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Digital intelligence for depression governance: an environome framework to bridge research and policy

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Background: Digital intelligence platforms are transforming how policymakers synthesize and translate mental health evidence into actionable strategies. Depression research is vast but highly fragmented, limiting its effective use in policy design. We introduce the Interactive Depression Dashboard (InDepDash), designed to integrate and operationalize multidisciplinary evidence on depression.

Methods: InDepDash aggregates and analyzes 139,761 depression-related studies (from 2005 to 2025) spanning clinical, social, and environmental domains. The platform maps evidence across multiple determinants of mental health, conceptualized as the "environome," including personal, social, natural, and built factors. Ontology-based annotation, semantic search, and co-occurrence analysis enable real-time exploration of research trends, gaps, and priorities, while case study applications illustrate its policy relevance.

Results: The platform identified substantial imbalances in the evidence base. Natural and built environmental determinants represented 14.3% of the analyzed corpus; within this domain, climate-change-specific evidence was comparatively sparse. InDepDash effectively highlights underexplored domains and supports prioritization of interventions, including neuroinclusive policies, disaster resilience strategies, and climate-informed mental health planning.

Conclusion: Evidence-mapping platforms such as InDepDash provide critical infrastructure for adaptive and evidence-informed governance in mental health. By enhancing the accessibility, transparency, and integration of complex data, they enable policymakers to respond to emerging challenges with greater speed. This study supports the Trustworthiness, Reproducibility, Explainability, Applicability, and Transparency (TREAT) framework as a foundation for ethical AI deployment, addressing key gaps in research translation while working toward global mental health equity.

KEYWORDS

depression, digital intelligence dashboard, environome, health equity, health policy, mental health, one health, transdisciplinary

1 Introduction

Depression represents a major global health burden, shaped by complex interactions across biological, social, and environmental domains (Smith, 2014; Li et al., 2025). The volume of depression-related research has increased dramatically, Figure counts imply 288.6%, not over 300% between 2016 and 2022 (Santomauro et al., 2021; Solmi et al., 2022). While this rapid expansion reflects growing scientific attention, it has also created a critical challenge: the ability of policymakers to efficiently synthesize and translate large-scale, multidisciplinary evidence into actionable strategies. This challenge is particularly evident in the context of evolving policy priorities. The European Commission's comprehensive approach to mental health (European Commission, 2023) emphasizes resilience, prevention, and equity through cross-sectoral approaches. However, traditional evidence synthesis methods, such as systematic reviews and meta-analyses, are often too slow and narrow to support timely decision-making (Haby et al., 2016). Moreover, depression research is increasingly fragmented across diverse disciplines, including neuroscience, epidemiology, environmental science, and urban planning, limiting the integration of knowledge across domains (McLaughlin, 2011). Advances in artificial intelligence (AI) and data-driven analytics provide new opportunities to address this gap. Digital intelligence platforms can augment human expertise by enabling large-scale evidence integration, pattern detection, and real-time exploration of complex datasets (Asch et al., 2018). Rather than replacing domain experts, such systems support more efficient and transparent navigation of heterogeneous evidence landscapes, making them increasingly essential for modern evidence-based governance. However, the evidence base itself can be unevenly distributed across regions and languages, meaning that any tool built to synthesize it, however fast or scalable, must contend with these same imbalances rather than being assumed to resolve them. Moreover, despite the availability of vast amounts of depression-related research, policymakers face significant barriers in translating this evidence into effective interventions. The scale, heterogeneity, and fragmentation of available data make it difficult to identify priorities, detect knowledge gaps, and align findings across disciplines. Research outputs are typically organized within disciplinary silos, limiting the ability to understand how different determinants interact. This fragmentation reduces the visibility of emerging risks and underexplored domains, especially those related to environmental and societal factors (Gopalkrishnan, 2018). Furthermore, the lack of scalable and transparent tools for evidence synthesis constrains the responsiveness of policy systems. Decision-making processes must increasingly operate within narrow timeframes, particularly in the context of global crises such as pandemics, climate change, and socioeconomic instability. Without advanced analytical frameworks, there is a risk that critical insights remain inaccessible or underutilized, leading to suboptimal or delayed policy responses. While recent efforts have explored the use of AI for literature analysis, these are often restricted to specific domains or methodological frameworks, without addressing the broader needs of policy translation. In particular, there is limited work on platforms that systematically map depression research across interconnected determinants spanning personal (meaning individual-level factors such as physical health, sleep behavior, and emotional regulation), social, and environmental dimensions (Adisasmito et al., 2022).

The designed concept of the "environome" (von Stumm and d'Apice, 2022) offers a comprehensive framework to capture these interactions. Additionally, current tools rarely provide actionable outputs tailored to policymakers, such as identification of research gaps, prioritization of interventions, or alignment with policy frameworks. There is a need for integrated systems that not only aggregate data but also support interpretation, transparency, and equitable decision-making across diverse contexts. At the same time, such systems may inherit structural biases from the underlying evidence base, including uneven geographic, linguistic, and disciplinary coverage. To address these limitations, we present the InDepDash, a digital intelligence platform designed to synthesize and operationalize large-scale depression research (Herrman et al., 2022). Unlike conventional bibliometric software, which primarily describes publication volume, citation structure, or keyword frequency, InDepDash integrates 139,761 multidisciplinary studies (from 2005 to 2025) and maps evidence across the "environome," encompassing personal, social, natural, and built environmental determinants of mental health European Commission (2025). The aim of this study is 3-fold: (i) to develop a computational text-mining framework for large-scale evidence integration, (ii) to combine semantic search, ontology-based annotation, concept-level relationships, and co-occurrence analysis to map the multidimensional determinants of depression across the so-called "environome," and (iii) to illustrate potential policy applications through case studies. In doing so, the platform enables exploration of research trends while acknowledging the uneven distribution of evidence across domains and regions. It can therefore support prioritization of interventions in areas such as neuroinclusion, disaster resilience, and climate-related mental health planning, while remaining attentive to the structural biases of the underlying literature (Figure 1).

This study is structured as follows. Section 2 describes the methodology, including data sources, ontology-based indexing, environome classification, and analytical framework used to synthesize large-scale depression research. It details the integration of semantic annotation, co-occurrence analysis, and participatory validation processes. Section 3 presents the results, including the distribution of research across personal, social, natural, and built determinants, as well as identification of structural gaps and geographic disparities in the evidence base. Section 4 introduces the policy translation possibilities offered by InDepDash and current limitations, examines implementation challenges, and illustrates how digital intelligence approaches may support rapid evidence synthesis, pattern recognition, and gap identification. Section 5 concludes the study.

2 Materials and methods

2.1 Study design and analytical framework

A full glossary of concepts and terminology adopted within the InDepDash framework is available in Supplementary Table S1 (Table 1). Key concepts are summarized in Table 1; a full glossary is provided in Supplementary Table S1.

InDepDash synthesizes evidence from PubMed Central (PMC) Open Access, analyzing 139,761 peer-reviewed publications spanning 2005–2025 (last accessed December 2025). Our search strategy targeted the field "depression" and related symptomatology to capture the condition's multidimensional manifestations, using the query: *termloc:*

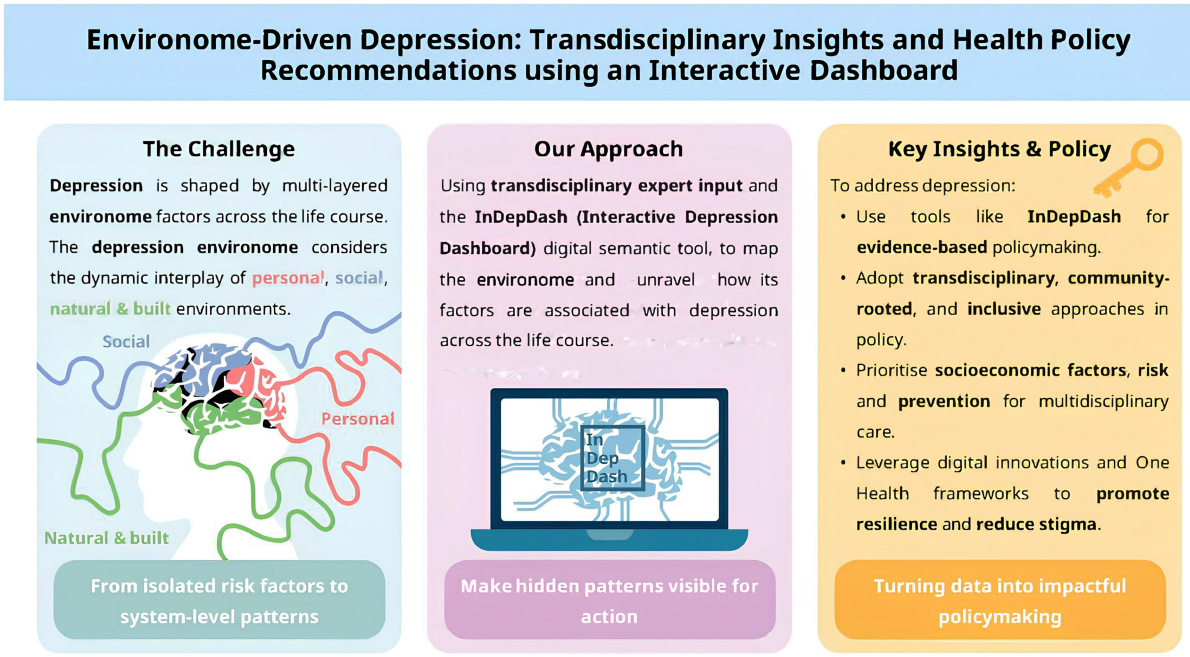


FIGURE 1
Depression environome framework and the InDepDash interactive dashboard. The figure summarizes the transdisciplinary approach adopted to explore how personal, social, natural, and built factors interact in shaping depression outcomes across the life course. InDepDash is presented as a semantic and educational tool to support evidence-based policymaking, prevention strategies, and resilience-oriented public health interventions.

TABLE 1 Key concepts of the InDepDash depression environome framework.

Concept	Definition
Environome	The integrated set of personal, social, natural, and built environmental influences shaping health and depression across the life course.
Depression environome	A multidimensional framework describing how personal, social, natural, and built interacting environmental determinants contribute to depression vulnerability, resilience, and outcomes.
InDepDash	A semantic dashboard developed to synthesize, visualize, and operationalize depression-related evidence across the environome.
Semantic annotation	The ontology-based tagging of textual content to enable structured large-scale analysis of depression-related concepts and relationships.
Participatory validation	A multidisciplinary review process involving researchers, clinicians, policymakers, and individuals with lived experience to contextualize and refine InDepDash-derived outputs.
Evidence-informed policy	Policymaking guided by scientific evidence together with contextual, societal, ethical, and feasibility considerations.
TREAT framework	A framework emphasizing Trustworthiness, Reproducibility, Explainability, Applicability, and Transparency to guide responsible AI use. Source: https://www.nature.com/articles/s41746-025-01596-0.

"ta" + (t:"depression" ocid: "206010012375"). InDepDash builds upon the Dimensions Processor (formerly SciWalker) semantic search engine, which indexes roughly 160 million full-text documents using (OCIDS) that are FAIR ("Findable," "Accessible," "Interoperable," and "Re-usable") (Weber and OntoChem Team, 2020). These ontologies integrate public and proprietary vocabularies, organized hierarchically with inter-domain relationships that connect classes and concepts. The PMC Open Access subset, defined at https://pmc.ncbi.nlm.nih.gov/tools/openftlist/, encompasses publications classified into 47 distinct domains. A detailed description of these ontologies is provided in the Digital Science Ontology White Paper (see Supplementary material). For this study, multiple ontology branches were used to characterize depression's multidimensional environome, i.e., the totality of personal, social, natural, and built influences:

- *Depression query*: Concepts annotated under the diseases ontology.
- *Natural environment*: Domain effects and processes, methods, toxicology, magnitudes, and substances, focusing on ecologically and environmentally relevant branches.
- *Personal environment*: Concepts from effects and processes, emphasizing proximal individual-level factors relevant to depression, including behavior-related processes and embodied determinants such as physical health, sleep, emotional regulation, memory, and lifestyle-related influences.
- *Social environment*: Indexing based mainly on magnitudes (particularly sociological magnitude) and industries.

Additional analytical layers included the following:

- *Drugs* (Drugs Ontology),
- *Diet* (Nutrition Ontology),
- *Experimental studies* (Clinical Trials domain), and
- *Comorbidities and endocrine dysfunction* (Disease, Drugs, and Natural Products ontologies).

All entities were automatically annotated and linked to standardized OCIDs using the Digital Science annotation engine Dimensions

Processor (formerly OC Processor) annotation engine. A detailed description of the annotation process is available in the Supplementary material.

2.2 Co-occurrence analysis and environome classification

To capture contextually meaningful relationships, paragraph-level co-occurrence analysis was applied. Specifically, ontology concepts were considered associated when they co-occurred with "depression" (or its ontological descendants) within the same paragraph. This approach allows identification of semantically relevant associations beyond simple keyword matching. The environome classification was derived from co-occurrence frequency patterns across ontology branches. For example, studies linking depression with climate or disaster-related terms were categorized under the natural environment, while those involving income, education, or employment were classified within the social environment. OCID normalization ensured that synonyms and lexical variants were mapped to unified identifiers, supporting cross-disciplinary consistency and reproducibility. Full methodological specifications, including ontology hierarchies, validation procedures, and technical architecture, are documented in the Supplementary material. Of note, the co-occurrence described in this manuscript should be interpreted as hypothesis-generating evidence of research attention, not as causal evidence.

2.3 Participatory validation and policy integration

Quantitative outputs from InDepDash were complemented by participatory validation through workshops conducted in April 2023 and June 2024. These sessions involved multidisciplinary stakeholders, including clinicians, researchers, individuals with lived experience, and European Commission policymakers. The workshops served to contextualize InDepDash-derived findings, validate interpretability, and align outputs with policy priorities. Insights from these sessions directly informed the interpretation of results and the development of policy-relevant recommendations. The dashboard further supports transparency by providing direct access to source documents for in-depth exploration.

3 Results

3.1 Distribution of research across the *environome*

The analysis (Figure 2) revealed substantial imbalances in research attention across the depression environome:

1) The personal environment accounted for 50.1% of the total analyzed corpus ($n = 139{,}761$), with strong emphasis on

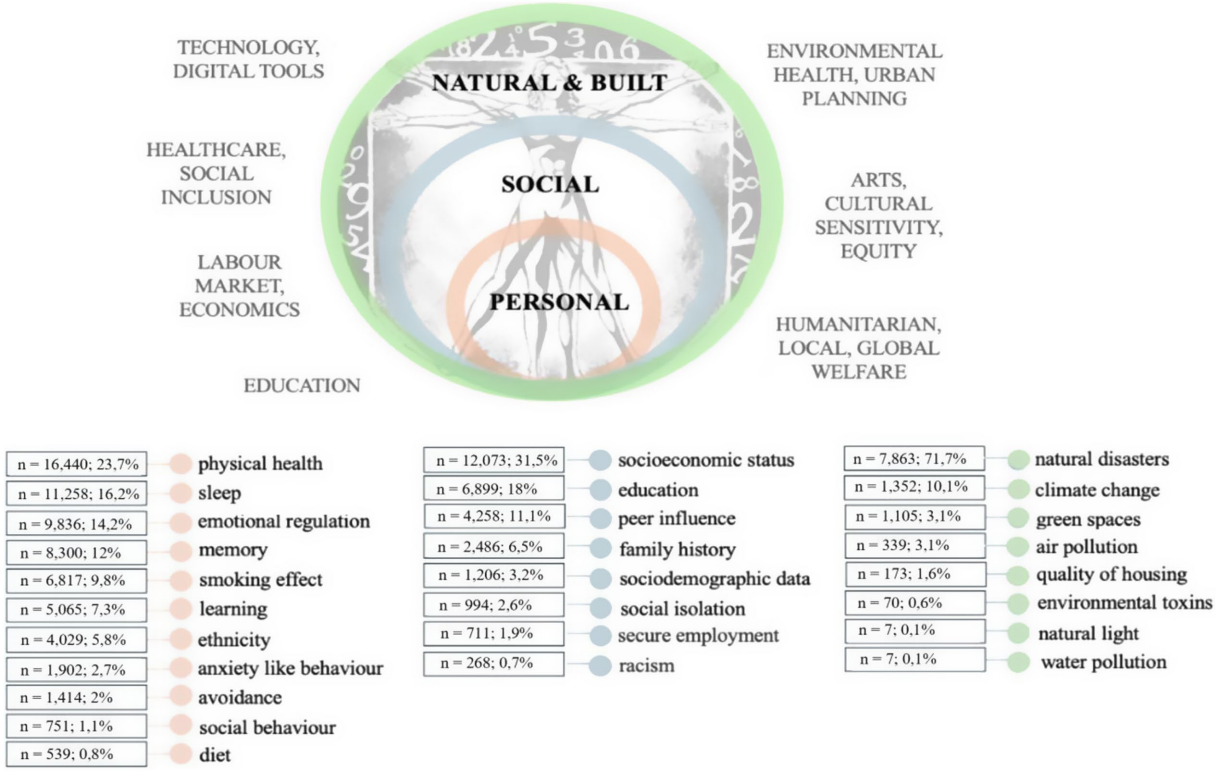


FIGURE 2
Individual's comprehensive environome: InDepDash is crafted to integrate the extensive and ever-evolving corpus of evidence-based knowledge and scientific literature—covering data from 2005 to 2025 facilitating the mapping of the depression environome (last access to the platform: 15 December 2025). Percentages indicate the proportion of the total analyzed corpus ($n = 139{,}761$) represented by each category, adapted from Coecke et al. (2025).

physical health (23.7%), sleep (16.2%), emotional regulation (14.2%), memory (12%), and smoking history (9.8%). Notably, physical health comorbidities alone were represented in 16,440 publications;

2) The social environment represented 28.6% of the analyzed literature corpus, with a focus on socioeconomic status (31.5%), education (18%), family history (6.5%), and social isolation (2.6%). However, important populations, including neurodivergent individuals and ethnic minorities, remain underrepresented.
3) In contrast, the natural and built environment accounted for only 14.3% of the total analyzed publications. Despite increasing recognition of the impact of natural disasters (71.7%), climate change (10.1%), and green spaces (3.1%) on mental health, these areas remain significantly understudied. For instance, natural disasters were addressed in 7,863 studies, while climate change appeared in only 1,352 publications.

These findings highlight critical structural gaps in the evidence base. While biological and social determinants are relatively well-studied, environmental determinants, particularly those related to climate change, remain underexplored despite their growing relevance. Geographic disparities further exacerbate these imbalances. Research output was concentrated in a small number of countries, including the United States (26,551 papers), China (19,220), and Germany (12,775), whereas low- and middle-income countries, which often bear a disproportionate burden of mental health challenges, are underrepresented (World Health Organization, 2017). In particular, the "geography of the environome" "in the retrieved literature", shows that research in high-income countries such as the U. S. and Germany primarily focuses on lifestyle-related factors (diet, smoking history, sleep) and chronic care. On the other hand, in low- and middle-income countries, such as Kosovo (147 papers), Mozambique (144 papers), and Albania (131 papers), the environome burden is seems driven more by foundational environmental issues, such as basic infrastructure, housing quality, and urban safety. This would suggest a regional bias in the scientific evidence base, i.e., unequal accessibility of research production across regions, where 'evidence-informed' policy in one context may not be translatable to another. Future research should prioritize mapping the environome specifically within low- and middle-income country contexts to support the development of culturally and geographically relevant, scalable mental health strategies. Additionally, regarding the distribution of research, further temporal analysis has revealed a notable evolution in scientific attention. While research addressing personal environmental factors (e.g., physical health and sleep) has maintained a steady presence throughout the 2005–2025 period, the focus on natural and built environments has shown a distinct shift. Specifically, studies addressing climate change, natural disasters, and environmental toxins have exhibited a significant increase in output over the 2020–2025 timeframe. This trend could suggest a growing recognition of the environmental determinants of mental health, aligning with recent advances in transdisciplinary research and the global integration of One Health frameworks.

3.2 Additional InDepDash-enabled evidence synthesis

The application of semantic analysis has enabled the identification of specific research clusters within the broader environome categories. These insights, presented in the "Additional Analysis" section of the dashboard, highlight notable imbalances in the density of available evidence across different determinants. For example, nutrition-related research appears highly granular. The platform identified 376 publications on the Mediterranean diet and 49 papers on the ketogenic diet, indicating a larger evidence base for certain dietary interventions compared to others. Additional findings include 843 papers related to omega-3 fatty acids, 276 papers related to milk consumption, 524 papers associated with folic acid, and 292 papers associated with zinc. Furthermore, flavonoids were examined through co-occurrence within the polyphenols domain, while probiotics were linked to 755 papers in the synbiotics ontology research field. These results quantify the relative research volume across individual determinants, providing a useful baseline for identifying both well-studied areas and potential knowledge gaps. However, it is important to note that these counts describe co-occurrence with depression-related concepts and do not establish causal effects or treatment efficacy. Rather, the ontology-based evidence-mapping approach facilitates pattern recognition across heterogeneous datasets, uncovering associations that may not be readily apparent through manual review. These associations should not be interpreted as evidence of causation and require further investigation to determine their relevance to depression outcomes.

4 Discussion

4.1 Implications for governance and ethical InDepDash deployment

InDepDash illustrates how natural language processing and semantic analysis can transform large-scale evidence synthesis. By leveraging ontology-based indexing and co-occurrence analysis (Panzarella et al., 2023; Tong and Renaudin, 2024), the platform enables automated mapping of relationships between depression and its determinants across the environome. This approach offers several advantages. First, it enables rapid processing of large volumes of literature: processing nearly 140,000 papers would require years of manual review. Automated analysis provides near-real-time synthesis as new evidence emerges. Moreover, automated semantic platform tools can automatically translate and analyze studies published in multiple languages, substantially widening the evidence base beyond English-language publications. Second, it facilitates pattern recognition across heterogeneous datasets, identifying associations that may not be apparent through manual review. Third, it supports systematic gap identification, highlighting underrepresented factors: urban design, transportation, and service access remain largely absent. Finally, the platform is inherently adaptive, allowing continuous updating as new evidence becomes available. These capabilities have direct implications for policy development. Indeed, despite existing syntheses, policymakers may benefit from more accessible, regularly updated maps of climate-related mental-health evidence; a critical gap given escalating climate impacts on vulnerable populations. Using InDepDash, targeted queries could identify relevant literature in hours rather than the 6–18 months required for traditional systematic reviews. A search for "climate change" co-occurrences with depression would reveal both evidence clusters (such as extreme weather events and heat stress) and critical research gaps in climate-vulnerable regions. The environome framework highlights that while 14.3% of research addresses natural

environmental factors, climate-specific mental health evidence remains sparse (1,352 papers). Such rapid, comprehensive synthesis, yet not equivalent to completing a quality-assessed systematic review, supports evidence-informed policy development, and policymakers navigating fragmented research landscapes. While such applications demonstrate InDepDash's potential, the integration of evidence-mapping platforms into policy processes raises important considerations related to trust, validation, and human–AI interaction. The TREAT framework (Hartung et al., 2025), encompassing Trustworthiness, Reproducibility, Explainability, Applicability, and Transparency, provides a useful foundation for guiding ethical AI deployment in this context. For policy dashboards such as InDepDash, these principles define the ethical perimeter for deploying AI in public health—setting the boundaries within which innovation must operate to remain trustworthy, transparent, and socially accountable. InDepDash exemplifies how semantic data analysis can bridge the evidence–policy divide, highlighting the importance of maintaining human oversight and validation.

4.2 From evidence-based to evidence-informed policy

Beyond evidence synthesis, digital intelligence platforms could support actionable decision-making. Based on InDepDash findings, as well as extensive consultation with interdisciplinary experts including mental health researchers, clinicians, individuals with lived experience, social and economic scientists, and contributors from the arts—conducted through *ad hoc* meetings and workshops, several key priority areas have been identified.

1) Integrating mental health into disaster preparedness: Natural disasters accounted for a substantial proportion of the research attention within the natural environment domain (71.7%), with approximately 7,863 studies identified. This indicates considerable research interest in the relationship between natural disasters and environmental and human health impacts. However, the extent of research attention should not be interpreted as direct evidence of the effectiveness of specific mental health interventions. Although Psychological First Aid (PFA) is recommended in international clinical practice guidelines as an early intervention for survivors of potentially traumatic events (https://pubmed.ncbi.nlm.nih.gov/21916629/), these recommendations are largely consensus-based, and evidence evaluating its effectiveness remains limited (Forbes et al., 2011). Furthermore, a systematic review and meta-analysis by Yani et al. (2025) reported only a very small reduction in depressive symptoms following universal educational interventions (SMD = −0.06), with very low-certainty evidence, highlighting the need for caution when interpreting intervention outcomes. In this context, the inclusion of psychological first aid, mobile mental health units and long-term psychosocial support in emergency response systems is proposed as an expert-informed recommendation emerging from the workshop discussions, rather than as an established evidence-based intervention effect.
2) Prioritizing natural and built environmental determinants in research funding: The analysis demonstrates that natural and built environment factors account for only 14.3% of the total evidence base, despite their growing relevance. Within this category, climate change is particularly underrepresented (approximately 1,400 publications), especially relative to its projected global impact. This imbalance highlights a critical research gap and justifies targeted investment toward natural and built environmental determinants such as heat exposure, air, water and noise pollution, biodiversity loss, and urban design.
3) Addressing demographic and population-level gaps: The results reveal significant disparities in population representation, with research heavily skewed toward adults (39,210 papers) compared to children (14,619 papers) and older populations (13,368 papers), groups particularly vulnerable to loneliness and isolation. Similarly, ethnic minority representation (non-Hispanic whites as the most studied group with 580 papers) reveals concerning disparities. These gaps limit the generalizability of findings and support policies that promote inclusive research and targeted mental health interventions for underserved groups.
4) Embedding depression literacy in education systems: The strong emphasis on personal environment factors (50.1% of the corpus), particularly emotional regulation, memory, and behavioral determinants, emphasizes the importance of early-life interventions. This evidence supports the integration of mental health literacy into education systems, addressing resilience-building, stress management, and accessing support networks (Yani et al., 2025).
5) Promoting neuroinclusive approaches: The results identify neurodivergent populations as underrepresented within the social environment domain. Given the known differences in how depression manifests in individuals with conditions such as autism and ADHD, this gap supports the development of neuroinclusive research agendas and tailored clinical and policy approaches.
6) Leveraging nature-based solutions: Although the overall share of environmental research is limited, the available evidence particularly within urban design and green space research (10.1% of the environmental category) consistently links access to natural environments with reduced depression risk. These findings identify nature-based approaches as a priority for further evidence assessment (Nieuwenhuijsen and Khreis, 2017).
7) Developing integrated monitoring systems: The temporal analysis highlights a recent increase (2020–2025) in research on environmental stressors such as climate change, natural disasters, and environmental exposures. This emerging trend suggests the need for forward-looking policy tools. Integrating mental health indicators into existing monitoring systems such as wastewater surveillance, early warning systems for water insecurity, and extreme heat could mental health data to enable proactive interventions (Gawlik et al., 2026; Bowes et al., 2023).
8) Expanding InDepDash: In addition to climate change, natural disasters, and environmental exposures, contemporary humanitarian stressors such as armed conflict, forced displacement, refugee and asylum status, relocation, family separation, detention, legal uncertainty, and post-migration living conditions should be incorporated into future InDepDash

iterations. These exposures are not only traumatic events but also sustained socio-environmental determinants of depression and related mental health outcomes (Blackmore et al., 2020), and their inclusion would improve the dashboard's relevance for conflict-affected, migrant, and displaced populations. InDepDash maps research attention and generates hypotheses, but policy relevance can be further strengthened when environmental and social signals can be linked to biologically plausible pathways. Human-relevant systems such as induced pluripotent stem cell (iPSC)-derived neural cultures, brain organoids, and microphysiological systems could help test whether determinants identified by the dashboard converge on pathways relevant to depression, including neuroinflammation, stress-response biology, endocrine disruption, synaptic function, mitochondrial dysfunction, and neuronal network activity. This would be particularly valuable for early-life exposures and neurodivergent populations, where vulnerability and symptom presentation may differ from the general adult literature.

9) Implementation considerations and challenges: The deployment of digital intelligence platforms in policy contexts requires addressing several challenges. Ethical considerations, including equity, privacy, and transparency, are central to responsible implementation. Human–AI collaboration models must ensure that computational outputs are complemented by expert interpretation. Additional requirements include international coordination for data sharing—the Global Coalition for Regulatory Science Research provides a model for such collaboration (Hamburg, 2011)—continuous validation of models and ontologies, and capacity building to support effective use by policymakers. These factors are essential for ensuring that such platforms deliver reliable and equitable outcomes at scale.

4.3 Limitations and mitigation strategies

This study has several limitations. Following analytical revisions, a 7% discrepancy remained between the total analyzed corpus and the proportions accounted for by the three domains. The analysis is restricted to PMC Open Access publications, potentially underrepresenting subscription-based and non-English literature. Consequently, the dashboard's coverage is determined by PMC's indexing and the Dimensions Processor's OCID mappings and does not include a substantial body of literature that may be relevant to environmental and global mental health research. Readers should therefore interpret geographic and thematic deficits with caution. Future study could incorporate multilingual semantic search, neural machine translation, cross-lingual embeddings, and language-specific ontology expansion, thereby allowing global mental health research to be mapped into the environome framework. However, such approaches should be implemented with safeguards, including native-speaker or domain-expert validation, transparent reporting of language coverage, uncertainty labels for translated or automatically mapped concepts, and evaluation of performance across languages and cultural contexts. Thus, AI should be framed not as eliminating language bias but as a scalable mechanism to reduce and audit it, making geographic and ethnic inequities in the evidence base more visible and actionable. The environome classification is based on co-occurrence patterns and does not imply causal relationships. To mitigate this limitation, InDepDash outputs should be interpreted as hypothesis-generating evidence maps rather than causal evidence; high-priority co-occurrence signals should be followed by targeted validation through systematic reviews, longitudinal or experimental studies, causal-inference approaches, and mechanistic evidence where available. A future dashboard version could add evidence-strength labels distinguishing literature density/co-occurrence from replicated associations, causal epidemiology, and biologically plausible mechanisms, thereby supporting responsible policy interpretation. While workshop validation with multidisciplinary experts enhances interpretability, formal inter-observer reliability assessment and comparison with manual systematic reviews remains ongoing. Clinicians should interpret InDepDash as a transparent evidence-mapping tool that supports literature navigation and hypothesis generation, rather than as a clinical decision support system. The platform requires continuous expert validation to ensure ontology coverage adapts to emerging research domains. These limitations highlight the role of InDepDash as a complementary tool that augments, rather than replaces, conventional evidence synthesis methods.

5 Conclusion

The rapid expansion of depression research presents both an opportunity and a challenge for policy translation. InDepDash demonstrates how digital intelligence platforms help bridge this gap. By operationalizing the environome framework and leveraging text-mining analytics, the platform provides a scalable approach to navigating fragmented research landscapes. However, realizing its full potential requires sustained investment in ethical AI, interdisciplinary collaboration, and human-centered design. As global challenges such as climate change and pandemics continue to shape mental health outcomes, such tools will become increasingly essential for supporting responsive, equitable, and data-informed governance. The next generation of mental health policy must be data-informed, transdisciplinary, and adaptive. Dashboards such as InDepDash are not standalone solutions, but they are indispensable scaffolding for 21st-century mental health governance. The challenge is not whether to use them, but how to deploy them responsibly, equitably, and at scale.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/Supplementary material.

Author contributions

SaC: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. GP: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. ER: Formal

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Conflict of interest

CB and SP are affiliated with Digital Science. MP was employed at SEIDOR Italy S.r.l., PR was employed at PERISO SA, and SG was employed at Fincons S.p.a. The primary authors SaC and GP independently designed and conducted the study analyses and prepared the manuscript, with input from scientists affiliated with the company limited to verifying technical details and addressing accessibility-related issues. JF is supported by a UK Research and Innovation Future Leaders Fellowship (MR/Y033876/1) and the NIHR Manchester Biomedical Research Centre (NIHR203308). JF has received honoraria, consultancy and/or advisory fees from Atheneum, Informa, Bayer, HedoniaUSA, Strive Coaching, Angelini, ParachuteBH, Arthur D Little Ltd., and the Richmond Foundation, independent of this study. SL is Chairholder of the Canada Excellence Research Chair in Neuroplasticity, Laval University, CERVO Brain Research Centre, Quebec, Canada and Research Director at the National Fund for Scientific Research, Belgium. SL is supported by Mind Care International Foundation; the National Natural Science Foundation of China (grant no. 81920108023), European Foundation of Biomedical Research FERB Onlus, fund Generet of King Baudouin Foundation. JS is an Executive Director of Neurala Biosciences and the connected not-for-profit Psyche Institute. JS is employed and holds equity with Neurala Biosciences. JS is also an advisory board representative for HedoniaUSA. JS also has received either presentation honoraria, travel support, clinical trial grants, book royalties, or independent consultancy payments from: Integria Healthcare & MediHerb, Pfizer, Scius Health, Key Pharmaceuticals, Taki Mai, Fiji Kava, Noetic Foundry, FIT-BioCeuticals, Blackmores, Soho-Flordis, Healthworld, HealthEd, Health Masters, Kantar Consulting, Angelini Pharmaceuticals, Grunbiotics, Polistudium, Global Pharma Group, Australian Natural Therapeutics Group, Research Reviews, Elsevier, Chaminade University, International Society for Affective Disorders, Complementary Medicines Australia, SPRIM, Terry White Chemists, ANS, Society for Medicinal Plant and Natural Product Research, Sanofi-Aventis, Omega-3 Centre, the National Health and Medical Research Council, CR Roper Fellowship, Medical Research Futures Fund, CSIRO Australia, Launch Victoria, Genesis Fund, Tin Alley Ventures.

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The author(s) declared that Generative AI was used in the creation of this manuscript. As non-native speakers, we used Grammarly and ChatGPT for checking grammar and language.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frai.2026.1903745/full#supplementary-material

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