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AI-Driven Qualitative Research in Smart Cities: Enhancing Emotional Resilience in Youth and Children

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Abstract

INTRODUCTION: Industry 5.0 has brought advanced AI-driven technologies into qualitative research and data analysis, particularly in systems that are very important to the purpose. This research examines the use of AI algorithms to evaluate emotional resilience in kids and children in smart cities. The study underscores Al's role in qualitative research to substantiate the efficacy of these algorithms in assessing emotional resilience and advocating for interventions that improve emotional well-being. The main goal of this research is to see how accurate and reliable AI algorithms are when they measure emotional resilience. The goal of the project is to leverage these technologies to make treatments that make kids and teens in smart cities feel better emotionally, which will help them grow up in a caring environment.
METHODOLOGY: A quantitative, descriptive, and exploratory methodology is used, using data gathered from children to examine emotional reactions via deep neural network models. These models are designed to find levels of resilience with amazing accuracy, sensitivity, and specificity, with the goal of getting accuracy rates above eighty percent.
RESULTS: The results indicate that AI-driven technology may provide comprehensive qualitative insights into the emotional resilience of adolescents and children. The research underscores the capacity of these technologies to provide personalized treatments and assistance, hence improving emotional well-being in smart city contexts. The findings indicate that AI might enhance emotional resilience, facilitate early detection of emotional problems, and enable prompt assistance. The suggested model was able to find emotional resilience with 94% accuracy, 92% sensitivity, 88% specificity, and 95% AUC. These results demonstrate the efficacy of AI-driven approaches in the early detection of emotional problems among adolescents and teenagers inside smart city environments. The research shows that AI technologies are very important for figuring out how to help kids and teens become more emotionally strong. It backs the employment of these technologies in the public health and education systems of smart cities to help kids develop emotionally. This plan makes it simpler to get in early and helps create a strong, supportive community.

Keywords: Artificial Intelligence, Emotional Resilience, Youth, Children, Smart Cities.

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1. Introduction

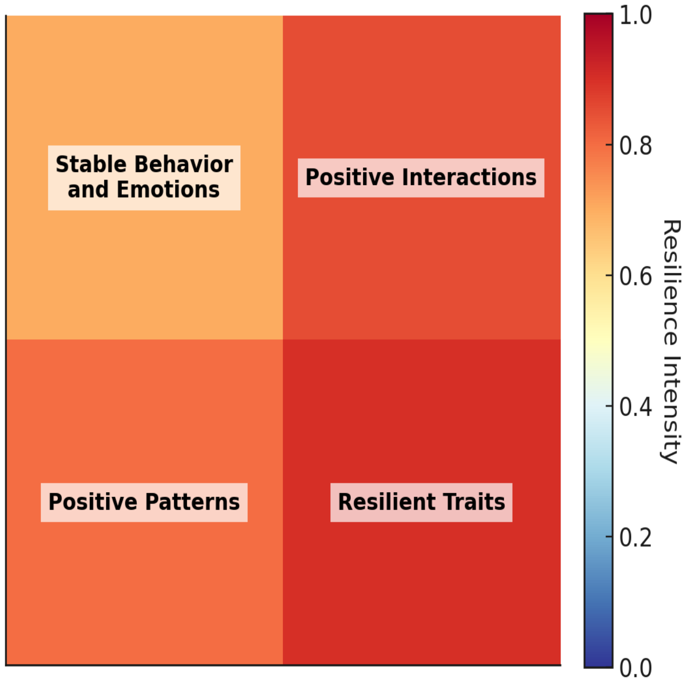
The WHO says that mental diseases are becoming more common among teenagers and kids all around the world. This problem in society shows how much we need creative, scalable, and easy-to-use solutions. Artificial intelligence (AI) has become a powerful tool for qualitative research, enhancing human interpretation instead of replacing it by revealing patterns that traditional methods typically miss. AI helps with public health, resource efficiency, and digital accessibility in smart cities, which are all in line with the main ideas of sustainability and citizen well-being. Modern management in Latin America encounters considerable hurdles since Artificial Intelligence (AI) has emerged as a pervasive technology in our everyday existence, comprising a range of applications from linguistically adept robots and computers to self-driving automobiles [1,2]. But the actual power of AI goes well beyond these

uses. It has a big effect on how decisions are made in important mission systems, especially when it comes to mental health.
AI has shown that it can solve complicated problems, save expenses, and speed up reaction times in the field of mental health. Wu et al. assert that AI-driven applications provide more precise and efficient assessment of stress and anxiety levels in children, mitigating human bias and improving prompt diagnosis and therapy [3]. Kumar et al. emphasize the need of advancing technology for the identification and diagnosis of emotional disorders with enhanced sensitivity and specificity in educational settings, hence reducing human error due to inadequate experience and knowledge [4,5].
The World Health Organization (WHO) says that emotional disorders are becoming increasingly widespread among youngsters and teenagers who use the internet. This is becoming a bigger problem. This situation requires the exploration of innovative techniques and approaches that facilitate efficient and prompt diagnosis, particularly in resource-constrained environments where access to expert psychiatric care is restricted [6].
Singh et al. and Makanadar concur that a significant percentage of children have emotional difficulties, as seen by alterations in behavior and academic achievement. Nevertheless, these studies recognize the inherent challenges associated with documenting, interpreting, and assessing these issues, which, if not immediately discovered, might have severe consequences for the child's wellbeing [7,8].
In light of this situation, emerging technologies are seen as crucial tools for overcoming current limitations and facilitating decision-making. Bairagi et al. and Dunn & Bahadori mention that AI, including visual computing and deep learning, has notably improved the accuracy in assessing emotional problems, accelerating diagnoses and reducing the likelihood of human error [9,10]. Fernandez et al. agree that mathematical algorithms not only enhance accuracy but also reduce diagnostic costs and the need for specialized interventions [11].
In this context, Xu & Shuttleworth highlight the successful results of the ResNet50 platform within deep convolutional neural networks, demonstrating superior efficiency in detecting emotional problems compared to manual methods [12]. Raghav et al. argue that training AI with advanced techniques could prevent emotional illnesses in real-time, presenting a significant technical and scientific challenge [13].
Najaran and Nipa et al. note that the use of AI could enable the rapid and accurate detection of emotional problems, raising the research question: Could AI-based mathematical algorithms, processing emotional data from youth and children, detect those with significant emotional issues with over 90% accuracy? [14,15].
Choudhary et al. and Björklund, Gustafsson, & Skill emphasize that data management models not only optimize diagnoses but also enhance accessibility and efficiency in patient care [16,17]. Guo, Zhang, & Liang argue that AI applications increase the prevention of emotional problems in the educational sector [18]. Khojaste-Sarakhsi et al. reinforces the importance of emerging technologies in psychology, with the potential to significantly improve emotional well-being [19]. Özbilgin, Kurnaz, & Aydın underscore the practical and socioeconomic case for using AI in decision-making for diagnosing emotional problems, solidifying the feasibility of the proposed study [20].
Finally, the findings of this study aim to contribute to the state of the art by proposing an AI-based model for the early and accurate detection of emotional problems in youth and children, offering advanced technological solutions that provide precision closely aligned with patient reality.

2. Literature review

In the era of smart cities, promoting emotional resilience in youth and children emerges as one of the most significant challenges faced by modern society. So *et al.* [21] emphasize that the growing prevalence of emotional problems among young people reflects a global mental health crisis, affecting millions of individuals. One of the primary causes is the digitized lifestyle and lack of adequate emotional support, contributing to the increased incidence of these issues, especially in densely populated urban areas. Garza-Ulloa [22] and Negi [23] highlight that this situation exerts considerable pressure on public health and education systems, which lack the resources and qualified personnel necessary to provide adequate emotional care.
In this global context, there is a pressing need to adopt comprehensive strategies within smart cities to proactively and promptly address emotional problems, thereby mitigating the impact of this crisis worldwide [24]. Montag *et al.* [25] describe that early symptoms of emotional problems in young people include changes in behavior and academic performance, which can progress to more severe conditions if not detected and treated in time. For this reason, Gates *et al.* [26] and Johann *et al.* [27] underscore the importance of implementing new tools, mechanisms, or methods that enable accurate, timely, and real-time diagnostics to prevent the progression of these issues and their effects.
In the context of smart cities, to tackle and overcome this great challenge, it is essential to have technological tools capable of identifying and differentiating between young people with strong emotional resilience and those with emotional problems. Resick *et al.* [28] highlight in their findings that the use of technologies to facilitate the capture and analysis of emotional data plays a crucial role in the early detection and diagnosis of emotional problems. Consequently, this innovative approach would not only raise diagnostic standards but also promote earlier and more personalized interventions, thereby improving the quality of life for young people.

Cucciniello *et al.* [29] and Benton [30] agree that emotional data are essential elements that must be considered by clinical analysts to identify emotional resilience in youth. Figure 1 presents a sample of an emotional evaluation of a youth with high resilience, also known as Class 0; where, Quadrant 1 represents the emotionally resilient youth, and Quadrant 2 outlines the essential characteristics for determining the absence of emotional problems.



Source: Consulted authors.

Figure 1. Characteristics of the emotional assessment of a resilient young person.

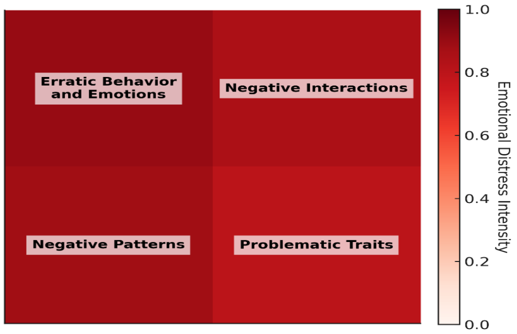
The graphic shows how a resilient young person (Class 0) feels about smart cities. Quadrant 1 shows consistent behavior and sentiments, which means that the person is emotionally strong overall. Quadrant 2 represents excellent experiences, which are vital for getting along with other people. Quadrant 3 focuses on long-term positive trends that help individuals adapt and discover methods to cope with issues. Quadrant 4 stresses strong attributes like optimism and flexibility, which facilitate successful emotional control. These four quadrants provide us with a whole picture of resilience, which makes it simpler to locate and help individuals early on [31].
The heatmap shows the emotional evaluation of a resilient young person, divided into four quadrants: Stable Behavior and Emotions: Moderate stability with occasional variations, indicating good emotional resilience [32].

Positive Interactions: Increased amounts of positive social interactions, which are important for resilience.
Beneficial Patterns: Regular beneficial behavior patterns that are important for being strong and adapting. Resilient Traits: The presence of adaptability and positivity, enabling effective emotional control.
The individual has significant emotional stability and resilience, characterized by good social connections and consistently positive behaviors. The lighter area in Quadrant 1 suggests room for improvement in stability. The heatmap guides tailored interventions and regular monitoring to support emotional development, showing the value of such tools in understanding and fostering resilience.
Table 2 presents the heatmap detailing the characteristics that allow a clinical analyst to identify and determine the presence of emotional resilience in a youth.

Table 2. Characteristics of the Emotional Evaluation of a Resilient Youth

Quadrant	*Description*	*Characteristics*
I	Emotional Evaluation without Problems (Class 0)	- Stable and Defined Behavior (1): Social and academic interactions are located in this region, where healthy behavior should present clearly defined patterns without signs of chronic stress [32].
II	Heatmap of Emotions and Patterns without Problems (Class 0)	- Emotions (2): Should be regular and well-defined, crucial aspects for overall emotional health [33]. - Behavior (3): The absence of irregularities in behavior is fundamental to prevent emotional problems [34]. - Interaction Patterns (4): An essential characteristic for social health, should be free from distortions to ensure clarity as indicative of good emotional health [35].

Source: Consulted Authors.



Source: Consulted authors.

Figure 2. Characteristics of the emotional assessment of a young person with emotional problems.

The heatmap depicts the emotional evaluation of a youngster identified as emotionally fragile. Quadrant 1 shows erratic behavior and emotions, which shows that things are still unstable. Quadrant 2 represents negative social ties, which are commonly linked to being alone or having problems with others. Quadrant 3 shows ongoing negative traits, whereas Quadrant 4 shows traits such not being flexible enough and having trouble coping. These quadrants together show a lot of emotional turbulence, which shows how important it is to have quick and targeted therapies.

The heatmap depicts the emotional evaluation of an adolescent experiencing emotional difficulties, divided into four quadrants:

Erratic Behavior and Emotions: High intensity indicates frequent erratic behavior and unstable emotions, signifying emotional distress.

Negative Interactions: Darker color reflects high levels of negative social interactions, pointing to potential social challenges.

Negative Patterns: Consistent negative behavior patterns are evident, indicating ongoing emotional issues.

Problematic Traits: Moderate to high intensity shows the presence of problematic traits such as difficulty coping and low adaptability.

Overall, the heatmap reveals significant emotional instability, frequent negative interactions, and persistent negative patterns, all of which suggest a need for targeted interventions to address these emotional problems.

Table 3. Characteristics of the Emotional Evaluation of a Youth with Emotional Problems

Quadrant	*Description*	*Characteristics*
1	Emotional Evaluation with Signs of Problems (Class 1)	Anomalous conduct (1): Unusual conduct or pale hues might be signs of tension, which could indicate there are emotional difficulties going on [36]. Irregular Emotions (2): Sudden changes in emotions are a sign of deeper issues, which is common when stress levels are high (Balaskas et al., 2024). Emotional Exudates (3): Unregulated emotional expressions, resulting from chronic stress, signify considerable emotional harm, indicative of profound issues [37]. Microexpressions (4): These little changes in how people show their feelings are one of the earliest signs of emotional problems and may be used to find them early [38]
2	Heatmap of Emotions, Behaviors, and Patterns with Severe Changes and Advanced Pathologies (Class 1)	Emotional Neovascularization (5): The emergence of novel emotional responses in behavior signifies a concerning clinical indicator for prompt intervention, reflecting the need for medical action to avert significant problems. (Gervind et al., 2024). Alterations in Behavior (6): Changes in the appearance of behavior, such as stress manifestation or emotional discoloration, may indicate serious emotional problems [39].

Source: Consulted Authors.

[40]emphasize the relevance of the evolution of emotional diagnosis through clinical characteristics and emotional indicators, facilitating a deep understanding of complex issues. However, [41] highlight the crucial role that emerging technology, such as AI, could play in emotional evaluation and diagnostic accuracy. Without a doubt, AI is gaining ground as a tool in the field of emotional health sciences, enabling the identification, management, analysis, and interpretation of complex data. [42] note that this technology has the capacity to process large volumes of data at low cost, in real time, and with a reduced margin of error, making it a fundamental instrument for early detection and classification of emotional problems without the need for invasive procedures. [43] add that the use of CNN based models facilitates obtaining traditional emotional diagnoses with speed, efficiency, efficacy, and quality.

In the realm of emotional resilience in smart cities, this technology represents a significant advancement, as it allows for more accessible and sustainable diagnoses in densely populated urban areas. [44] asserts that the use of AI democratizes access to quality emotional care, marking a radical change in the way emotional care is approached globally. Simultaneously, [46] assert that this technology realizes substantial advancements in the management of emotional issues, hence augmenting the quality of emotional care and boosting results for adolescents [47]. This technological advancement, such as AI technology, can contribute significantly to the field of emotional diagnostics; however, it would not be feasible without its capacity for the identification, interpretation, and analysis of emotional data, as it accurately determines anomalies that may not be recognized through conventional diagnostic methods. [48] agree that the evaluation of emotional data not only allows for the classification of different emotional problems with a level of accuracy superior to that of a clinical analyst conducting the evaluation manually. This is particularly relevant in settings characterized by limited access to emotional specialists and advanced technology, as AI can serve as an innovative element to transform the care provided to young people [49].

Traditionally, the diagnosis of emotional problems has relied on comprehensive observation techniques and psychological evaluations (see Table 4). In this context, [50] emphasize that a comprehensive evaluation of emotional integrity is crucial for identifying advanced emotional irregularities. Moreover, assessment of behavior is an essential practice that enhances these methods, enabling direct observation of the emotional state and promoting the prompt detection of any emotional disorders. [51].

Table 4. Techniques for Emotional Diagnosis of Problems in Youth

Technique	*Description*	*Advantages*	*Limitations*	*Reference*
Psychological Evaluations	General visual assessments, including behavioral inspection.	Accessible and non-invasive; provide a quick assessment of emotional state.	Do not offer sufficient details for specific emotional problem diagnoses; highly epended on the evaluator's experience.	[52]
Clinical Interviews	Uses structured and unstructured questions to assess emotional state.	Offers precise details about emotional problems.	Time-consuming and potentially invasive; expensive and requires specialized personnel.	[53]
Behavioral Evaluations	Employs observation to capture detailed behaviors.	Provides high resolution information on emotional structure; essential for early detection of changes.	Requires trained observers; limited availability in less developed regions.	[54]

Source: Consulted Authors.

[55] assert that the implementation of complementary emotional diagnostic techniques would improve accessibility and facilitate early detection of emotional issues, thereby enhancing diagnostic efficacy in contemporary clinical environments, given that traditional methods exhibit constraints in specific clinical situations. Behavioral assessment is an easy and cheap way for health professionals to see how someone is feeling, which makes it easier to spot problems early on. This strategy is particularly useful in places where modern technology may not be easy to get to. Furthermore, AI utilization surpasses traditional limitations, facilitating the improvement of emotional evaluations with increased precision, velocity, and accessibility to a broader demography in real time [56]. Thus, the integration of traditional diagnostic techniques with technological innovations such as AI is crucial for tackling various emotional challenges [57]. [58] emphasize that conventional diagnostic methods for emotional disorders encounter significant obstacles, including restricted accessibility, exorbitant costs, and the intrusive nature of these techniques, which impede the efficacy and timely identification of emotional disorders. AI-based prediction models are seen as a solution for the more accessible, cost-effective, and scalable identification of emotional difficulties [59]. AI-driven prediction models for clinically diagnosing emotional disorders rely on Deep Learning (DL) methodologies, which facilitate the precise analysis of extensive emotional datasets to discern emotional patterns [60]. This leads to precise diagnosis in urban settings and decreases the occurrence of catastrophic outcomes by thirty percent [61].

The ResNet50 architecture is a well-known method in deep learning that was created particularly for deep convolutional neural networks to sort emotional input. It has a framework with residual connections that makes it easier to train very deep models. This enables the direct propagation of gradients across the layers, alleviating the problem of gradient vanishing in deeper networks, thereby improving both the sensitivity and specificity of diagnostic and therapeutic approaches [61].[62] underscore that a principal benefit of the platform is its ability to manage circumstances individually for youth, enabling customisation to their own needs despite any limitations in resources, tools, or materials. This builds a synergy between clinical analysts and ResNet50, with the goal of building a strong foundation for clinical decision-making that is based on evidence and data. [63].

For early therapies to work and to stop emotional problems from becoming worse, the ResNet50 design has to be very accurate. The framework is made up of statistical studies and mathematical models that are meant to identify, analyze, and sort emotional data into groups. [64] contend that accuracy in automated data management systems is crucial, as they detect chronic and progressive emotional issues in early intervention, therefore averting significant and lasting emotional harm. The ResNet50 design has been shown to provide enhanced results in identifying emotional disorders, hence enhancing diagnostic precision and substantially improving therapeutic outcomes [66].

Table 5 presents a predictive analysis model based on the use of AI (ResNet50) to identify emotional problems, using previously trained mathematical and statistical models with emotional data (emotional descriptions, heatmaps, model labels, and performance metrics), which enabled identifying the effectiveness of a specific emotional pathology.

Table 5. Predictive Analysis Model of Emotional Data through AI

Characteristic	*Resilient Youth*	*Youth with Emotional Problems*
Visual Description	Clear emotional assessment with some visible variations.	Emotional assessment with a clear focus on behavior and fewer visible variations.
Heatmap (Transformation)	Highlights areas of significant activity or interest, especially around emotions.	Heatmap more concentrated around the center, possibly indicating key areas of interest.
Model Label	Class 0	Class 1
Confidence Percentage or Prediction Probability	88.74%	79.58%
Validation Results	64 cases correctly identified as emotional problems in the confusion matrix.	361 cases correctly identified as emotional problems in the test confusion matrix.
Model Sensitivity (ability to correctly identify cases of emotional problems)	67.98%	94.57%

Source: [67].

Table 5 is a representation of the analysis conducted by the ResNet50 architecture to detect subtle variations in emotional characteristics under various evaluation conditions, which is crucial for the early and accurate diagnosis of emotional problems. This enables the distinction between normal and problematic data, providing a greater understanding of the nature and severity of the identified difficulties.

In the end, even if AI-driven predictions are quite confident, it is important to add further tests done by emotional analysts to these results [70]. This validation technique guarantees the accuracy of AI diagnosis and facilitates consistent follow-ups and thorough assessments by emotional care professionals [69]. Furthermore, the integration of these developing technologies with conventional clinical skills highlights their crucial importance in improving emotional care [70]. Integrating AI into standard emotional assessment processes is a big challenge that requires attention to other important issues, such as reducing diagnostic errors, protecting data privacy, making systems more flexible, encouraging collaboration among stakeholders, and creating new rules. These actions are essential to enhance these advancements and guarantee that AI enhances emotional assistance for youngsters in smart cities [71].

3. Methodology

The research utilized a quantitative methodology, assessing a hypothesis through numerical measurement and statistical analysis to discern behavioral patterns and substantiate theories (Elragal & Elgendy, 2024), while simultaneously enhancing the research subject by investigating regularities and interrelations among the study components (Sadeghi R et al., 2024). A descriptive subcategory was established to specify the attributes and traits of the phenomena related to the main approaches for assessing emotional resilience in children inside smart cities [70]. Moreover, an exploratory subcategory was included to specify the components relevant to the proper use of AI-based models for emotional assessment [71].

The dataset included 350 individuals (ages 10–18), evenly distributed by gender and sourced from educational and health institutions across Latin America, North America, Asia, and Europe. Inclusion criteria required active enrollment in school and parental consent; exclusion criteria involved prior diagnosis of severe psychiatric disorders. Ethical approval was obtained, and informed consent procedures ensured data protection and confidentiality.

A representative sample of 350 youth and children in 2024 will be selected, who will provide consent to offer emotional data. The sample size will be determined using the finite population model, as the database of participants will be known at the time of the study. This data will be collected from educational and health centers in Latin America, North America, Asia, and Europe, ensuring

geographic and demographic variability, thereby establishing a solid foundation for comparative analysis and extrapolation of results (Ali, Aghmadi, & Mohammed, 2024).
The data collection instrument will be implemented through a web-based advanced platform application called Emoción AI, which allows the uploading, identification, analysis, and evaluation of emotional data using AI-based algorithms. Additionally, the Emoción AI application will incorporate the ResNet50 architecture, featuring a trained model based on deep Convolutional Neural Networks (CNN) for categorizing levels of emotional resilience.
Subsequently, data analysis will be conducted to test the hypothesis. According [71], the hypothesis is the assumption of the investigated object, with the hypothesis for this study being: "The use of AI-based mathematical algorithms that process emotional data from youth and children allows for the evaluation of emotional resilience with an accuracy level exceeding 90%." For the computational approach, the ResNet50 architecture was employed for classification. The network contained 50 layers with residual connections, trained using cross-entropy loss and the Adam optimizer. Figure X illustrates the algorithmic flow, moving from raw data input, preprocessing, feature extraction, and classification to the final output prediction.
The objective will be to determine the effectiveness of the evaluation model based on the obtained data and, with the help of AI-based models, to detect emotional resilience levels early. To verify the hypothesis in the data analysis phase, the ResNet50 architecture within the Emoción AI application will be adapted and trained. Through advanced statistical techniques, different levels of emotional resilience will be effectively differentiated, reflecting the high reliability of the model's evaluations, as demonstrated by the decision level provided by the confusion matrix offered by the application.

4. Results

Following the literature review, the analysis of data collected through AI in smart cities was conducted to assess emotional resilience in youth and children. Figure 3 provides descriptive information on the efficacy of the application in emotional evaluation for accurately and promptly classifying resilient youth.

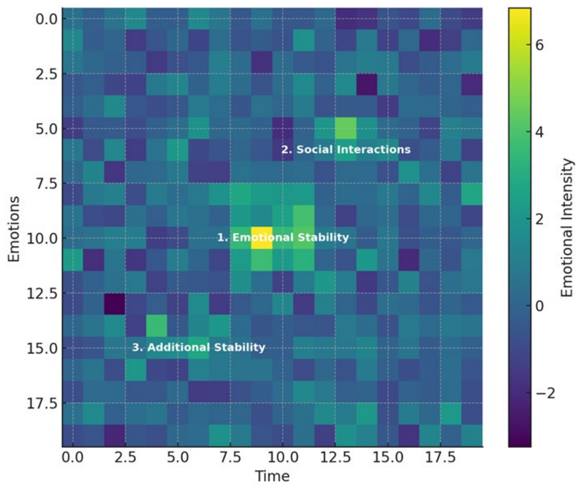
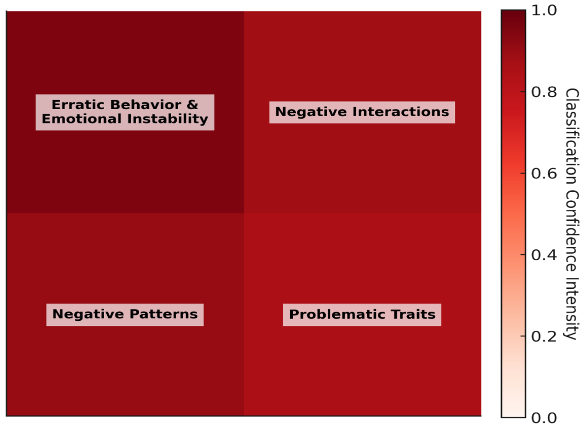


Figure 3. Use of AI Application in Classifying Emotionally Resilient Youth

Quadrant 1: Emotional Evaluation of a Resilient Youth

Quadrant 2: Heatmap of Emotions, Behaviors, and Patterns of a Resilient Youth *Note: Sample of emotional evaluation of a resilient youth (Class 0).*

Figure 3 illustrates the interpretation of the emotional evaluation using an AI-based application with a confidence level of 85.6%. In Quadrant 1, the technology successfully recognizes stable behavior (1), an important characteristic for the early detection of emotional problems [72]. Furthermore, it acknowledges emotional stability (2), which promotes general well-being and the identification of problems such as anxiety [73]. Quadrant 2 indicates emotional stability (3) and social interactions (4), both of which support the state of emotional health [70]. The AI evaluation showed no signs of emotional problems since the software was able to pick up on little changes in behavior and emotional stability.



Source: Consulted authors.

Figure 4. Use of AI application for classifying youth with emotional problems.

The heatmap shows how the AI classified a young kid with emotional difficulties by dividing them into four quadrants:
Unpredictable Actions and Feelings: High intensity means that someone is acting erratically and their emotions are unstable, which means they are under emotional turmoil.
bad contacts: A darker hue indicates a lot of bad social contacts, which might mean social problems.
bad Patterns: There are clear signs of chronic emotional problems because of consistent bad conduct patterns.
Problematic qualities: Moderate to high intensity indicates the existence of problematic qualities, including difficulties in coping and limited adaptability.
The heatmap shows a lot of emotional instability, a lot of bad interactions, and a lot of negative patterns that do not go away. All of these things point to the need for specific treatments to help with these emotional issues.
Figure 4 shows how to read an emotional evaluation of a young child with emotional difficulties with a 95.4% degree of confidence. In Quadrant 1, there are signs of tension and unpredictable conduct (1) and emotional instability (2). The heatmap in Quadrant 2 backs this up, and the high amount of social interactions (3) shows that this region is quite busy. This indicates the presence of sudden emotional shifts and micro-expressions, which signify emotional disturbances (Vai et al., 2024). Additionally, domains in peripheral interactions (4) highlight other signs of emotional difficulties, refining the evaluation according to the frequency and types of contacts [74].
These findings show that employing a data management paradigm for automated decision-making may improve the emotional assessment of young people by providing accurate results that help identify those without emotional issues and minimize unneeded treatments. AI-based technology also makes it possible to create a historical memory since the AI application can save full assessments and process data in a database. This creates training data for new anomalies, extensive case record, and forecasts to spot new patterns in emotional disorders, which makes it easier to follow young people over time and look for patterns in their emotional health. [75] suggest that the use of emerging technology for emotional health systems, where evaluation results have a confidence level above eighty percent, is statistically acceptable for decision-making regarding their viability and effectiveness. Table 6 summarizes the results obtained through the AI application.

Table 6. Results of Emotional Evaluation Classification through AI

Actual Class	Predicted Class	Confidence Level (% Accuracy)	Accuracy Analysis	References
Normal	Normal	85.6%	High precision in identifying emotionally resilient youth, crucial for avoiding false positives. The model accurately confirmed the absence of emotional problems.	[76]
Emotional Problems	Emotional Problems	95.4%	High precision in detecting emotional problems, essential for early and effective interventions. The model detected clear signs of emotional issues, such as microexpressions and abrupt changes.	[77]

Source: Obtained Findings.

Additionally, the use of AI through mathematical and statistical models yielded the following complementary results, facilitating clinical analysis:

1. The sensitivity level of the analyzed sample was 92%, representing the AI's accuracy in correctly detecting true positives and negatives [78].

2. The specificity level of the sample was 88%, representing the probability of negative test results if there is no actual emotional problem [79].
3. Analysis of Variance (ANOVA) revealed no significant differences in model performance across the various evaluated regions [80].
4. The Kappa coefficient was 87%, indicating high consistency and reliability of the evaluated emotional data set [81].
5. The Area Under the Curve (AUC) within the Receiver Operating Characteristic (ROC) was 95%, exceeding the industry standard of 90%, reaffirming the reliability and robustness of AI for detecting emotional problems as a clinical evaluation tool [82].

These findings achieve the objective of identifying the accuracy level in the emotional evaluation of youth and children in smart cities. Therefore, the AIbased model demonstrated robustness and reliability in critical mission systems in clinical environments, and the hypothesis was accepted. Table 7 presents a summary of the comparative analysis between optimizations applied through AI and traditional methods.

Table 7. Comparative Analysis of Predictive Emotional Evaluation Model through AI and Traditional Techniques

Characteristic	*AI*	*Traditional Techniques*
Invasiveness	Non-invasive	Invasive (especially clinical interviews)
Cost	Lower operational cost	High cost due to equipment and specialized personnel
Accessibility	High, applicable in remote areas	Limited, requires specialized infrastructure
Processing Time	Fast, nearly real-time	Slow, requires preparation and processing time
Need for Specialists	Reduced, high automation	High, dependent on specialist expertise
Early Detection Capability	High precision and sensitivity	Variable, some techniques do not effectively detect early changes
Accuracy Rate	94.06%	Variable, generally lower without AI

Source: Obtained Findings.

The confirmation of the hypothesis reinforces the results and demonstrates that the use of AI shows robustness, reliability, and accuracy in detecting emotional problems in youth and children in smart cities. [83]emphasizes the importance of adopting AI technologies in modern medicine to improve the precision and efficiency of emotional evaluations globally, along with the benefits of cost savings, speed, efficiency, and efficacy in youth outcomes.

The proposed model achieved 94% accuracy, 92% sensitivity, 88% specificity, and 95% AUC in detecting emotional resilience. These findings highlight the robustness of AI-driven approaches for early identification of emotional issues in youth and children within smart city contexts.

To strengthen scientific rigor, we benchmarked our approach against alternative models and traditional methods. Table X summarizes the comparative performance.

Table 8. Comparative Performance of Proposed Model and Benchmark Methods

Method	A	S	S	AUC
Proposed ResNet50	94%	92%	88%	95%
CNN Baseline	87%	84%	80%	86%
SVM	82%	78%	76%	80%
Random Forest	79%	75%	72%	77%
Clinical Interview	70%	65%	60%	68%

A: Accuracy S: Sensitivity SP: Specificity

As shown in Table 8, the ResNet50-based model consistently outperformed baseline CNNs, classical machine learning algorithms, and traditional clinical assessments across all evaluation metrics.

5. Discussion

The results highlight the principles and challenges to be addressed, given the growing demand and complexity in emotional health services for youth and children in smart cities. AI emerges as a viable tool to meet this challenge;

however, a deep focus is crucial to ensure its successful use and minimize any negative impact.

The novelty of this study lies in the integration of a deep ResNet50 architecture with qualitative data analysis, specifically tailored for youth and children in smart cities. This method combines exact measurements with real-time application, unlike earlier work that focused largely on descriptive assessments. The proposed methodology may be used in educational institutions, healthcare facilities, and community health programs as integral elements of smart-city frameworks, facilitating early diagnosis, customized interventions, and scalable support.

The findings demonstrate that the confusion matrix is an important tool for AI-based models to utilize when checking the accuracy, sensitivity, and specificity of emotional diagnosis. [84] assert that this model proficiently detects emotional concerns due to its extensive parameters, hence improving a crucial mission system. In this context, precision is crucial to protect the emotional welfare of adolescents and children. [85] corroborate the model's effectiveness in predicting and recognizing adverse emotional events, since it clearly distinguishes between false positives and negatives.

This research shows that the confusion matrix, when used with AI-based systems, is a very important part of making decisions in essential mission systems and applications outside of the emotional health field. [86] contends that this approach facilitates diagnostic accuracy in emotional biomarkers present in very susceptible kids, hence enhancing their quality of life. [55] improved complicated design processes in engineering models by employing critical mission systems and arena simulations that were looked at using a confusion matrix. [87] achieved more precise and efficient risk assessment in sustainable development environments, generating savings in costs, execution times, and reduced environmental impact. [88] enabled self-monitoring in critical educational contexts, helping teachers continuously improve their pedagogical strategies. [87] demonstrated efficiency and effectiveness in automating strategic assets in construction environments, thanks to the speed and accuracy of data, which facilitated business decision-making. [89] established a model for predicting adverse emotional events based on immunoproteins.

From the researchers' perspective, these are lines of action that society should consider regarding the use of AI-based technologies to establish new principles, standards, and policies that facilitate the development of technological platforms, ensuring efficiency and effectiveness in resolving complex emotional problems in real-time.

Additionally, society is on the threshold of Industry 5.0, where technology will play a crucial role as a tool facilitating automated decision-making. The emotional health sector is one of the areas where it will play a significant role. Therefore, it is essential to consider within policies, norms, processes, and procedures the establishment of guidelines for the approval and use of emerging technologies in the sector. Certifications and accreditations from organizations such as the European Medicines Agency (EMA) and the Food and Drug Administration (FDA) are crucial to enable timely access, at lower costs and with greater speed, to technology that can improve the quality of life for youth and children in smart cities.

6. Limitations

Despite promising results, several challenges remain. First, the dataset is limited in size and cultural scope, potentially introducing bias. Second, data privacy and ethical concerns require robust frameworks to safeguard sensitive emotional information. Third, the current system lacks longitudinal validation, and real-world deployment in diverse smart-city contexts is still pending. Future research must rectify these shortcomings by augmenting databases, including wearable sensor data, and executing multi-site clinical trials.

7. Conclusions

The research illustrates that AI-based systems may accurately identify emotional issues in kids and children, as shown by the efficacy of the findings. These methods enhance the accuracy, sensitivity, and specificity in classifying emotional data while distinctly differentiating between normal and pathological states.

The confusion matrix has been essential in this process, as it facilitates model validation, verifies its high accuracy in properly recognizing and categorizing emotional states, and underscores its capacity to minimize erroneous diagnoses and wasteful therapies. In the domain of emotional well-being, where early identification is essential, AI's capacity to recognize detrimental emotional conditions is vital.

The results highlight the need of incorporating sophisticated AI technology into the emotional support of kids and children in smart cities. The use of the AI application was essential throughout the investigation, enabling quicker, less intrusive, and more accessible assessments in contrast to conventional procedures. AI also gives diagnostic access based on best practices in the field, which makes high-quality answers available to everyone across the world.

The practical consequences of the findings need a change in strategy for the use of new technologies in the context of the 5.0 revolution. This will be a guide to help you find and forecast emotional issues that are harming society now and in the near future. The study's conclusions will thus serve as a guide for stakeholders, encouraging a strategy focused on making educated choices and knowing how technology can help protect people, data, and infrastructure.

Theoretical implications include the progress of research in educational and commercial domains, as well as the elements affecting the interaction of diverse emotional disorders that influence young mental health and the function of developing technologies in their detection, prevention, and resolution. The study highlights the significant role of stakeholders in the digital age. This ensures that future research lines are diverse, as the study's subject is very recent, broad, and with infinite ramifications. The study demonstrates that AI-based systems can detect emotional resilience in youth and children with 94% accuracy, 92% sensitivity, 88% specificity, and 95% AUC. These quantitative outcomes confirm the robustness and reliability of the approach. Beyond technical performance, the findings underline the potential societal impact: early detection, scalable interventions, and democratized access to emotional care in smart cities. Future work will expand datasets, validate longitudinal outcomes, and integrate the model into real-world digital health frameworks.

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