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IoT-Based Preventive Mental Health Using Knowledge Graphs and Standards for Better Well-Being

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Abstract

Mental health is a highly regulated domain where AI systems must ensure accuracy, explainability, fairness, and safety while complying with frameworks such as HIPAA, MHPAEA, and emerging AI governance requirements. Neurosymbolic AI, which combines neural networks with symbolic reasoning, offers interpretable and transparent solutions aligned with the UN Sustainable Development Goal 3 ("Good Health and Well-Being"). This hybrid approach addresses the scalability and integration challenges of regulated healthcare while maintaining robust performance for complex mental health applications. In the United States, more than one-fifth of adults face mental health issues, with conditions like depression and burnout requiring preventive interventions. Explainable AI systems can support these needs by offering clear clinical justifications and maintaining audit trails for regulatory compliance. To this end, we present a *neurosymbolic AI-enabled Digital Twin (DT) framework* integrated with Mental Health Knowledge Graphs to support proactive care. The Digital Twin continuously monitors emotional states using wearable signals while ensuring transparency and interpretability for compliance. It delivers personalized insights and predictive analytics with explainability, meeting the need for systems that demonstrate medical necessity and clinical reasoning to auditors. Our Mental Health Knowledge Graph encodes compliance requirements, clinical guidelines, and regulatory policies in symbolic form. This enables the integration of explicit clinical knowledge (e.g., nutritional interventions such as magnesium for depression management) with neural models, ensuring fairness, transparency, and accountability. The Knowledge Graph builds on ontology-based mental health resources classified within specialized catalogs, forming the symbolic reasoning backbone of our system. The framework further addresses Digital Twin challenges by using standardized data formats, communication protocols, and regulatory-compliant exchange mechanisms. We incorporate standards including ISO/IEC JTC 1/SC 41 IoT specifications, W3C Semantic Web technologies (RDF, RDFS, OWL, SPARQL), ETSI SmartM2M SAREF4EHAW for medical devices, and ISO/IEC 21838 ontology standards. This standards-driven approach ensures interoperability, preserves compliance documentation, and maintains audit trails, ultimately bridging the gap between intelligence and regulation through neurosymbolic AI.

Introduction

More than one-fifth of adults in the United States have dealt with mental health issues, according to the National Institute of Mental Health (National Institute of Mental Health 2024). This situation has led to the government setting aside $280 billion to improve the availability and quality of mental health services (Council of Economic Advisers 2022). Mental health can increase productivity and efficiency, improve staff morale, and reduce absenteeism (Albraikan 2019). There are numerous reviews on mental health using Wearable sensors and Artificial Intelligence Techniques (Gedam and Paul 2021).

The *Sustainable Development Goals (SDGs)* (United Nations 2015) provide the UN a roadmap for development with Agenda 2030 as a target. SDG3 "Good Health and Well-Being" ensures healthy lives and promotes well-being for all ages. Digital technologies, particularly neurosymbolic AI approaches that combine neural networks with symbolic reasoning, can support SDG3 through more interpretable and explainable AI systems that are crucial for regulated healthcare domains.

Mental Health as a Regulated Domain Use Case: Mental health represents a highly regulated domain with complex compliance requirements that demand robust, interpretable, and transparent AI solutions. Behavioral health facilities operate within a complex regulatory framework that encompasses federal, state, and local regulations, including those set by the Substance Abuse and Mental Health Services Administration (SAMHSA) and the Centers for Medicare and Medicaid Services (CMS). Current regulations include HIPAA protections specific to mental health information, with new regulations expected in 2025, and the Mental Health Parity and Addiction Equity Act (MHPAEA) requirements that took effect in 2024. Recent legislative developments, such as New York's 2025 AI Companion laws requiring disclosure and suicide prevention measures for

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emotionally interactive AI systems, highlight the emerging regulatory focus on AI safety in mental health applications.

This regulatory complexity makes mental health an ideal domain for neurosymbolic AI systems that can provide accuracy, explainability, fairness, safety, and assurance - key criteria for regulated domains. Mental health providers must demonstrate medical necessity, maintain detailed documentation for audit compliance, and ensure proper billing accuracy under CMS requirements. These compliance demands require AI systems that can provide clear reasoning and justifications for their decisions, making neurosymbolic approaches particularly valuable for bridging intelligence and compliance requirements.

We review hereafter definitions relevant to mental health, the necessity for neurosymbolic AI-enabled Digital Twins for Mental Health that ensure compliance with regulatory requirements, and the benefit of Knowledge Graphs for achieving transparency and interpretability in this regulated domain.

Mental health (World Health Organization 2024) is a state of mental well-being that enables people to cope with the stresses of life, realize their abilities, learn well, and work well, and contribute to their community. It has intrinsic and instrumental value and is integral to our well-being. *IEEE 7010* (IEEE Standards Association 2020) defines *well-being* as ”the continuous and sustainable physical, mental, and social flourishing of individuals, communities, and populations where their economic needs are cared for within a thriving ecological environment.”

Stress vs. *Anxiety:* People under stress (American Psychological Association 2024) experience mental and physical symptoms, such as irritability, anger, fatigue, muscle pain, digestive troubles, and difficulty sleeping. Anxiety, on the other hand, is defined by persistent, excessive worries that don't go away even in the absence of a stressor (American Psychological Association 2024). *Burnout* and even *depression* (World Health Organization 2023) could be reduced by encouraging better preventive health. Lack of patient knowledge and focus to take care of their health before it is too late. New trends such as positive psychology (Seligman 2008) and mindfulness (MBSR) (Kabat-Zinn 2003) are highly encouraged in the USA.

Depression is considered the main mental health crisis by the *World Health Organization (WHO)* (Mullick et al. 2022). Mental health includes emotional, psychological, and social well-being changes. *DSM-V (Diagnostic and Statistical Manual of Mental Disorders)* (American Psychiatric Association 2022) references more than 70 mental disorders that complement the International Classification of Diseases (ICD). DSM-V helps clinicians and researchers define and classify mental disorders, which can improve diagnoses, treatment, and research. DSM-V provides a form with checklists of symptoms for better diagnosis. Burnout does NOT appear in DSM and ICD.

Mental illness is a type of health condition that changes a person's mind, emotions, or behavior and has been shown to impact an individual's physical health (Su 2020). *Depressive disorders*, or unipolar depression's symptoms are low mood, loss of interest in day-to-day activities, significant weight changes, reduction of mobility, constant fatigue, difficulty concentrating, and feelings of worthlessness that can be diagnosed, and severity, using the Patient Health Questionnaire-9 (PHQ-9) (Gutierrez et al. 2021).

The Necessity of Neurosymbolic AI-enabled IoT Digital Twin using Knowledge Graphs for Achieving SDG-3: An IoT Digital Twin designed for proactive mental health care, powered by neurosymbolic AI, corresponds with four of the United Nations' Sustainable Development Goals. Neurosymbolic AI, which combines neural networks with symbolic reasoning, is positioned to revolutionize healthcare in 2025 by offering more accurate, interpretable, and adaptable solutions to complex healthcare challenges, with companies like Amazon releasing neurosymbolic AI features that minimize hallucinations and ensure 99

This hybrid approach addresses the limitations of traditional AI systems by providing robust, interpretable, and efficient solutions to complex problems particularly crucial in highly regulated domains like mental health. By requiring alignment of neural network behaviour with compliance requirements specified as rules, regulations, guidelines, and policies encoded in symbolic representation, these systems can provide clear reasoning and justifications for their decisions, making it easier to ensure compliance with regulatory requirements.

We provide a pragmatic approach to developing neurosymbolic IoT Digital Twins using domain-specific standards and knowledge graphs, which would advance mental health care and well-being while ensuring fairness, transparency, and accountability. Disparities in mental health care access are prevalent, varying among regions, socioeconomic statuses, and genders. By prioritizing preventive strategies using domain-specific standards (e.g., questionnaires, guidelines) and leveraging neurosymbolic AI-enabled IoT technology, this endeavor can potentially mitigate these access gaps while maintaining scalability and integration complexity management.

Why do we need Neurosymbolic Digital Twins for Mental Health? The *StandICT landscape of Digital Twins (DT)* (StandICT Project Consortium 2023) reminds that ”Digital Twin” was first introduced by Professor Michael Grieves from the University of Michigan in 2002. According to *ISO/IEC 30173 Digital twin – concepts and terminology* (International Organization for Standardization 2021c), DTs are defined as a ”digital representation of a target entity with data connections that enable convergence between the physical and digital states at an appropriate rate of synchronization.”

Recent advances in neurosymbolic AI have enabled the creation of digital twins that meet regulatory requirements for trustworthy, interpretable decision support in complex healthcare systems. The Alan Turing Institute is developing neuro-symbolic AI models deployable within digital twins specifically designed for applications where trust and interpretability are paramount - essential characteristics for regulated healthcare domains. Digital twin technology in healthcare enables patient-specific approaches while maintaining compliance documentation requirements by analyzing data from multiple sources including genetics, medical history, vital signs, and lifestyle choices.

Notable implementation of DTs include Siemens Healthineers (Erol et al. 2020), IBM Maximo Application Suite (IBM Corporation 2024) and Philips HeartModel (Philips

Healthcare 2018). In the context of mental health as a regulated domain, neurosymbolic DTs can help with emotion monitoring using physiological signals (e.g., collected via wearables) while providing the explainability and interpretability requirements necessary for compliance with healthcare regulations. These systems must demonstrate medical necessity, maintain audit trails, and provide clear justifications for clinical decisions to meet regulatory standards.

Digital twins in neuroscience enable modeling of brain functions and pathology while maintaining regulatory compliance, offering approaches to studying complex relationships between brain network dynamics and clinical outcomes with full audit trails. Healthcare DTs facilitate monitoring, understanding, and optimization of human functioning while meeting regulatory requirements for documentation and compliance (Laamarti et al. 2020), (Ferdousi et al. 2022), (Albraikan 2019), (Anand and Dhanalakshmi 2024) with better personalization (Bagaria et al. 2020) using neurosymbolic AI technologies that ensure explainability and accountability in regulated mental health applications. Healthcare DT challenges in regulated mental health domains highlight the need for standardizing data format, communication protocols, and data-exchange mechanisms that meet regulatory compliance requirements (Turab 2023).

Why do we need Knowledge Graphs for Regulated Mental Health Applications? *The European Human Brain Project (150 000 000 Euros, 161 partners), more precisely, the EBRAINS KG* (EBRAINS Consortium 2023), is a synergy project between neuroscience, computing, informatics, and brain-inspired technologies, encouraging open-science through a web-based system to share tools, etc. However, when looking for keywords such as cortisol (the stress hormone), limited resources can be found, highlighting the need for more comprehensive knowledge representation in mental health domains.

Knowledge Graphs (Sheth et al. 2019) can use ontologies to structure data and provide the symbolic reasoning component essential for neurosymbolic AI systems in regulated domains. An ontology provides a shared common understanding of a domain (Gruber 1995). The use of ontologies is already recognized in the biomedical domain with BioPortal ontology catalog (National Center for Biomedical Ontology 2024). In mental health applications, Knowledge Graphs enable the encoding of compliance requirements, clinical guidelines, and regulatory policies in symbolic representations that can be integrated with neural network behavior to ensure fairness, transparency, and accountability.

Ontology Development 101 methodology (designed by the creators of the Stanford Protégé Ontology Editor tool) encourages reusing domain knowledge by reusing ontologies in Step 2 "Consider reusing ontologies." In this paper, we describe semantic interoperability applied to mental health as a regulated domain, building upon our health IoT semantic interoperability past work (Gyrard and Sheth 2020) (Gyrard et al. 2022) while addressing the specific challenges of scalability, integration complexity, and ensuring fairness and transparency in neurosymbolic systems designed for regulatory compliance.

Toward Converging Standards and Semantic Web Technologies for Regulated Mental Health AI: We illustrate the vision of aligning neurosymbolic AI technologies with Semantic Web and Data spaces and Standards such as ISO, IEC, and W3C as depicted in Figure 1. This convergence is essential for developing AI systems that can meet the key criteria for regulated domains: accuracy, explainability, fairness, safety, and assurance. W3C Standards are more adapted to Semantic Web technologies such as W3C RDF, W3C RDFS, W3C OWL, W3C SPARQL, etc. Semantic Web technologies include Knowledge Graphs with ontologies and Linked Data that provide the symbolic reasoning foundation for neurosymbolic AI approaches.

There are also ISO standards about ontologies such as ISO/IEC 21838-1:2021 Information technology — Top-level ontologies (TLO) — Part 1: Requirements (International Organization for Standardization 2021a), ISO/IEC 21838-2:2021 Information technology — Top-level ontologies (TLO) — Part 2: Basic Formal Ontology (BFO) (International Organization for Standardization 2021b), which provide standardized frameworks for representing clinical knowledge and regulatory requirements in mental health as a regulated domain.

"Charting past, present, and future research in the semantic web and interoperability" highlights the importance of semantic interoperability (Rejeb et al. 2022) for regulated healthcare domains. The recommendation is that interoperability should remain a primary research focus with closer collaborations between industry, governments, and standards organizations to develop compliant AI models that can address the complex regulatory landscape of mental health as a regulated domain while ensuring the robustness, interpretability, and efficiency required for regulatory approval and audit compliance.

Despite the promising advancements in neurosymbolic AI for mental health as a regulated domain, challenges such as scalability, integration complexity, and ensuring fairness and transparency remain critical for regulatory compliance. Addressing these challenges through interdisciplinary research focused on regulatory requirements is crucial for fully realizing the potential of neurosymbolic AI in regulated healthcare domains. The convergence of neural networks, symbolic reasoning, knowledge graphs, and compliance-aware digital twins represents a pathway toward AI systems that can bridge the gap between intelligence and regulatory compliance in mental health applications requiring audit trails, explainability, and accountability.

Our vision has been shared with the EUCloudEdgeIoT Concentration and Consultation Meeting on Computing Continuum: Uniting the European ICT community for a digital future in May 2023 (EUCloudEdgeIoT 2023).The remainder of this chapter is organized as follows: Related Work: IoT, Digital Twin, and AI for Mental Health, Stress and Well-Being, Standards for Mental Health and Well-Being: Artificial Intelligence (Semantic Web, Ontologies), LOV4IoT Ontology Catalog for IoT-Based Depression and Mental Health KGs (which includes mapping to standards ontologies), the project use cases in Ontology-Based Mental Health Recommender System and Project Use Cases: ACCRA, etc, and Conclusion and Future Work.

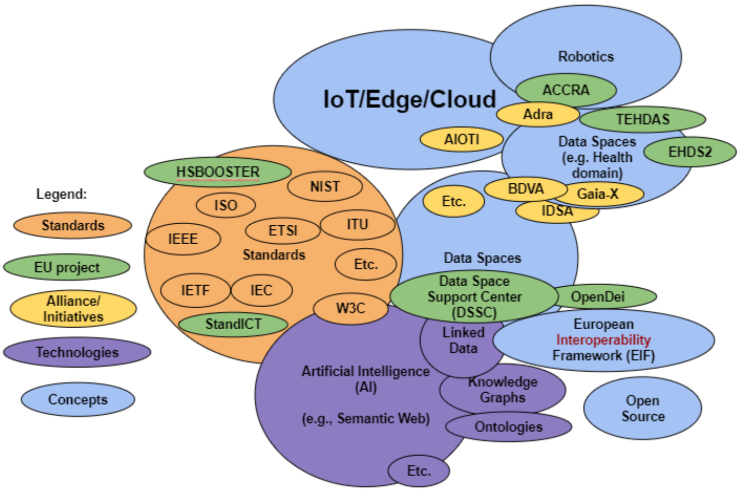

Figure 1. Standards, Semantic Web and Data Spaces applied to Health

Related Work: IoT, Digital Twin, and AI for Mental Health, Stress and Well-Being

This section reviews (i) IoT-based monitoring for mental health and stress, (ii) Digital Twin (DT) approaches for health and well-being, and (iii) AI methods for mental-health inference. Table 1 summarizes representative systems, sensors, and reasoning methods.

IoT for mental health. Garcia-Ceja et al. (2018) survey 23 mental-health monitoring systems that use IoT sensors and machine learning across conditions such as bipolar disorder, migraine, depression, anxiety, stress, and epilepsy. Devices span eye trackers, heart-rate variability, electrodermal activity, accelerometers/gyroscopes, GPS, smartphone usage, and wearables. Our focus is on disorders most relevant to preventive care—stress, anxiety, and depression—rather than bipolar or migraine. Gutiérrez et al. review 24 IoT applications (2010–2020) designed for data acquisition, self-organization, SLA, and identity management, with DSM-5 used to categorize disorders (Gutierrez et al. 2021). Sensors include proximity, ambient light, inertial units, sound, barometers, temperature, and humidity. The *HealthyOffice* app targets eight workplace mood states using smartphones and wearables (Zenonos et al. 2016). Notably, these surveys rarely address ontologies or knowledge graphs (KGs), leaving gaps in semantic interoperability. This motivates our ontology catalog (LOV4IoT Mental Health Ontology Catalog and Knowledge Graph section; Table 2).

IoT for stress detection. Stress—an adaptive response to challenging conditions (Gedam and Paul 2021)—is commonly inferred from ECG, EEG, PPG, and related wearable signals with ML classifiers. Reviews and systems report multimodal sensing of cardiac, neural, muscular, electrodermal, respiratory, blood-volume pulse, and skin temperature signals (Chen et al. 2021). Recent prototypes also combine heart rate, SpO_2, temperature, and pressure for emergency detection and management (Mullick et al. 2022).

Digital Twins for health and well-being. Mental health as a regulated domain requires DTs that ensure accuracy, explainability, fairness, safety, and assurance while maintaining compliance with complex regulatory frameworks including HIPAA privacy requirements, MHPAEA parity standards, and CMS documentation mandates. Surveys categorize DT applications across sports, well-being, and rehabilitation, yet fail to address the regulatory compliance challenges specific to mental health applications, particularly the need to report not only ML methods, devices, and performance, but also audit trails, clinical decision justifications, and regulatory compliance documentation (Gámez Díaz et al. 2020).

A consistent theme in regulated healthcare domains is standardization for compliance: DTs require common data formats, communication protocols, and exchange mechanisms that support regulatory audit requirements, making ISO's work increasingly relevant for maintaining accountability and transparency in clinical decision-making (Turab 2023). For Well-being Digital Twins (WDTs) applied to mental health as a regulated domain, key challenges extend beyond technical considerations to include regulatory compliance with heterogeneous data and standards, bias mitigation and fairness assurance, trust and transparency for clinical decisions, consent management under HIPAA requirements, and visualization of clinical reasoning for audit purposes. Mental health WDTs operating within regulated environments demand large-scale data management with full audit trails, predictive analytics with explainable AI justification, quality of experience (QoE) metrics tied to clinical outcomes, personalization within regulatory guidelines, and pathway understanding that supports medical necessity documentation (Ferdousi et al. 2022).

An ISO/IEEE 11073-compliant architecture demonstrates how personal health devices can feed standardized DT pipelines while maintaining the documentation and compliance requirements essential for regulated mental health applications, though current implementations lack the neurosymbolic AI integration necessary for explainability and regulatory transparency (Laamarti et al. 2020). Existing WDT examples highlight the regulatory gap. *inHarmony* is a workplace well-being DT that combines emotion detection and biofeedback, evaluated in a study with 35 participants using the Empatica E4 wearable sensor (Albraikan 2019). While effective for general wellness, it lacks the clinical

Authors	Year	Research Problem Addressed & Project	Sensor or Measurement Type	Reasoning
Garcia-Ceja et al.	2018	*Mental Health Monitoring* Systems (NHMS) Survey	✓Heart rate, GSR, body or skin temperature	Survey paper ✓ML algorithm
Kim	2017	*Depression* Severity Elderly People, AAL	✓Infrared motion sensor	✓Bayesian Network Decision Tree, SVM, ANN
Zhou et al.	2015	Monitoring *mental health* states	✓Heart rate, pupil variation, head movement, eye blink, facial expression	✓ML (Logistic regression, SVM)
Garcia-Ceja et al.	2016	*Stress*	✓Accelerometer data (from smartphone)	✓Naive Bayes, Decision Tree
Yoon et al.	2016	New *stress* monitoring patch	✓Skin conductance, pulse wave, skin temperature	✗-
Lu et al.	2012	*Stress*Sense	✓Voice data (smartphone)	✓GMMs
Chang et al.	2011	AMMON: *Stress* detector	✓Voice data	✓SVM
Erol et al.	2020	*DT* for patients and medical devices	✗No	✗No
Liu et al.	2019	CloudDTH - *DT* healthcare	✓Yes Wearable medical devices	✗No
Albraikan	2019	inHarmony - Emotional Well-being *DT*	✓Yes Empatica E4	✗No

Table 1. Digital Twin for Mental Health, Depression, Stress, and Well-Being: sensors, reasoning, and applications.

justification and audit-trail features needed for regulated mental health diagnosis and treatment. Similarly, *CloudDTH*, a cloud-based DT framework for elderly care that integrates wearables with big-data analytics, shows technical feasibility but does not meet the explainability and transparency requirements essential for mental health regulatory compliance (Liu et al. 2019).

Industry DT implementations such as Siemens Healthineers' hospital DTs and Philips' HeartModel for 3D, CT-guided cardiac procedures represent technically advanced solutions, yet these focus on physical health applications where regulatory requirements differ significantly from the complex compliance landscape of mental health domains requiring explainable AI, bias mitigation, and transparent clinical reasoning. Sooma's exploration of brain-signal stimulation for depression with remote monitoring approaches regulated mental health DT applications but lacks the neurosymbolic AI framework necessary to provide the symbolic reasoning, clinical justification, and regulatory compliance documentation required for mental health as a regulated domain.

Despite growing momentum in healthcare DTs, we identify a critical gap: no neurosymbolic AI-enabled WDTs are purpose-built for regulated mental health diagnosis and treatment that can simultaneously ensure accuracy in clinical outcomes, explainability for regulatory audits, fairness in algorithmic decision-making, safety in clinical recommendations, and assurance of compliance with mental health regulatory frameworks. Existing WDT efforts target general well-being or organ-specific applications but cannot address the unique challenges of mental health as a regulated domain, where AI systems must provide transparent reasoning, maintain comprehensive audit trails, demonstrate medical necessity, and ensure compliance with specialized mental health privacy and parity regulations while managing the scalability and integration complexity inherent in regulated healthcare environments.

AI for mental health. "Positive AI" advocates designs that intentionally support human well-being, outlining knowledge and motivation challenges (e.g., operationalizing well-being, incentives, risks, access) (van der Maden et al. 2023). Classical ML approaches—SVMs, decision trees, naïve Bayes, k-NN, and logistic regression—remain common for mental-state identification (Srividya et al. 2018). However, most prior work underutilizes health data standards and rich semantic models. In contrast, our approach centers KGs/ontologies (LOV4IoT Ontology Catalog for IoT-Based Depression and Mental Health KGs section) and standards (Standards for Mental Health and Well-Being: Artificial Intelligence (Semantic Web, Ontologies) section) to improve interoperability, transparency, and regulatory readiness.

Standards for Mental Health and Well-Being: Artificial Intelligence (Semantic Web, Ontologies)

We review Standards Development Organizations (SDOs) relevant to (mental) health and AI—especially Semantic Web and ontology work—including ETSI, ITU/WHO, ISO, W3C, NIST, and IEEE. These bodies define health and IoT ontologies, device models, and data exchange standards that underpin interoperability for sensing and reasoning systems (Figure 2).

ETSI SmartM2M SAREF for EHealth/Ageing-Well Ontology

SAREF4EHAW (ETSI SmartM2M Technical Committee 2020) surveys standards (e.g., IEEE, ETSI, oneM2M, SNOMED) and platforms, and targets use cases such as daily activity monitoring, cognitive stimulation for mental-decline prevention, social-isolation prevention, and home safety. It reuses sensor/measurement ontologies (OGC O&M, SensorML; W3C/OGC SOSA/SSN; NASA QUDT) and domain ontologies (ISO/IEEE 11073 PHD, ETSI SmartBAN, FHIR RDF, FIESTA-IoT, Bluetooth LE profiles, MIMU-Wear, AHA wearables). SAREF is mapped to the oneM2M base ontology (2017) and captures 43 ontological requirements and 59 service-level assumptions for the eHealth/Ageing-Well domain; for example, ECG device concepts (Muthalagu et al. 2023). *SAREF4WEAR* (ETSI SmartM2M Technical Committee 2024) extends SAREF for wearables. **Note:** We did not find ETSI standards specific to mental health beyond well-being/ageing contexts.

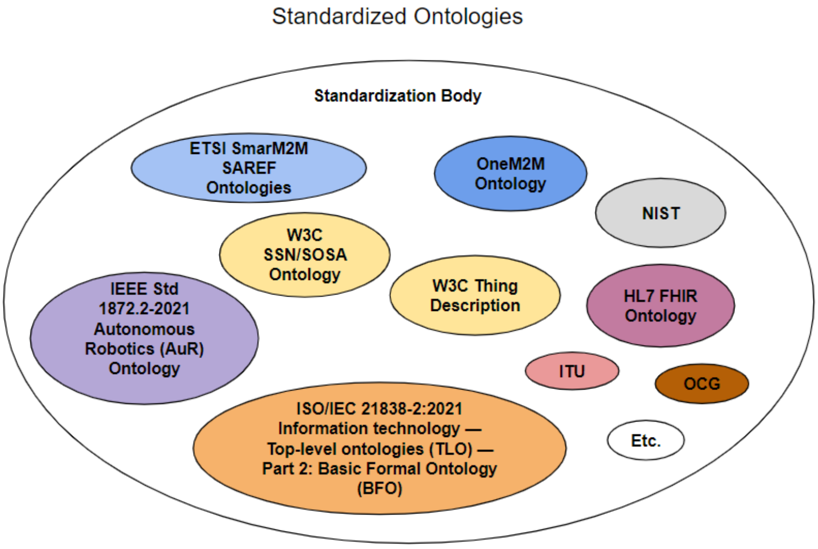

Figure 2. Standardized Ontologies

ITU/WHO Focus Group on Artificial Intelligence for Health

The *FG-AI4H* (International Telecommunication Union (ITU) and World Health Organization (WHO) 2018) develops assessment frameworks, benchmarking tools, and guidance for AI in health, emphasizing explainability and interpretability. Its use cases span traditional medicine, psychiatry, neurological disorders, and fall detection, with recommendations on ontology/NLP for knowledge extraction, decision support, predictive analytics, monitoring, and virtual assistants. **Note:** No dedicated mental-health standard was identified within this group.

ISO Health Standards

CEN/ISO EN 13606 specifies an EHR communication architecture for semantic interoperability across systems. Within *ISO/IEC JTC 1/SC 41* (IoT and Digital Twin), work is underway on *IEC 30197 / IoT for Stress Management, Good Health & Well-Being*. A joint *SC 42 AI* effort on "AI-enabled Health Informatics" surveys impacts on ISO/TC 215 standards. The *ISO/IEEE 11073* family enables plug-and-play personal health device communication and is widely adopted (e.g., Laamarti et al. 2020); it does not itself cover privacy/security. NIST collaborations have produced XML schemas and tooling aligned with 11073 (Garguilo et al. 2007). **Note:** Beyond EHR and device communication, ISO mental-health–specific standards remain limited and warrant further exploration.

W3C Semantic Web Health Care and Life Sciences Community Group (HCLS CG)

The *W3C HCLS CG* (W3C Health Care and Life Sciences Community Group 2006) promotes Semantic Web technologies for healthcare, life sciences, and clinical research, developing use cases and liaising with standards bodies. **Note:** Outputs emphasize areas like drug–drug interaction; we did not find mental-health–specific standards.

NIST Health Standards

NIST advances semantic interoperability for medical devices, including tooling based on *ISO/IEEE 11073* (Garguilo et al. 2007). **Note:** Work focuses on device semantics rather than mental-health–specific content.

IEEE Health Standards

IEEE digital health standards target interoperability, efficiency, and quality of care. Relevant items include: (1) *IEEE 7010* (well-being definition/assessment), (2) *IEEE 1752.1-2021* for open mobile health data (metadata, sleep, physical activity), (3) *ISO/IEEE 11073* medical device communication, and (4) *IEEE P1157 MEDIX* for exchanging medical information across heterogeneous systems. **Note:** IEEE 7010's well-being framing is useful for preventive perspectives on mental health.

Standards: Conclusion

Across SDOs, we find rich foundations for data models, devices, and interoperability, but few standards tailored to mental health. ETSI SAREF4EHAW and W3C HCLS emphasize semantics; ITU/WHO FG-AI4H guides AI evaluation; ISO/EN 13606 and ISO/IEEE 11073 enable EHR and device exchange; IEEE 7010 and 1752.1 address well-being and mHealth data. Ongoing efforts—e.g., SC 41's IoT for Stress Management and SC 42's AI-enabled Health Informatics—indicate momentum. Our work builds on these standards while addressing mental-health–specific semantic needs via ontologies and knowledge graphs.

LOV4IoT Ontology Catalog for IoT-Based Depression and Mental Health KGs

Ontology catalogs such as BioPortal (Noy et al. 2009), Linked Open Vocabularies (LOV) (Vandenbussche et al. 2016) do not cover sensors (Internet of Things). For this reason, we built the LOV4IoT ontology catalog (introduced in LOV4IoT Mental Health Ontology Catalog and Knowledge Graph section), with a subset specific to mental health and depression (demonstrated in Table 2), and emotion ontologies explained in (Gyrard et al. 2021; Gyrard and Boudaoud 2022). Mapping to Standards such as ETSI SmartM2M SAREF4EHAW is mentioned in Mapping to Standards: ETSI SmartM2M SAREF4EHAW section. Mapping to standardized health KGs/ontologies/terminologies such as SNOMED-CT, FMA, RXNORM, MedDRA, LOINC, ChEBI, or well-known knowledge graphs such as DBpedia is described in Mapping to Standardized Health KGs/Ontologies/Terminologies section.

LOV4IoT Mental Health Ontology Catalog and Knowledge Graph

We have designed an ontology catalog for depression and mental health, called *LOV4IoT Mental Health* (Gyrard, Amelie and contributors 2025) (Table 2).

GENA (Graph of mEntal-health and Nutrition Association) (Dang et al. 2023) encodes relationships between nutrition and mental health, extracting knowledge from PubMed abstracts. It contains 43,367 relationships across nutrition, biochemical, and disease concepts, and integrates multiple ontologies such as DOID, CHEBI, FMA, ASDTTO, FOODON, MFOMD, PR, and SYMP.

DSM-V (Diagnostic and Statistical Manual of Mental Disorders) (American Psychiatric Association 2013) defines and classifies more than 70 mental disorders, complementing ICD. It is widely used by clinicians and researchers to guide diagnosis and treatment.

The *Mental Health Ontology* (Hadzic et al. 2008) models disorders, factors, and treatments, while the *Mental Functioning Ontology (MF)* and *Mental Disease Ontology (MD)* (Hastings et al. 2012) represent mental processes and disorders, aligned with BFO and OBO Foundry principles.

Depression KG (Huang et al. 2017) applies KG reasoning to major depressive disorder, addressing dataset heterogeneity and inconsistency. *MDepressionKG* (Fu et al. 2021) integrates microbial metabolism and human disease data to study comorbidities. *CSMH Ontology* (Zhang and Chen 2020) structures information resources for college student mental health services.

Ontology for Schizophrenia Spectrum Disorders (Amoretti et al. 2019) models DSM-5 compliant classes, symptoms, and patient entities. *Ontology for Mental Health Management in Brazil* (Yamada et al. 2018) supports Semantic Web decision support in regional healthcare networks.

Mapping to Standards: ETSI SmartM2M SAREF4EHAW

Mapping to the *ETSI SmartM2M SAREF4EHAW* ontology (SAR 2020; ETSI SmartM2M Technical Committee 2024) is detailed in (Gyrard and Kung 2022), focusing on the sensor types used.

Mapping to Standardized Health KGs/Ontologies/Terminologies

Mappings to SNOMED-CT, FMA, RXNORM, MedDRA, LOINC, MESH, GALEN, and CHEBI are discussed in (Gyrard and Boudaoud 2022), along with DBpedia links for emotion concepts. Only a subset of emotion ontologies, such as Hastings's Emotion Ontology (Hastings et al. 2011), are indexed on BioPortal.

Ontology-Based Mental Health Recommender System and Project Use Cases: ACCRA, etc.

This section outlines representative use cases: (i) social robots for active and healthy aging (the ACCRA EU–Japan project; ACCRA European–Japan Project: Social robots to support active and healthy aging section), (ii) large language models (LLMs) for mental health (Large Language Models (LLMs) for Mental Health section), and (iii) additional mental-health projects spanning depression and suicide (Other Projects on Mental Health section).

ACCRA European–Japan Project: Social robots to support active and healthy aging

ACCRA (Agile Co-Creation of Robots for Ageing) (ACCRA Consortium 2017; Gyrard et al. 2021) develops emotion-aware social robots co-created with older adults, clinicians, and engineers. Three robots—Buddy, ASTRO, and RoboHon—target daily living, mobility, and conversational support. The systems fuse IoT sensing with AI/knowledge-based reasoning to perceive and convey emotions in real time, aiming to reduce social isolation and support independent living through co-creation with end users and multidisciplinary teams.

Large Language Models (LLMs) for Mental Health

LLMs demonstrate strong fluency and broad task coverage (QA, summarization, recommendation) (Minaee et al. 2024), but face well-documented issues with hallucination, inconsistency, and explanation quality (Rawte et al. 2023; Mohammadi et al. 2024; Zhang et al. 2023b). These concerns limit adoption in sensitive domains like mental health (Gaur and Sheth 2024). Work on instruction tuning and retrieval-augmentation (Zhang et al. 2023a; Sheth et al. 2022; Lewis et al. 2020; Tilwani et al. 2024) is promising, yet effectiveness in clinical contexts remains mixed; e.g., LLMs struggle with clinical questionnaires (Gupta et al. 2022), and architecture changes have been proposed to improve safety (Roy et al. 2023b). Domain-specific models (e.g., Mental-LLM, MentaLLaMA) show potential but uneven reliability (Yang et al. 2023; Hua et al. 2024; Chen et al. 2023). Retrieval-augmented agents and KG-augmented approaches continue to advance (Gaur et al. 2022; Sarkar et al. 2023; Abbasian et al. 2023; Yang et al. 2024).

Other Projects on Mental Health

Growing demand and workforce shortages motivate automated early screening and decision support. Traditional

Authors	Year	Project	Ontology-based project	Reasoning
Hastings et al. Hastings et al. (2012)	2012	Mental Disease (MD) Ontology	✓(online code)	No
Amoretti et al. Amoretti et al. (2019)	2019	Mental Disorder / Schizophrenia Ontology	✓(online code)	OWL-DL
Chang et al. Chang et al. (2013, 2015)	2013–2015	Depression Ontology	✓(not shared)	Bayesian networks, Jena rules
Huang et al. Huang et al. (2017)	2017	DepressionKG	✓(datasets)	No
Hadzic et al. Hadzic et al. (2008)	2008	Mental Health Ontology	✓(not shared)	No
Jung et al. Jung et al. (2017, 2015)	2015–2017	Depression Ontology (Twitter, adolescents)	✓(not shared)	No

Table 2. Ontology-based depression and mental health projects

methods rely on lengthy questionnaires and interviews (e.g., DSM-5 assessment measures) (National Institute of Mental Health (NIMH) 2024) and public policy responses emphasize cost and access (Council of Economic Advisers (CEA) 2022). Research spans (a) statistical, data-driven ML for detection and monitoring (De Choudhury et al. 2013, 2016; Saha et al. 2019; Chancellor and De Choudhury 2020; Shing et al. 2018; Gkotsis et al. 2017) and (b) knowledge-driven methods using clinical instruments, ontologies, and KGs for explainability and interoperability (Alambo et al. 2019; Gupta et al. 2022; Gaur et al. 2021a; Manas et al. 2021; Gaur et al. 2018; Kursuncu et al. 2018; Lokala et al. 2022b,a; Gaur et al. 2021b; Dalal et al. 2024; Roy et al. 2023a; Alsentzer et al. 2019; Vajre et al. 2021; Ji et al. 2021; Sheth et al. 2021; Gaur et al. 2019). Project overviews and datasets are documented in community resources (AIISC (Artificial Intelligence Institute of South Carolina) 2024a,b).

Conclusion and Future Work

A *Mental Health KG* (ontology and dataset) has been developed by integrating ontology-based projects from the LOV4IoT catalog (Depression, Mental Health, and Emotion). This catalog supports researchers through: 1) a systematic literature survey—an otherwise time-consuming task requiring detailed exploration of existing projects, and 2) adherence to FAIR principles that encourage sharing reproducible experiments, including online ontologies, datasets, and rules.

Short-term challenges: The LOV4IoT catalog is already valuable for the IoT community, but requires continuous updates with additional domains and ontologies. The results contribute to broader initiatives such as the AIOTI IoT ontology landscape survey and analysis (European Commission / AIOTI Semantic Interoperability Expert Group 2020; AIOTI Semantic Interoperability Expert Group 2020), which guide practitioners in identifying, selecting, and maintaining relevant ontologies. AIOTI's Health Working Group has also published white papers on topics such as health data spaces (AIOTI Health Working Group 2022c), AI for better health (AIOTI Health Working Group 2022a), and healthy urban living (AIOTI Health Working Group 2022b).

Mid-term challenges: Automatic knowledge extraction from ontologies and scientific publications remains difficult. The AI4EU KE4WoT Challenge demonstrated the importance of reusing expert-designed ontologies and making them machine-usable. Our released resources—including dumps, web services, and tutorials—contribute to this vision.

Long-term challenges: Improving the veracity of the Mental Health KG requires deeper involvement of domain experts such as psychologists and neuroscientists. Their expertise can validate knowledge and strengthen reasoning. Future extensions include integrating additional fields such as psychophysiology and psychobiology, as well as emphasizing emotional dimensions (e.g., fear, pessimism, sadness), which directly impact mental health. The reasoning engine can also be broadened to domains such as mindfulness, yoga, and complementary therapies.

Overall, this work demonstrates that ontology-driven catalogs like LOV4IoT can bridge gaps between IoT, AI, and mental health, while also aligning with standardization and reproducibility efforts for regulated domains.

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