Advancing AI-Enhanced Environmental Health Models to Predict Climate- and Pollution-Driven Mental Health Vulnerabilities Among Adolescents within One Health Systems

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Abstract: The accelerating convergence of climate change, environmental degradation, and rising pollution levels presents profound implications for adolescent mental health, particularly within rapidly urbanizing and resource-strained regions. Traditional public health frameworks often assess these risks in isolation, overlooking the interconnected ecological, human, and animal health dimensions emphasized by the One Health approach. At the same time, advances in artificial intelligence (AI) including multimodal sensing, deep learning, and predictive environmental analytics now offer unprecedented opportunities to identify, model, and mitigate climate- and pollution-related mental health vulnerabilities among adolescents. This study presents a forward-looking synthesis of AI-enhanced environmental health modeling, highlighting how integrated systems can detect early psychosocial stressors linked to temperature extremes, poor air quality, toxic exposures, and disrupted ecological conditions. The paper outlines how machine learning models can incorporate satellite data, environmental sensor streams, electronic health records, and behavioural indicators to generate risk predictions with high spatial and temporal resolution. It also explores how these models can map environmental injustice patterns, revealing how marginalized adolescent populations experience disproportionate exposure to environmental harms and associated mental health burdens. As the focus narrows, the analysis demonstrates how hybrid One Health–AI architectures can enable early-warning systems that identify adolescents at elevated risk of anxiety, depression, emotional dysregulation, and cognitive impairment triggered or intensified by climate-induced stressors. The article further discusses ethical considerations, including data privacy, transparency, algorithmic bias, and the need for culturally competent implementation within schools, community health structures, and digital mental health platforms. Ultimately, this work argues that AI-augmented One Health models represent a transformative pathway for safeguarding adolescent mental well-being amid escalating climate volatility and environmental pollution. Strengthening these systems will be essential for building resilient public health responses capable of protecting the next generation in an era of accelerating ecological change.

Keywords: Artificial intelligence; One Health; Adolescent mental health; Environmental pollution; Climate vulnerability; Predictive modeling

1. INTRODUCTION

1.1 Escalating climate and pollution exposures affecting adolescent health globally

Across many regions of the world, adolescents are increasingly exposed to a combination of climate variability and deteriorating environmental conditions that heighten their vulnerability to physical and psychological stressors. Rising temperatures, air-quality degradation, and recurring extreme weather events have created ecological pressures that intersect directly with developmental stages in adolescence, a period marked by heightened emotional and neurobiological sensitivity [1]. Communities experiencing rapid urbanisation often present intensified pollution levels, with particulate matter and ozone concentrations linked to sleep disturbances, irritability, and cognitive strain among young people [2].

In several countries, seasonal heatwaves have been associated with spikes in mental distress, behavioural dysregulation, and increased emergency presentations for emotional crises [3]. Adolescents living in low-resource or densely populated environments often bear a disproportionate burden because they have limited access to cooling systems, green

infrastructure, and clean air zones, magnifying their susceptibility to environmental stress exposure [4].

The ecological drivers of adolescent well-being extend beyond air pollution to include water contamination, deforestation, and habitat disruption, each altering daily living conditions in ways that amplify psychosocial strain [5]. Evidence suggests that the cumulative effect of these environmental pressures interacts with social and familial stressors, creating a multi-layered risk environment for developing mental health vulnerabilities. These evolving patterns underscore the need for sophisticated approaches capable of predicting, monitoring, and contextualising environmental risks affecting youth populations [6].

1.2 Mental health as an emerging environmental health frontier

Mental health challenges among adolescents are increasingly recognised as outcomes shaped by a combination of environmental, biological, and social determinants. This recognition has led many public health systems to broaden the definition of environmental health to include psychological well-being influenced by ecological stressors [7]. Heat exposure, pollution-driven inflammation, and chronic noise

have demonstrated links to anxiety, mood instability, and difficulty with emotional regulation during adolescence, a period defined by rapid neurological maturation [8].

Traditional mental health frameworks have often emphasised interpersonal and socioeconomic drivers. However, growing empirical evidence suggests that ecological exposures can serve as early triggers for psychological strain, creating a new frontier that demands interdisciplinary attention [9]. By understanding mental health through this broader environmental lens, health systems can better anticipate risk patterns and design more preventive, youth-centred interventions. Integrating environmental factors into adolescent mental health monitoring therefore represents an essential evolution in global public health thinking [10].

1.3 Why integrate AI and One Health frameworks for adolescent risk prediction

AI offers a powerful foundation for modelling how climate stressors, pollution levels, and ecological disruptions jointly influence adolescent mental health. Unlike traditional analytic methods, AI can integrate heterogeneous datasets, detect early risk patterns, and produce actionable forecasts for prevention. When embedded within a One Health framework, these tools link human, environmental, and ecological indicators into a unified system capable of revealing cross-sectoral interactions. This integration strengthens the ability of policymakers, educators, and clinicians to anticipate emerging vulnerabilities. By combining AI's predictive capacity with One Health's holistic orientation, stakeholders gain a proactive pathway to protect adolescent well-being within rapidly shifting environmental conditions.

2. CONCEPTUAL FRAMEWORK: AI, ONE HEALTH, AND ADOLESCENT MENTAL HEALTH

2.1 The One Health paradigm linking ecosystems, climate, pollution, and human well-being

The One Health paradigm has increasingly been used to explain how human well-being is inseparable from the conditions of surrounding ecosystems, climate patterns, and environmental quality. This integrated perspective emphasises that disturbances in natural systems such as air degradation, rising temperatures, altered rainfall cycles, and biodiversity stress eventually manifest as health challenges affecting entire communities [6]. For adolescents, who rely on stable environmental conditions for healthy cognitive and emotional development, these disruptions introduce heightened vulnerabilities.

Within the One Health framework, climate variability and pollution are understood not as isolated risks but as interconnected drivers of biological and psychosocial change. For example, shifts in vegetation, soil quality, and atmospheric composition affect water safety, food systems, and airborne exposures that influence physiological stress responses in young populations [7]. Urban zones characterised

by heavy traffic emissions often show patterns of behavioural strain among adolescents, illustrating how environmental pressures can cascade into youth mental health outcomes.

The approach also recognises the bidirectional nature of environmental influences. Human activities such as industrial expansion, transportation growth, and poorly regulated waste systems intensify ecological pressures, which in turn contribute to community-level health concerns [8]. Incorporating adolescent mental health into this ecological model allows policymakers to identify how environmental imbalances may trigger emotional dysregulation or behavioural difficulties.

A One Health lens further highlights the importance of cross-sector partnerships involving environmental scientists, clinicians, data analysts, and educators. Such collaboration is essential for detecting early warning signals and shaping preventive strategies that address both ecological and psychological determinants of well-being [9]. By framing adolescent mental health within this interconnected model, public health systems gain a deeper understanding of how environmental degradation and climate instability intersect with youth vulnerability patterns [10].

2.2 Environmental determinants of adolescent mental health (air quality, temperature, toxins)

Environmental exposures have long been recognised as significant contributors to the emotional and cognitive development of adolescents. Poor air quality, particularly elevated concentrations of particulate matter and nitrogen dioxide, has been associated with increased irritability, attention difficulties, and heightened stress reactivity among young people [11]. These pollutants influence inflammatory pathways and oxidative stress, mechanisms linked to mood instability and reduced psychological resilience.

Temperature patterns are another determinant. Periods of prolonged heat can disrupt sleep, impair concentration, and amplify anxiety, especially for adolescents living in densely built environments with limited cooling resources [12]. Rising temperatures also intensify ground-level ozone formation a pollutant known to influence both respiratory health and neurobehavioural functioning in youth.

Exposure to environmental toxins, including heavy metals, pesticides, and industrial residues, compounds these risks by affecting hormonal regulation and neurological development [13]. Communities situated near industrial corridors or major traffic routes often report higher levels of adolescent behavioural complaints and stress symptoms.

Environmental stressors do not operate in isolation; their combined effects may heighten emotional sensitivity and reduce adaptive coping during a critical developmental period [14]. When these exposures overlap with social pressures or limited access to supportive services, adolescents experience amplified mental health risks that require early detection and targeted intervention [15].

2.3 AI as a transformative tool for environmental–mental health modelling

Artificial intelligence offers a powerful set of tools for analysing how environmental conditions shape adolescent mental health outcomes. Traditional statistical models often struggle to process the complex interactions between climate patterns, pollution levels, ecological disturbances, and psychological indicators. AI systems, however, can integrate diverse datasets and detect subtle, nonlinear relationships that would otherwise remain obscured [6].

Machine-learning algorithms can map real-time air quality changes, temperature fluctuations, and toxin distributions while simultaneously evaluating behavioural or emotional indicators from health records, surveys, or digital platforms [8]. By identifying early patterns of vulnerability, AI-driven models support preventive action before mental health challenges escalate among adolescents.

AI also enhances environmental surveillance by predicting high-risk periods linked to pollution surges or heat events, allowing health agencies to prepare targeted outreach strategies [12]. Within a One Health orientation, these models synthesise data from environmental, social, and biological domains, creating a unified picture of risk that reflects real-world complexity [14].

Furthermore, AI tools enable scenario modelling to anticipate how shifting ecological conditions may influence future mental health trends in youth populations [10]. Such predictive capacity equips communities, educators, and health practitioners with evidence-based insights for designing interventions that protect adolescent well-being amidst ongoing environmental change [15].

3. CLIMATE AND POLLUTION EXPOSURES INFLUENCING ADOLESCENT MENTAL HEALTH

3.1 Climate stressors: heatwaves, temperature anomalies, extreme events

Climate-related stressors have increasingly emerged as critical determinants of adolescent mental health, particularly in regions experiencing recurrent heatwaves, seasonal temperature anomalies, and acute climate disturbances. Heatwaves can alter sleep patterns, elevate physiological stress responses, and impair adolescents' ability to regulate emotions effectively, especially in neighbourhoods lacking cooling infrastructure or shaded environments [14]. Temperature anomalies whether unusually warm nights or persistently high daytime temperatures disrupt the stability of daily routines and place additional strain on thermoregulatory systems that are still developing during adolescence [16].

Extreme climate events such as floods, storms, or sudden heat surges amplify these vulnerabilities by triggering displacement, food insecurity, and heightened uncertainty within households [18]. These events can indirectly shape adolescents' psychological states through the stress experienced by parents and caregivers, reducing emotional support at critical developmental moments. Adolescents exposed to repeated climate stress often exhibit heightened irritability, diminished concentration, and increased symptoms associated with anxiety or stress-related behaviours [20].

Importantly, climate stress does not operate in isolation. Its influence interacts with existing socioeconomic pressures, such as inadequate housing and limited access to green space, which intensify emotional strain and reduce coping capacity [22]. Understanding these dynamics is essential for building predictive models that reflect how climate variability shapes long-term mental health vulnerability in youth.

3.2 Pollution stressors: PM2.5, ozone, PM10, industrial pollutants, vehicular emissions

Air pollution remains one of the most consistent environmental determinants of adolescent mental health, with fine particulate matter (PM2.5) being particularly harmful due to its capacity to penetrate deep into the respiratory and circulatory systems [15]. Long-term exposure has been associated with oxidative stress and systemic inflammation, both of which have behavioural and neurodevelopmental implications for adolescents [17]. PM10, though less deeply penetrating, still contributes to respiratory irritation and cognitive fatigue, potentially increasing emotional instability during sensitive developmental periods [19].

Ground-level ozone represents an additional stressor. It is formed through complex photochemical reactions and exacerbated by heat, making adolescents in urban and peri-urban regions especially vulnerable during warmer seasons [21]. Ozone exposure has been linked to altered attention, increased headaches, and reduced overall well-being.

Industrial pollutants including sulfur compounds, volatile organics, and heavy metals pose further risks to adolescents living near manufacturing zones, refineries, or informal waste-burning sites [16]. Vehicular emissions, particularly nitrogen oxides and carbon-rich particulates, disproportionately affect adolescents in congested urban corridors where school commutes and recreational activities occur [14].

These pollution stressors do not merely influence physical health; they intersect with psychosocial experiences, altering mood stability and increasing susceptibility to emotional strain over time [22]. As pollution patterns intensify, so does the complexity of predicting adolescent mental health trajectories.

3.3 Combined exposures: heat + pollution interactions and compounded stress

Combined environmental exposures represent a critical yet often underestimated driver of adolescent mental health vulnerability. Heat can intensify the formation of ozone and elevate concentrations of PM2.5, creating a hazardous atmospheric mix that places additional physiological and psychological stress on adolescents [20]. When heat and

pollution co-occur, adolescents experience amplified respiratory strain, dehydration risk, and neural stress responses, which may manifest as irritability, anxiety, or emotional fatigue [18].

Emerging analyses suggest that adolescents exposed to concurrent heat and pollution events may face compounded risks that exceed the sum of individual exposures, reflecting synergistic rather than additive effects [17]. For populations living in densely built environments, the combination of stagnant air, elevated temperatures, and traffic emissions can create persistent behavioural and cognitive challenges [21]. Understanding these interactions is essential for AI-driven prediction models capable of identifying high-risk windows for adolescent mental health disruption [22].

3.4 Social–ecological mediators (urban crowding, noise, loss of green space)

Social–ecological conditions shape how environmental stressors translate into mental health outcomes among adolescents. Urban crowding increases exposure to interpersonal conflict, overstimulation, and reduced privacy, all of which exacerbate emotional stress during a critical developmental stage [15]. Noise pollution stemming from traffic, commercial activity, and dense residential patterns interferes with concentration and sleep, factors strongly linked to emotional balance and cognitive performance [19].

Loss of green space further amplifies vulnerability by reducing opportunities for recreation, stress recovery, and social cohesion among young people [14]. Adolescents living in neighbourhoods with limited natural buffers experience heightened psychological strain, particularly when paired with persistent heat or pollution exposure [22].

These mediators illustrate the layered nature of environmental risk. They also highlight why predictive modelling must integrate ecological and social indicators simultaneously. As illustrated in Figure 1, social-ecological pressures interact with climate and pollution drivers to shape mental health outcomes across adolescent populations [16].

Figure 1: Social-ecological pressures interact with climate and pollution drivers to shape mental health outcomes across adolescent populations

4. AI-ENHANCED ENVIRONMENTAL HEALTH MODELLING APPROACHES

4.1 Machine learning for environmental exposure classification

Machine learning offers powerful tools for classifying environmental exposures that influence adolescent mental health, especially in contexts where climate and pollution signals fluctuate across short temporal windows. Traditional environmental monitoring systems often struggle to capture variations at granular scales, but supervised learning models can identify subtle exposure patterns by integrating air quality indices, temperature fluctuations, and neighbourhood-level ecological indicators [21]. Algorithms such as random forests, support vector machines, and ensemble classifiers have shown capacity to distinguish between high-risk and low-risk exposure clusters even under noisy field conditions [20].

For adolescents, these classification outputs provide foundational inputs for more complex vulnerability assessments. Machine learning models help determine how frequently young people encounter harmful particulate concentrations, rapid heat shifts, or pollutant spikes in densely populated regions [25]. In peri-urban settings, where environmental records may be incomplete, algorithms can interpolate missing values and create more consistent exposure datasets [23].

Importantly, exposure classification forms the basis of integrated behavioural prediction frameworks, linking environmental signatures with psychological indicators. Such frameworks strengthen early detection capacities by identifying exposure categories that repeatedly correspond with mood instability, stress responses, or concentration

deficits among adolescents [27]. As these models evolve, they allow researchers and public health actors to monitor exposure burdens with far greater resolution than traditional surveillance systems.

4.2 Deep learning for multimodal climate–pollution fusion

Deep learning has unlocked new possibilities for integrating diverse environmental datasets into unified prediction pipelines. Convolutional networks, long short-term memory (LSTM) architectures, and hybrid multimodal models allow climate and pollution variables to be fused into coherent risk profiles for adolescent mental health disparities [24]. These systems excel at capturing nonlinear interactions between heatwaves, humidity shifts, particulate density, and photochemical pollutants relationships that are difficult to characterize through classical statistics alone [22].

By processing satellite imagery, meteorological feeds, and air-quality sensor outputs simultaneously, deep learning models can map fine-scale gradients that shape adolescent exposure trajectories. These models recognize temporal rhythms such as morning traffic emissions or afternoon heat intensification and combine them with contextual features like vegetation cover or roadway density [26]. When psychological indicators sleep cycles, daily activity logs, or school absence trends are included, multimodal models yield holistic representations of environmental-behavioural synchrony [21].

This fusion capacity is essential for predicting mental health shifts during climate-pollution overlap events. For example, LSTM-based models can learn from historical sequences to anticipate periods when adolescents may experience heightened emotional strain due to concurrent ozone surges and elevated temperatures [23]. Deep learning thus provides the computational backbone for next-generation environmental mental health forecasting systems.

4.3 Spatiotemporal modelling of environmental and psychological vulnerability

Spatiotemporal approaches extend AI's predictive value by mapping how environmental stressors evolve across neighbourhoods and how adolescents' psychological responses align with those changes. Spatially explicit models capture heterogeneity between communities some burdened by industrial emissions, others by traffic congestion or sparse green space [22]. Techniques such as geographically weighted regression, spatial clustering, and graph-based neural networks reveal localized risk signatures that might otherwise remain hidden in aggregate datasets [25].

Temporally, models incorporating lag structures illustrate how environmental exposures influence adolescent mental health not only in real time but over delayed intervals. Heat spikes, for instance, may correlate with sleep disturbance or irritability several days later, while particulate exposure may manifest as anxiety or behavioural withdrawal after prolonged accumulation [27]. These delayed effects reinforce the importance of modelling exposure sequences rather than isolated events.

By integrating spatial and temporal components, spatiotemporal frameworks provide predictive surfaces that highlight hotspots where adolescents may be disproportionately affected by environmental stressors [20]. These surfaces guide targeted interventions, such as prioritizing cooling resources in high-temperature districts or intensifying counselling availability in pollution-dense corridors [26]. In doing so, they help bridge environmental science and mental health practice through context-specific, data-driven insights.

4.4 AI-enabled early warning systems for high-risk adolescent populations

AI-enabled early warning systems (EWS) leverage predictive analytics to flag periods of elevated environmental and psychological risk before crises emerge. These systems integrate exposure forecasts, pollution projections, and historical behavioural patterns to generate alerts that support families, schools, and frontline practitioners [24]. When calibrated accurately, EWS platforms can anticipate vulnerability windows related to heat surges, ozone peaks, or high-traffic emission cycles, enabling proactive mental health support for adolescents [21].

EWS dashboards also translate complex model outputs into actionable insights by clustering adolescents into dynamic risk categories informed by real-time environmental and social conditions [23]. Such classification helps optimize limited mental health resources by directing support to the most impacted communities [25]. By combining environmental sensing with AI-driven risk intelligence, early warning systems strengthen the protective capacity of public-health structures and help reduce mental-health deterioration linked to acute environmental events [27].

4.5 Ethics, algorithmic equity, and youth-focused data protections

The application of AI to adolescent mental health within environmental contexts requires careful ethical governance. One central concern involves algorithmic bias, which may arise when models trained on incomplete or unrepresentative datasets incorrectly predict vulnerability in marginalized communities [20]. These biases risk deepening existing inequities by directing interventions toward groups already receiving attention while overlooking others [22].

Youth-focused privacy protections are especially critical given the sensitivity of combining psychological indicators with environmental exposure metadata [26]. Without strong safeguards, adolescents may face unintended risks related to data misuse or stigmatizing interpretations of model outputs [24]. Ethical frameworks must therefore ensure transparency around data collection, model logic, and responsibility for decision-making, particularly in settings where environmental burdens and mental-health stigma intersect [27].

Embedding equity checks, community engagement, and protective policy design into AI pipelines ensures that predictive models serve adolescents fairly and safely across diverse ecological and social environments [25].

5. DATA ECOSYSTEMS FOR AI-ENHANCED ONE HEALTH MODELLING

5.1 Environmental data streams: satellite, climate models, air-quality monitoring

Robust AI-driven mental-health modelling for adolescents depends heavily on environmental data streams that capture spatial and temporal variations in climate and pollution exposures. Satellite Earth-observation platforms remain foundational because they provide high-resolution imagery for surface temperature, land cover transitions, aerosol concentrations, and vegetation stress indicators that influence local living conditions [25]. These satellite outputs complement gridded climate-model projections, which simulate temperature anomalies, precipitation patterns, and humidity shifts relevant to understanding cumulative environmental stressors affecting youth [29].

Air-quality monitoring networks add ground-level specificity by offering hourly and daily recordings of particulate matter, ozone, sulphur dioxide, nitrogen oxides, and carbon monoxide. In regions lacking dense monitoring coverage, mobile sensors and community-based low-cost air-quality units help fill observational gaps, enabling spatial interpolation of pollutant profiles over time [31]. Such real-time streams are essential for models that aim to detect rapid changes such as heat spikes or PM surges that disproportionately affect adolescents' emotional stability and cognitive performance [26].

By combining satellite, climate, and sensor datasets, AI models can better characterise exposure intensity, variability, and persistence. This multi-tiered environmental data foundation is critical for mapping ecological pressures that influence adolescent vulnerability across diverse households, schools, and neighbourhood systems [30].

5.2 Health and psychosocial data sources: school mental health surveys, wearable data

Understanding adolescent vulnerability requires integrating environmental indicators with health and psychosocial data reflecting daily experiences, behavioural responses, and emotional states. School-based mental-health surveys remain one of the most consistent sources, capturing stress levels, sleep quality, mood patterns, academic performance, and interpersonal challenges among young people [27]. These surveys often serve as early warning markers for environmental sensitivity by revealing fluctuations coinciding with seasonal or neighbourhood exposure variations [28].

Wearable technologies such as activity trackers, heart-rate monitors, and mobile applications extend these insights by offering fine-grained physiological data. Metrics like sleep duration, step counts, and heart-rate variability provide objective markers of stress reactivity, fatigue, and circadian rhythm disruption linked to climate and air-quality fluctuations [31]. When combined with self-reported daily logs, these wearable datasets help AI systems identify subtle patterns that may precede mental-health decline, allowing researchers to connect ecological shifts with behavioural or emotional responses among adolescents [26].

5.3 Pollution exposure databases and ecological monitoring systems

Pollution-focused databases provide essential detail on chemical and particulate profiles that shape adolescent exposure risks. These repositories track concentrations of PM2.5, PM10, black carbon, ozone precursors, heavy metals, and volatile organic compounds across industrial, urban, and peri-urban zones [30]. They often include emission inventories from transportation, manufacturing, refuse burning, and energy-generation sources, enabling more accurate attribution of exposure burdens among young populations [25].

Ecological monitoring systems add contextual layers by documenting environmental degradation, soil contamination, water quality deterioration, and biodiversity loss factors that interact with atmospheric conditions and influence human well-being [29]. When integrated with meteorological and pollutant datasets, these ecological records help AI models establish how environmental complexity amplifies or mitigates adolescent mental-health vulnerabilities [28]. Such exposures accumulate differently across time and space, making these databases crucial for high-resolution modelling frameworks that aim to detect environmentally mediated psychological risks [27].

5.4 Integration pipelines: multimodal fusion, harmonisation, and real-time ingestion

AI-enabled vulnerability prediction requires integration pipelines capable of harmonising environmental, psychosocial, and pollutant data into unified analytical streams. Multimodal fusion architectures combine numerical climate indicators, satellite imagery, wearable metrics, and school survey outputs to ensure that each dataset contributes complementary information to the prediction engine [31]. Data harmonisation processes standardise formats, resolve temporal misalignments, and correct spatial inconsistencies so that heat readings, PM spikes, and behavioural markers can be analysed together without distortion [26].

Real-time ingestion frameworks enable continuous updating of exposure classifications and mental-health risk scores, ensuring models remain responsive during acute events like extreme heat or sudden pollution spikes [30]. These pipelines support dashboards that provide timely alerts for researchers, schools, and community systems.

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

Data Category	Specific Data Types	Primary Sources	Relevance to AI-Enabled One Health Modelling
Climate & Meteorological Data	Temperature, humidity, heat index, heatwave events, precipitation, UV intensity	Satellite climate datasets (e.g., MODIS), national meteorological agencies, global climate reanalysis systems	Enables modelling of heat-related stress pathways, temporal anomaly detection, and environmental exposure profiling.
Air Quality & Pollution Data	$PM_{2.5}$, PM_{10}, ozone (O_3), NO_2, SO_2, CO, industrial emissions, vehicular emission density	Air-quality monitoring stations, atmospheric chemistry models, environmental protection agencies	Supports identification of pollution-driven mental health risk clusters; allows multimodal fusion with climate indicators.
Ecological & Land Use Data	Green space density, vegetation index (NDVI), land-use change, urbanisation levels, soil contamination	Satellite earth observation systems, environmental ministries, GIS repositories	Provides context for social–ecological mediators such as loss of green space, urban crowding, and habitat degradation.
Built Environment & Urban Stressors	Noise levels, traffic density, crowding metrics, housing quality	Local urban planning authorities, smart-city sensors, transport databases	Helps quantify non-chemical environmental stressors linked to adolescent anxiety and behavioural changes.
Health & Psychosocial Data	School mental health surveys, self-reported	Ministries of education and health, school	Enables detection of psychological
	emotional states, behavioural health screening, resilience indicators	health programmes, community health centres	vulnerability patterns and supports linkage with environmental exposures.
Wearable & Digital Biomarker Data	Heart rate variability, sleep patterns, physical activity, stress biomarkers	Wearable devices, mobile health apps, adolescent digital health studies	Provides real-time physiological proxies for stress and early signs of environmental mental health strain.
Community & Social Determinant Data	Socioeconomic status, household conditions, access to health services, family stress indicators	National demographic surveys, social welfare databases, community organisations	Essential for understanding moderating factors and developing equitable AI prediction models.

6. MODEL DEVELOPMENT PIPELINE FOR ENVIRONMENTAL–MENTAL HEALTH PREDICTION

6.1 Identifying key variables and constructing exposure–response pathways

Developing effective AI-enhanced models requires careful identification of variables that capture the interplay between climate stressors, pollution burdens, and adolescent psychological outcomes. Environmental indicators such as temperature variability, humidity shifts, particulate concentrations, and seasonal air-quality fluctuations form the core exposure metrics used to map ecological pressures that influence adolescent well-being [29]. These exposures interact with behavioural, physiological, and psychosocial markers, including sleep disruption, concentration difficulty, emotional reactivity, and stress-sensitive routines that adolescents commonly experience during environmental instability [34].

Constructing exposure–response pathways involves linking these variables through causal chains that show how climatic or pollution changes influence neurobiological and psychological vulnerability [31]. This process requires multidisciplinary integration across atmospheric science, public health, and behavioural research, allowing AI models

to capture both immediate responses to acute exposures and cumulative effects of long-term environmental burdens [36]. The resulting pathways provide the structural blueprint upon which predictive algorithms operate, ensuring outputs remain grounded in real-world ecological and developmental processes [33].

6.2 Feature engineering and building predictive climate–pollution risk indicators

Feature engineering plays a foundational role in shaping AI systems capable of detecting environmental drivers of adolescent mental-health vulnerability. Raw environmental variables such as hourly pollutant concentrations, thermal anomalies, and seasonal particulate cycles are transformed into structured indicators that reflect intensity, persistence, and fluctuation patterns relevant to psychological stress [30]. Derived features such as heat-stress indices, air-toxicity composites, and multi-day pollution accumulation totals allow models to recognise cumulative pressures that often precede emotional or behavioural changes in young populations [35].

In addition, contextual features school density, neighbourhood vegetation, traffic proximity, and household crowding are incorporated to refine exposure specificity and identify hotspots where environmental burdens disproportionately affect adolescents [29]. These engineered predictors allow climate–pollution interactions to be quantified across different time windows, enabling AI models to detect latent vulnerability signatures. By converting heterogeneous environmental signals into unified, interpretable indicators, feature engineering strengthens model capacity to anticipate mental-health risks with higher precision and developmental relevance [32].

6.3 Model training, validation, and interpretability frameworks

Training robust predictive models requires assembling multimodal datasets that combine pollutant trends, climate observations, psychosocial survey responses, and physiological readings. Machine learning algorithms ranging from gradient-boosting ensembles to temporal neural networks are trained to uncover patterns linking fluctuating environmental exposures with adolescent behavioural or emotional outcomes [37]. Cross-validation procedures help ensure that the models maintain stability across different data partitions, reducing the risk of overfitting while improving general predictive reliability [31].

Model interpretability remains essential for linking predictions to actionable public-health decisions. Techniques such as partial-dependence plots, feature-importance rankings, and surrogate decision-tree explanations provide insight into how environmental variables shape predicted mental-health outcomes [30]. These interpretability layers allow researchers, clinicians, and school systems to understand the environmental triggers most strongly associated with vulnerability. By grounding model outputs in transparent analytical structures, interpretability ensures AI systems can

support practical decision-making in adolescent health protection across varying ecological conditions [29].

6.4 Bias mitigation and cross-regional generalisability

Environmental mental-health models must address potential biases arising from uneven data coverage, socio-economic disparities, and geographic variation in environmental exposures. Bias mitigation begins with adjusting for unequal sampling density, ensuring that adolescents from resource-constrained or highly polluted neighbourhoods are accurately represented in the training datasets [34]. Cross-regional harmonisation procedures help reduce distortions caused by differing monitoring capacities, allowing AI models to generalise across urban centres, peri-urban zones, and rapidly changing ecological landscapes [29].

To strengthen generalisability, external validation datasets are used to test whether predictive patterns hold across new settings with distinct climatic or structural characteristics [33]. This step ensures the AI system does not overfit to local idiosyncrasies that might limit practical use in broader One Health applications [36].
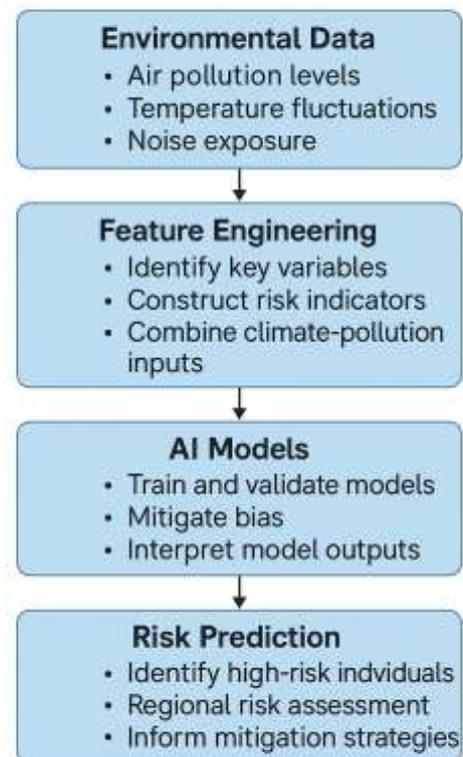

Figure 2, titled *"AI-Driven Predictive Pipeline for Modelling Environmental Mental Health Risks in Adolescents,"*

7. SCENARIO MODELLING AND APPLICATION IN REAL-WORLD SETTINGS

7.1 Heat and air pollution episodes predicting anxiety and depression spikes

Periods of elevated temperatures and intensified air pollution often coincide with noticeable increases in adolescent emotional distress, making these environmental episodes critical predictors of mental-health vulnerability. Heatwaves disrupt sleep cycles, heighten physiological stress responses, and amplify irritability, all of which contribute to elevated anxiety symptoms among young people [33]. Air pollution particularly fine particulate matter and ozone has been associated with neuroinflammatory responses that can exacerbate depressive tendencies during prolonged exposure [36].

AI-enabled predictive systems are well suited to detect these patterns by integrating temperature anomalies, multi-day pollution surges, and behavioural indicators into unified risk estimates [37]. When models capture recurring associations between heat–pollution interactions and emotional instability, they provide early warnings that can support proactive mental-health interventions, such as hydration reminders, adjusted school workloads, shaded outdoor spaces, and indoor air-filtration guidance [35].

These predictive capabilities are especially valuable in regions where environmental variations occur rapidly, making it difficult for traditional monitoring systems to anticipate adolescent responses. By analysing trends across heat-intensity cycles, air-quality index shifts, and past behavioural records, AI systems can signal periods when adolescents may be more susceptible to mood fluctuations or stress-related symptoms [40]. Such insights ensure that supportive actions occur before crises escalate, aligning environmental monitoring with youth-focused mental-health protection.

7.2 Urban vs rural exposure pattern differences among adolescents

Environmental burdens affecting adolescent mental health differ considerably between urban and rural settings, making spatial context central to predictive modelling. Urban adolescents often face higher exposure to vehicular emissions, industrial pollutants, and sustained noise levels, all of which have been linked with anxiety, reduced concentration, and emotional fatigue [34]. Heat-retaining built environments intensify thermal stress, compounding risks related to air pollution and sleep disturbance [38]. AI models that incorporate satellite-derived surface temperatures, road-density maps, and neighbourhood air-quality indicators can therefore detect elevated vulnerability among city-based youths [36].

Rural adolescents, by contrast, typically experience lower pollution levels but face other environmental pressures such as agricultural chemical exposure, limited access to mental-health services, and climate-related livelihood instability that affects household well-being [33]. These stressors can influence depressive symptoms, especially during periods of environmental hardship.

By analysing these spatial differences, AI-enhanced systems can generate risk profiles that reflect local ecological realities rather than relying on uniform assumptions [39]. Such differentiation ensures that interventions whether school counselling sessions, community awareness campaigns, or heat-response planning are grounded in conditions specific to each region. Predictive modelling therefore enables targeted public-health strategies that recognise the uneven environmental challenges facing adolescents across diverse landscapes.

7.3 School- and community-level decision dashboards for preventive interventions

Integrating AI predictions into operational dashboards provides schools and community health teams with practical tools to act on early warning signals. These dashboards synthesise climate projections, pollution forecasts, and behavioural indicators into clear visualisations that highlight when adolescents may be entering elevated risk tiers for anxiety or depression [37]. By translating complex environmental data into accessible formats, decision dashboards allow teachers, counsellors, and local health workers to anticipate vulnerability and apply preventive actions, such as adjusting school schedules, increasing shaded outdoor activity options, or implementing community cooling centres [33].

Dashboards can also incorporate socio-ecological metrics including green-space availability, household crowding, and transportation burdens to help communities understand compounded environmental pressures [40]. Incorporating these contextual indicators ensures that interventions extend beyond individual counselling and address environmental inequities that contribute to mental-health stress.

Table 2. Scenario Outputs of AI Models and Implications for Adolescent Mental Health Risk Tiers

Scenario Type	AI Model Output Characteristics	Environmental & Psychosocial Conditions	Implications for Adolescent Mental Health Risk Tiers
Scenario A: High Heat + Moderate Pollution	Elevated spatiotemporal risk scores; sharp increases in short-term stress markers	Heatwave days >90th percentile; PM2.5 moderately elevated; limited green space	**Moderate–High Risk Tier:** Increased anxiety, irritability, and sleep disruption

Scenario Type	AI Model Output Characteristics	Environmental & Psychosocial Conditions	Implications for Adolescent Mental Health Risk Tiers
			among adolescents; requires targeted school-based coping interventions.
Scenario B: High Pollution + Stable Temperature	Strong correlation between pollutant spikes and behavioural anomalies	PM2.5 and NO_2 exceed safe thresholds; industrial or traffic-driven emissions peak	**High Risk Tier:** Heightened depressive symptoms, reduced cognitive performance; requires rapid public health messaging and exposure mitigation strategies.
Scenario C: Combined Heat–Pollution Extremes	Nonlinear interaction curves; AI flags compounding stress exposure	Consecutive heatwave events coinciding with $PM10/O_3$ surges; low ventilation and urban density	**Severe Risk Tier:** Increased likelihood of acute mental distress episodes; prioritisation of emergency support, community cooling centres, and monitoring.
Scenario D: Low Environmental Stress but High Social Stressors	Model clusters show psychosocial dominance over environmental metrics	Stable climate and air quality; economic strain, household conflict, poor school resources	**Moderate Risk Tier:** Behavioural changes driven by social–ecological pressures; requires counsellor involvement and social-support

Scenario Type	AI Model Output Characteristics	Environmental & Psychosocial Conditions	Implications for Adolescent Mental Health Risk Tiers
			interventions.
Scenario E: Rural Exposure with Seasonal Agricultural Pollution	Periodic peaks in risk curves aligned with biomass burning periods	Seasonal burning of fields, pesticide drift, low access to mental health services	**Variable Risk Tier (Low–High):** Spikes in stress and irritability during exposure periods; requires seasonal risk-communication and outreach.
Scenario F: Urban Micro-Climate Hotspots	High-resolution mapping shows concentrated vulnerability pockets	Urban heat islands, traffic congestion, high noise levels	**High Risk Tier:** Persistent anxiety symptoms, reduced attention and academic performance; suggests need for micro-climate mitigation and youth-centred urban planning.

By linking predictive outputs with actionable protocols, such dashboards support coordinated One Health strategies that strengthen resilience at both school and community levels, ensuring timely protective responses across diverse environmental conditions [38].

8. STRUCTURAL AND GOVERNANCE ARCHITECTURE FOR ONE HEALTH AI SYSTEMS

8.1 National environmental–mental health surveillance networks

Developing national surveillance systems that integrate environmental and adolescent mental-health indicators is essential for proactive risk mitigation. Such networks allow governments to track climate-related stressors, pollution fluctuations, and psychosocial vulnerabilities simultaneously,

creating a unified platform that informs early interventions [35]. By linking meteorological data with school-level behavioural signals, these systems generate real-time alerts that support targeted community responses without depending solely on retrospective reporting. National surveillance structures also encourage standardised protocols for data collection, harmonisation, and quality control, ensuring that information used for policymaking meets consistent scientific standards [38].

Strengthening these networks further enables cross-regional comparisons, helping authorities identify hotspots where heat, pollution, and socioeconomic pressure converge to heighten adolescent mental-health risks [34]. Centralised data systems foster long-term resilience planning by tracking emerging environmental patterns and population responses. As the complexity of environmental influences grows, comprehensive surveillance platforms become crucial for anticipating vulnerabilities before they manifest in widespread psychological impacts [39].

8.2 Digital infrastructure, cloud computing, and GIS for data synthesis

Robust digital infrastructure forms the backbone of AI-enhanced One Health analytics, enabling large-scale ingestion, storage, and interpretation of diverse environmental and psychosocial datasets. Cloud-based frameworks support rapid computation and facilitate continuous data flows from satellite sensors, climate models, and local air-quality stations [36]. When combined with GIS systems, these infrastructures enable spatial mapping of exposure hotspots, allowing public agencies to visualise where adolescents face elevated risks linked to temperature spikes or pollutant accumulation [34].

Centralising these datasets in cloud environments also enhances scalability, making it possible to incorporate new variables, expand regional coverage, or integrate additional behavioural markers without redesigning entire systems [40]. GIS-enabled analytics help decision-makers overlay school locations, healthcare resources, and climate indicators in ways that reveal disparities that may otherwise remain unnoticed [35]. Through this digital backbone, environmental signals become actionable intelligence, supporting pre-emptive strategies that protect adolescent mental health across diverse ecological contexts [37].

8.3 Intersectoral ecosystem linking health, climate, education, and environment agencies

A fully operational One Health model requires strong intersectoral collaboration, bringing together health ministries, climate agencies, educational institutions, and environmental regulators into a single coordinated ecosystem [34]. This collaborative structure allows diverse agencies to share datasets, harmonise alerts, and implement preventive actions aligned with adolescent mental-health needs. When communication channels are streamlined, climate warnings can be linked immediately with school preparedness strategies

or community counselling initiatives, creating rapid-response pathways that reduce vulnerability [38].

Joint governance frameworks also strengthen accountability by ensuring that each sector contributes its expertise climate analysts interpret heat patterns, educators monitor behavioural shifts, and environmental regulators track pollutant thresholds [36]. Integrating these domains supports stronger decision-making, particularly when AI-generated predictions highlight cross-cutting risks.
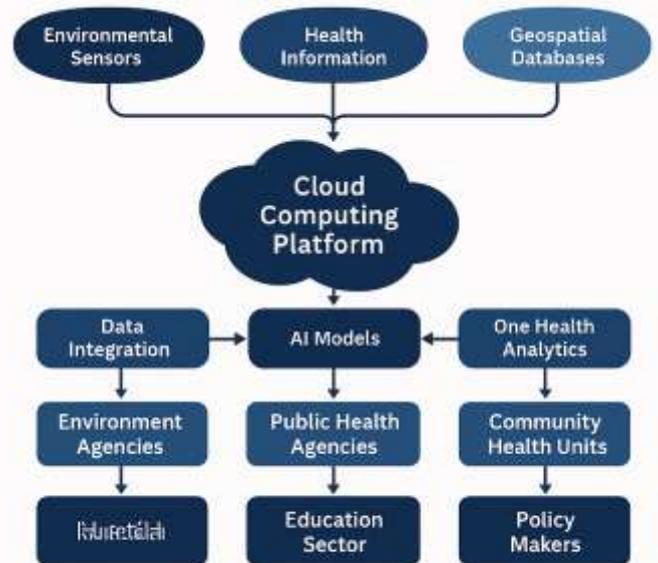

Figure 3 System Architecture for National AI-Enhanced One Health Surveillance

Figure 3, *System Architecture for National AI-Enhanced One Health Surveillance,"*

By fostering intersectoral alignment, national systems become more agile, equitable, and capable of addressing complex adolescent mental-health challenges [40].

9. POLICY IMPLICATIONS AND STRATEGIC GUIDANCE

9.1 Evidence-based environmental mental health policymaking

Evidence-based policymaking in environmental mental health requires linking validated scientific findings with actionable public interventions that protect adolescents from climate- and pollution-driven vulnerabilities. To achieve this, policymakers must rely on structured environmental datasets paired with behavioural indicators, allowing decisions to reflect real-world exposure patterns rather than assumptions [37]. Integrating temperature anomalies, particulate levels, and ecological changes with psychological trends helps identify priority regions where adolescents may experience heightened emotional distress. The strength of this approach lies in its capacity to translate environmental signals into early policy

responses, such as school preparedness guidelines, heatwave protocols, or pollution-reduction initiatives [39].

Governments can also benefit from adopting cross-sectoral advisory committees that connect environmental scientists, mental-health experts, and public-health planners, ensuring that policy development remains holistic [41]. When combined with longitudinal monitoring systems, these measures support adaptive strategies that evolve as new exposure trends emerge. Evidence-driven governance thus builds resilience, enhances resource allocation, and establishes a sustainable pathway for safeguarding adolescent well-being within broader environmental health frameworks [43].

9.2 Youth-centered data privacy, transparency, and algorithmic accountability

Protecting adolescent data is pivotal when deploying AI-enabled environmental mental-health tools. Youth-centered privacy standards require strict limitations on identifiable information, clear disclosure of data use, and transparent communication regarding how predictive models operate [40]. Ensuring accountability also involves monitoring algorithmic behaviour to detect biases that may inadvertently reinforce inequities among different population groups [38]. Adolescents and their guardians must be informed participants in this ecosystem, with accessible explanations of how risk predictions function and why certain interventions are recommended. Embedding transparency and responsibility into AI workflows strengthens trust and promotes ethical technology adoption aligned with public-health objectives [42].

9.3 Integrating AI-mental health predictions into existing One Health policy frameworks

Integrating AI-based mental-health prediction systems into One Health frameworks requires aligning environmental surveillance, clinical services, and community-level initiatives within a unified governance model. Doing so allows predictions about climate and pollution stressors to inform school counselling programs, community outreach, and local environmental planning [37]. Embedding predictive outputs into existing regulatory mechanisms enhances preparedness, enabling faster adaptation to emerging risks [41]. Coordination across health, environmental, and educational sectors ensures that AI-generated insights are not siloed but instead drive comprehensive preventive strategies [43]. This integration strengthens the operational capacity of One Health systems and supports more responsive adolescent mental-health protection nationwide.

10. LIMITATIONS AND EMERGING RISKS
10.1 Data sparsity, monitoring infrastructures, and geospatial coverage gaps

A major barrier to building robust AI-enhanced environmental mental-health models is the persistent scarcity of high-resolution environmental and psychosocial datasets across many regions. Several countries face fragmented monitoring networks, inconsistent satellite–ground integration systems, and inadequate temporal sampling frequencies, which weaken model reliability [41]. These gaps are especially pronounced in peri-urban and rural communities where geospatial coverage remains thin, limiting the ability to map adolescent vulnerabilities with precision [40]. Without consistent, long-term tracking of air pollutants, climatic variables, and youth mental-health indicators, predictive algorithms may generate unstable outputs, underscoring the need for stronger national surveillance infrastructures [44].

10.2 Algorithmic bias and population-level disparities

AI models used to evaluate climate- and pollution-related mental-health risks often inherit biases embedded within their training data. When certain demographic groups are underrepresented, predictions may skew toward the profiles of data-rich populations, reinforcing pre-existing disparities [42]. This becomes particularly problematic for adolescents living in low-resource settings where environmental exposures differ substantially from urban centres. If uncorrected, such algorithmic distortions can lead to misplaced interventions and uneven policy outcomes [45]. Ensuring model fairness requires integrating diverse datasets, validating frameworks across regions, and routinely auditing prediction pathways to prevent systemic inequities from shaping youth mental-health risk evaluation [43].

10.3 Economic, ethical, and institutional constraints

Beyond technical limitations, economic and governance-related constraints restrict the large-scale adoption of AI-supported environmental mental-health systems. Many institutions lack sustainable funding mechanisms to maintain advanced analytics platforms or support multidisciplinary collaborations needed for long-term data stewardship [44]. Ethical considerations also arise around youth data rights, consent processes, and the responsible communication of predictive results to families and schools [40]. In addition, bureaucratic fragmentation across health, education, and environmental sectors often slows integration efforts, reducing institutional readiness to adopt innovative tools [45]. Addressing these constraints requires coordinated policy reforms, stable financing, and well-defined ethical oversight structures [41].

11. FUTURE RESEARCH AND INNOVATION PATHWAYS
11.1 Development of personalised environmental mental health forecasting tools

Future innovations point toward personalised forecasting systems that integrate individual exposure histories, behavioural routines, and vulnerability markers to predict shifts in adolescent mental health. Such tools would merge environmental signals with personalised baselines to generate adaptive risk alerts tailored to each young person's lived context [45]. By leveraging household-level climate and pollution data, forecasting models could anticipate

psychological stress fluctuations before symptoms escalate [43]. Incorporating school attendance patterns, sleep variability, and micro-environmental exposure cycles would further refine individual profiles, enabling precision-prevention approaches. These systems could support clinicians, families, and community health workers by facilitating early, customised interventions [47].

11.2 Wearables + AI + One Health next-generation hybrid platforms

The next wave of integrated systems will combine wearable technologies with AI-driven analytics and One Health environmental layers to create hybrid platforms capable of continuous monitoring. Wearable devices tracking physiological stress responses, heart-rate variability, and sleep quality can be synchronised with ambient heat, particulate matter, and noise exposure datasets [48]. This convergence would help detect early deviations in mental-wellbeing trajectories among adolescents exposed to climate and pollution stressors [44]. Hybrid platforms could also support school-based and community programmes by offering real-time dashboards for counsellors and health teams [46]. Such systems mark a shift toward dynamic, ecosystem-informed youth monitoring [43].

11.3 Longitudinal ecosystem studies across climate-vulnerable youth populations

Sustained longitudinal studies are critical for understanding how environmental stressors interact over time to shape adolescent mental-health outcomes. Tracking cohorts across diverse ecological zones would reveal cumulative and lagged effects of heatwaves, pollution plumes, and seasonal variability on psychological vulnerability [47]. These long-term datasets would also help clarify resilience factors, including social support networks and protective community features [45]. Embedding One Health metrics into these studies allows researchers to assess cross-species and environmental parallels that illuminate broader ecosystem shifts [48]. Such longitudinal evidence is essential for building stable predictive models and informing durable public-health strategies [46].

12. CONCLUSION

AI-enhanced environmental modelling represents a transformative frontier in understanding and predicting how climate stressors and pollution exposures shape mental health vulnerabilities among adolescents. As environmental instability intensifies and young populations face escalating risks from heat extremes, toxic air, degraded ecosystems, and rapid urbanisation, the ability to anticipate psychological impacts before they emerge has become a critical public-health priority. Artificial intelligence makes this shift possible by processing vast, complex, and dynamic environmental signals temperature anomalies, particulate concentrations, ecological disruptions and linking them with behavioural and psychosocial indicators to detect early patterns of distress that traditional systems often overlook.

Central to this progress is the integration of One Health principles, which recognise that adolescent mental well-being cannot be separated from the ecosystems, animals, and climatic processes that surround human communities. This interconnected perspective allows environmental, climatic, and health datasets to be harmonised into a single predictive framework, enabling more holistic assessments of risk. When AI systems draw from satellite imagery, pollution monitoring grids, land-use changes, school health data, and community-level observations, they generate deeper insights into how environmental pressures translate into emotional, cognitive, and behavioural challenges for young people.

These models are not only diagnostic but preventive. They support the design of early-warning systems that alert schools, families, and health agencies to periods of heightened vulnerability such as upcoming heatwaves or severe pollution episodes allowing for timely interventions. They also support decision-makers by identifying high-risk geographic zones, evaluating shifts in exposure patterns, and guiding policies that strengthen resilience across communities, particularly those with fewer resources to adapt.

Beyond prediction, AI-enabled One Health systems provide an evidence base for designing youth-centred policies that protect mental health in an era of environmental uncertainty. They encourage improved environmental governance, strengthen surveillance infrastructures, expand cross-sector collaboration, and promote sustainable urban planning that prioritises green spaces, clean air, and climate-adaptive services.

Overall, AI-enhanced environmental modelling, anchored in the One Health framework, offers a powerful pathway for safeguarding adolescent mental health. By uniting technology, ecology, and public health, these systems help societies anticipate emerging threats, support vulnerable youth, and build long-term resilience in a rapidly changing world.

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