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OntoKratos: An Ontology for Problematic Smartphone Use Identification and Intervention Suggestion

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Abstract: Smartphone use has increased globally and has become essential in daily life. Although benefits exist, concerns arise about the negative effects of prolonged hyperconnectivity. The excessive use of smartphones combined with demographic and mental health related risk factors can lead to problematic smartphone use (PSU). PSU is characterized as the compulsive use of smartphones that disrupts an individual's daily life, work, and relationships. Considering this scenario, the present paper proposes OntoKratos as an ontology designed to detect and prevent PSU. The ontology enables inferences, such as determining the individual's mental health and PSU state, inferring context information, identifying PSU demographic and emotional risk factors, and suggesting interventions. OntoKratos includes 89 classes, 43 object properties, 35 data properties, and 1,113 axioms. Evaluations performed through a simulated dataset demonstrated the ontology's effectiveness regarding PSU identification and interventions for PSU behaviors. Ontology's rules allowed the definition of accurate axioms, improving the correct classification and inference of eight instantiated individuals. This study presents the first ontology for PSU identification and intervention suggestions on PSU behaviors. OntoKratos allows to identify and assist individuals by considering mental health and PSU status, inferring potential PSU risk factors, and providing tailored intervention suggestions to cope with PSU.

Keywords: Technology Addiction, Problematic Smartphone Use, Mental Health, Ontology, Reasoning
Categories: D.0, D.2.13, H.3.4, M.8
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1 Introduction

Smartphone use has increased around the world over the years [Lu et al., 2024]. Forecasts show that smartphone users will increase even more since the smartphone penetration rate is still lower than 70% in highly populated countries [Turner, 2021]. This trend is closely linked to the continuous enhancement of smartphone functionalities and their convergence with emerging technologies, such as the Internet, which have transformed smartphones into multifunctional platforms. Today, smartphone use extends beyond basic communication to include gaming, web browsing, and even online gambling [Busch and McCarthy, 2021], reflecting a society increasingly reliant on integrated digital solutions.

Individuals have progressively exhibited addictive behaviors toward digital technologies, contributing to adverse mental health outcomes [Zara and Monteiro, 2021]. This issue was exacerbated by home confinement measures implemented during the global COVID-19 pandemic [Lewnard and Lo, 2020], which significantly increased the use of digital technologies for remote work, online social interaction, and coping with boredom [Elhai et al., 2020]. Studies revealed an increase in the daily time spent on smartphones during the COVID-19 pandemic, reporting a 40% growth in overall screen time among adults [Chemnad et al., 2022].

This growth in smartphone use has contributed to the emergence of a behavioral pattern known as Problematic Smartphone Use (PSU), characterized by the excessive and compulsive use of smartphones that leads to impaired daily functioning in terms of productivity, social relationships, physical health, or emotional well-being [Horwood and Anglim, 2018]. Additionally, PSU impacts mental health [Elhai et al., 2021] and may aggravate symptoms of anxiety and depression [Busch and McCarthy, 2021]. Improving mental health among individuals encountering PSU requires technological solutions to decrease excessive use and psychotherapeutic interventions to boost perceived social support [Elhai et al., 2017]. Although most studies recognize the need to identify and support individuals with PSU, only a few studies have deployed assistive methods and evaluated these strategies [King et al., 2013, Yang et al., 2019].

Considering this scenario, ontologies emerge as a strategic resource for structuring and representing PSU-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 and are applied in recommendation systems [Parthasarathy and Sathiya, 2022]. The Web Ontology Language (OWL) is a semantic web standard that enables formal representation and reasoning through machine-interpretable constructs, including Classes, Individuals, and Properties [Noy and McGuinness, 2001].

In the ontology definition, classes serve as identifiers for objects. Individuals represent specific concept instances and can establish connections with other individuals through properties that describe binary relationships between two individuals. Constraints define boundaries for individuals who belong to a class. SPARQL is a query language designed for querying and manipulating data represented in the RDF (Resource Description Framework) format and provides means to query data within ontologies [Sirin and Parsia, 2007]. Semantic Web Rule Language (SWRL) is a rule language that enables the representation of rules in the Semantic Web and allows making inferences about classes and individuals in ontologies. Thus, ontologies represent domains and infer knowledge [Gruber, 1995].

Context Awareness and Context Histories are essential elements in ontological models, playing an important role in capturing, representing, and reasoning about contextual information [Cardoso et al., 2021]. Context Awareness allows intercepting PSU behaviors by tailoring smartphone interactions to the user's specific context and needs, providing personalized interventions based on individual habits and preferences [Goetz et al., 2025]. Additionally, smartphones can suppress non-essential notifications and distractions, minimizing problematic behavior triggers [Marciano and Camerini, 2022].

Context Histories organize the information in a temporal series of contexts [García Martins et al., 2021], enabling pattern exploration and facilitating similarity tracing [Helfer et al., 2025]. Integrating Context Histories into ontologies enhances the understanding of entities' temporal dynamics, improving the accuracy of context-aware recommendations and decisions based on users' contexts [Cardoso et al., 2021].

Therefore, this work presents a novel ontology that systematically models the knowledge required to identify individuals' PSU behaviors and associated risk factors, thereby enabling personalized support and intervention. OntoKratos introduces a methodological innovation by formally integrating psychological constructs with computational intervention mechanisms, creating a bridge between behavioral science and Artificial Intelligence. Through SWRL rules, the ontology allows automated reasoning to detect demographic and emotional risk indicators, recognize PSU behavioral patterns, and recommend appropriate intervention strategies. This research addresses key challenges in knowledge representation and automated reasoning within context-aware systems. Through formal ontology design, rule-based inference, and semantic integration, OntoKratos advances intelligent systems capable of operating over heterogeneous behavioral data. This approach advances the integration of Artificial Intelligence and Semantic Web technologies in behavioral health modeling, delivering a formal, reusable, and extensible framework for assessing and mitigating PSU. To the best of our knowledge, this is the first ontology specifically developed for PSU detection and intervention suggestions. This contribution provides a conceptual framework that can serve as a foundation for future research in behavioral informatics, digital addiction assessment, and intelligent health support systems.

Although OntoKratos has been developed as part of a broader agent-based model called Kratos, which combines context awareness, machine learning, and ontological reasoning to manage and intervene in PSU scenarios, such integration is not the focus of this paper. Instead, the present work positions OntoKratos as a standalone and reusable semantic resource. Developed in compliance with Semantic Web standards, OntoKratos is designed to ensure interoperability and reusability across mental health decision support systems, particularly those focused on identifying and managing technology-related behavioral issues. This ontology provides a formal and computationally interpretable foundation to support the PSU theoretical modeling and the development of intelligent systems for assessing and mitigating problematic smartphone use.

This study consists of six sections. The second section investigates the literature to establish a foundation for the study. The third section presents related works to this study. The fourth section describes the methodology and tools used to construct the ontology. The fifth section presents the findings obtained through the OntoKratos testing, analyzes the results, and discusses implications related to the literature. Finally, the sixth section synthesizes the main findings, underscores the study's contributions, and outlines directions for future research.

2 Background

This section explores the areas of PSU, Context Awareness, and Context Histories in order to provide a comprehensive foundation for OntoKratos development.

2.1 Problematic Smartphone Use

With the widespread availability of smartphones, PSU has become a growing concern [Busch and McCarthy, 2021]. Furthermore, forecasts show that the number of smartphone users will continue to grow [Turner, 2021]. Smartphone portability, ubiquitous accessibility, and the multitude of Internet-based applications facilitated the expansion of PSU [Marciano and Camerini, 2022]. Despite the advantages of smartphones, such as facilitating communication, entertainment, and instant access to information, excessive usage may result in unfavorable consequences [Busch and McCarthy, 2021], including decreased productivity, social isolation, and psychological discomfort [Horwood and Anglim, 2018]. Due to the COVID-19 pandemic and social distancing, the time spent on smartphones reached the highest growth [Pitt et al., 2021].

PSU refers to a pattern of excessive and compulsive use that leads to impaired daily functioning regarding productivity, social relationships, physical health, or emotional well-being [Horwood and Anglim, 2018]. Empirical evidence has linked PSU to a range of adverse psychological outcomes, including elevated levels of depression, anxiety, stress, sleep problems, and rumination on negative thoughts [Busch and McCarthy, 2021, Schroeder et al., 2022]. PSU is also closely related to "nomophobia", which refers to discomfort, anxiety, nervousness, and fear of feeling disconnected from the digital world [Rodríguez-García et al., 2020]. Another problem is the fear of missing out (FOMO) on rewarding and fun experiences and important events [Yuan et al., 2021].

Many scales have been explored for measuring smartphone dependency, but a standard is yet to be defined [Schroeder et al., 2022]. These scales are usually self-report questionnaires that assess an individual's smartphone use behavior, attitudes, and consequences associated with smartphone use. Although these scales are useful in identifying PSU, recognizing PSU behavior patterns can be challenging since individuals experiencing PSU may not realize or refuse to acknowledge the idea of being addicted to the smartphone [Park, 2019].

Interventions targeting PSU aim to reduce excessive use and enhance perceived social support [Elhai et al., 2017]. Strategies include delaying app access to reduce impulsivity [Kim et al., 2019], minimizing notifications to decrease distractions [Fitz et al., 2019], and using grayscale displays to lessen device appeal [Zou et al., 2019]. Disabling social media apps has also proven effective in curbing overuse [Hunt et al., 2018]. Mindfulness-based approaches, such as meditation, help mitigate PSU's mental health impacts [Brailovskaia et al., 2021], while physical activity serves as a healthy behavioral substitute [Gao et al., 2018]. Lastly, adopting sleep hygiene practices, like disconnecting before bedtime, can improve sleep quality [Demirci et al., 2015]. Collectively, these interventions foster healthier smartphone use and mitigate PSU-related harms.

2.2 Context Awareness and Context Histories

The growing use of mobile computing and the potential of smartphones to sense the user's environment promoted Context-Aware Computing [Ferreira et al., 2015]. Context-aware systems observe and gather information from the users' contexts [Goetz et al., 2025]. Context refers to the environmental or situational factors that can influence the system's behavior, such as the user's location, time of day, social setting, or personal preferences [Chen et al., 2022].

Context Histories are information organized in a temporal series of contexts [García Martins et al., 2021]. Context data is collected in a particular period and can differentiate occurrences of entities, such as a place, person, or object [Shuai et al., 2019]. The Context Histories data may contain information from different domains, including distinct sources [Helfer et al., 2025]. Context Histories allow the exploration of patterns and the tracing of similarities [Goetz et al., 2025], permitting prediction models to infer users' future contexts by analyzing past data combined with present information [García Martins et al., 2021]. Hence, applications can provide recommendations based on users' contexts [Goetz et al., 2025].

Together, Context Awareness and Context Histories empower applications to reason about the past, react in the present, and anticipate the future [García Martins et al., 2021]. These capabilities have proven valuable in mental health research, especially for behavior prediction and targeted interventions [Santos Paula et al., 2021].

The massive use of mobile computing and the diffusion of sensors promoted Context-Aware Computing, allowing applications to track interaction with these devices unobtrusively [Ferreira et al., 2015]. Context Awareness and Context Histories enable the OntoKratos to monitor smartphone use, recognizing and anticipating context changes, thereby enhancing awareness of the impact of users' behavioral changes [Chen et al., 2022].

3 Related Works

Ontology-based approaches for semantically interpreting smartphone sensor data have been explored in various domains [Ali et al., 2017, Meditskos and Kompatsiaris, 2017, Cardoso et al., 2021]. However, their application in the context of technology addiction remains limited. To identify related works, a systematic search was conducted across PubMed Central, ACM Digital Library, IEEE Xplore, Springer, and Scopus, using key terms such as Technology Addiction, Context Awareness, and Ontology. Table 1 outlines the search terms and string composition. The search, covering publications from 2012 onward, yielded five relevant studies, most of which developed context-aware ontologies for analyzing and inferring data from smartphones and sensors. Only one study specifically addressed digital addiction using an ontology.

Major Terms	**Search Terms**
Technology Addiction	(("Smartphone Addiction" OR "Smartphone Overuse" OR "Problematic Smartphone Use" OR "Mobile Phone Overuse" OR "Mobile Phone Dependency" OR "Internet Addiction" OR "Game Addiction") OR
Context Awareness	("Context-aware") OR ("Context Awareness")) AND
Ontology	("Ontolog*")

Table 1: Definition of the search string for filtering the ontology-related works.

Ali et al. [2017] developed an ontology allowing semantic interpretation of smartphone sensors, named *SmartOntoSensor*. The proposed ontology consists of a formal conceptualization of smartphones in general and smartphone sensors for context representation. The authors aimed to develop a model consisting of a formal conceptualization of smartphone resources and sensors, including taxonomy, relationships, performance, reliability, and metadata regarding sensor characteristics. *SmartOntoSensor* allowed semantic annotation of smartphones and sensors to increase data interoperability, support to intelligent decision making, sensing description, and measurement capabilities of sensors.

Aguilar et al. [2018] proposed a meta-ontology for context modeling called *CAMeOnto*. The proposed ontology allows the autonomous behavior of context-aware applications, like reasoning about contexts and discovering contexts. The proposed meta-ontology depicts the main components of knowledge necessary in a context-aware system, which can be extended with specific information about the application domain.

Iqbal et al. [2021] presented an ontology for adaptive mobile devices, allowing developers to offer optimized, efficient, and user-friendly products that increase the usability and satisfaction of users. The proposed ontology models the context over mobile device, user, environment, and activity. The ontology presents the reasoning base for intelligent adaptation in user interfaces.

Meditskos and Kompatsiaris [2017] presented iKnow, defined as an ontology-driven framework for human activity recognition, focusing on activities of daily living. iKnow used OWL ontological knowledge to capture domain relationships between low-level observations and high-level activities. Furthermore, context-aware fusion allowed context aggregation and activity interpretation. The capabilities of the proposed ontology were demonstrated through integration with a multi-sensor system designed for monitoring individuals with Alzheimer's disease.

Alrobai and Dogan [2015] presented an initial ontology for digital addiction. The proposed ontology encompasses four definitions: Problematic Internet Use, Generalized Pathological Internet Use, Internet Addiction, and Technological Addiction. The ontology aimed to add meaning to the notion of digital addiction and help to develop less addictive software systems. No formal development or inferences were presented.

Cardoso et al. [2021] proposed a recommender system based on a context histories ontology called Vulcont. The ontology utilizes reasoning to examine the semantic value of context histories. The system uses context-aware information, such as location, goals, and close entities to predict users' interests and preferences. The evaluation occurred through four scenarios using an offline approach.

Table 2 provides a comparative assessment of OntoKratos and related ontological models based on a set of evaluation criteria. These criteria were selected to highlight design and implementation aspects relevant to the domain. Specifically, **Scope** refers to the defined objective or thematic focus of the ontology; **Rules** assess the use of formal logical statements to express relationships between entities; **Inferences** examine the ontology's capacity to support reasoning and knowledge derivation; **Query** evaluates the implementation of query languages for knowledge extraction; **Context Awareness** considers the integration of contextual information within the ontology; and **Evaluation** indicates whether the ontology has undergone any form of validation or assessment.

Reference	Scope	Rules	Inferences	Queries	Context Awareness	Evaluation
[Alrobai and Dogan, 2015]	Digital Addiction	No	No	No	No	No Evaluation
[Ali et al., 2017]	Context Awareness	Yes	Yes	Yes	Yes	Integrating with an existing application for automatic changing of smartphone modes according to the varying contexts.
[Meditskos and Kompatsiaris, 2017]	Context Awareness	Yes	Yes	Yes	Yes	Integrating with a multi-sensor framework for monitoring people with Alzheimer's disease.
[Aguilar et al., 2018]	Context Awareness	Yes	Yes	Yes	Yes	Smart classroom, Surgery room, and Semantic workplace learning framework.
[Iqbal et al., 2021]	Context Awareness	Yes	Yes	Yes	Yes	The Pellet and HermiT Reasoner were used to verify the rules, relations, and constraints to avoid inconsistency between classes.
[Cardoso et al., 2021]	Context Awareness	Yes	Yes	Yes	Yes	The evaluation occurred through four scenarios using an offline approach.
OntoKratos	PSU	Yes	Yes	Yes	Yes	Simulated Dataset

Table 2: Comparison of related works.

The proposed ontology stands out in modeling knowledge directed to the detection and monitoring of PSU. Although related work has presented context-aware ontologies and an ontology on digital addiction, to the best of our knowledge, no work has explored the detection of PSU or technology addiction using ontologies and context-aware information. Although OntoKratos suggests personalized interventions based on user context and behavioral indicators, this ontology should not be considered a traditional recommendation system ontology. This type of ontology is typically designed to predict user preferences and rank items such as products, services, or media content using collaborative filtering, content-based filtering, or hybrid approaches [Parthasarathy and Sathiya, 2022]. In contrast, the OntoKratos domain is mental health and behavioral monitoring. The designed ontology employs semantic web technologies, including OWL and SWRL rules, to infer mental health-related risk factors and recommend evidence-based interventions. This approach aligns with the use of ontologies as assistance methods in mental healthcare, where the primary goal is domain reasoning and user state classification rather than content recommendation [Ghorbani et al., 2023]. While OntoKratos incorporates context awareness, as seen in some advanced recommendation ontologies [Cardoso et al., 2021], the objectives and reasoning mechanisms distinguish OntoKratos from traditional recommendation systems.

4 Modeling and Implementation

In general, there is no requirement to follow a specific methodology or approach when constructing ontologies. However, definitions for ontology projects are available to assist researchers in achieving clarity, consistency, reusability, and scalability. The OntoKratos development occurred based on the Ontology Development 101 methodology [Noy and McGuinness, 2001], which provided a balanced approach to knowledge representation, the use of restrictions, and the possibility of extending the ontology, facilitating the incorporation of future definitions. This methodology consists of an iterative process divided into 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.

4.1 Determine the Domain, Scope, and Competency Issues

The knowledge domain addresses PSU identification, related context information, questionnaire responses, and demographic information. The purpose is to identify PSU and environmental conditions, suggesting possible interventions for individuals experiencing PSU. *Competency Questions* (CQ) [Gruninger, 1995] was also used in the ontology modeling. These questions are instrumental in identifying relevant concepts, relationships, and constraints within the domain, and also serve as criteria for evaluating the ontology's effectiveness. The competency questions formulated for this study include: (CQ1) "Which gender shows a higher prevalence of PSU?"; (CQ2) "Which age group shows a higher prevalence of PSU?"; (CQ3) "Do demographic risk factors affect PSU?"; (CQ4) "Do emotional risk factors affect PSU?"; (CQ5) "Which symptoms of mental health problems (depression, anxiety, and stress) are most related to PSU?"; (CQ6) "What category of applications do people with PSU tend to use more?"; and (CQ7) "What interventions are recommended once harmful smartphone usage patterns are detected?".

4.2 Consider Reusing Existing Ontologies

This step involved the exploration of existing ontologies for potential reuse. Regarding the representation of PSU concepts, no ontologies were found. To address this limitation, the ontology creation took place based on the *CAMeOnto* [Aguilar et al., 2018] and the *SmartOntoSensor* [Ali et al., 2017], which incorporated context-aware concepts, such as capturing an individual's location during an activity. The reused classes in the ontology construction comprised activity, context, location, time, and user.

4.3 List Important Ontology Terms

The definition of the important ontology terms followed the focal theme: "PSU identification and intervention". Initially, questions were posed to aid in the construction of knowledge. Additionally, the bibliographic research [Schroeder et al., 2022] assisted in answering the questions. The defined terms were based on the questions and answers. Subsequently, propositions were formulated to illustrate the relationships between the concepts. The following are four questions and their respective answers:

Question 1: 'Which mental health problems are associated with problematic smartphone use?" *Answer 1*: Depression, Anxiety, Stress, nomophobia, and FOMO [Rodríguez-García et al., 2020, Yuan et al., 2021, Stankovic et al., 2021, Wang et al., 2021].

Question 2: "What scales are currently used to identify factors that lead to PSU?" *Answer 2*: SAS and SAS-SV [Kwon et al., 2013], DASS-21 [Lovibond and Lovibond, 1995], NMP-Q [Yildirim and Correia, 2015], and FOMO Scale [Przybylski et al., 2013].

Question 3: "Which factors lead people to use their smartphones in a problematic way?" *Answer 3*: Demographics factors, such as being younger [Sohn et al., 2019, Grant et al., 2019] and female [Demirci et al., 2015, Sohn et al., 2019, Grant et al., 2019, Annoni et al., 2021]. Mental health factors also appear as a significant influence on PSU [Elhai et al., 2020, Li et al., 2021].

Question 4: "Which strategies are being used to assist people with PSU?" *Answer 4*: CBT [King et al., 2013, Mohamed and Mostafa, 2020, Zhang et al., 2020], Physical Exercises [Mohamed and Mostafa, 2020, Zhang et al., 2020], Medication [King et al., 2013], Mindfulness [Yang et al., 2019], Limiting Smartphone Access [Holte et al., 2021].

4.4 Define the Classes and Hierarchy

This step organizes the terms listed in Section 4.3. The definition of the classes occurred in the singular form. Each concept can describe one or more instances. Figure 1 illustrates the structured class hierarchy.

In OWL notation, the root class of the hierarchy is "thing", which serves as the base for all other classes [Djuric et al., 2005]. The class hierarchy is based on inheritance, meaning that subclasses inherit the same information as the superclasses to which they are linked, as well as the specific features. In addition, subclasses permitted the representation of other classes. Protégé software version 5.5.0 [1] allowed the development of the ontology using the OWL language.

OntoKratos combines data from different sources, aiming to aid the identification of patterns and correlations between risk factors and PSU behavior. The *Context* class represents the context of a person. It includes information about an individual's routine, smartphone use habits (smartphone sensor data), environmental information, and

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

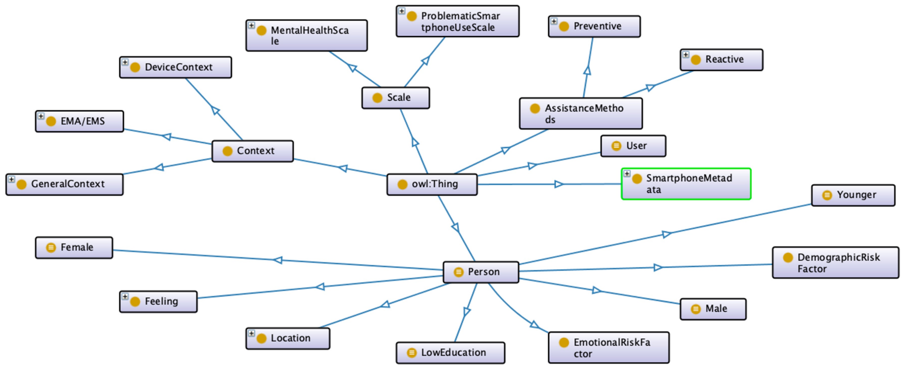


Figure 1: OntoKratos class hierarchy.

Ecological Momentary Assessment (EMA). This class represents time-related dynamic information, for example, device context (battery level, applications used, screen status, etc.), EMA (anxiety, mood, and sleep status), and general context (ambient light, day shift, and place).

The *Assistance Methods* refers to strategies aimed at intervening and preventing PSU. The *Assistance Methods* divide into reactive and preventive methods. The *Scale* refers to the questionnaires used to identify mental health conditions, as well as PSU, nomophobia, and other related disorders. The class is divided into mental health scales and assessment tools designed to identify PSU.

The *Person* describes demographic information, individuals' mood information, and demographic and emotional risk factors. *SmartphoneMetadata* class represents information about the smartphone device of an individual. Finally, *User* class depicts a smartphone user.

4.5 Define Relationships and Class Properties

Figure 2 illustrates the intricate relationships between the ontology classes. Each class is connected to others through lines that illustrate the classes' associations and dependencies. The right frame of the diagram draws attention to the specific names assigned to these relationships. Furthermore, the *Arc Type* list showcases the existing relationships between the classes.

4.6 Define the Semantic Rules

Restrictions for the demographic classes *Female*, *LowEducation*, *Male*, and *Younger* were specified within the ontology. Figure 3 depicts the restriction rules defined to describe the entities' relationships and characteristics. The *Female* class considers entities that belong to the *Person* class and have the object property *hasGender* with value *"female"^^xsd:string*, where the value *"female"* represents a string literal. The *"^^"* symbol denotes the datatype annotation, and *"^^xsd:string"* indicates that the data type of the value is a string, as defined by the XML Schema Definition (XSD). XSD is a specification that provides rules and structures for defining datatypes in XML documents

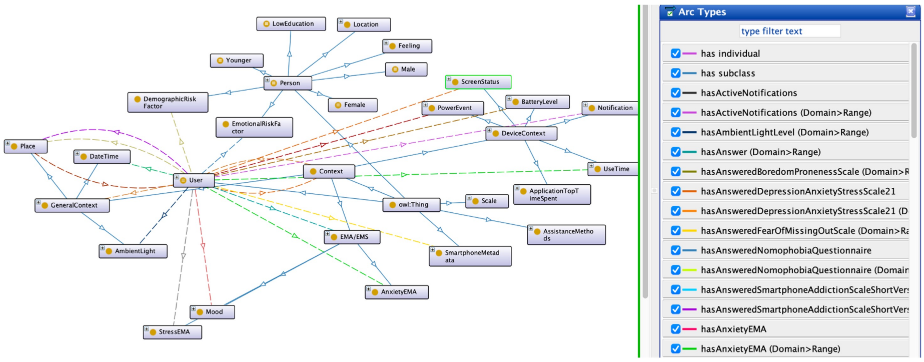


Figure 2: Hierarchical view of ontology classes and relationships.

[Peterson et al., 2012]. The *Male* class adheres to the same rule but requires the value *"male"^^xsd:string*. The *Low education* class considers individuals that belong to the *Person* class and have the object property *hasEducationLevel* with value *xsd:int[<= "2"^^xsd:int]*, where the rule restricts that the *Education Level* must be *xsd:int* data type, and the values must be less than or equal to the integer 2. The *Younger* class complies with the identical principle but considers entities that belong to the *Person* class and have the object property *hasAge* with value *xsd:int[<= "18"^^xsd:int])*.

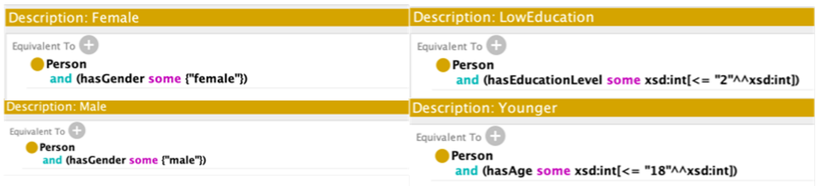


Figure 3: Restriction rules defined for demographic classes.

SWRL extends constraints and classifications through a high-level abstract language [Horrocks et al., 2004]. In contrast to OWL, SWRL offers the additional capacity of supporting clauses in Horn format, like implication sentences (if a -> b), which represent logical rules in a specific format using "if-the" statements with conjunctions [O'Connor et al., 2005], facilitating the development of complex rules that enable the utilization of ontologies to draw inferences and reason about knowledge. The SWRL rules enabled inferences based on literature-derived knowledge about PSU [Schroeder et al., 2022].

Table 3 presents the PSU risk factors inference rules on OntoKratos. The SWRL rules for PSU risk factors are divided into demographics, mental health, and high smartphone use. The demographic risk factors indicate that being female (Rule 1) [Grant et al., 2019, Yoon et al., 2021], younger (Rule 3) [Sohn et al., 2019, Annoni et al., 2021], and having low education (Rule 2) [Bragazzi et al., 2019] are indicators of a higher likelihood of developing PSU.

Another factor that may suggest a predisposition to developing PSU is emotional instability (Rules 4-11) [Arrivillaga et al., 2020]. Individuals considered emotionally

ID	Rule Name	SWRL Expression
1	RiskFactor_Female	Person(?p) ^ Female(?p) -> DemographicRiskFactor(?p)
2	RiskFactor_LowEducation	Person(?p) ^ LowEducation(?p) -> DemographicRiskFactor(?p)
3	RiskFactor_Younger	Person(?p) ^ Younger(?p) -> DemographicRiskFactor(?p)
4	RiskFactor_BoredomProneness	Person(?p) ^ hasAnsweredBoredomPronenessScale(?p, ?s) ^ BoredomProneness(?p) -> EmotionalRiskFactor(?p)
5	RiskFactor_ExtremelySevereAnxiety	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ ExtremelySevereAnxiety(?p) -> EmotionalRiskFactor(?p)
6	RiskFactor_ExtremelySevereDepression	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ ExtremelySevereDepression(?p) -> EmotionalRiskFactor(?p)
7	RiskFactor_ExtremelySevereStress	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ ExtremelySevereStress(?p) -> EmotionalRiskFactor(?p)
8	RiskFactor_SevereAnxiety	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ SevereAnxiety(?p) -> EmotionalRiskFactor(?p)
9	RiskFactor_SevereDepression	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ SevereDepression(?p) -> EmotionalRiskFactor(?p)
10	RiskFactor_SevereStress	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ SevereStress(?p) -> EmotionalRiskFactor(?p)
11	RiskFactor_HighUseTime	Person(?p) ^ hasUseTime(?p, ?s) ^ hasAppUseTime(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 15.0) -> AppHighUseTime(?p)

Table 3: SWRL rules for Risk Factors content inference.

unstable have high scores on the DASS-21 questionnaire for anxiety [Elhai et al., 2020, Stankovic et al., 2021], depression [Yuan et al., 2021, Stankovic et al., 2021, Wang et al., 2021], and stress [Hong et al., 2021], indicating greater severity of these negative emotional states. Furthermore, a high tendency to experience boredom indicates an increased need for external stimulation and a low ability to focus attention, also considered a risk factor for PSU [Elhai et al., 2021, Yuan et al., 2021]. Finally, excessive time spent on the smartphone is also considered a risk factor for PSU, since individuals who spend higher amounts of time on smartphones may be more likely to experience negative consequences associated with excessive smartphone use [Woo et al., 2021].

Table 4 presents five SWRL rules developed on EMA information to infer individuals' behaviors and experiences, including mental status (Rules 12, 14, and 18), sleep information (Rules 13 and 17), and mood at the time of data collection (Rules 15 and 16). These rules enabled a better understanding of the data gathered through EMA. For example, the SWRL Rule 14 *Feeling_Stressed* infers that "If a *Person* has an associated stress *EMA* with a stress value between 2 and 3, then the *Person* should be classified as *Stressed*".

ID	Rule Name	SWRL Expression
12	Feeling_Anxious	Person(?p) ^ hasAnxietyEMA(?p, ?s) ^ hasAnxietyEMAValue(?s, ?ss) ^ swrlb:lessThanOrEqual(?ss, 1) -> Anxious(?p)
13	Feeling_Sleepy	Person(?p) ^ hasSleepRate(?p, ?s) ^ hasSleepRateValue(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 4) -> Sleepy(?p)
14	Feeling_Stressed	Person(?p) ^ hasStressEMA(?p, ?s) ^ hasStressValueEMA(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 2) ^ swrlb:lessThanOrEqual(?ss, 3) -> Stressed(?p)
15	Mood_Happy	Person(?p) ^ hasMood(?p, ?s) ^ hasMoodValue(?s, ?ss) ^ swrlb:lessThanOrEqual(?ss, 1) -> Happy(?p)
16	Mood_Not_Happy	Person(?p) ^ hasMood(?p, ?s) ^ hasMoodValue(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 2) -> NotHappy(?p)
17	Feeling_Sleepy	Person(?p) ^ hasSleepRate(?p, ?s) ^ hasSleepRateValue(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 4) -> Sleepy(?p)
18	Feeling_Stressed	Person(?p) ^ hasStressEMA(?p, ?s) ^ hasStressValueEMA(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 2) ^ swrlb:lessThanOrEqual(?ss, 3) -> Stressed(?p)

Table 4: SWRL rules for inferring the interpretation of the EMA results.

Table 5 shows the SWRL rules developed to infer the results of the questionnaires DASS-21 (Rules 19-33), Boredom Proneness Scale (Rule 34), FOMO Scale (Rule 35), NMP-Q (Rules 36-39), and SAS (Rules 40 and 41). The rules are derived from the data properties of each questionnaire. For example, the SWRL Rule 40 (*Smartphone_Addicted_Female*) denotes "If a *Person* belongs to the *Female* class, *has answered* the *Smartphone Addiction Scale Short Version* and the questionnaire result has a score greater than or equal to 31, then the *Person* is considered *Smartphone Addicted*".

ID	Rule Name	SWRL Expression
19	DASS21_Anxiety_ExtremelySevereAnxiety	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasAnxietyDASS21(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 34) -> ExtremelySevereAnxiety(?p)
20	DASS21_Anxiety_MildAnxiety	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasAnxietyDASS21(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 15) ^ swrlb:lessThanOrEqual(?ss, 18) -> MildAnxiety(?p)
21	DASS21_Anxiety_ModerateAnxiety	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasAnxietyDASS21(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 19) ^ swrlb:lessThanOrEqual(?ss, 25) -> ModerateAnxiety(?p)
22	DASS21_Anxiety_NormalAnxiety	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasAnxietyDASS21(?s, ?ss) ^ swrlb:lessThanOrEqual(?ss, 7) -> NormalAnxiety(?p)
23	DASS21_Anxiety_SevereAnxiety	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasAnxietyDASS21(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 26) ^ swrlb:lessThanOrEqual(?ss, 33) -> SevereAnxiety(?p)
24	DASS21_Depression_ExtremelySevereDepression	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasDepressionDASS21(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 28) -> ExtremelySevereDepression(?p)
25	DASS21_Depression_MildDepression	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasDepressionDASS21(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 10) ^ swrlb:lessThanOrEqual(?ss, 13) -> MildDepression(?p)
26	DASS21_Depression_ModerateDepression	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasDepressionDASS21(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 14) ^ swrlb:lessThanOrEqual(?ss, 20) -> ModerateDepression(?p)
27	DASS21_Depression_NormalDepression	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasDepressionDASS21(?s, ?ss) ^ swrlb:lessThanOrEqual(?ss, 9) -> NormalDepression(?p)
28	DASS21_Depression_SevereDepression	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasDepressionDASS21(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 21) ^ swrlb:lessThanOrEqual(?ss, 27) -> SevereDepression(?p)
29	DASS21_Stress_ExtremelySevereStress	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasStressDASS21(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 34) -> ExtremelySevereStress(?p)
30	DASS21_Stress_MildStress	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasStressDASS21(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 15) ^ swrlb:lessThanOrEqual(?ss, 18) -> MildStress(?p)
31	DASS21_Stress_ModerateStress	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasStressDASS21(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 19) ^ swrlb:lessThanOrEqual(?ss, 25) -> ModerateStress(?p)
32	DASS21_Stress_NormalStress	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasStressDASS21(?s, ?ss) ^ swrlb:lessThanOrEqual(?ss, 14) -> NormalStress(?p)
33	DASS21_Stress_SevereStress	Person(?p) ^ hasAnsweredDepressionAnxietyStressScale21(?p, ?s) ^ hasStressDASS21(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 26) ^ swrlb:lessThanOrEqual(?ss, 33) -> SevereStress(?p)
34	BoredomProneness	Person(?p) ^ hasAnsweredBoredomPronenessScale(?p, ?s) ^ hasBoredomPronenessScale(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 135) -> BoredomProneness(?p)
35	FearOfMissingOut	Person(?p) ^ hasAnsweredFearOfMissingOutScale(?p, ?s) ^ hasAnsweredFomoScale(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 35) -> FearOfMissingOut(?p)
36	Nomophobia_AbsenceNomophobia	Person(?p) ^ hasAnsweredNomophobiaQuestionnaire(?p, ?s) ^ hasAnsweredNMPQ(?s, ?ss) ^ swrlb:lessThanOrEqual(?ss, 20) -> AbsenceNomophobia(?p)
37	Nomophobia_MildNomophobia	Person(?p) ^ hasAnsweredNomophobiaQuestionnaire(?p, ?s) ^ hasAnsweredNMPQ(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 21) ^ swrlb:lessThanOrEqual(?ss, 59) -> MildNomophobia(?p)
38	Nomophobia_ModerateNomophobia	Person(?p) ^ hasAnsweredNomophobiaQuestionnaire(?p, ?s) ^ hasAnsweredNMPQ(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 60) ^ swrlb:lessThanOrEqual(?ss, 99) -> ModerateNomophobia(?p)
39	Nomophobia_SevereNomophobia	Person(?p) ^ hasAnsweredNomophobiaQuestionnaire(?p, ?s) ^ hasAnsweredNMPQ(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 100) -> SevereNomophobia(?p)
40	Smartphone_Addicted_Female	Female(?p) ^ hasAnsweredSmartphoneAddictionScaleShortVersion(?p, ?s) ^ hasAnsweredSAS(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 31) -> SmartphoneAddicted(?p)
41	Smartphone_Addicted_Male	Male(?p) ^ hasAnsweredSmartphoneAddictionScaleShortVersion(?p, ?s) ^ hasAnsweredSAS(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 33) -> SmartphoneAddicted(?p)

Table 5: SWRL rules for inferring the Mental Health and PSU questionnaires score.

Table 6 presents the SWRL rules developed to suggest interventions based on the questionnaire responses, context information, and existing risk factors. The proposed intervention's goal is to help individuals cultivate healthier smartphone habits, mitigating the negative consequences of excessive smartphone use. Research has shown that displaying a grayscale color palette on phone screens, as defined by Rule 42 *AssistanceMethod_GrayScaleDisplay*, can be beneficial. The rule states that "If a *Person* has *EmotionalRiskFactor* and their battery level is less than or equal to 20%, the phone screen should be displayed in grayscale (*GrayScaleDisplay*)". A grayscale color palette may help reduce screen time, anxiety, problematic smartphone use, and the motivation to use the phone [Demirci et al., 2015, Zou et al., 2019]. Furthermore, research indicates that introducing a delay (Rule 50) before accessing phone apps can decrease usage [Kim et al., 2019]. The rules also include assistance methods aimed at enhancing mental health. For instance, alternative behaviors such as physical exercises (Rules 47 and 48) can assume the addiction place and reduce smartphone use [Gao et al., 2018]. Additionally, interventions focused on cultivating mindfulness (Rules 43 and 44) can help to attenuate the effect of PSU on mental health [Yang et al., 2019, Brailovskaia et al., 2021].

ID	Rule Name	SWRL Expression
42	AssistanceMethod_GrayScaleDisplay	Person(?p) ^ EmotionalRiskFactor(?p) ^ hasBatteryLevel(?p, ?s) ^ hasLevelBattery(?s, ?ss) ^ swrlb:lessThanOrEqual(?ss, 20.0) -> GrayScaleDisplay(?p)
43	AssistanceMethod_Mindfulness_Anxious	Person(?p) ^ Anxious(?p) ^ hasScreenStatus(?p, ?s) ^ hasStatusScreen(?s, ?ss) ^ swrlb:equal(?ss, “Unlocked”) -> Mindfulness(?p)
44	AssistanceMethod_Mindfulness_EmotionalRiskFactor	Person(?p) ^ EmotionalRiskFactor(?p) ^ hasScreenStatus(?p, ?s) ^ hasStatusScreen(?s, ?ss) ^ swrlb:equal(?ss, “Unlocked”) -> Mindfulness(?p)
45	AssistanceMethod_NotificationDisable	Person(?p) ^ SmartphoneAddicted(?p) ^ hasPlace(?p, ?s) ^ hasSemanticPlace(?s, ?ss) ^ swrlb:equal(?ss, “Home”) -> NotificationDisable(?p)
46	AssistanceMethod_NotificationDisable1	Person(?p) ^ hasActiveNotifications(?p, ?s) ^ hasNumberActiveNotifications(?s, ?ss) ^ swrlb:greaterThanOrEqual(?ss, 10) -> NotificationDisable(?p)
47	AssistanceMethod_PhysicalExercises_DemographicRiskFactor	Person(?p) ^ DemographicRiskFactor(?p) ^ hasShift(?p, ?s) ^ hasDayShift(?s, ?ss) ^ swrlb:equal(?ss, “Evening”) -> PhysicalExercises(?p)
48	AssistanceMethod_PhysicalExercises_EmotionalRiskFactor	Person(?p) ^ EmotionalRiskFactor(?p) ^ hasShift(?p, ?s) ^ hasDayShift(?s, ?ss) ^ swrlb:equal(?ss, “Evening”) -> PhysicalExercises(?p)
49	AssistanceMethod_SleepProcedures	Person(?p) ^ Sleepy(?p) ^ Home(?p) ^ hasShift(?p, ?s) ^ hasDayShift(?s, ?ss) ^ swrlb:equal(?ss, “Night”) -> SleepProcedures(?p)
50	AssistenceMethod_AppDelay1	Person(?p) ^ SmartphoneAddicted(?p) -> AppDelay(?p)
51	AssistenceMethod_SocialMediaDisabling	Person(?p) ^ EmotionalRiskFactor(?p) ^ AppHighUseTime(?p) ^ hasApplicationInUse(?p, ?s) ^ hasAppInUse(?s, ?ss) ^ swrlb:equal(?ss, “Social Media”) -> SocialMediaDisabling(?p)
52	AssistenceMethod_SocialMediaDisabling_FOMO	Person(?p) ^ FearOfMissingOut(?p) -> SocialMediaDisabling(?p)
53	AssitanceMethod_PhysicalExercises_SmartphoneAddicted	Person(?p) ^ SmartphoneAddicted(?p) ^ hasShift(?p, ?s) ^ hasDayShift(?s, ?ss) ^ swrlb:equal(?ss, “Evening”) -> PhysicalExercises(?p)

Table 6: SWRL rules for suggesting interventions for PSU.

4.7 Create the Instances

The last phase consisted of creating individuals to perform inference and validate the ontology. Individuals are a formal part of an ontology and represent a concrete reality in knowledge [Noy and McGuinness, 2001]. The defined instances aimed to represent users’ context information, patterns of smartphone use, and mental health status. The creation of instances occurred for the classes *Person*, *Context*, and their respective subclasses, as well as for the *Scale* class and its subclasses. Figure 4 displays the instances of their corresponding classes, such as “person8_instance”, “person45_instance”, and “person34_instance”.

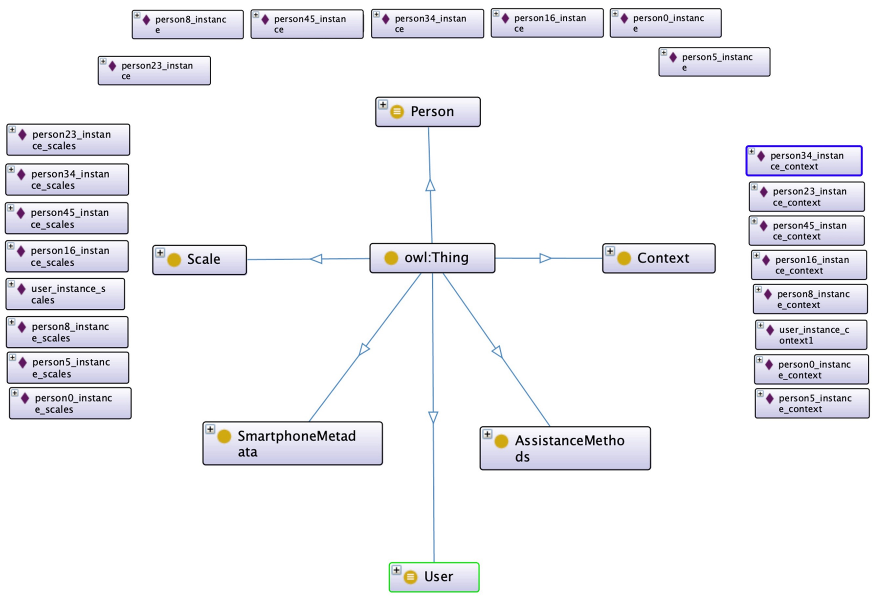


Figure 4: Instances created in Protégé.

5 Results and Discussion

According to Gangemi et al. [2006], assessing the structure and content of an ontology is essential for ensuring its quality. The authors suggested the following measures to ensure ontology quality: verification, which checks the semantic and logical integrity of the ontology, ensuring consistency, non-redundancy, and error-free relationships; and validation, which confirms that the ontology accurately represents real-world concepts and fulfills its intended purpose.

The ontology was populated with individuals by employing a data generation tool. The dataset simulator considers the domain represented in the ontology as a basis for development and performs information fusion using six public datasets: Student Life Dataset [Wang et al., 2014], LSApp [Aliannejadi et al., 2021], ami2018-notifications [Komninos et al., 2018], NMP-Q data [2], Depression Anxiety Stress Scales Responses [Greenwell, 2020], and Datasets for Smartphone Addiction and Cyberbullying Prevalence in Early Adolescents [Suprianto, 2021]. The reason for using different datasets is to base the simulated data on real-world information, bringing the generated information closer to reality.

The data generation tool simulates smartphone use by creating synthetic users who interact with an application that collects contextual information, EMA responses, and questionnaire data. The data generation tool generates 30 consecutive days of data for each simulated user, with 24 hours of activity per day. The simulation accounts for variations between weekdays and weekends when selecting data samples. Contextual data is generated by randomly selecting user-specific conditions based on the type of day

[2] https://figshare.com/articles/dataset/NMPQ_data_sav/21507951

and hour, converting raw data into higher-level information. Regarding EMA responses, the tool simulates four daily entries per user, selecting responses randomly according to the time of day. The ontology instances were defined by randomly selecting eight simulated contexts from distinct users within the simulation.

5.1 OntoKratos Reasoning Verification

Initially, a coherence test was executed through a reasoner to assess the ontology's consistency and classification. The ontology underwent an automated reasoning process using the Pellet reasoner in Protégé. This tool analyzed properties, rules, and restrictions, identifying inconsistencies within the ontology structure. Figure 5 shows the result of executing Pellet reasoning services of class hierarchy, object property hierarchy, data property hierarchy, class assertions, and object property assertions. The results indicate that the model is logically correct and does not present inconsistencies.

```
INFO  17:42:21  ------------------------------ Running Reasoner ------------------------------
INFO  17:42:21  Pre-computing inferences:
INFO  17:42:21      - class hierarchy
INFO  17:42:21      - object property hierarchy
INFO  17:42:21      - data property hierarchy
INFO  17:42:21      - class assertions
INFO  17:42:21      - object property assertions
INFO  17:42:21      - same individuals
INFO  17:42:22  Ontologies processed in 1499 ms by Pellet
```

Figure 5: Pellet plugin reasoning tasks log.

Figure 6 displays the reasoning process for *Person23*, illustrating the classification of *DemographicRiskFactor* (1) and *EmotionalRiskFactor* (2). *Person23* is a 17-year-old female, and after running the reasoner, it was inferred that the *Person23* exhibits both *DemographicRiskFactor* (1) and *EmotionalRiskFactor* (2). The SWRL rule validated the classification of *Person23* as *Younger* based on her age and *Female* based on her gender, which indicates that *Person23* belongs to the *DemographicRiskFactor* class (3). Additionally, *EmotionalRiskFactor* was identified through the analysis of *Person23*'s DASS-21 response, which indicated severe depression, further confirming the presence of *EmotionalRiskFactor* (4).

5.2 OntoKratos Validation

After the reasoning verification process, the ontology's effectiveness in meeting its intended domain can be assessed through queries using SPARQL, the W3C-recommended query language for RDF [Pérez et al., 2006]. This enables a comprehensive examination of the ontology's capabilities and suitability. The validation process involves applying the Competency Questions to assess the ontology's completeness using SPARQL. Table 7 exhibits the queries created for each Competency Question defined in Section 4.1.

Figure 7 illustrates a SPARQL query that retrieves all the individuals of the *Person* class from the ontology, and for each instance, retrieves their gender, age, and SAS response value. The results are ordered in descending order based on the age of the individuals. The purpose of the query is to retrieve individuals classified as *Person* who possess a SAS questionnaire score.

Figure 8 presents the results of CQ1 and CQ2. The CQ1 SPARQL query results exhibit the individuals who are part of the *SmartphoneAddicted* and *Person* classes, showing

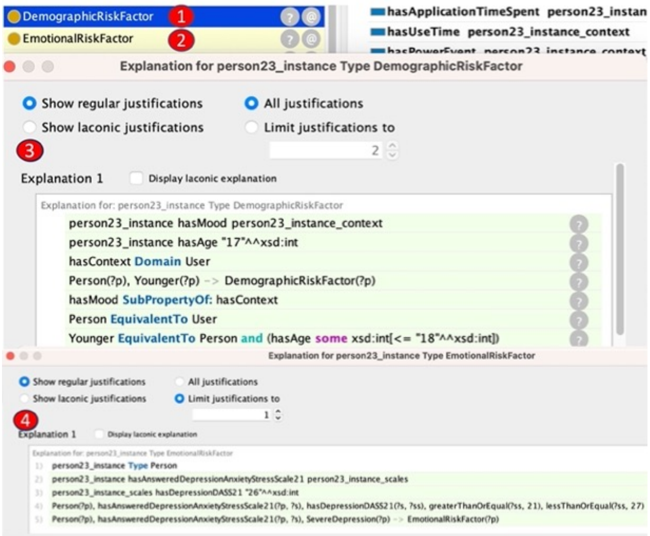


Figure 6: Reasoner inferences for Person23.

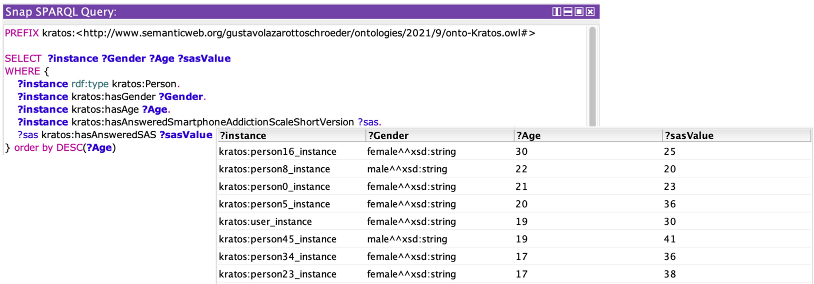


Figure 7: SPARQL query for instance name, gender, age, and SAS score

the instance name, gender, and SAS score. The CQ2 SPARQL query results also show individuals part of the *SmartphoneAddicted* and *Person* classes, showing instance name, age, and SAS score. The results align with the literature findings, indicating that PSU is more prevalent among females [Grant et al., 2019, Yoon et al., 2021] and young individuals [Sohn et al., 2019].

Figure 9 shows the results of CQ3, CQ4, and CQ5. The first one returned four individuals exhibiting PSU and *Demographic Risk Factors*, including age, gender, and education level, thereby classifying them as *problematic smartphone users*. The findings suggest the influence of demographic risk factors, such as being female and young on PSU. The second query returned three individuals who exhibited PSU and *Emotional Risk Factors*. Among the four individuals who experienced PSU, three exhibited emotional risk factors, suggesting a significant influence of these factors on PSU development and manifestation. The third query output shows mental health issues most related to PSU, as determined by the DASS-21 scoring. The query output shows that individuals who presented PSU have greater severity in symptoms of mental health problems, such as

Code	Query
CQ1	*SELECT ?instance ?Gender ?Age ?sasValue WHERE { ?instance rdf:type kratos:Person. ?instance kratos:hasGender ?Gender. ?instance kratos:hasAge ?Age. ?instance kratos:hasAnsweredSmartphoneAddictionScaleShortVersion ?sas. ?sas kratos:hasAnsweredSAS ?sasValue } ORDER BY DESC(?Age)*
CQ2	*SELECT ?instance ?Gender ?sasValue WHERE { ?instance rdf:type kratos:SmartphoneAddicted. ?instance rdf:type kratos:Person. ?instance kratos:hasGender ?Gender. ?instance kratos:hasAnsweredSmartphoneAddictionScaleShortVersion ?sas. ?sas kratos:hasAnsweredSAS ?sasValue } ORDER BY ?instance ?Gender*
CQ3	*SELECT ?instance ?Age ?Gender ?edLevel WHERE { ?instance rdf:type kratos:DemographicRiskFactor. ?instance rdf:type kratos:SmartphoneAddicted. ?instance rdf:type kratos:Person. ?instance kratos:hasAge ?Age. ?instance kratos:hasGender ?Gender. ?instance kratos:hasEducationLevel ?edLevel. }*
CQ4	*SELECT * WHERE { ?instance rdf:type kratos:EmotionalRiskFactor. ?instance rdf:type kratos:SmartphoneAddicted. ?instance rdf:type kratos:Person. ?instance kratos:hasAge ?Age. }*
CQ5	*SELECT * WHERE { { ?SevereDep rdf:type kratos:Person. ?SevereDep rdf:type kratos:SmartphoneAddicted. ?SevereDep rdf:type kratos:SevereDepression. } UNION { ?ExtremelySeverexD rdf:type kratos:Person. ?ExtremelySeverexD rdf:type kratos:SmartphoneAddicted. ?ExtremelySeverexD rdf:type kratos:ExtremelySevereDepression. } UNION { ?ModerateDepression rdf:type kratos:Person. ?ModerateDepression rdf:type kratos:SmartphoneAddicted. ?ModerateDepression rdf:type kratos:ModerateDepression. } UNION { ?SevereAnx rdf:type kratos:Person. ?SevereAnx rdf:type kratos:SmartphoneAddicted. ?SevereAnx rdf:type kratos:SevereAnxiety. } UNION { ?ExtremelySeveresAnx rdf:type kratos:Person. ?ExtremelySeveresAnx rdf:type kratos:SmartphoneAddicted. ?ExtremelySeveresAnx rdf:type kratos:ExtremelySevereAnxiety. } UNION { ?ModerateAnx rdf:type kratos:Person. ?ModerateAnx rdf:type kratos:SmartphoneAddicted. ?ModerateAnx rdf:type kratos:ModerateAnxiety. } UNION { ?SevereTr rdf:type kratos:Person. ?SevereTr rdf:type kratos:SmartphoneAddicted. ?SevereTr rdf:type kratos:SevereStress. } UNION { ?ExtremelySeveresTr rdf:type kratos:Person. ?ExtremelySeveresTr rdf:type kratos:SmartphoneAddicted. ?ExtremelySeveresTr rdf:type kratos:ExtremelySevereStress. } UNION { ?ModerateStr rdf:type kratos:Person. ?ModerateStr rdf:type kratos:SmartphoneAddicted. ?ModerateStr rdf:type kratos:ModerateStress. } }*
CQ6	*SELECT ?appCategory WHERE { { ?instance rdf:type kratos:SmartphoneAddicted. } UNION { ?App rdf:type kratos:ApplicationCategoryTopInUse. ?App kratos:hasAppInUse ?appCategory. } } ORDER BY ?appCategory*
CQ7	*SELECT ?mindfulness ?physicalExercises ?sleepProcedures ?appDelay ?grayScaleDisplay ?notificationDisable ?socialMediaDisabling WHERE { { ?mindfulness rdf:type kratos:Mindfulness. } UNION { ?physicalExercises rdf:type kratos:PhysicalExercises. } UNION { ?sleepProcedures rdf:type kratos:SleepProcedures. } UNION { ?appDelay rdf:type kratos:AppDelay. } UNION { ?grayScaleDisplay rdf:type kratos:GrayScaleDisplay. } UNION { ?notificationDisable rdf:type kratos:NotificationDisable. } UNION { ?socialMediaDisabling rdf:type kratos:SocialMediaDisabling. } }*

Table 7: SPARQL queries for the competency questions.

severe and moderate depression (1), severe anxiety (2), and severe stress (3).

Finally, Figure 10 displays the outcomes of CQ6 and CQ7. The CQ6 SPARQL query results exhibit the application categories that individuals who exhibited PSU tend to use more. The CQ7 SPARQL query illustrates the suggested interventions based on the smartphone use pattern, questionnaire responses, and environmental context. The suggested interventions on smartphone use aim to reduce or eliminate excessive use [Zou et al., 2019] and boost perceived social support [Elhai et al., 2017], assisting users in managing their smartphone use through preventive and reactive strategies.

In the CQ7 SPARQL query outcome, the interventions are outlined in the header.

CQ1

?instance	?Gender	?sasValue
kratos:person23_instance	female^^xsd:string	38
kratos:person34_instance	female^^xsd:string	36
kratos:person45_instance	male^^xsd:string	41
kratos:person5_instance	female^^xsd:string	36

CQ2

?instance	?Age	?sasValue
kratos:person5_instance	20	36
kratos:person45_instance	19	41
kratos:person34_instance	17	36
kratos:person23_instance	17	38

Figure 8: Result of the SPARQL queries for CQ1 and CQ2.

CQ3

?instance	?Age	?Gender	?edLevel
kratos:person5_instance	20	female^^xsd:string	3
kratos:person34_instance	17	female^^xsd:string	2
kratos:person23_instance	17	female^^xsd:string	2
kratos:person45_instance	19	male^^xsd:string	2

CQ4

?instance
kratos:person34_instance
kratos:person23_instance
kratos:person45_instance

CQ5

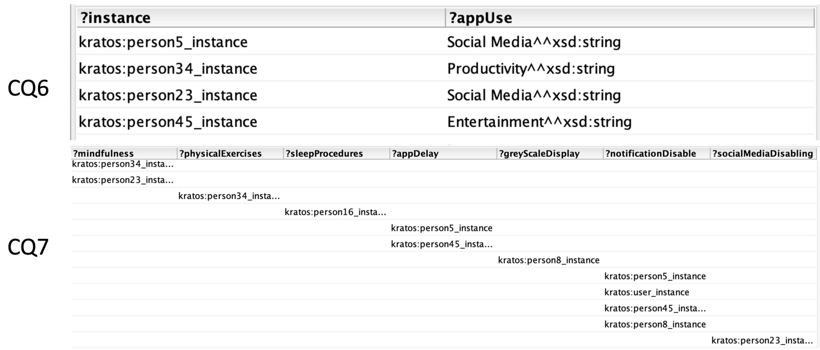
?SevereDep 1	?ExtremelySeverexD	?ModerateDepressi 1	?SevereAnx 2	?ExtremelySeveresAnx	?ModerateAnx	?SevereTr 3	?ExtremelySeveresTr	?ModerateStr
kratos:person34_instance								
kratos:person23_instance								
		kratos:person5_instance						
			kratos:person34_instance					
			kratos:person23_instance					
						kratos:person34_instance		
						kratos:person23_instance		

Figure 9: Results of the SPARQL queries for CQ3, CQ4, and CQ5.

Two individuals were recommended to undergo the *Mindfulness* intervention. Studies have demonstrated that incorporating mindfulness-based practices, including meditation and mindfulness training, can effectively mitigate the detrimental effects of PSU on mental well-being [Yang et al., 2019, Brailovskaia et al., 2021]. One individual had *Physical Exercise* as a suggestion for PSU behavior. Alternative behaviors, such as physical exercises, can assume the addiction place and reduce smartphone use [Gao et al., 2018]. Another individual received the *Sleep Procedures* intervention recommendation. Implementing sleep procedures, such as turning off devices before bedtime, can help improve sleep quality [Zou et al., 2019]. Two individuals received the intervention that delays the opening of applications, aiming at reducing the immediacy of opening an application [Kim et al., 2019]. One individual received the intervention suggestion to change the smartphone display color palette to *Grayscale* to reduce the smartphone's attractiveness and thus limit usage [Demirci et al., 2015, Zou et al., 2019]. Another individual had *Social Media Apps Disabled*, a popular intervention to reduce excessive smartphone use [Hunt et al., 2018]. Lastly, four individuals received the *Notification Disabling* intervention, which can help reduce distractions and promote better focus [Fitz et al., 2019]. Overall, the suggested PSU interventions aimed to promote healthy smartphone use behaviors and reduce the negative consequences associated with excessive use.

6 Conclusion

This study presented OntoKratos, a domain-specific ontology developed to formally represent and infer knowledge related to PSU. The ontology offers a comprehensive semantic framework integrating demographic attributes, Context Histories, EMA, and


CQ6

?instance	?appUse
kratos:person5_instance	Social Media^^xsd:string
kratos:person34_instance	Productivity^^xsd:string
kratos:person23_instance	Social Media^^xsd:string
kratos:person45_instance	Entertainment^^xsd:string

CQ7

?mindfulness	?physicalExercises	?sleepProcedures	?appDelay	?greyScaleDisplay	?notificationDisable	?socialMediaDisabling
kratos:person34_insta...						
kratos:person23_insta...						
	kratos:person34_insta...					
		kratos:person16_insta...				
			kratos:person5_instance			
			kratos:person45_insta...			
				kratos:person8_instance		
					kratos:person5_instance	
					kratos:user_instance	
					kratos:person45_insta...	
					kratos:person8_instance	
						kratos:person23_insta...

Figure 10: Result of the SPARQL queries for CQ6 and CQ7.

standardized questionnaire scores to support automated reasoning about PSU behaviors and associated risk factors. Through semantic rules and structured knowledge representation, the ontology supports the identification of both demographic and emotional risk indicators, while also recommending personalized and context-aware interventions for mitigating the psychological and behavioral consequences of PSU. As a formal, reusable, and extensible knowledge model, OntoKratos advances the field by supporting both preventive and reactive strategies for digital behavior regulation.

An ontology for detecting PSU behavior, emotional, and demographic risk factors is crucial because it provides a structured and formalized representation of relevant knowledge, making it easier to manage, share, and reuse. OntoKratos integrates heterogeneous data sources to uncover patterns and correlations between PSU risk factors and behaviors. This comprehensive approach provides a robust framework for personalized interventions and preventive strategies, potentially enhancing mental health outcomes for individuals affected by PSU.

This paper conducted the ontology development following the Ontology Development 101 [Noy and McGuinness, 2001] due to the balance between knowledge representations, use of constraints, and the possibility of extending the ontology. The concept maps theory created by [Novak et al., 1984] served as a method to map knowledge about mental health problems related to PSU, questionnaires used to identify PSU, demographic and emotional risk factors, and possible interventions for PSU. One of the contributions of this research is the conceptual model, which enhances the comprehensibility of the domain by converting questions and answers from text format to well-structured models.

Regarding the reuse of existing ontologies, the research work reviewed five ontologies. No ontology for the PSU domain was found. Despite the growing concern regarding excessive smartphone use and its impact on mental health, there seems to be a lack of investigation focused on ontologies regarding the understanding and prevention of PSU. The related work section presented the state-of-the-art of digital addiction and context-aware ontologies. Furthermore, the related work made it possible to reuse definitions for representing entities in the ontology. The OntoKratos modeling considered characteristics of the individual's context, such as sociodemographic information, context-aware information, activities, time, smartphone use patterns, EMA information, and scales. This information constitutes the individual's profile and is incorporated into the user's Context Histories.

This study contributes to ongoing research in knowledge-based systems and the

Semantic Web, offering a domain ontology that supports reasoning tasks typical of intelligent, human-centered applications [Zhang and Lobov, 2024]. Furthermore, the reuse potential of OntoKratos aligns with computer science goals of formal abstraction, modularity, and automation. The ontology development using an iterative model allows for flexibility, and each iteration may require incorporating new elements. The choice of using Protégé software for the development was due to the widespread usage in ontology construction as an open-source tool. The ontology includes 89 classes, 43 object properties, 35 data properties, and 1,113 axioms. The definition of 53 SWRL rules allowed automatic inference. Lastly, the ontology underwent internal evaluation using SPARQL queries. These queries enabled answering the seven competency questions that an ontology should satisfy. Additional questions can be created considering the ontology domain and scope. The systematic literature review conducted by Schroeder et al. [2022] allowed this study to develop OntoKratos through consolidated knowledge sources such as books, international standards, and scientific papers.

The competency questions' results demonstrated the ontology's effectiveness in identifying PSU, interconnected risk factors, and smartphone use patterns associated with PSU while suggesting interventions targeted toward PSU behaviors. Despite the contributions, this study presents three limitations. Firstly, OntoKratos testing was conducted using eight instances to evaluate the ontology. This limited sample size may not fully capture the complexity and diversity of the domain, potentially affecting the generalizability of the results. Secondly, the interventions implemented in the ontology were literature-based, without the involvement of professionals in the field. The absence of expert information may have implications for the effectiveness and appropriateness of the suggested interventions. Finally, another limitation is that the knowledge incorporated into the ontology was derived solely from one systematic review. While the review provided a comprehensive synthesis of relevant literature, relying on a single source may introduce biases and limit the scope and diversity of the knowledge base.

Future studies should prioritize collecting real-world user data to replace the current simulated evaluation. This will allow for more robust validation of OntoKratos under naturalistic conditions and enhance its ability to model nuanced behavioral patterns. One key avenue for future work involves the development of a real-world smartphone-based intelligent assistant that integrates OntoKratos to deliver on-the-fly, context-aware intervention suggestions. This assistant would continuously monitor user behavior and environmental context, triggering preventive or reactive recommendations in real-time. Such a system would extend the practical relevance of the ontology by embedding it directly into user devices, enabling dynamic responses to behavioral risks as they occur. To enhance the realism and reliability of the ontology validation, future work should also involve domain experts, such as mental health professionals and behavioral researchers in assessing intervention rules and reasoning outcomes. This expert input would contribute to refining the ontology's practical relevance, interpretability, and applicability in clinical or behavioral health settings. Finally, usability studies and pilot deployments can be conducted to assess the effectiveness, user acceptance, and ethical considerations of using such technology in everyday life. These efforts aim to transition OntoKratos from a theoretical framework to a practical, scalable solution for promoting healthier smartphone use behaviors.

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