A-Track: An Ontological Approach to Assisting Anxiety Management

Gustavo Lazarotto Schroeder[1], **Leonardo dos Santos Paula**[1],
Rosemary Francisco[1], **Jorge Luis Victória Barbosa**[1]

[1]Universidade do Vale do Rio dos Sinos (Unisinos)
Av. Unisinos, 950 - Cristo Rei, São Leopoldo - RS, 93022-750 - Brazil

gschroeder@edu.unisinos.br, leonardopaula@gmail.com,

{rosemaryf,jbarbosa}@unisinos.br

Abstract. *Anxiety, a natural survival mechanism, becomes chronic under modern stressors, escalating into chronic disorders with multifaceted health impacts. While early detection is crucial, healthcare systems struggle with scalability. This study introduces the A-Track Ontology, a digital tool designed to model anxiety through personalized context histories. Validated through logical consistency, domain coverage, and utility assessments, the ontology synthesizes multimodal data into actionable insights for proactive intervention. Integrating ontological reasoning with real-world context awareness, this approach addresses clinical scalability gaps, enabling personalized, data-driven strategies for anxiety management.*

1. Introduction

The World Health Organization estimates that anxiety disorders affect 4% of the global population [World Health Organization, 2023]. These conditions impair quality of life, functional capacity, and economic productivity [Umar et al., 2023]. Compounding this crisis, the demand for psychological interventions keeps increasing, with many specialists unable to accommodate new patients despite the escalating need [APA, 2022]. Stress and anxiety function as evolutionarily conserved adaptive mechanisms, serving protective roles by mobilizing physiological and behavioral responses to perceived threats [APA, 2019; APS, 2022]. However, chronic or dysregulated activation of these systems transitions from adaptive to pathological, inducing maladaptive physiological dysregulation and increasing vulnerability to neuropsychiatric disorders [Rosmond et al., 1998]. Empirical evidence highlights the detrimental psychological impacts, including impaired cognitive function [Zhao et al., 2024], elevated risk of mood disorders [Sultson et al., 2024], and epigenetic modifications linked to stress susceptibility [dos Santos Paula et al., 2021].

Rapid advancements in mobile and ubiquitous computing technologies, driven by declining production costs and near-universal adoption of connected devices, have facilitated continuous, context-aware data collection. This capability enables granular observation of human behavior and supports targeted behavioral modification strategies [Can et al., 2019]. Concurrently, the growth of IoT technologies has catalyzed significant advancements in data analytics, facilitating the development of methodologies to process the vast datasets generated by interconnected sensor networks [Jain et al., 2024]. These innovations extract actionable insights from sensor-rich environments, enhancing the capacity to interpret complex data [Xu et al., 2023]. Concurrently, advancements in sensor technology have expanded the scope of data acquisition to encompass physiological parameters and environmental variables. This dual capability supports identifying behavioral and health-related patterns, underpinning continuous user monitoring and proactive intervention strategies [Pejovic et al., 2015].

Considering this scenario, ontologies emerge as a strategic resource for structuring and representing anxiety-related knowledge. Ontologies are explicit formal specifications of the terms in a domain and relations among them [Gruber, 1995], which must be formal, shareable, and composed of well-defined concepts and rules. Ontologies define a common vocabulary for researchers [Goetz et al., 2025] and are applied in recommendation systems [Bobadilla et al., 2013]. Web Ontology Language (OWL) is a semantic web language designed to represent and reason knowledge in a machine-readable format [Antoniou and Harmelen, 2009]. An OWL ontology consists of Classes, Individuals, and Properties [Noy and McGuinness, 2001; Helfer et al., 2025].

This study presents A-Track, an ontology developed to formalize knowledge related to anxiety disorders by modeling relationships between anxiety risk factors, behavioral patterns, dynamic context data, and demographic variables. A-Track enables the derivation of personalized intervention strategies and preemptive actions tailored to individual anxiety profiles. The ontology integrates heterogeneous data sources, supporting the development of adaptive systems capable of assisting anxiety-related behaviors, context-aware triggers, and mental health trajectories. Furthermore, A-Track allows reasoning about temporal and spatial dependencies in anxiety escalation, fostering the creation of context-aware tools for real-time feedback and therapeutic guidance. This formalization enhances precision in tracking mental health trajectories and establishes a scalable foundation for AI-driven systems to mitigate anxiety escalation through timely, evidence-based interventions [Mathew, 2022].

This article consists of five sections. Section 2 details the methodology and tools employed in constructing the ontology. Section 3 presents the findings obtained through the A-Track testing and analyzes the results. Section 4 contextualizes these findings within the existing literature, addressing the theoretical and practical implications. Finally, Section 5 summarizes the main findings, highlights the significance of the study, and offers insights for future research.

2. Modeling and Implementation

Ontology construction does not require adherence to a specific methodology or approach. However, structured frameworks and guidelines are available to assist researchers in ensuring conceptual clarity, logical consistency, reusability, and scalability. For this work, the development followed the Ontology Development 101 methodology [Noy and McGuinness, 2001], a recognized framework that balances knowledge representation, constraint implementation, and extensibility. This iterative methodology comprises seven steps: (1) Determine the domain, scope, and competence issues of the ontology, (2) Consider reusing existing ontologies, (3) List important ontology terms, (4) Define the classes and hierarchy, (5) Define relationships and class properties, (6) Define the semantic rules, and (7) Create the instances.

2.1. Determine the Domain and Scope

The ontology's knowledge domain encompasses anxiety-related constructs, context factors influencing anxiety states, validated screening questionnaires, and associated behavioral manifestations. The A-Track Ontology aims to achieve three primary objectives: (1) systematize risk stratification for individuals exhibiting elevated anxiety levels, (2) discern behavioral patterns correlated with fluctuations in anxiety severity, and (3) generate actionable insights to support personalized anxiety management strategies.

Nine competency questions (CQs) were formulated to guide the ontology development. Competency questions allowed the formalization of queries and the evaluation of the ontology's ability to represent domain-specific knowledge and address targeted use cases [Gruninger, 1995]. The CQs for the A-Track Ontology are as follows:

- (CQ1) "Which persons have a high risk for anxiety?"
- (CQ2) "Which persons have a medium risk for anxiety?"
- (CQ3) "Which persons have a low risk for anxiety?"
- (CQ4) "Which persons have a good sleep pattern?"
- (CQ5) "Which persons have a poor sleep pattern?"
- (CQ6) "Which persons have good physical activity habits?"
- (CQ7) "Which persons have bad physical activity habits?"
- (CQ8) "Which insights are indicated to help people with poor sleep patterns?"
- (CQ9) "Which insights are indicated to help people with poor physical activity patterns?"

2.2. Consider Reusing Existing Ontologies

The step of reusing ontologies compatible with the scope of *A-Track Ontology* considered the context-aware and mental health domain. The CAMeOnto ontology [Aguilar et al., 2018] allowed the definition of the entities *User*, *Activity*, *Location*, related to the individual and the context in which the subject is inserted (context awareness). Regarding mental health, the reuse step found only ontologies focused on mental disorders representing diseases [Hadzic et al., 2008; Ceusters and Smith, 2010]. While the A-Track Ontology does not aim to classify or map mental illnesses, the ontology design incorporated hierarchical structures from disease classification systems to contextualize mental states (e.g., associations between anxiety severity and behavioral indicators). This selective reuse ensures alignment with the ontology's objectives while avoiding scope creep into clinical diagnostics.

2.3. Enumerate the Relevant Terms

The identification of core terminology was conducted through methodological triangulation, integrating two complementary approaches: (1) systematic analysis of peer-reviewed studies on anxiety and stress dynamics [Paula et al., 2022], and (2) semi-structured interviews with four clinical psychologists specializing in cognitive-behavioral therapy (CBT). The literature review synthesized state-of-the-art terminologies spanning mental health constructs and computational modeling techniques. Concurrently, interviews were conducted with CBT practitioners, aiming to ground terminology in clinical expertise. Sessions were conducted remotely via videoconferencing platforms or asynchronous messaging, based on participant preference. Three sessions were recorded with prior consent for transcription and thematic analysis, while one opted for unrecorded text-based communication. Each interview followed a semi-structured protocol, initiated with the prompt: How do stress and anxiety typically manifest in your clinical observations? (mean duration: 15 minutes). Supplementary inquiries focused on diagnostic criteria, therapeutic interventions, and longitudinal changes in symptom presentation. This dual approach ensured terminological alignment with empirical research and practitioner insights, forming a robust foundation for ontology classes and relationships.

2.4. Define the Classes and Hierarchy

Based on the definition of the main terms, the hierarchical organization stage constructed the ontology classes in OWL language, using the Protégé tool (version 5.5.0)[1]. Figure 1 shows the core classes of the ontology. The class *Thing* is the root element that serves as a basis for all other classes in the OWL notation [Djuric et al., 2005]. The *User* class represents all model users, which can be either *Person* (who is monitored) or *Caregiver* (who monitors). The *MentalStates* class groups the possible mental states in the domain. The classes *Device*, *Location*, and *Activity* encompass the context in which *Person* is inserted. Finally, the *Insight* class represents the resources to be made available to *Person* in high-risk anxiety situations.

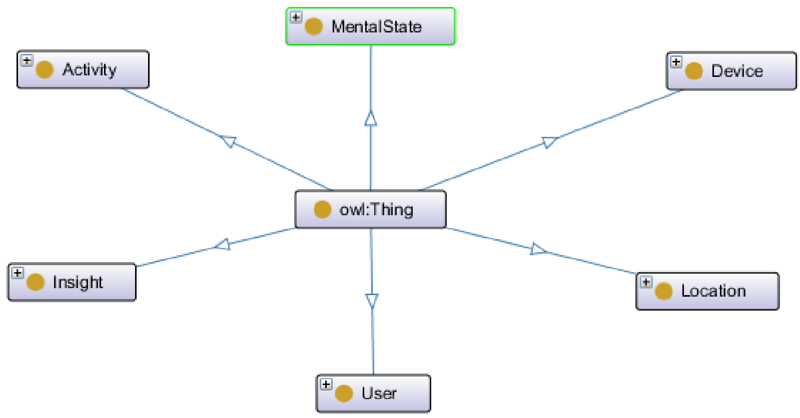

Figure 1. Core classes of the *A-Track Ontology*

The *MentalState* class hierarchy, shown in Figure 2, displays the screening tools supported by the ontology (General Anxiety Disorder-7 and Beck Anxiety Inventory). Both tools estimate the users' anxiety level through self-reporting [Sapra et al., 2020]. The tools in the *AnxietyAssessment* may have different weights or quantifiers, which may lead to misclassifications. To deal with this situation, the members *LowRiskAnxiety*, *MildRiskAnxiety*, and *HighRiskAnxiety* are present to generate a standardized internal classification.

2.5. Define the Semantic Rules

With the classes and relationships established, this study defined equivalence rules to enable the inference process. The ontology used the GAD7 and BAI screening tools to

[1] https://protege.stanford.edu/

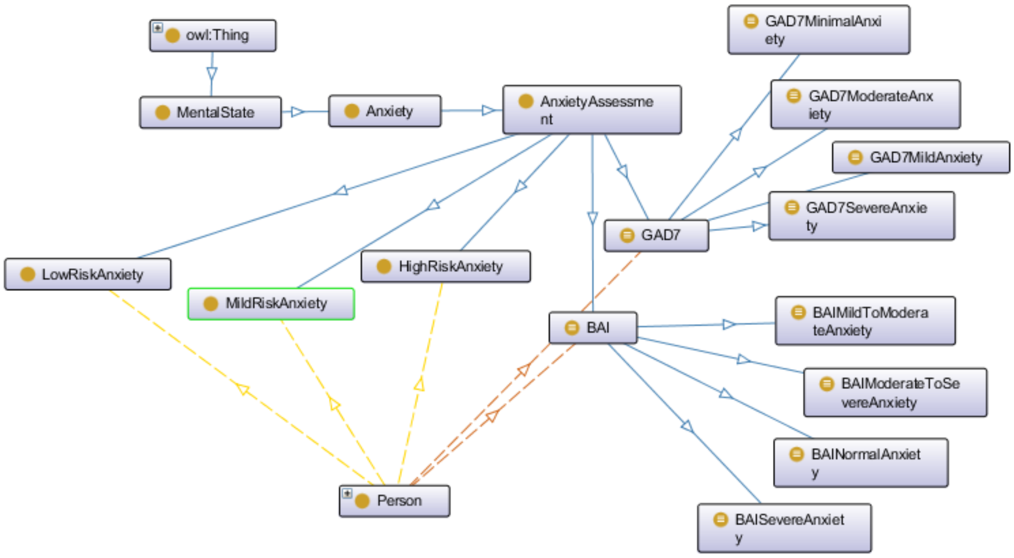

Figure 2. Expansion of the class *MentalState*.

answer the competency questions CQ1, CQ2, and CQ3. These tools have categorizations based on a score to indicate the level of anxiety [Sapra et al., 2020].

Another way to create rules is to use SWRL, which provides a mechanism for defining inference rules that extend the reasoning capabilities of OWL by enabling Horn-clause implications (if a $\rightarrow$ b). This feature allows for the derivation of new knowledge from existing ontological data [O'Connor et al., 2005]. The A-Track Ontology incorporates a set of 56 SWRL rules, which enhance the ontology inferential capacity. Table 1 presents an overview of these rules. Among them, specific rules establish a unified classification for anxiety risk by mapping screening tool outputs to the ontology classes *LowRiskAnxiety*, *MildRiskAnxiety*, and *HighRiskAnxiety*. This design ensures adaptability to various screening instruments, as the ontology can integrate new tools while maintaining consistency in classification. These rules are referenced by the prefixes *bai_risk_* and *gad_risk_*.

Additionally, SWRL rules in the *A-Track Ontology* categorize individuals into age groups based on established guidelines for recommended sleep duration [Hirshkowitz et al., 2015] and physical activity levels [Bull et al., 2020]. These rules, prefixed with *Age_group_*, classify individuals as *Newborn*,*Infant*, *Toddler*, *Preschooler*, *SchoolAgedChild*, *Teenager*, *YoungAdult*, *Adult*, or *OlderAdult*. Furthermore, rules governing sleep and physical activity patterns attribute classifications such as *BadSleepPattern* and *GoodSleepPattern* as well as BadPhysicalActivityPattern and *GoodPhysicalActivityPattern*. These rule sets enhance the ontology's ability to infer behavioral patterns, providing a structured approach to assessing health-related factors in individuals.

2.6. Create the Instances

Finally, the instance creation step created instances to perform inference and validate the ontology. Individuals represent the concrete reality in knowledge and are a formal part of an ontology [Lord, 2010]. The classes that received instances were *Person*, *PhysicalActivityMetric*, and *SleepMetric*. These classes were chosen because they enable integration with the *Prediction Agent* (using the same dataset).

Table 1. Set of rules and questions that address.

Name	Rule
Age_group_1	Person(?p) ˆ age(?p, ?ag) ˆ swrlb:greaterThanOrEqual(?ag, ”14.0”ˆˆxsd:decimal) ˆ swrlb:lessThan(?ag, ”18.0”ˆˆxsd:decimal) -¿ Teenager(?p)
Age_group_7	Person(?p) ˆ age(?p, ?ag) ˆ swrlb:greaterThanOrEqual(?ag, ”65.0”ˆˆxsd:decimal) -¿ OlderAdult(?p)
Ins_sleep	Person(?p) ˆ hasSleepMetric(?s, ?m) ˆ Insight(?i) ˆ match(?i, ”sleep”ˆˆrdf:PlainLiteral) ˆ BadSleepPattern(?m) -¿ hasInsight(?p, ?i)
Sleep_bad_00	Newborn(?p) ˆ hasSleepMetric(?p, ?s) ˆ totalSleepTime(?s, ?ss) ˆ swrlb:greaterThan(?ss, ”19”ˆˆxsd:integer) -¿ BadSleepPattern(?p)
Sleep_bad_81	OlderAdult(?p) ˆ hasSleepMetric(?p, ?s) ˆ totalSleepTime(?s, ?ss) ˆ swrlb:greaterThan(?ss, ”9”ˆˆxsd:integer) -¿ BadSleepPattern(?p)
Sleep_good_00	Newborn(?p) ˆ hasSleepMetric(?p, ?s) ˆ totalSleepTime(?s, ?ss) ˆ swrlb:greaterThanOrEqual(?ss, ”11”ˆˆxsd:integer) ˆ swrlb:lessThanOrEqual(?ss, ”19”8sd:integer) -¿ GoodSleepPattern(?s)
activity_1	Person(?p) ˆ Teenager(?p) ˆ hasPhysicalActivityMetric(?p, ?x) ˆ physicalActivitySum(?x, ?s) ˆ swrlb:greaterThanOrEqual(?s, ”420”ˆˆxsd:integer) -¿ GoodPhysicalActivityPattern(?p)
activity_5	Person(?p) ˆ OlderAdult(?p) ˆ hasPhysicalActivityMetric(?p, ?x) ˆ physicalActivitySum(?x, ?s) ˆ swrlb:greaterThanOrEqual(?s, ”150”ˆˆxsd:integer) -¿ GoodPhysicalActivityPattern(?p)
bad_activity_1	Person(?p) ˆ Teenager(?p) ˆ hasPhysicalActivityMetric(?p, ?x) ˆ physicalActivitySum(?x, ?s) ˆ swrlb:lessThan(?s, ”420”ˆˆxsd:integer) -¿ BadPhysicalActivityPattern(?p)
bad_activity_5	Person(?p) ˆ OlderAdult(?p) ˆ hasPhysicalActivityMetric(?p, ?x) ˆ physicalActivitySum(?x, ?s) ˆ swrlb:lessThan(?s, ”150”8sd:integer) -¿ BadPhysicalActivityPattern(?p)
bai_risk_1	BAINormalAnxiety(?t) -¿ LowRiskAnxiety(?t)
bai_risk_2	BAIMildToModerateAnxiety(?t) -¿ MildRiskAnxiety(?t)
bai_risk_3	BAISevereAnxiety(?t) -¿ HighRiskAnxiety(?t)
bai_risk_4	BAIModerateToSevereAnxiety(?t) -¿ HighRiskAnxiety(?t)
gad_risk_1	GAD7MinimalAnxiety(?t) -¿ LowRiskAnxiety(?t)
gad_risk_2	GAD7MildAnxiety(?t) -¿ MildRiskAnxiety(?t)
gad_risk_3	GAD7SevereAnxiety(?t) -¿ HighRiskAnxiety(?t)
gad_risk_4	GAD7ModerateAnxiety(?t) -¿ HighRiskAnxiety(?t)

Table 2 illustrates the ontology metrics extracted from Protégé. The *Axiom* metric represents the number of logical statements applied in a concept definition. The *Class Count* and *Subclass Count* metrics represent the number of elements in the ontology. *Data Property Count* presents the total number of literal data types, such as numbers, dates, or text. *Object Property Count* denotes the number of relationships between two instances. Finally, *Individual Count* represents the number of instances created.

Table 2. *A-Track Ontology* metrics.

Metric	Value
Axiom	646
Logical Axiom Count	326
Declaration Axioms Count	139
Class Count	67
SubClassOf	63
EquivalentClasses	24
Object Property Count	13
SubObjectPropertyOf	1
Data Property Count	18
SubDataPropertyOf	5
Individual	35

3. Ontology Evaluation

The evaluation of the A-Track Ontology consisted of three steps: (1) inclusion of data from a public database, (2) executing the inference engine, and (3) performing SPARQL queries. The publicly available StudentLife dataset [Wang et al., 2014] served as the basis for creating the instances. In this way, this study extracted data for one week from two users (U19 and U59) to create two personas (Jack and Sara) and populate the instances.

3.1. Reasoning Verification

After creating the instances, the automatic *reasoning* process evaluated the ontology. Pellet in version 2.2.0 was the engine used to check for any inconsistencies between the classes declared in the ontology. Figure 3 shows the log of the checks performed after running the Pellet plugin.

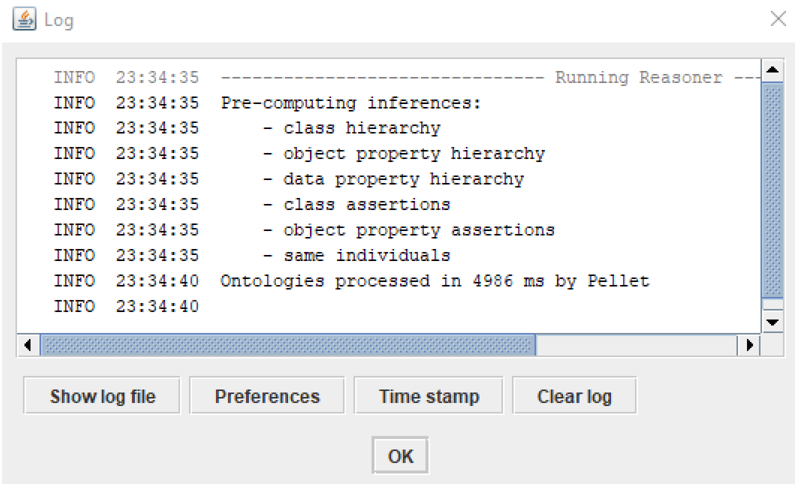

Figure 3. Pellet Plugin Reasoning Tasks Log.

3.2. Competency Questions Validation

The validation process uses the nine Competency Questions defined in Section 2.1 to access the ontology using SPARQL queries. To this process, this study exported the ontology created in Protégé to the StarDog [2] tool, which supports using the latest versions of SPARQL and allows the use of APIs to perform queries by other applications.

Table 3 presents the queries created for each competence question. Questions CQ1, CQ2, and CQ3 search for users with high, medium, and low anxiety levels, respectively. The anxiety level uses the GAD7 and BAI forms as the source of the normalized information through SWRL rules. Figure 4 illustrates the result of the three queries, where "Jack" shows high anxiety risk, and "Sara" is classified as medium risk. The query found no user with low risk.

Figure 4. Result of the SPARQL Queries for CQ1, CQ2, and CQ3.

[2]https://www.stardog.com

Table 3. SPARQL queries for competence questions.

Question	Query
CQ1	*SELECT ?name ?age ?anxietyLevel ?ageGroupName WHERE ?Person base:name ?name. ?Person base:age ?age. ?Person a ?anxietyLevelType. ?anxietyLevelType rdfs:subClassOf base:AnxietyAssessment. ?anxietyLevelType rdfs:label ?anxietyLevel. ?Person a ?ageGrouptype .?ageGrouptype rdfs:subClassOf base:AgeGroup. ?ageGrouptype rdfs:label ?ageGroupName. FILTER(?anxietyLevel = "High Risk of Anxiety")*
CQ2	*SELECT ?name ?age ?anxietyLevel ?ageGroupName WHERE ?Person base:name ?name. ?Person base:age ?age. ?Person a ?anxietyLevelType. ?anxietyLevelType rdfs:subClassOf base:AnxietyAssessment. ?anxietyLevelType rdfs:label ?anxietyLevel. ?Person a ?ageGrouptype. ?ageGrouptype rdfs:subClassOf base:AgeGroup. ?ageGrouptype rdfs:label ?ageGroupName. FILTER(?anxietyLevel = "Mild Risk of Anxiety")*
CQ3	*SELECT ?name ?age ?anxietyLevel ?ageGroupName WHERE ?Person base:name ?name. ?Person base:age ?age. ?Person a ?anxietyLevelType. ?anxietyLevelType rdfs:subClassOf base:AnxietyAssessment. ?anxietyLevelType rdfs:label ?anxietyLevel. ?Person a ?ageGrouptype. ?ageGrouptype rdfs:subClassOf base:AgeGroup. ?ageGrouptype rdfs:label ?ageGroupName. FILTER(?anxietyLevel = "Low Risk of Anxiety")*
CQ4	*SELECT ?name ?anxietyLevel ?ageGroupName ?sleepPattern WHERE ?Person base:name ?name. ?Person a ?anxietyLevelType. ?anxietyLevelType rdfs:subClassOf base:AnxietyAssessment. ?anxietyLevelType rdfs:label ?anxietyLevel. ?Person a ?ageGrouptype. ?ageGrouptype rdfs:subClassOf base:AgeGroup. ?ageGrouptype rdfs:label ?ageGroupName. OPTIONAL SELECT ?Person ?badPattern (COUNT(?badPattern) AS ?badPatternCount) WHERE ?Person base:hasSleepMetric ?sleepMetric. ?sleepMetric a ?sleepPattern. ?sleepPattern rdfs:subClassOf base:SleepMetric. ?sleepPattern rdfs:label ?badPattern. FILTER(?badPattern = "Bad Sleep Pattern") GROUP BY ?Person ?badPattern . OPTIONAL SELECT ?Person ?goodPattern (COUNT(?goodPattern) AS ?goodPatternCount)WHERE ?Person base:hasSleepMetric ?sleepMetric. ?sleepMetric a ?sleepPattern. ?sleepPattern rdfs:subClassOf base:SleepMetric. ?sleepPattern rdfs:label ?goodPattern.FILTER(?goodPattern = "Good Sleep Pattern") GROUP BY ?Person ?goodPatternBIND(if ((COALESCE(?goodPatternCount, 0) ¿ COALESCE(?badPatternCount, 0)), ?goodPattern, ?badPattern) as ?sleepPattern) FILTER(?sleepPattern = "Good Sleep Pattern")*
CQ5	*SELECT ?name ?anxietyLevel ?ageGroupName ?sleepPattern WHERE ?Person base:name ?name. ?Person a ?anxietyLevelType. ?anxietyLevelType rdfs:subClassOf base:AnxietyAssessment. ?anxietyLevelType rdfs:label ?anxietyLevel. ?Person a ?ageGrouptype. ?ageGrouptype rdfs:subClassOf base:AgeGroup. ?ageGrouptype rdfs:label ?ageGroupName. OPTIONAL SELECT ?Person ?badPattern (COUNT(?badPattern) AS ?badPatternCount) WHERE ?Person base:hasSleepMetric ?sleepMetric. ?sleepMetric a ?sleepPattern. ?sleepPattern rdfs:subClassOf base:SleepMetric. ?sleepPattern rdfs:label ?badPattern. FILTER(?badPattern = "Bad Sleep Pattern") GROUP BY ?Person ?badPattern . OPTIONAL SELECT ?Person ?goodPattern (COUNT(?goodPattern) AS ?goodPatternCount)WHERE ?Person base:hasSleepMetric ?sleepMetric. ?sleepMetric a ?sleepPattern. ?sleepPattern rdfs:subClassOf base:SleepMetric. ?sleepPattern rdfs:label ?goodPattern.FILTER(?goodPattern = "Good Sleep Pattern") GROUP BY ?Person ?goodPatternBIND(if ((COALESCE(?goodPatternCount, 0) ¿ COALESCE(?badPatternCount, 0)), ?goodPattern, ?badPattern) as ?sleepPattern) FILTER(?sleepPattern = "Bad Sleep Pattern")*
CQ6	*SELECT ?name ?age ?anxietyLevel ?ageGroupName ?physicalActivityPattern WHERE ?Person base:name ?name. ?Person base:age ?age. ?Person a ?anxietyLevelType. ?anxietyLevelType rdfs:subClassOf base:AnxietyAssessment. ?anxietyLevelType rdfs:label ?anxietyLevel. ?Person a ?ageGrouptype. ?ageGrouptype rdfs:subClassOf base:AgeGroup. ?ageGrouptype rdfs:label ?ageGroupName. ?Person a ?physicalActivity. ?physicalActivity rdfs:subClassOf base:PhysicalActivityMetric. ?physicalActivity rdfs:label ?physicalActivityPattern. FILTER(?physicalActivityPattern = "Good Physical Activity Pattern")*
CQ7	*SELECT ?name ?age ?anxietyLevel ?ageGroupName ?physicalActivityPattern WHERE ?Person base:name ?name. ?Person base:age ?age. ?Person a ?anxietyLevelType. ?anxietyLevelType rdfs:subClassOf base:AnxietyAssessment. ?anxietyLevelType rdfs:label ?anxietyLevel. ?Person a ?ageGrouptype. ?ageGrouptype rdfs:subClassOf base:AgeGroup. ?ageGrouptype rdfs:label ?ageGroupName. ?Person a ?physicalActivity. ?physicalActivity rdfs:subClassOf base:PhysicalActivityMetric. ?physicalActivity rdfs:label ?physicalActivityPattern. FILTER(?physicalActivityPattern = "Bad Physical Activity Pattern")*
CQ8	*SELECT ?theme ?url WHERE ?Insight a ?content. ?Insight base:url ?url. ?Insight base:theme ?theme. ?Insight base:match ?category. FILTER(?category = "sleep")*
CQ9	*SELECT ?theme ?url WHERE ?Insight a ?content. ?Insight base:url ?url. ?Insight base:theme ?theme. ?Insight base:match ?category. FILTER(?category = "physical_activity")*

Questions CQ4 and CQ5 are related to the user's sleep pattern. The *A-Track Ontology* analyzes data in a seven-day window, so the sleep pattern follows this metric. The SPARQL query considers the class with the highest occurrence to define the individual's sleep pattern. For instance, "Jack" had six days with good sleep time and one day with few hours, so the ontology classifies the user as *Good Sleep Pattern*. Figure 5 shows the result of the queries with the user's name, age group they belong to (sleep times vary according to this information), and sleep pattern.

The metrics related to physical activity are referenced by CQ6 and CQ7. The ontology calculates this standard using the sum of the daily activity time and applies SWRL rules to classify the user based on age group. Figure 6 illustrates the result of this query.

CQ4

name	anxietyLevel	ageGroupName	sleepPattern
"Jack"	"High Risk of Anxiety"	"Adult"	"Good Sleep Pattern"

CQ5

name	anxietyLevel	ageGroupName	sleepPattern
"Sara"	"Mild Risk of Anxiety"	"Young Adult"	"Bad Sleep Pattern"

Figure 5. Result of the SPARQL Queries for CQ4 and CQ5.

CQ6

name	age	anxietyLevel	ageGroupName	physicalActivityPattern
"Jack"	30	"High Risk of Anxiety"	"Adult"	"Good Physical Activity Pattern"

CQ7

name	age	anxietyLevel	ageGroupName	physicalActivityPattern
"Sara"	18	"Mild Risk of Anxiety"	"Young Adult"	"Bad Physical Activity Pattern"

Figure 6. Result of the SPARQL Queries for CQ6 and CQ7.

Finally, Figure 7 displays the outputs for CQ8 and CQ9, which address user recommendations. Both questions 8 and 9 return the URL with relevant content for users with sleep or sedentary problems, respectively.

CQ8

theme	url
"Sleep"	"https://www.tuasaude.com/higiene-do-sono/"
"Sleep"	"https://pneumosono.com.br/blog/124-10-dicas-para-melhorar-a-qualidade-do-seu-sono"

CQ9

theme	url
"Physical Activity"	"https://www.desenvolvimentosocial.sp.gov.br/beneficios-do-esporte-para-a-saude-mental"

Figure 7. Result of the SPARQL Queries for CQ8 and CQ9.

4. Discussion

The A-Track Ontology promotes anxiety management by establishing a framework that integrates behavioral, contextual, and physiological data. The A-Track addresses scalability constraints inherent in conventional healthcare systems by integrating multimodal data, such as smartphone usage, sleep patterns, physical activity, geolocation, environmental data, and self-reported emotional states. The A-Track's ability to integrate multimodal data into anxiety-related profiles enhances accuracy and enables personalized interventions. This integration effectively bridges the gap between clinical requirements and technological advancements, establishing a foundation for proactive mental health strategies.

Validation through assessments of logical consistency, domain coverage, and practical utility underscores A-Track's potential to help in anxiety management practices. These evaluations highlight the ontology's ability to support timely, evidence-based interventions that align with the dynamic nature of real-world contexts. Looking ahead, expanding the ontology to incorporate emerging data sources, such as social media interactions and biometric sensor inputs, could further refine its predictive accuracy and adaptability. Such enhancements would advance the development of individualized mental healthcare solutions, positioning A-Track as a tool for addressing the complexities of anxiety in evolving environments. The A-Track emphasizes interoperability and real-world applicability, establishing a foundation for advancing mental health technologies while enabling more responsive and personalized care frameworks through future innovation.

5. Conclusion

This paper proposed the A-Track, an ontology designed to model anxiety-related patterns by integrating heterogeneous data, including smartphone use routine, sleep metrics, physical activity, geolocation, self-reported emotions, and environmental factors. The ontology transforms raw sensor data into real-time insights by formalizing temporal, spatial, and physiological relationships, enabling the identification of anxiety triggers and the generation of personalized intervention strategies.

The ontology modeling elucidated the development from the conception to the creation of instances. The ontology construction consisted of seven development stages: determining the domain and scope, reusing existing knowledge, enumerating relevant terms, defining the class hierarchy, specifying relationships and class properties, establishing semantic rules, and creating individuals. The evaluation of A-Track assessed structural and conceptual aspects, ensuring the correctness of the ontology semantic and logical construction through a verification process. The validation process sought to illustrate that the ontology fulfills its intended purpose. This assessment used the reasoning process and data extraction with SPARQL queries to answer nine competency questions. The results reached the expected answers, showing possible stressful contexts, environmental conditions, and anxiety risks identified.

The A-Track ontology for anxiety detection offers a structured, scalable representation of complex mental health knowledge, facilitating data integration, pattern recognition, and tailored interventions. The A-Track Ontology advances this goal by unifying IoT-enabled data sources, such as activity levels, sleep disruptions, and environmental stressors, to infer anxiety states and correlate them with behavioral contexts. This capability allows for dynamic, individualized recommendations aimed at mitigating anxiety's physical and psychological impacts, fostering preventive mental health care.

The limitations of this study include the preliminary evaluation conducted on constrained datasets, which may not fully capture the diverse manifestations of anxiety. Additionally, while the ontology's knowledge base is comprehensive, it relies predominantly on predefined data streams, potentially omitting novel or evolving anxiety triggers. To enhance the model's generalizability, future research should focus on large-scale validation in real-world settings. Expanding the ontology's knowledge base by integrating emerging data sources, such as social media interactions and biometric sensors, could further improve its predictive accuracy and adaptability.

Acknowledgements

The authors would like to thank the National Council for Scientific and Technological Development (CNPq), the Coordination for the Improvement of Higher Education Personnel (CAPES) - Funding Code 001, and the University of Vale do Rio dos Sinos (Unisinos) for supporting the development of this work.

References

Aguilar, J., Jerez, M., and Rodríguez, T. (2018). Cameonto: Context awareness meta ontology modeling. *Applied Computing and Informatics*, 14(2):202–213.

Antoniou, G. and Harmelen, F. v. (2009). *Web Ontology Language: OWL*, page 91–110. Springer Berlin Heidelberg.

APA (2019). Stress relief is within reach. *https://www.apa.org/topics/stress*. Accessed: 2025-01-11.

APA (2022). Increased need for mental health care strains capacity. *https://www.apa.org/news/press/releases/2022/11/mental-health-care-strains*. Accessed: 2025-01-13.

APS (2022). Anxiety disorders. *https://psychology.org.au/for-the-public/psychology-topics/anxiety*. Accessed: 2025-01-11.

Bobadilla, J., Ortega, F., Hernando, A., and Gutiérrez, A. (2013). Recommender systems survey. *Knowledge-Based Systems*, 46:109–132.

Bull, F. C., Al-Ansari, S. S., Biddle, S., Borodulin, K., Buman, M. P., Cardon, G., Carty, C., Chaput, J.-P., Chastin, S., Chou, R., Dempsey, P. C., DiPietro, L., Ekelund, U., Firth, J., Friedenreich, C. M., Garcia, L., Gichu, M., Jago, R., Katzmarzyk, P. T., Lambert, E., Leitzmann, M., Milton, K., Ortega, F. B., Ranasinghe, C., Stamatakis, E., Tiedemann, A., Troiano, R. P., van der Ploeg, H. P., Wari, V., and Willumsen, J. F. (2020). World health organization 2020 guidelines on physical activity and sedentary behaviour. *British Journal of Sports Medicine*, 54(24):1451–1462.

Can, Y. S., Arnrich, B., and Ersoy, C. (2019). Stress detection in daily life scenarios using smart phones and wearable sensors: A survey. *Journal of Biomedical Informatics*, 92:103139.

Ceusters, W. and Smith, B. (2010). Foundations for a realist ontology of mental disease. *Journal of Biomedical Semantics*, 1(1):10.

Djuric, D., Gaševi, D., and Devedžic, V. (2005). Ontology modeling and MDA. *The Journal of Object Technology*, 4(1):109.

dos Santos Paula, L., Barbosa, J. L. V., and Dias, L. P. S. (2021). A model for assisting in the treatment of anxiety disorder. *Universal Access in the Information Society*, 21(2):533–543.

Goetz, C., Simon Bavaresco, R., Heckler, W. F., Lazarotto Schroeder, G., Kunst, R., and Barbosa, J. L. V. (2025). Ontokaire: an ontology-based reasoning for work-related stressors in industrial settings. *JUCS - Journal of Universal Computer Science*, 31(5):445–468.

Gruber, T. R. (1995). Toward principles for the design of ontologies used for knowledge sharing? *International Journal of Human-Computer Studies*, 43(5–6):907–928.

Gruninger, M. (1995). Methodology for the design and evaluation of ontologies. In *International Joint Conference on Artificial Intelligence*.

Hadzic, M., Chen, M., and Dillon, T. S. (2008). Towards the mental health ontology. In *Proceedings of the 2008 IEEE International Conference on Bioinformatics and Biomedicine*, BIBM '08, page 284–288, USA. IEEE Computer Society.

Helfer, G. A., da Costa, A. B., and Barbosa, J. L. V. (2025). Soilbr-onto: An ontology for soil fertility management and classification in brazil. *Applied Ontology*, page 15705838251315571.

Hirshkowitz, M., Whiton, K., Albert, S. M., Alessi, C., Bruni, O., DonCarlos, L., Hazen, N., Herman, J., Katz, E. S., Kheirandish-Gozal, L., Neubauer, D. N., O'Donnell, A. E., Ohayon, M., Peever, J., Rawding, R., Sachdeva, R. C., Setters, B., Vitiello, M. V., Ware, J. C., and Adams Hillard, P. J. (2015). National sleep foundation's sleep time duration recommendations: methodology and results summary. *Sleep Health*, 1(1):40–43.

Jain, S. K., Rani R, H. J., and Paikaray, D. (2024). Enhancing iot networking through predictive big data processing. In *2024 2nd International Conference on Artificial Intelligence and Machine Learning Applications Theme: Healthcare and Internet of Things (AIMLA)*, page 1–6. IEEE.

Lord, P. (2010). Components of an ontology. *https://ontogenesis.knowledgeblog.org/514*. Accessed: 2025-01-11.

Mathew, B. (2022). Effectiveness of psychological intervention package on anxiety and wellness level among patients with anxiety disorders. *Journal of Family Medicine and Primary Care*, 11(11):6704–6713.

Noy, N. F. and McGuinness, D. L. (2001). Ontology development 101: A guide to creating your first ontology.

O'Connor, M., Knublauch, H., Tu, S., Grosof, B., Dean, M., Grosso, W., and Musen, M. (2005). Supporting rule system interoperability on the semantic web with SWRL. In *The Semantic Web ISWC 2005*, pages 974–986. Springer Berlin Heidelberg.

Paula, L. d. S., Pfeiffer Salomão Dias, L., Francisco, R., and Barbosa, J. L. V. (2022). Analysing iot data for anxiety and stress monitoring: A systematic mapping study and taxonomy. *International Journal of Human–Computer Interaction*, 40(5):1174–1194.

Pejovic, V., Mehrotra, A., and Musolesi, M. (2015). Anticipatory mobile digital health: Towards personalised proactive therapies and prevention strategies.

Rosmond, R., Dallman, M. F., and Björntorp, P. (1998). Stress-related cortisol secretion in men: Relationships with abdominal obesity and endocrine, metabolic and hemodynamic abnormalities1. *The Journal of Clinical Endocrinology & Metabolism*, 83(6):1853–1859.

Sapra, A., Bhandari, P., Sharma, S., Chanpura, T., and Lopp, L. (2020). Using generalized anxiety disorder-2 (GAD-2) and GAD-7 in a primary care setting. *Cureus*.

Sultson, H., Murd, C., Havik, M., and Konstabel, K. (2024). Negative affect instability predicts elevated depressive and generalized anxiety disorder symptoms even when negative affect intensity is controlled for: an ecological momentary assessment study. *Frontiers in Psychology*, 15.

Umar, Z., Tahir, Z., and Nizami, A. (2023). Impact of severe mental illnesses on health-related quality of life among patients attending the institute of psychiatry, rawalpindi from 2019 to 2021: A cross-sectional study. *PLOS ONE*, 18(8):e0289080.

Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., Zhou, X., Ben-Zeev, D., and Campbell, A. T. (2014). Studentlife: Assessing mental health, academic performance and behavioral trends of college students using smartphones. In *UbiComp 2014 - Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, UbiComp '14, pages 3–14, New York, NY, USA. ACM.

World Health Organization (2023). Anxiety disorders fact sheet. Accessed: 16-Feb-2025.

Xu, A., Darbandi, M., Javaheri, D., Navimipour, N. J., Yalcin, S., and Salameh, A. A. (2023). The management of iot-based organizational and industrial digitalization using machine learning methods. *Sustainability*, 15(7):5932.

Zhao, R., Xu, C., Shi, G., Li, C., Shao, S., Shangguan, F., and Cui, L. (2024). Connection of social anxiety to impaired pattern of cognitive control and underlying motivational deficiencies: Evidence from event-related potentials. *Psychophysiology*, 61(9).