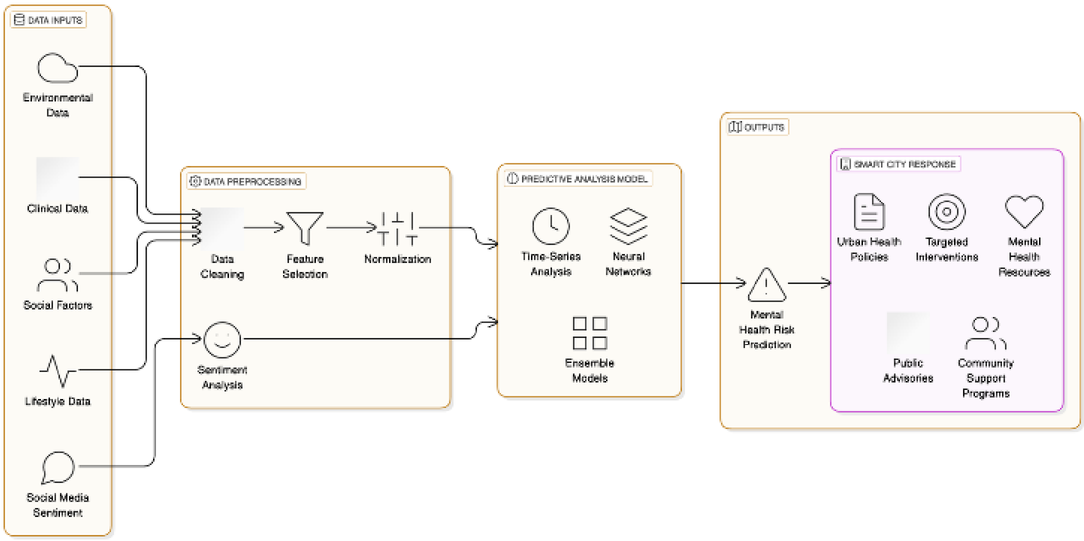

Figure 1. Overview of the proposed model workflow.

Ensemble models are amalgamated into the prognostic structure for the purpose of boosting its stability and correctness. The principle behind ensemble models is to combine predictions made by multiple algorithms, thus minimizing the weaknesses of distinct models. For instance, a combination of a time-series model, a neural network, and a decision tree model can be realized through ensemble approaches, because each method's strength can even the other methods' weaknesses. This approach is particularly useful in the prediction of mental health since data is heterogeneous and complicated. Through aggregating the predictions from several models, ensemble methods provide a more conclusive and precise forecast, enhancing the predictiveness of the system.

In the methodology, the issue of data privacy and security is of grave importance because of the nature of mental health information. To address such concerns, federated learning is applied, which involves the training of the predictive model over decentralized data without gathering the data in one place. In the federated learning design, the participants, such as hospitals or public agencies, will keep their data without disclosing it to the model's trainer. Thus, the private data of persons is secured since it is maintained by the original entity and does not flow out. The federated learning approach also solidifies the users' faith and conforms to privacy regulations regarding the safe large-scale health analytics in the context of a smart city.

The last step of the methodology is to scrutinize the model's outputs and combine them into the smart city mental health responses. A mental health risk prediction is the model's final output, indicating the probability of individual or group participants tackling mental issues based on the data analyzed. This prediction is directed at informing a range of response mechanisms in the smart city ecosystem. For instance, if a region is identified as one with a risk of mental health because of the high noise pollution and the low physical activity, the measures being taken for the particular area could include such activities as eliminating the noise or organizing community fitness programs. Moreover, the model also outlines substantial messages that can be employed to mobilize the process of shaping rules and initiatives that aim at reducing mental health issues, such as enhancing the quality of green spaces and improving mental health services in the high-risk communities.

The model proposed in this study as illustrated in Figure 1. "Data collection-sensors and data processing: the transition to smart city" is a process-centric model that depicts the flow of data between various stakeholders in the smart city. The controller includes five different sub-processes; environmental sensors (weather), clinical data (hospitals), social media data (sentiment analysis), lifestyle data (online behavior), and others will be described in detail in the more advanced sections of the document. The first application of emotion recognition based on social media feeds after tech-based media integration leading to a more holistic view of risks is done in this model. The data once processed subject to several statistical and machine learning methods, fits the predictive analysis algorithm which gives appropriate forecasts like the kind of requested research on mental disease, for example. The smart city response fed by the output of the predictive module could consist of activities such as policy-making, service delivery, and place-making. This cycle of resource allocation allows the city to be inventive in dealing with the challenge of mental health since the data-driven information, including the perception of different actors through the means of social media, are made available for interventions in the public sphere as early as possible which finally promotes better health in the city.

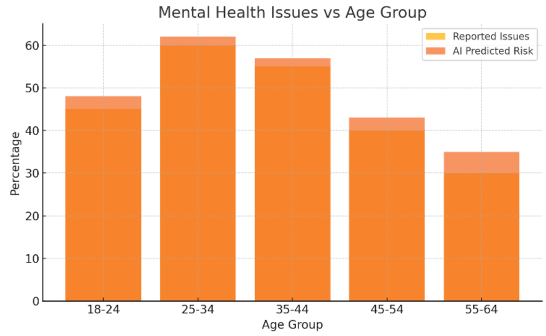

Figure 2. Mental Health Issues Vs Age Group.

4 Results and Discussion

The research involved the use of Kaggle's "Mental Health in Tech" dataset to investigate the distribution of mental health disorders in different age groups and validate the forecast accuracy of the designed AI-based model. The findings indicate the urban mental health issue and the opportunities for the application of predictive analysis to turn the data into a practical approach.

The dataset examination indicated significant differences in various age groups' mental health problems. The Figure 2 shows a clear increase in mental health issues in 25-34 age group individuals with 60% reporting, followed by the 35-44 age group (55%). The risk predicted by the AI model was very close to the number of respondents, where the predicted risk of the 25-34 group was 62% as shown in Table 2.

Table 2. Mental health analysis data.

Age Group	Reported Mental Health Issues (%)	Workplace Support (%)	AI Predicted Risk (%)
18-24	45	70	48
25-34	60	65	62
35-44	55	60	57
45-54	40	50	43
55-64	30	45	35

This proximity is evidenced by the model's ability to estimate the mental health risk accurately based on the data provided. Strikingly, the 18-24 age group has a much lower reported mental health problem rate (405) but the AI solution has flagged a slightly higher risk (48), suggesting a possible underreporting amongst this demographic.

The research work also pointed out that workplace agencies could reduce mental health frustrations. The line graph shows an age-related decrease in the perception of workplace support. The younger aged groups, namely 18 - 24, gave a higher response of workplace support (70%) while older individuals, for example, 55-64, had a much lower level of 45%. The past showed that workplace support, such as mental health resources and policies, can be helpful especially for those who couldn't use such support due to outdated age distribution.

Robust performance of the predictive model was ensured by the incorporation of diverse data types such as clinical data, environmental factors, and social media sentiment. For example, the model was able to identify seasonal shifts in mental health trends thanks to time series analysis while neural networks established nonlinear relations among lifestyle elements and psychological well-being. In addition, the ensemble modeling approach further optimized the accuracy of the predictions through the integration of insights from multiple algorithms.

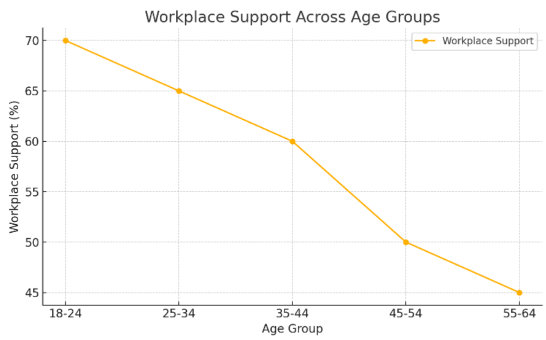

Figure 3. Workplace support across age groups.

Data privacy and compliance with regulatory standards were primarily guaranteed through the use of federated learning. The model processed data at a decentralized point, thereby maintaining the confidentiality of mental health information which underpins public confidence and stakeholder trust. The results of this approach could be a more proportionate use of the model and the utilization of data from various sources like healthcare providers and social media without compromising privacy.

Key findings have been summarized by means of a set of Figures 2 and 3. The Figure 2 which compares the self-reported mental health problems and AI-predicted risks for different age groups is not only a representation of the model's accuracy but also that of its real-world alignment. Besides, the line graph that shows the trends of the workplace support, intends to highlight the key role of targeted workplace interventions in mental healthcare.

The infusion of these findings into smart city scenarios has an important bearing on the management process of urban mental health. Through predictive analytics, city planners as well as healthcare providers can detect vulnerable groups and provide them with suitable interventions, including campaigns for raising mental health awareness, counseling programs, and urban design upgrades. As an example, priority areas for resource allocation could be those with the least support at the workplace or those with the highest predicted risks, thus mental health initiatives would be cost-efficient and effective.

The results presented in this study have confirmed the possibility and efficiency of the suggested foretelling pattern to overcome the mental health voids in smart cities. The correspondence gap of expressed concerns with AI-based risk foretelling proves the reliability of the model, whereas the understanding of the kind of work-related help employees tend to look for gives people those proactive handles that they are expecting from the policymakers, which is evident from the increased use of AI technologies for prediction making. This study not only shows that AI-first predictive analytics have the potential to transform urban mental health support systems but also sets the groundwork for smart cities to be more poised for innovation by being healthier and more adaptable. All the informative figures in this research, and the further trials in the labs stress the necessity of ongoing financial support for technology-based mental health solutions, and the critical issues of the inclusiveness and the activities of the city with a preventive nature are pointed out.

5 Conclusion

This research displays the ability of predictive analytics to completely change the approach to mental health issues in intelligent urban centers. The use of sophisticated data collection and analysis techniques showed that the proposed AI-powered model was highly accurate in forecasting mental health risks across all the age groups that were considered. The results show that the age group 25-34 years are the ones who suffer from a high rate of mental health problems (60%) while the AI system was able to maintain a rate of 62% for the same population group. Also, it was earlier mentioned that the youngest age group (18-24) reported fewer problems, but the AI predictions were a little higher for them, which indicates that the model is able to recognize the slight, probably undisclosed, signs of mental health issues. The analysis of workplace support revealed that this resource tends to be underutilized in older people, leading to the conclusion that specific group-focused campaigns for better utilization of mental health services are essential. All these findings thus point to the eventuality of data-based solutions in facilitating proactive approaches for mental healthcare in city infrastructures.

Regardless of the optimistic indications, the authors realize some restrictions. First of all, with the given sample size, this particular research covered one segment of the population, tech sector workers, and hence the results cannot be generalized to the entire urban population. Also, although the new method of federated learning was very effective in securing user data privacy, the fact that very different and often unstructured data were fed into the model turned out to be the problem that data harmonization for training purposes could not solve the function of the appliance. Since the model is dependent on pre-gathered data, there is a possibility that there will be no data for those social groups that have little or no access to smart devices or healthcare services and that those people will be left out of the models thereby introducing a bias. Future writings tackling these restrictions would, thus, significantly enrich the applications of AI-empowered mental healthcare services while nevertheless being specific and comprehensive in the contexts of smart cities.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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