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Applying AI-driven surveillance frameworks to detect emerging mental health risks among adolescents using integrated One Health environmental indicators

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Abstract

Escalating environmental stressors including climate variability, air pollution, water contamination, and ecological disruption are increasingly recognized as significant contributors to mental health challenges among adolescents. Yet, conventional public health monitoring systems remain fragmented, reactive, and insufficient for timely identification of emerging psychosocial risks. Artificial intelligence (AI) presents a transformative opportunity to bridge this gap by integrating environmental, human, and ecological indicators within the One Health framework to create advanced surveillance systems capable of detecting early mental health vulnerabilities. This article provides a comprehensive analysis of AI-driven surveillance architectures that leverage multimodal datasets such as satellite climate observations, urban pollution sensors, microbial and vector-distribution data, school health reports, and behavioural digital footprints to model adolescent mental health risk trajectories with high precision. The broader discussion highlights how machine learning, pattern-recognition algorithms, and anomaly-detection techniques can identify subtle environmental–behavioural interactions that precede clinical symptoms, including stress, anxiety, sleep dysregulation, and mood disturbances. As the analysis narrows, the paper demonstrates how integrated One Health surveillance models can stratify risk across communities, detect geographically clustered environmental triggers, and flag early shifts in mental well-being linked to temperature extremes, toxic exposures, allergens, zoonotic influences, and degraded living conditions. Additionally, the study explores how AI-enabled dashboards and early-warning systems could support schools, mental health practitioners, and policymakers by offering real-time indicators and predictive alerts. Ethical considerations including responsible data governance, adolescent privacy, algorithmic fairness, and transparent model communication are emphasized to ensure safe and equitable adoption. The findings argue that AI-driven surveillance systems anchored in One Health principles offer a crucial pathway toward proactive, preventive, and environmentally informed adolescent mental health strategies. Strengthening these systems will be essential for safeguarding youth resilience in an era marked by accelerating ecological and climatic instability.

Keywords: AI Surveillance; One Health; Adolescent Mental Health; Environmental Indicators; Predictive Analytics; Early-Warning Systems

1. Introduction

1.1. Background: Rising adolescent mental health challenges in climate-stressed environments

Adolescents are increasingly exposed to environmental conditions that heighten psychological vulnerability, particularly in regions experiencing rapid climatic shifts and worsening pollution patterns [1]. Fluctuating temperatures, recurrent heatwaves, erratic rainfall, and deteriorating air quality have been linked to emotional strain, sleep disturbances, and heightened anxiety among young populations [2]. As environmental pressures accumulate,

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adolescents already navigating social and biological transitions face intensified risks that place additional burden on family and school support systems [3].

Urban centres are especially affected, with growing traffic emissions, industrial particulates, and reduced green spaces creating everyday stressors that interact with developmental sensitivities [4]. These exposures can disrupt cognitive function and emotional regulation, particularly in youths with limited access to mental-health resources or stable living environments [5]. Evidence from environmental health studies suggests that climate-associated disturbances to daily routines, such as increased nighttime heat or heavily polluted mornings, may amplify irritability, stress responsiveness, and behavioural difficulties [6].

Communities with constrained infrastructure are disproportionately exposed to such environmental challenges, leaving adolescents in vulnerable settings more likely to experience cumulative psychological impacts [7]. As climate stressors continue to intensify, the need to examine how environmental shifts shape adolescent mental-health outcomes becomes increasingly urgent [2]. Understanding these dynamics provides a necessary foundation for developing responsive surveillance tools that can capture early warning signs of risk across diverse ecological contexts [8].

1.2. Limitations of traditional mental-health surveillance systems

Conventional mental-health surveillance systems often struggle to detect emerging risks among adolescents exposed to climate-related environmental burdens. Many rely on periodic surveys, manual reporting, or facility-based records that miss subtle early indicators of stress or community-level disturbances [5]. These approaches tend to operate retrospectively, capturing symptoms long after environmental triggers have intensified psychological strain.

Furthermore, traditional systems rarely integrate environmental datasets such as temperature anomalies, air-quality fluctuations, or ecological disruptions which limits their ability to recognise the environmental precursors of mental-health shifts [10]. Fragmented data streams, inconsistent reporting practices, and limited cross-sector collaboration impede timely response capacity [4].

In addition, adolescents in marginalised or rapidly changing environments may not access formal care pathways, leaving their experiences undocumented within existing surveillance frameworks [1]. These gaps reduce the effectiveness of early intervention strategies and underscore the need for models that can capture environmental signals alongside psychosocial indicators, enabling more proactive forms of monitoring [7].

1.3. Rationale for AI-driven One Health integration

Integrating AI within a One Health framework offers a transformative approach to understanding how environmental stressors influence adolescent mental well-being. One Health encourages evaluation of human health within ecosystems shaped by climate, pollution, and socio-ecological dynamics [6]. By leveraging machine learning techniques, large volumes of environmental, behavioural, and psychosocial data can be processed to uncover patterns that traditional systems overlook [3].

AI models can detect early deviations in exposure–response relationships, helping identify adolescents most susceptible to climate-linked mental-health risks [9]. This integration provides a unified platform for anticipating vulnerability, supporting targeted prevention, and strengthening community-level resilience strategies [2].

2. Conceptual foundations of one health and adolescent mental health

2.1. One Health paradigm: Linking environmental, ecological, and human well-being

The One Health paradigm provides a unifying framework for understanding how environmental conditions, ecological stability, and human health outcomes interact across shared systems. This approach emphasises that adolescent mental well-being cannot be separated from the broader environmental pressures shaping their daily experiences [9]. Ecosystem disruptions such as degraded air quality, diminishing green spaces, and unstable climatic patterns contribute to physiological and psychological strain among young people navigating sensitive developmental periods.

Within this paradigm, ecosystems are conceptualised as dynamic networks in which changes to one component create ripple effects that influence human psychological resilience [12]. For adolescents, exposures to shifting temperatures, noise pollution, and overcrowded urban settings can disrupt sleep patterns, intensify emotional reactivity, and reduce opportunities for restorative interactions with natural environments [8]. These stressors accumulate over time, underscoring the need for holistic frameworks capable of tracking interconnected influences rather than viewing mental health in isolation.

The One Health perspective also recognises the role of ecological degradation in shaping household stressors, community instability, and resource scarcity all of which can heighten mental-health vulnerability [14]. By connecting these environmental and social dimensions, the paradigm expands the scope of surveillance systems to include climate variables, pollution indicators, and ecological signals that traditional mental-health monitoring often overlooks [16]. This cross-sectoral emphasis provides a foundation for developing models that integrate environmental determinants with psychosocial data, supporting more robust identification of emerging risks. As environmental disruptions continue to intensify, a One Health orientation offers a strategic lens for understanding the environmental roots of adolescent mental-health challenges [11].

2.2. Environmental determinants of adolescent mental health

Adolescent mental health is closely shaped by environmental exposures that influence neurodevelopment, emotional processing, and physiological stress responses. Air pollution including particulate matter, ozone, and traffic-related emissions has been linked to cognitive strain, irritability, and heightened anxiety among young people living in densely populated regions [13]. Such pollutants can disrupt inflammatory pathways and neurochemical balance, contributing to mood instability during a developmental stage already marked by hormonal transitions [10].

Temperature fluctuations and prolonged heat episodes further intensify stress responses, particularly in adolescents lacking cooling resources or safe outdoor environments [15]. High nighttime temperatures may disturb sleep, reducing coping capacity and contributing to fatigue-related emotional dysregulation [9]. Additionally, environmental toxins from industrial sites or waste-burning activities pose risks to cognitive performance and behavioural stability, especially in communities with prolonged exposure and limited health safeguards [12].

Green-space loss and reduced opportunities for contact with natural environments compound these risks by eliminating restorative outlets that promote emotional resilience [8]. These determinants highlight the importance of integrating environmental metrics directly into adolescent mental-health surveillance systems, ensuring that the environmental triggers of psychological strain are identified early enough to enable targeted prevention and intervention.

2.3. Multi-sectoral requirements for integrated surveillance

Effective environmental–mental-health surveillance requires multi-sectoral coordination across public health, environmental science, education, urban planning, and community-based organisations [14]. Traditional systems, which operate largely within health-sector boundaries, often lack access to environmental datasets or ecological monitoring tools capable of capturing early warning signals [16]. Creating comprehensive systems requires collaboration that allows environmental agencies to share air-quality metrics, meteorological data, and ecological observations that can be used to predict mental-health risks among adolescents [11].

Schools, youth services, and local community structures also play central roles by providing psychosocial indicators that complement environmental datasets [8]. These sources offer essential insights into behavioural changes, stress manifestations, and early signs of distress that may correspond with environmental fluctuations. Integrating these datasets requires harmonised data standards, interoperable platforms, and governance frameworks capable of protecting youth privacy while enabling multi-directional data flow [15].

Urban-planning stakeholders further contribute by providing information on crowding levels, noise exposure, and green-space availability variables that significantly influence adolescent coping capacity [9]. When combined, these multi-sectoral inputs create a surveillance ecosystem capable of detecting environmental precursors of mental-health shifts. Such integration strengthens early-intervention strategies, supports rapid response efforts, and aligns with One Health principles emphasising shared responsibility across human, ecological, and environmental domains [13].

3. Environmental indicators relevant to adolescent mental health

3.1. Climate variables: Heatwaves, temperature variability, humidity, extreme weather

Climate variables are central determinants of adolescent mental-health vulnerability due to their direct and indirect effects on physiological stress, cognitive functioning, and emotional stability. Sudden increases in temperature or prolonged heatwaves have been linked to heightened irritability, reduced concentration, and elevated anxiety, particularly among adolescents already experiencing psychosocial strain [15]. Heat stress can disrupt sleep cycles, intensify dehydration risk, and alter hormonal regulation, all of which influence emotional processing and coping capacity in young people [18].

Temperature variability rather than absolute temperature alone has also emerged as a significant factor influencing mood instability. Rapid fluctuations over short periods challenge thermoregulation and increase physiological stress loads that manifest as restlessness and agitation [16]. High humidity further contributes to discomfort by impairing the body's cooling mechanisms, thereby aggravating fatigue and limiting adolescents' participation in outdoor or school-related activities.

Extreme weather events including flooding, storms, and prolonged drought introduce additional psychological stressors through community disruptions, displacement, and heightened uncertainty about safety and stability [20]. These events often lead to damaged homes, school closures, and restricted mobility, all of which compound emotional distress and amplify underlying vulnerabilities. Understanding these climate variables allows predictive systems to capture a fuller spectrum of climate-driven mental-health triggers among adolescents.

3.2. Air-quality indicators: PM2.5, ozone, soot, allergens, wildfire smoke

Air-quality indicators play a crucial role in modelling environmental determinants of adolescent mental-health outcomes. Fine particulate matter such as PM2.5 can penetrate deeply into the respiratory system, triggering inflammatory responses that have been associated with mood disturbances, cognitive strain, and behavioural challenges among young populations [14]. Ozone exposure, particularly in high-traffic urban corridors, contributes to respiratory irritation and oxidative stress that elevate fatigue and stress sensitivity in adolescents [19].

Soot and black carbon, often produced through diesel combustion and informal waste burning, pose additional risks by increasing airway inflammation and reducing overall physical comfort, which can indirectly exacerbate emotional instability. Airborne allergens including pollen and mould intensify seasonal stress by impairing sleep and elevating physiological discomfort, both linked to heightened emotional reactivity [17].

Wildfire smoke, even when transported across long distances, contributes to atmospheric haze and the presence of harmful chemical compounds that impair respiratory health and increase reports of anxiety and restlessness among adolescents exposed during critical developmental stages [21]. By tracking these air-quality indicators, predictive health models can more accurately identify environmental peaks associated with increased mental-health vulnerability.

3.3. Ecological and zoonotic indicators (vector shifts, microbial contamination)

Ecological and zoonotic indicators reflect broader ecosystem changes that indirectly shape adolescent mental-health risks. Shifts in vector populations such as mosquitoes and ticks signal climatic alterations that contribute to heightened community anxiety, especially where disease outbreaks or pest infestations coincide with inadequate public-health infrastructure [22]. Microbial contamination of water sources due to rising temperatures or runoff from extreme rainfall events increases household stress as families struggle to secure safe resources [18]. These ecological disruptions interact with psychosocial dynamics, reducing adolescents' sense of environmental safety and stability [14].

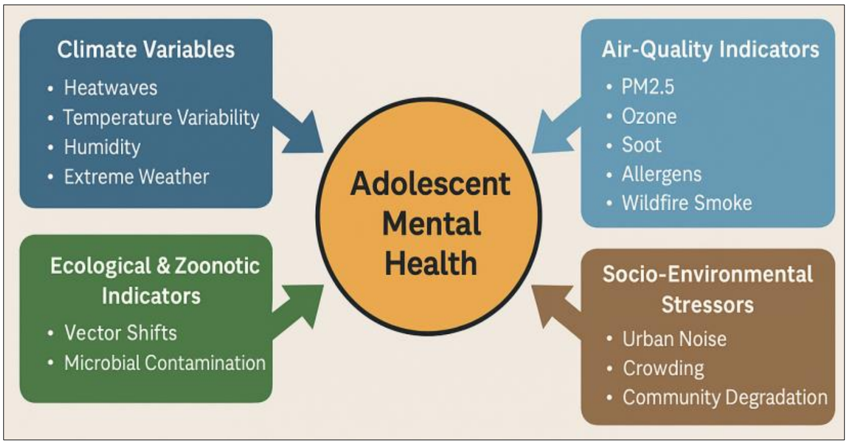

Figure 1 Interconnected pathways linking ecological risks to youth mental-health outcomes

Such indicators also form part of the integrated environmental profiles illustrated in *Figure 1*, which map interconnected pathways linking ecological risks to youth mental-health outcomes. Incorporating ecological signals into predictive frameworks enables earlier recognition of cascading stressors within One Health systems.

3.4. Socio-environmental stressors (urban noise, crowding, community degradation)

Socio-environmental stressors interact with climatic, air-quality, and ecological variables to magnify mental-health risks among adolescents. Urban noise from traffic, construction, and dense neighbourhood activity disrupts sleep, elevates physiological arousal, and reduces adolescents' capacity for emotional regulation [16]. Chronic exposure to high-noise environments has been associated with concentration challenges, irritability, and aggressive behavioural responses that reflect sustained stress activation [20].

Crowding in households, schools, and public spaces further increases tension by reducing privacy, limiting personal agency, and intensifying conflict cycles conditions that can heighten anxiety and depressive symptoms. Community degradation, including the presence of litter, decaying infrastructure, or poorly maintained recreational spaces, erodes adolescents' sense of belonging and safety, contributing to social withdrawal and reduced coping resilience [19].

When combined with climatic and ecological disruptions, these socio-environmental stressors form layered exposure pathways a pattern emphasised in One Health surveillance models [21]. Their cumulative effects underscore the importance of integrated environmental indicators for adolescent mental-health risk assessment.

4. AI-driven surveillance frameworks

4.1. Machine learning models for environment–behaviour prediction

Machine learning models provide a foundational layer for understanding how environmental exposures influence adolescent behaviour by learning patterns that traditional surveillance systems often overlook. These models can analyse relationships between climatic conditions, pollution levels, ecological stressors, and behavioural outcomes captured through surveys or digital interactions, offering nuanced predictions about risk trajectories [22]. Techniques such as random forests and gradient boosting machines are widely used in environmental–health modelling because of their ability to accommodate noisy data and capture nonlinear interactions among environmental variables that affect emotional stability and stress regulation in adolescents [24].

Support vector machines have shown strong performance in identifying behavioural deviations associated with heat exposure, sleep disruption, and air-quality deterioration, which are key indicators of psychological strain among young populations [27]. Integrating environmental datasets such as temperature fluctuations, humidity changes, and particulate concentration allows machine learning systems to build predictive profiles that identify which adolescents may experience heightened vulnerability under specific environmental conditions [20].

Ensemble learning methods further enhance prediction accuracy by combining outputs from multiple algorithms, reducing uncertainty and strengthening generalisability across diverse settings. This approach is especially important when modelling adolescents' responses to rapidly changing climatic patterns, or to pollution events that evolve over hours or days [28]. As data availability expands, these models support adaptive environmental–behaviour forecasting systems capable of informing targeted interventions.

4.2. Deep learning for multimodal environmental data fusion

Deep learning offers advanced capabilities for modelling complex environmental inputs by integrating multimodal data streams including climate signals, pollution measurements, ecosystem indicators, and socio-environmental metrics into unified predictive architectures. Convolutional neural networks (CNNs) have been applied to spatial datasets such as satellite-derived pollution maps and urban heat-island imagery, enabling more granular identification of environmental stress clusters that may influence adolescent mental health [25]. Recurrent neural networks (RNNs), particularly long short-term memory (LSTM) models, are effective for learning temporal dependencies across environmental fluctuations and behavioural shifts, capturing how gradual or sudden changes in heat, air quality, and ecological disturbances correlate with emotional distress [29].

The ability to fuse diverse datasets enables deep learning systems to model intricate relationships that might be missed by conventional approaches [23]. These architectures allow simultaneous processing of spatial–temporal data, population demographics, mobility patterns, and digital behavioural markers, producing more comprehensive environmental–risk maps for adolescent populations. By scaling across regions with varying ecological and climatic profiles, deep learning supports broader and more precise environmental mental-health forecasting.

4.3. Natural language processing for digital behavioural signals

Natural language processing (NLP) provides a novel avenue for detecting subtle mental-health cues embedded within adolescents' digital communication patterns. Text-based signals from online discussions, diary entries, or school counselling logs can reveal shifts in emotional tone, engagement patterns, or stress-laden vocabulary that correlate with environmental exposures such as heatwaves, pollution spikes, or community disruptions [26]. Sentiment analysis and topic modelling enable the automatic detection of emerging concerns, capturing fluctuations that mirror environmental stressors without relying on direct clinical reporting [20].

NLP tools can also identify context-specific expressions linked to anxiety, irritability, or withdrawal symptoms that may intensify when adolescents experience cumulative environmental burdens. By cross-referencing these behavioural signals with climate and pollution datasets, predictive systems can generate early indicators of population-level vulnerability [29]. This integration enhances the responsiveness of One Health surveillance by linking digital expressions to ecological stress patterns.

4.4. Real-time anomaly detection for early warning

Real-time anomaly detection systems allow One Health surveillance platforms to identify abrupt or unusual shifts in adolescent well-being patterns associated with environmental disruptions. Algorithms such as isolation forests and dynamic thresholding models monitor continuous data streams including temperature anomalies, pollution surges, mobility patterns, and school attendance flagging deviations that warrant immediate assessment [23].

When integrated with behavioural or psychosocial indicators, anomaly detection tools can provide early warnings of rising mental-health strain linked to heatwaves, air-quality deterioration, or ecological disturbances [21]. These systems operate by continuously learning baseline conditions and identifying outlier events that diverge from typical seasonal or community trends, enabling rapid, targeted responses.

Early-warning capabilities strengthen the predictive usefulness of environmental monitoring by offering real-time visibility into the interactions between ecosystem stressors and adolescent behavioural responses [27]. This helps public-health actors mobilise timely interventions during periods of heightened risk.

4.5. Ethical AI, privacy protection, adolescent safety protocols

The integration of AI into adolescent mental-health surveillance intensifies the need for robust ethical safeguards, particularly concerning data privacy, algorithmic fairness, and youth protection. Adolescents generate diverse digital footprints from online communication to biometric data that require strong governance frameworks to prevent misuse and ensure ethical compliance across sectors [24]. Clear guidelines for data minimisation, anonymisation, and secure storage are critical for maintaining trust and protecting adolescents' rights, especially when combining environmental, behavioural, and ecological indicators into unified predictive systems [28].

Algorithmic equity is also paramount because disparities in environmental exposure disproportionately affect marginalised communities. Without deliberate bias-mitigation strategies, predictive AI models may amplify systemic inequities by misclassifying risk levels or overlooking vulnerable subpopulations [20]. Techniques such as fairness auditing, cross-regional validation, and transparency reporting help ensure that adolescent mental-health predictions are both accurate and equitable [26].

Safety protocols must further consider adolescents' developmental stage, ensuring that AI-supported interventions are guided by trauma-informed approaches and grounded in multidisciplinary oversight [29]. By embedding ethical principles into design and implementation, One Health AI systems can balance predictive capability with responsibility, protection, and social accountability.

5. Data sources and integration pipelines

5.1. Environmental data ingestion (satellite, IoT sensors, air-quality stations)

Environmental data ingestion forms the backbone of AI-enabled predictive systems that seek to understand how shifting climatic and pollution patterns influence adolescent mental health. Satellite observations offer geographically expansive, high-resolution insights into changing surface temperatures, particulate concentrations, and land-use modifications, enabling surveillance systems to detect environmental anomalies that may correlate with stress or behavioural disruptions among young populations [28]. Complementing these remote datasets are IoT sensor networks, which provide hyperlocal monitoring of neighbourhood-level temperature variability, humidity fluctuations, and pollution spikes, capturing micro-exposures that satellite systems may overlook [27].

Air-quality monitoring stations add further precision by generating continuous data streams for pollutants such as PM2.5, ozone, and sulphur dioxide, indicators known to exacerbate psychological and physiological stress responses [30]. When ingested together, these environmental data sources allow AI systems to construct dynamic exposure profiles that reflect the immediate and cumulative pressures adolescents experience in rapidly changing environments. The integration of multi-source environmental inputs supports the development of timely predictions and allows surveillance models to capture daily, seasonal, and episodic patterns that influence mental health outcomes [33]. Such comprehensive environmental mapping strengthens early-warning capabilities and improves risk-stratification accuracy for youth-focused health interventions.

5.2. Health and psychosocial datasets (school screenings, clinic records, surveys)

Health and psychosocial datasets provide essential insights into how environmental exposures translate into emotional, cognitive, and behavioural outcomes. School mental-health screenings, conducted through behavioural checklists or structured assessments, offer population-level indicators of stress, anxiety, and academic functioning within adolescent groups [29]. These datasets frequently reveal early deviations in mood, concentration, or attendance that may reflect underlying exposure-related pressures.

Clinic records, including visits for sleep disturbances, respiratory symptoms, or psychosomatic complaints, provide clinically validated outcomes that can be correlated with environmental stressors [31]. Surveys administered within schools or youth programmes add subjective perspectives, capturing self-reported anxiety, social withdrawal, and environmental discomfort across different contexts [34]. Together, these datasets support AI-driven models that track emerging behavioural trends and facilitate more responsive mental-health monitoring tailored to adolescents lived environments.

5.3. Ecological and One Health surveillance inputs (vector ecology, zoonotic mapping)

One Health surveillance inputs broaden mental-health prediction models by incorporating ecological variables that interact with climate and pollution to shape adolescent well-being. Vector ecology datasets such as mosquito abundance, breeding-site density, or pathogen circulation provide indicators of environmental instability that may heighten community anxiety or influence behavioural patterns during outbreak-prone periods [28]. Zoonotic mapping systems track animal-human interface risks, wildlife movement, and microbial contamination in air, soil, or water, offering early signals of ecosystem stress that can indirectly affect social and psychological environments [32].

These ecological datasets allow models to capture how multi-species interactions reflect broader environmental disturbances. When combined with environmental and psychosocial inputs, One Health ecological datasets improve the robustness of risk-prediction frameworks and support integrated environmental mental-health forecasting. As shown in Table 1, these inputs form one of the three primary pillars of AI-enabled data sources.

Table 1 Primary Environmental, Pollutant, and Psychosocial Data Sources for AI-Enabled One Health Modelling

Category	Data Source	Description / Examples	Relevance to Adolescent Mental Health Modelling
Environmental Data	Satellite Observations	NASA MODIS, ESA Sentinel, land surface temperature, vegetation index, humidity	Identifies climate stressors (heatwaves, temperature anomalies) influencing emotional regulation and cognitive strain.
	Meteorological Stations	National climate networks, local weather bureaus	Provides real-time readings on temperature, rainfall, wind, and extreme weather conditions affecting stress responses.
	IoT-Based Environment Sensors	Urban sensors for noise, temperature, particulate levels	Captures micro-environmental exposures especially relevant in dense city neighbourhoods.
Pollution Data	Air-Quality Monitoring Systems	PM2.5, PM10, ozone, nitrogen dioxide, sulfur dioxide	Tracks key pollutants linked to anxiety, sleep disruption, and inflammation-related neurological impacts.
	Industrial Emission Databases	Factory outputs, hydrocarbon emissions, chemical discharge logs	Identifies exposure hotspots in industrial corridors impacting adolescent mental health risks.
	Vehicular Pollution Monitoring	Traffic density sensors, roadside air monitors	Supports urban exposure modelling where motor emissions elevate stress and respiratory–neurological pathways.
Psychosocial and Health Data	School Mental Health Screenings	Behavioural surveys, self-report tools, counsellor assessments	Provides early behavioural indicators interacting with environmental exposures.
	Wearable and Mobile Health Data	Heart-rate variability, sleep patterns, physical activity	Allows continuous monitoring of physiological stress responses under environmental fluctuations.
	Community and Household Surveys	Stress, safety, crowding, noise, social cohesion	Captures social-ecological modifiers mediating environmental–mental health interactions.

5.4. Harmonisation, cleaning, and multimodal data fusion techniques

Effective mental-health prediction depends on the ability to harmonise heterogeneous datasets that differ in scale, resolution, and temporal frequency. This process begins with rigorous data cleaning, including removal of sensor artefacts, correction of satellite noise, and verification of school or clinic records for completeness and consistency [27]. Standardisation techniques ensure that climate, pollution, ecological, and psychosocial datasets share compatible formats, allowing seamless integration within AI systems [30].

Multimodal fusion frameworks utilise strategies such as hierarchical modelling, feature-level merging, and late-fusion neural architectures to combine disparate data types into coherent analytical pipelines [33]. These approaches allow simultaneous processing of environmental exposures, behavioural indicators, and ecological factors, producing richer representations of adolescent vulnerability patterns [31]. By aligning data streams across domains, harmonisation and fusion techniques enhance the precision, stability, and interpretability of AI-driven One Health surveillance systems [34], enabling integrated insights that support early detection and targeted intervention planning.

6. AI modelling approaches and predictive workflows

6.1. Feature engineering: Environmental–behavioural interaction terms

Feature engineering plays a critical role in transforming raw environmental and psychosocial inputs into meaningful predictors capable of capturing adolescent mental-health vulnerabilities. By creating interaction terms that link behavioural indicators with climate or pollution exposures, AI models can detect subtle patterns invisible to single-variable approaches [31]. For instance, combining daily PM2.5 concentrations with self-reported sleep difficulties reveals compounded stress signatures that often precede episodes of anxiety or mood instability. Similar interaction terms connecting heat variability with school attendance fluctuations offer insights into how environmental discomfort shapes functional behaviour among young people [35].

Temporal lag features also strengthen predictive depth by modelling delayed effects of extreme weather or pollution spikes on emotional reactivity, academic engagement, or clinic presentations [33]. Such engineered features ensure that models capture both immediate and cumulative pressures affecting adolescent well-being. When constructed systematically, these enriched variables provide the foundation for high-resolution environmental–behavioural forecasting models [38].

6.2. Multimodal model architecture

Multimodal AI architectures integrate diverse inputs including climate metrics, air-quality indices, ecological indicators, and psychosocial signals to generate comprehensive adolescent risk profiles. These architectures typically involve parallel processing streams, where environmental and behavioural data are encoded separately before being fused at intermediate or final layers [32]. Convolutional networks are well suited for spatial maps such as temperature grids or pollution rasters, while recurrent networks process longitudinal behavioural sequences captured through school or health-system data [36].

Hybrid models further enhance predictive performance by allowing different modalities to influence shared representations without overshadowing each other. Attention mechanisms, in particular, increase interpretability by highlighting which environmental factors exert the strongest influence on behavioural patterns at specific points in time [34]. This design helps reveal whether, for example, ozone surges or prolonged humidity swings are more strongly associated with short-term emotional instability. Multimodal model structures therefore allow for nuanced integration of diverse One Health datasets [37].

6.3. Temporal forecasting models for emerging adolescent mental health risks

Temporal forecasting models enable early detection of emerging mental-health risks by analysing how environmental and behavioural trends evolve over days, weeks, or seasons. Recurrent neural networks, including LSTM and GRU frameworks, are particularly effective at modelling sequences where past exposures influence future psychological responses [33]. These models capture lagged effects, such as delayed anxiety symptoms following heatwaves or extended irritability after pollution spikes, offering valuable insights into vulnerability escalation among adolescents [36].

Probabilistic forecasting approaches enhance predictive confidence by generating uncertainty intervals around risk estimates, allowing public-health teams to prioritise high-likelihood events while monitoring less certain patterns [31]. When these temporal models incorporate multimodal inputs from climate metrics to behavioural patterns they provide dynamic forecasts that reflect real-world adolescent experiences. As illustrated in Figure 2, such models serve as a critical stage within the broader workflow of AI-driven predictive modelling for youth mental-health risk detection [38]. These forecasting tools enable timely, context-sensitive interventions.

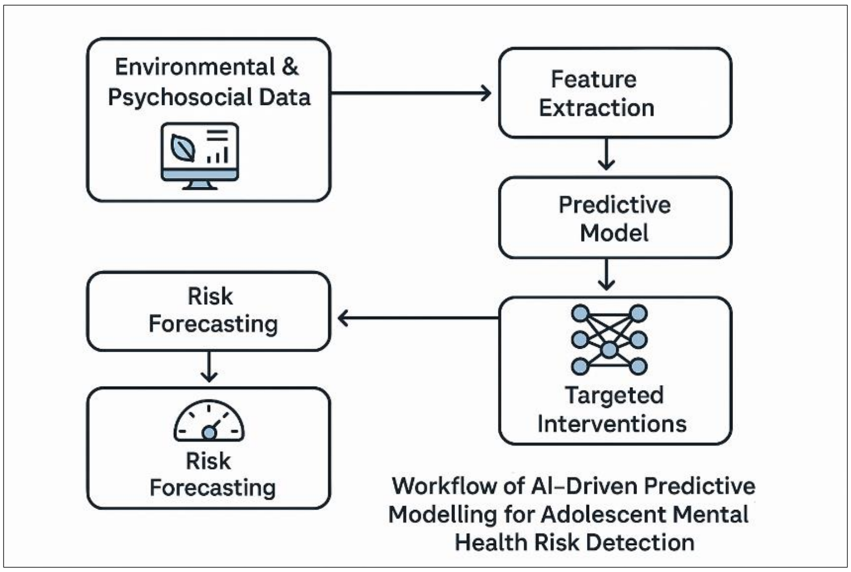

Figure 2 Workflow of AI-driven predictive modelling for youth mental-health risk detection

6.4. Model evaluation metrics, interpretability, and bias mitigation

Rigorous evaluation is essential to ensure that AI models function reliably across diverse adolescent populations and environmental settings. Metrics such as precision, recall, area-under-curve scores, and calibration measures help determine whether models accurately identify high-risk individuals without producing excessive false-positives [34]. Interpretability frameworks including feature-attribution methods and temporal saliency mapping support transparent decision-making by clarifying how specific environmental factors contribute to predicted outcomes [35].

Bias mitigation represents a key priority, particularly when environmental burdens or data availability differ across urban, rural, or socioeconomically marginalised regions [32]. Techniques such as re-sampling, fairness-constrained optimisation, and domain adaptation help ensure that predictive performance remains stable across demographic groups [37]. External validation across multiple climatic and social contexts further strengthens generalisability and protects against model drift over time [31]. Through these combined strategies, evaluation and fairness controls uphold the scientific integrity and ethical responsibility essential for youth-focused predictive systems [38].

7. Case study scenarios and hypothetical deployments

7.1. Urban Nigeria: Air pollution spikes predicting anxiety fluctuations

In densely populated Nigerian cities, where transportation density, informal industrial clusters, and inconsistent regulatory enforcement intersect, AI-enabled exposure models reveal strong links between pollution surges and fluctuations in adolescent anxiety symptoms. Daily variations in particulate matter, especially PM2.5 and soot from high-traffic corridors, often coincide with spikes in physiological arousal, irritability, and short-term concentration difficulties among young people [39]. By integrating continuous air-quality sensor outputs with school-based behavioural logs, machine-learning systems can map how exposure loads accumulate across hours or days before emotional dysregulation emerges [36].

Temporal patterns are particularly revealing, with evening pollution peaks aligning with disrupted sleep patterns, which then heighten vulnerability the following morning [41]. Neural networks trained on pollution intensity and behavioural-survey data can detect these micro-shifts long before they manifest as severe episodes requiring specialist attention. The ability to forecast emotional volatility tied to environmental burdens enables urban public-health units to deploy early, preventive communication to schools and families [40]. When applied across cities like Lagos or Port Harcourt, such systems help clarify how infrastructural and atmospheric stressors gradually shape adolescent psychological well-being [38].

7.2. Coastal regions: Heat and humidity as predictors of sleep and behavioural dysregulation

Coastal Nigerian environments present a different exposure landscape, dominated by persistent heat, fluctuating humidity, and sporadic extreme-weather conditions. AI models combining microclimate data with adolescent behavioural indicators show that prolonged humidity and elevated nighttime temperatures often correspond with reduced sleep quality, heightened restlessness, and diminished daily functioning [36]. These patterns emerge gradually, shaped by the discomfort associated with warm indoor environments that limit restorative sleep cycles.

Machine-learning algorithms that integrate thermal indices, rainfall variability, and household ventilation characteristics can detect how cumulative heat stress contributes to irritability, mood instability, and concentration difficulties among adolescents over time [42]. Humidity-driven discomfort also amplifies social stressors, such as interpersonal conflict at home or school, which further compounds behavioural concern patterns identified by counsellors [38].

The strength of these models lies in their ability to reveal interactions between environmental strain and psychological adaptation. For instance, sequences of high-humidity nights are consistently associated with fatigue-induced behavioural lapses, making them critical predictors in coastal risk models [41]. These AI-driven insights provide coastal health authorities with actionable intelligence for timing community awareness campaigns or coordinating heat-stress mitigation programs tailored for adolescents [37].

7.3. School-based surveillance dashboards for counsellors and administrators

Schools represent one of the most effective entry points for adolescent mental-health surveillance, particularly when AI-driven dashboards synthesise environmental and behavioural streams into actionable insights. These systems convert raw climate variables, pollution trends, and psychosocial indicators into simple, interpretable risk categories for use by counsellors, psychologists, and administrators [40]. Early-warning flags generated by anomaly-detection models help school teams identify students who may be vulnerable during periods of high environmental stress, such as pollution surges or heatwaves [36].

Dashboards also support longitudinal monitoring, displaying weekly trends in absenteeism, emotional complaints, classroom disengagement, or sleep-related fatigue, enabling informed decision-making that is grounded in objective environmental context [39]. Importantly, these school-level systems can incorporate scenario-based model outputs summarised in Table 2: "Scenario-Based Outputs of AI Models and Associated Risk Interpretation for Adolescents"to help staff interpret predictive alerts and tailor responses accordingly [42].

By integrating multimodal data streams, school dashboards reduce guesswork and offer a structured tool for triage, referral, and support-planning [41]. They also encourage collaboration between educators, health workers, and parents, strengthening the broader One Health surveillance network. When combined with community outreach, these AI-supported platforms enhance resilience and promote early interventions that align with local needs [38].

Table 2 Scenario-Based Outputs of AI Models and Associated Risk Interpretation for Adolescents

Scenario Type	Model Output	Environmental Trigger	Predicted Adolescent Mental Health Response	Recommended School or Counsellor Action
High Air-Pollution Day	Alert level ↑ (PM2.5 spike)	Traffic congestion, industrial emissions	Increased anxiety symptoms, reduced attention span, irritability	Provide indoor activities, activate air purifiers, monitor vulnerable students, brief counsellors.
Heatwave Stress Scenario	Heat-risk score ↑	Consecutive high-temperature days, poor ventilation	Sleep disruption, fatigue, emotional dysregulation	Implement hydration breaks, adjust outdoor schedules, flag high-risk students for check-ins.
Noise and Urban Crowding Surge	Noise-exposure index ↑	Markets, traffic peaks, school construction	Heightened stress, difficulty concentrating	Offer quiet rooms, stagger breaks, provide teacher guidance on classroom calming strategies.
Allergen or Smoke Exposure	Allergen/smoke index ↑	Wildfire smoke, dry-season dust, pollen bursts	Breathing difficulty, agitation, reduced cognitive stability	Limit outdoor exposure, inform parents, increase monitoring for students with asthma or anxiety.
Combined Heat + Pollution Event	Dual-exposure composite score ↑↑	Heatwave coinciding with PM2.5 elevation	Elevated risk of emotional outbursts, panic-like symptoms	Activate high-priority alerts, conduct short screening sessions, increase counsellor availability.
Community Safety or Environmental Shock	Sudden-risk anomaly flag	Flooding, storms, local hazards	Acute stress response, withdrawal, fear-based behaviours	Provide psychoeducation briefings, increase peer-support activities, arrange emergency counselling.

8. System architecture for national and regional one health surveillance

8.1. Technical infrastructure for scalable surveillance

Building a scalable national surveillance ecosystem for adolescent mental health requires a resilient technical foundation capable of integrating diverse environmental and behavioural data streams. Core infrastructure components include distributed sensor networks, interoperable data hubs, and secure transmission protocols that allow real-time ingestion of climate, pollution, and psychosocial variables [39]. For surveillance to operate efficiently, edge devices such as low-cost IoT air-quality monitors or microclimate loggers must synchronise continuously with central analytics servers while maintaining data reliability under varying field conditions [42].

Computational scalability is achieved through modular architectures that allow incremental expansion of storage, processing power, and the number of participating institutions [38]. Built-in redundancy ensures uninterrupted operations even when local networks fail or environmental disruptions occur. Equally important is secure user authentication, enabling authorised access by health, education, and environment agencies while reducing risks of data misuse [45]. Together, these components establish a stable foundation for advanced AI-driven analytics.

8.2. Cloud-based data pipelines and geographic information systems

Cloud-based data pipelines serve as the backbone for processing and analysing the multimodal datasets required for One Health surveillance. Elastic cloud environments allow large volumes of satellite imagery, IoT sensor outputs, and school-level behavioural data to be ingested, harmonised, and stored with flexible computational scaling [44]. Automated extract–transform–load workflows enable continuous cleaning, validation, and standardisation of incoming records, improving the accuracy of downstream predictive models [38].

Geographic Information Systems (GIS) add vital spatial context, mapping exposure hotspots such as industrial zones, traffic corridors, or flood-prone settlements that correlate with adolescent mental-health risk signals [43]. When integrated with cloud-based dashboards, GIS layers provide policy-makers with visual insights into regional disparities, helping them prioritise interventions. Spatial overlays also support micro-targeting of awareness campaigns and resource allocation, making it easier to align public-health actions with environmental dynamics [41]. Such cloud-GIS synergy strengthens nationwide resilience and planning capacity [46].

8.3. Inter-agency coordination (health, environment, education ministries)

For national-scale surveillance to function effectively, coordination across governmental sectors is essential. Health ministry's offer clinical oversight and mental-health expertise, environment agencies contribute pollution and climate monitoring, while education ministries provide access to school-based behavioural indicators [40]. Joint data-sharing agreements enable these institutions to exchange real-time insights without compromising privacy or institutional boundaries [44].

Inter-agency task forces also help harmonise reporting formats, ensuring consistent interpretation of exposure alerts and vulnerability classifications across regions [38]. Regular coordination meetings permit early identification of emerging risks, facilitating rapid deployment of protective actions such as heat-response plans or school-level counselling reinforcement [46]. Additionally, integrated workflow systems allow agencies to co-manage surveillance dashboards, ensuring that predictive warnings are acted upon promptly. The collaborative framework is visually represented in Figure 3: "National AI-Enabled One Health Surveillance Architecture for Adolescent Mental Health," which illustrates how sectoral responsibilities converge into a unified operational pipeline [42].

Such structured coordination enhances national preparedness and ensures that environmental and psychological risks are addressed comprehensively and proactively [45].

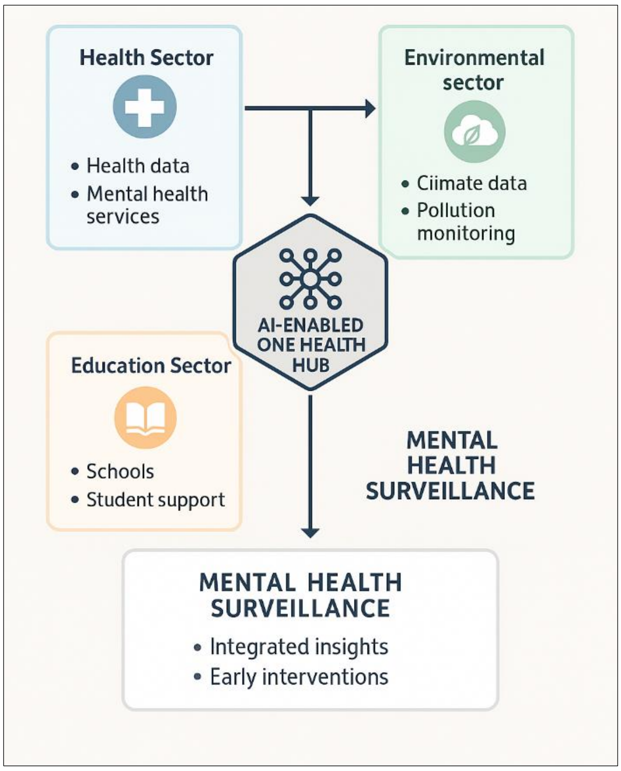

Figure 3 National AI-Enabled One Health Surveillance Architecture for Adolescent Mental Health

9. Policy implications and governance considerations

9.1. Regulatory frameworks for AI in adolescent mental health

Developing regulatory structures for AI-enabled adolescent mental health surveillance requires a balanced approach that protects young people while ensuring innovation is not stifled. Policymakers must define clear standards governing data collection, algorithmic fairness, and acceptable uses of predictive insights, especially when models intersect with school or clinical settings [44]. Because adolescents represent a sensitive population, oversight bodies must ensure that AI systems avoid harmful profiling, undue labelling, or biased decision-making, concerns that have been raised in early AI ethics debates [47].

Regulators should also mandate transparency requirements, including documentation of model assumptions, data sources, and uncertainty margins, enabling clinicians and educators to interpret predictions responsibly [43]. Cross-sector review committees comprising mental-health specialists, environmental scientists, child advocates, and data-governance experts can help evaluate emerging tools before deployment [48]. Such frameworks strengthen accountability and ensure that AI applications enhance well-being rather than introduce new forms of vulnerability within youth-focused systems.

9.2. Data governance, cybersecurity, and ethical safeguards

Robust data-governance protocols are essential when handling combined environmental, psychosocial, and behavioural datasets from adolescents. Effective governance requires controlled-access data environments, multi-layer encryption, and rigorous authentication procedures that reduce risks of unauthorised access or tampering [49]. Ethical safeguards must ensure minimal data collection, avoidance of sensitive identifiers, and strict separation of environmental metrics from personally revealing behavioural indicators [45]. Cybersecurity protocols should anticipate evolving threats by integrating continuous monitoring and rapid-response mechanisms [50]. Governance systems must also enable community oversight so that young people, caregivers, and educators remain informed participants in the surveillance ecosystem [46].

9.3. Aligning One Health policy with mental health strategies

Integrating One Health principles into national mental-health policy allows governments to address environmental and psychosocial vulnerabilities through unified planning mechanisms. Environmental ministries can contribute climate and pollution surveillance, while health agencies deploy preventive mental-health interventions informed by emerging risk patterns [43]. Education sectors support school-based monitoring, ensuring early detection of stress-related behavioural changes [47]. Policy harmonisation also reduces fragmentation by establishing joint action plans, shared resource frameworks, and coordinated implementation pathways [48]. Alignment with One Health ensures that adolescent mental-health strategies reflect ecological realities, enabling proactive responses to climate and pollution exposures that disproportionately affect young populations [50].

10. Challenges, risks, and limitations

10.1. Environmental data gaps and modelling uncertainty

Significant limitations persist in environmental datasets required for adolescent mental-health modelling, leading to uncertainty in exposure–response estimation. Many regions lack continuous monitoring for fine particulate matter, temperature anomalies, and ecological stressors, resulting in inconsistent temporal coverage [41]. Fragmented data across environmental agencies further complicates harmonisation efforts, especially when integrating climate indicators with school-level mental-health observations [44]. These gaps restrict the precision of AI models, which depend on stable longitudinal inputs to generate early-warning predictions [40]. Limited validation datasets also constrain efforts to quantify uncertainty, leaving models vulnerable to misclassification or overstating localised environmental risks [47].

10.2. Algorithmic bias and cross-population disparities

AI-enabled surveillance systems risk perpetuating inequities when underlying datasets lack representation across geographic, socioeconomic, and cultural subgroups. Bias emerges when models trained on urban or better-resourced populations are deployed in rural or marginalised communities, producing skewed vulnerability estimates [49]. Variation in environmental exposures such as differential pollution loads or local climate stressors further amplifies disparities when algorithms fail to incorporate local context [42]. Without continual retraining and fairness auditing, models may misinterpret behavioural signals or overestimate risk in particular demographic clusters [46]. These issues underscore the need for robust cross-cultural validation and policy mechanisms that ensure equitable adolescent mental-health prediction [50].

10.3. Infrastructure, funding, and capacity limitations

Implementing national AI-driven One Health surveillance requires infrastructure that many regions still lack, including reliable air-quality systems, resilient data pipelines, and scalable storage architectures [45]. Financial constraints limit the deployment of advanced environmental sensors, especially in rapidly growing urban centres where adolescent exposure risks fluctuate considerably [43]. Capacity gaps also persist, as schools and local health institutions may not have personnel trained to interpret AI outputs or maintain integrated monitoring platforms [48]. Without sustained funding commitments and coordinated investment in technical expertise, large-scale predictive systems remain difficult to operationalise, hindering timely responses to emerging mental-health vulnerabilities [40].

11. Future directions for research and innovation

11.1. Environmental data gaps and modelling uncertainty

Significant limitations persist in environmental datasets required for adolescent mental-health modelling, leading to uncertainty in exposure–response estimation. Many regions lack continuous monitoring for fine particulate matter, temperature anomalies, and ecological stressors, resulting in inconsistent temporal coverage [41]. Fragmented data across environmental agencies further complicates harmonisation efforts, especially when integrating climate indicators with school-level mental-health observations [44]. These gaps restrict the precision of AI models, which depend on stable longitudinal inputs to generate early-warning predictions [40]. Limited validation datasets also constrain efforts to quantify uncertainty, leaving models vulnerable to misclassification or overstating localised environmental risks [47].

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12. Conclusion

The integration of artificial intelligence and One Health frameworks offers a powerful pathway for transforming how societies understand, anticipate, and respond to adolescent mental health risks shaped by dynamic environmental conditions. As climate variability intensifies and pollution-related pressures grow, the ability to predict psychological vulnerability before crises emerge becomes increasingly essential. AI provides the computational strength to detect patterns that traditional surveillance systems cannot, drawing from complex interactions across climate signals, air-quality fluctuations, ecological changes, and behavioural indicators. By combining these analytical capabilities with One Health's holistic lens linking environmental, human, and ecological well-being stakeholders gain a more complete view of the multiple, interdependent forces influencing adolescent mental resilience.

Within this unified approach, early detection shifts from a reactive practice to a proactive public-health strategy. AI-driven classification, forecasting, and anomaly-detection tools can identify subtle shifts in environmental exposures or behavioural patterns that precede mental health deterioration. When integrated with school systems, community health programs, and environmental monitoring infrastructures, these tools support timely interventions that reduce the likelihood of long-term psychological harm. Furthermore, the One Health perspective ensures that mental health surveillance does not exist in isolation but is embedded within broader environmental and social systems that shape adolescent development.

Looking ahead, the synergy between AI and One Health can strengthen long-term resilience in climate-affected regions by informing targeted policies, adaptive educational support systems, and community-level preparedness strategies. As environmental conditions become more unpredictable, models that continuously learn from real-time data will help governments and institutions prioritise resources, anticipate emerging threats, and mitigate disparities. Ultimately, advancing AI-enhanced One Health systems empowers societies to safeguard the mental well-being of adolescents one of the most vulnerable groups facing the challenges of a rapidly evolving environmental landscape.

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