Kratos: An Intelligent Model for Assisting People with Problematic Smartphone Use Through Context Histories Analysis

Gustavo Lazarotto Schroeder, Rosemary Francisco, Jorge Luís Victória Barbosa

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

Abstract. *Global smartphone usage has surged, becoming indispensable in people's daily lives. Despite benefits, concerns arise about prolonged hyper-connected experiences. The excessive use of smartphones coupled with demographic and mental health-related risk factors can lead to problematic smartphone use (PSU), characterized as compulsive smartphone use disrupting daily life, work, and relationships. This article summarizes an Academic Master's Dissertation introducing Kratos, a computational model designed to identify PSU through context awareness, context histories, machine learning, and ontology. The main scientific contribution of the Kratos model is the automatic PSU identification and intervention proposals using machine learning and ontological inferences. In the assessment of the model, the Kratos Dataset Simulator (KDS) generated simulations for 49 individuals for 30 days. The machine learning and ontology experiments occurred based on the KDS simulated dataset. The creation of smartphone use behavior profiles allowed the use of Manhattan Distance to identify the behavior as normal or PSU. A silhouette analysis allowed the validation of the consistency of the clusters after the behavior identification process occurred. The results demonstrated the model's ability to consistently distinguish the smartphone use behaviors, correctly separating the clusters of behaviors. Based on the Machine Learning and Ontology results, Kratos recommends literature-based interventions for PSU behaviors. Thus, this research improves PSU identification and assistance through the proposed model.*

1. Introduction

Smartphone use has increased around the world over the years [O'Dea 2021]. Forecasts show that smartphone users will increase even more since the smartphone penetration rate is still lower than 70% in many highly populated countries [Turner 2021]. Besides the benefits of these new smartphone capabilities, there are concerns regarding this hyper-connected experience [Firth et al. 2019]. The World Health Organization (WHO) has already alerted public health's negative consequences when using these technologies in excess [Poznyak 2018]. Problematic smartphone use refers to a pattern of excessive and compulsive use that leads to impaired daily functioning in terms of productivity, social relationships, physical health, or emotional well-being [Horwood and Anglim 2018]. Furthermore, 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].

The Coronavirus (COVID-19) pandemic increased digital technology use for social contact, entertainment, and work [King et al. 2020], which as a result, may have worsened PSU on the population [Li et al. 2021]. Whereas most studies acknowledge the necessity of identifying and assisting people with PSU, only a few studies have deployed assistive methods and evaluated these strategies [Yang et al. 2019].

This scenario demands an intelligent computational model for identifying, preventing, and assisting people with PSU. Identifying dangerous smartphone use patterns combined with interventions on smartphone overuse can prevent PSU development and enhance the quality of people's lives. A computational model can combine information about questionnaires, EMA, environment, and smartphone use data, organizing this information in a temporal series of contexts called Context Histories [García Martins et al. 2021]. This arrangement allows exploring patterns and similarities among Context Histories and classifying these contexts [Filippetto et al. 2021] using Machine Learning (ML) techniques. Furthermore, EMA decreases bias in evaluations of psychological questionnaires and promotes data management by employing smartphones [Gratch et al. 2021], allowing the integration with a computational model. The Kratos model uses the fusion of smartphone sensor data, SAS, NMP-Q, and DASS-21 questionnaires, EMA information, and demographic information for identifying PSU behaviors in daily routines.

The organization of the remainder of this article is as follows. Section 2 describes the systematic literature review performed to seek related works. Next, Section 3 covers the proposed model overview and architecture. Section 4 presents the development and assessment of the OntoKratos ontology. Section 5 shows the experiments with ML models and model evaluation. Finally, Section 6 presents the conclusions and limitations.

2. Related Works

This research explored a systematic literature review to seek related works [Schroeder et al. 2022]. This review investigated PSU and its influence on mental health. Before focusing on PSU, the study broadly reviewed technology addiction. This analysis showed the main directions recommended by the literature for future research opportunities and supported the creation of a taxonomy related to technology addiction.

After investigating the final list of selected studies from the review, this study selected nine articles that applied strategies for identifying PSU or assisting people through strategies to help cope with PSU. Considering these related works, the principal scientific contribution of this research is the intervention suggestion for individuals experiencing PSU through the inference and detection of PSU behaviors based on Context Information.

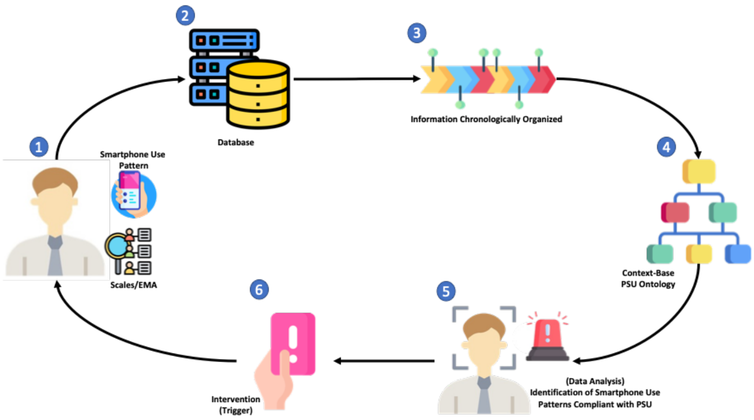
3. Kratos Model

The Kratos model aims to assist smartphone users with PSU, classifying smartphone use behavior and suggesting interventions for dangerous smartphone use behaviors. The model gathers data from different sources to classify the behavior and infer the current state of smartphone use, such as smartphone sensor data, questionnaires, and EMA. The model utilizes ML to analyze data, classifying smartphone use behavior based on historical data on healthy and PSU behaviors. The Kratos model also employs an ontology to infer and propose interventions regarding perilous smartphone usage behavior, leveraging rules grounded in scientific literature.

3.1. Model Overview

Figure 1 illustrates the model overview, where the first stage (1) describes the relationship between the model and a smartphone user. The Kratos model collects data regarding the smartphone user, creating the Context Histories. The model stores the information in a database (2), organizing the data into Context Histories (3) following the structure of the Context-Based PSU Ontology (4). Kratos uses the gathered data to identify individuals with use patterns compliant with PSU. The model continuously searches for smartphone use patterns that indicate PSU by analyzing the stored information using ontology inferences (4) and ML models (5). Kratos uses the gathered data to identify individuals with smartphone use patterns compliant with PSU. The model classifies and infers user behaviors, detecting PSU episodes and implementing proactive and reactive interventions (6). Post-intervention, Kratos assesses the impact, repeating the workflow to measure the influence on smartphone use behavior.

Figure 1. Kratos Model Overview

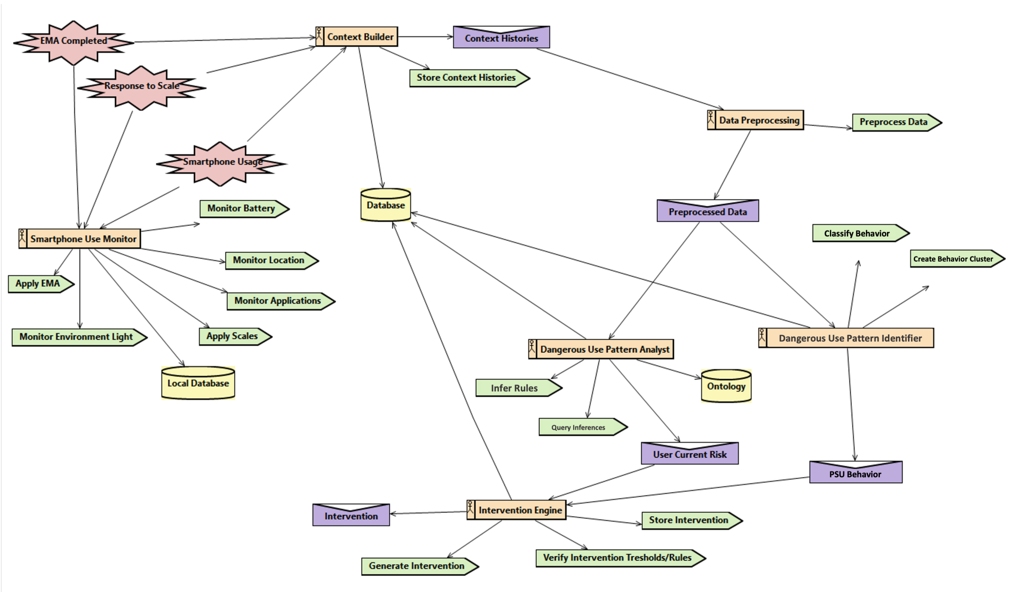


3.2. Kratos Multi-Agent Organization

Figure 2 illustrates the Multi-Agent System, elaborated using the Prometheus methodology [Padgham and Winikoff 2003]. This system encompasses autonomous that perceive environmental changes, act proactively, and make decisions based on the identified changes. The *Smartphone Use Monitor* agent continuously scans the user's smartphone routine, gathering usage logs. The agent monitors the time using the smartphone, applications in use, current notifications, light exposure, and datetime, which characterize agent perceptions while using the mobile application. The *Context Builder* agent handles the compilation of information from the current user context. This information refers to the user's activity on the smartphone, EMA, and questionnaire responses. The *Data Preprocessing* agent receives a set of Context Histories information and pre-processes the data for the ML models.

The *Dangerous Use Pattern Identifier* analyzes pre-processed data, categorizing user behavior into normal and PSU clusters to target interventions. Utilizing sensor data from the *Smartphone Use Monitor*, KDS employs Context Histories to identify PSU behaviors based on historical data. The *Dangerous Use Pattern Analyst* uses ontology for profile management, creating rules from context histories to track and recommend interventions based on the user's smartphone use and PSU status. The *Intervention Engine Agent* provides preventive and reactive interventions for identified dangerous smartphone use patterns, aiming to prevent PSU development and reduce stress caused by problematic smartphone use [Wagner et al. 2014].

Figure 2. Multi-Agent System Organization



4. OntoKratos Ontology

The OntoKratos ontology is part of the *Dangerous Use Pattern Analyst* agent. The ontology utilizes context histories to infer the current situation of users' smartphone use behavior, mood, sleep information, PSU-related risk factors, and mental health status. Based on the inferred information the OntoKratos can provide recommendations for potential smartphone use interventions.

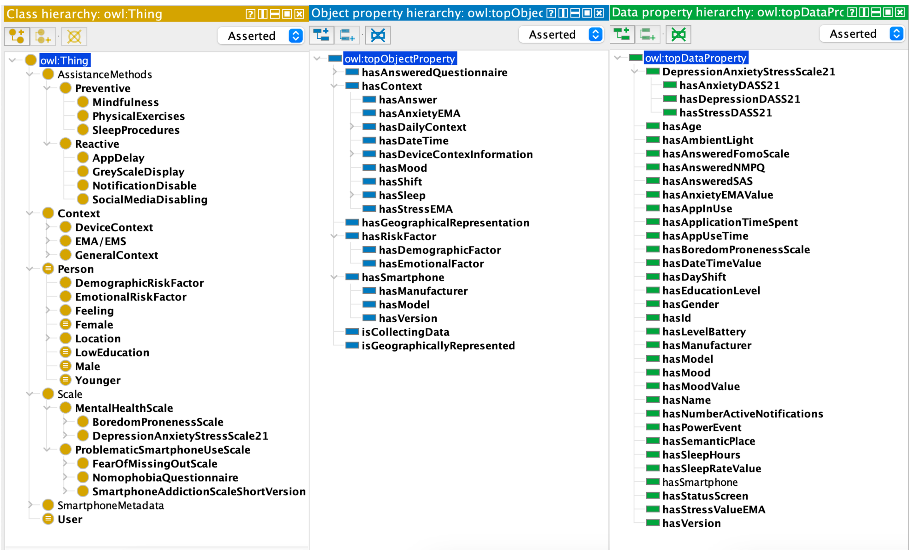
4.1. OntoKratos Development

The OntoKratos ontology is part of the *Dangerous Use Pattern Analyst* agent. The ontology utilizes context histories to infer the current situation of users' smartphone use behavior, mood, sleep data, PSU-related risk factors, and mental health status. Based on the inferred information the OntoKratos can provide recommendations for potential smartphone use interventions. The ontology construction followed the Ontology Development 101 methodology [Noy and McGuinness 2001].

The initial phase involved defining the domain, scope, and competency issues, and formulating competency questions designed to evaluate the ontology's capabilities, as outlined in [Gruninger and Fox 1995]. These competency questions 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?", (CQ7) "What interventions are recommended once harmful smartphone usage patterns are detected?".

The next step consisted of listing the important ontology terms, which occurred based on the systematic mapping study on PSU [Schroeder et al. 2022]. The third step defined the classes and hierarchy, which organized the terms listed in the previous step. The definition of the classes occurred in the singular form. Each concept can describe one or more instances. The *Context* class represents the context of a person. It includes information about an individual's routine, smartphone use habits, environmental data, and EMA. The *Assistance Methods* refers to strategies aimed at intervening in and preventing problematic smartphone usage. The *Person* represents demographic information, individuals' mood, and demographic and emotional risk factors. The next step is to define the relationships and class properties. Figure 3 shows (in yellow) a hierarchical view of the ontology asserted classes. The object property hierarchy (highlighted in blue) denotes the relationships between the classes, while the green color highlights the data property hierarchy, representing the classes' attributes.

Figure 3. Hierarchy of classes, relationships, and attributes.



The semantic rules were defined through the application of restrictions and Semantic Web Rule Language (SWRL).The rules created in the ontology allowed content inference considering the literature findings regarding PSU [Schroeder et al. 2022]. Finally, the last phase consisted of creating individuals to perform inference and validate the ontology. The creation of instances occurred for the classes *Person*, *Context*, and their respective subclasses, as well as for the *Scale* class and its subclasses.

4.2. Ontology Verification

Upon completion of the validation process, it is possible to perform queries with SPARQL, which is the W3C recommended query language for RDF [Pérez et al. 2006], allowing the validation of the ontology effectiveness in meeting its intended domain. The validation process involves applying the Competency Questions defined to assess the ontology's completeness using SPARQL.

Figure 4 presents the results of CQ1 and CQ2. The CQ1 SPARQL query results exhibit the individuals who are part of the classes *SmartphoneAddicted* and *Person*, showing the instance name, gender, and SAS score. The CQ2 SPARQL query results also show individuals part of the classes *SmartphoneAddicted* and *Person*, showing instance name, age, and SAS score. The results align with the literature findings, indicating that PSU is more prevalent among females and young individuals.

Figure 4. Result of the SPARQL queries for CQ1 and CQ2.

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

5. Evaluation methodology

This research focuses on identifying PSU behavior and proposing interventions for smartphone use. In this regard, the development of a synthetic dataset simulator called KDS occurred. KDS allowed the simulation of 30 days of smartphone use by 49 users, during which KDS simulated the data collection process from these individuals. Based on the smartphone users' simulated information this research performed experiments using ML to recognize normal and PSU behaviors. Hence, the experiments assess whether the synthetic context information permits the indication of PSU behaviors based on the smartphone use data, EMA, and questionnaire responses.

5.1. Kratos Dataset Simulator

The development of the Kratos Dataset Simulator (KDS) allowed the simulation of a smartphone application responsible for gathering data about smartphone use and sending data to the Kratos server through a local network. The KDS simulates the collection of sensor information, for example, ambient light, applications used, screen time, battery, and notifications. Furthermore, the KDS simulates an application capable of gathering information related to questionnaires and EMA. KDS performs information fusion using 6 public datasets.

5.2. Source Preprocessing

The *Data Preprocessing* agent in the KDS started by selecting the features that would be part of the Manhattan distance calculation. The Manhattan distance may be preferable for classifying high dimensional data [Wang et al. 2014], which is the case with this study. Feature selection is an important step when using Manhattan distance as a similarity metric [Yu et al. 2008]. Due to the Manhattan distance nature of measuring the absolute differences between features and calculating the sum of the differences [Aggarwal et al. 2001], the number of features can be computationally expensive and may lead to overfitting or underfitting. For feature selection, the technique information gain ratio was used. This method focuses on reducing the entropy of the target variable after splitting the data based on a given feature [Shouman et al. 2011]. After the feature selection phase, the process of data normalization occurred. This process aimed to scale the features to the same importance so that no feature would have an undue influence on the results [Norris 2001]. Normalizing data helps to improve the performance and stability of the machine learning models [Patel and Mehta 2011].

5.3. Distance-Based Model for PSU Identification

The dataset generated by KDS served to create the behavior clusters and allowed the *Dangerous Use Pattern Identifier* agent to identify normal and problematic smartphone use behavior using ML. The behavior identification process begins by retrieving the contexts generated by KDS from the database. The algorithm simulates receiving information hourly, allowing comparison between the synchronized information and the smartphone use pattern of normal and PSU users. The behavior identification process consisted of analyzing a sequence of hour-based Context Histories and the smartphone use behavior based on historical data. This approach allows the use of Manhattan Distance to categorize smartphone use behaviors.

5.4. Results

Among the individuals who answered the SAS questionnaire [Kwon et al. 2013], 31 scores suggested that they did not present PSU, whereas the responses of 18 individuals indicated PSU. Upon examination of the Normal and PSU behaviors groups, it was observed that individuals who did not present indications of PSU according to the SAS had 88.96% of their device usage time considered healthy. Regarding PSU individuals, 58.27% of device usage time was categorized as problematic, whereas 41.73% was considered normal. The results factored in the simulation of 24 synchronizations per day, representing a full day of smartphone use.

While studies propose a higher tendency for females to exhibit PSU compared to males [Yue et al. 2021], our data analysis did not reveal a significant difference in PSU behavior between the two genders. The SAS scores played a crucial role, with unintentionally proportional distributions: 36% of males and 37% of females indicated PSU. Mental health, notably anxiety, depression, and stress, is closely linked to PSU [Yuan et al. 2021]. For instance, those facing depression may use smartphones as a distraction [Volungis et al. 2020]. Additionally, PSU can also exacerbate existing mental health conditions [Busch and McCarthy 2021].

Data analysis identified smartphone usage differences between weekdays and weekends. On weekdays, functional purposes like emails and calls dominate [Derks et al. 2021], while weekends see more entertainment use, including gaming and social media [Brodersen et al. 2022]. The *Intervention Engine* proposes interventions based on time, day type, and smartphone use. For instance, using a phone in the evening on a weekday may prompt a suggested intervention like engaging in physical exercises to counter PSU.

6. Final Considerations

This article presented the Kratos model, a computational model for identifying PSU and assisting individuals through interventions. This research began with a study of the related areas, covering PSU, context awareness, context histories, ontologies, and AI. The subsequent step involved a search for related works in the literature, which occurred through a systematic literature review [Schroeder et al. 2022]. In addition, this study also described the proposed model's architecture, as well as requirements, multi-agent organization, and implementation details. Finally, this research presented the implementation and evaluation aspects of the proposed model.

The Kratos model development involved a comprehensive literature review, resulting in several contributions. The literature review introduced two taxonomies, organizing studies on technology addiction and categorizing mental disorders and symptoms related to PSU. The KDS allowed the model evaluation by simulating a smartphone application that collects data on various aspects of smartphone use, including smartphone sensor data, EMA collection, questionnaires, and demographic information from public datasets. Another contribution is the fusion of smartphone log data, questionnaires, EMA, and context awareness, enabling machine learning to identify behaviors based on smartphone use, demographics, and mental health status. Lastly, the proposal of OntoKratos, an ontology derived from a literature review, is the first for problematic smartphone use, providing a foundation for information inference and intelligent interventions.

This study acknowledges limitations in its research design and execution. Firstly, the use of simulated data in testing the model, despite the careful construction of the KDS, may compromise the model's generalizability due to a lack of individual diversity, potentially missing the intricacies of real-life contexts. Secondly, the utilization of the Manhattan Distance in the ML model, with only two clusters for each individual, might oversimplify data, potentially missing variations. Lastly, the limited instances (eight) used to test OntoKratos may not fully represent the domain, emphasizing the need for future studies to integrate the ontology with real context and demographic information for a more comprehensive evaluation with larger datasets.

Acknowledgments

The authors express their gratitude to the Coordination for the Improvement of Higher Education Personnel - Brazil (CAPES) – Funding Code 001, the National Council for Scientific and Technological Development (CNPq), and the University of Vale do Rio dos Sinos (Unisinos) for their support in the development of this work.

References

Aggarwal, C. C., Hinneburg, A., and Keim, D. A. (2001). On the surprising behavior of distance metrics in high dimensional space. In *Database Theory — ICDT 2001*, pages 420–434. Springer Berlin Heidelberg.

Brodersen, K., Hammami, N., and Katapally, T. R. (2022). Smartphone use and mental health among youth: It is time to develop smartphone-specific screen time guidelines. *Youth*, 2(1):23–38.

Busch, P. A. and McCarthy, S. (2021). Antecedents and consequences of problematic smartphone use: A systematic literature review of an emerging research area. *Computers in Human Behavior*, 114:106414.

Derks, D., Bakker, A. B., and Gorgievski, M. (2021). Private smartphone use during worktime: A diary study on the unexplored costs of integrating the work and family domains. *Computers in Human Behavior*, 114:106530.

Elhai, J. D., Dvorak, R. D., Levine, J. C., and Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. *Journal of Affective Disorders*, 207:251–259.

Elhai, J. D., Rozgonjuk, D., Alghraibeh, A. M., and Yang, H. (2021). Disrupted Daily Activities From Interruptive Smartphone Notifications: Relations With Depression and Anxiety Severity and the Mediating Role of Boredom Proneness. *Social Science Computer Review*, 39(1):20–37.

Filippetto, A. S., Lima, R., and Barbosa, J. L. V. (2021). A risk prediction model for software project management based on similarity analysis of context histories. *Information and Software Technology*, 131:106497.

Firth, J., Torous, J., Stubbs, B., Firth, J. A., Steiner, G. Z., Smith, L., Alvarez-Jimenez, M., Gleeson, J., Vancampfort, D., Armitage, C. J., et al. (2019). The "online brain": how the internet may be changing our cognition. *World Psychiatry*, 18(2):119–129.

García Martins, M., Nesi, L., Silva Pereira, P. R. d., and Barbosa, J. L. V. (2021). Delfos: A model for multitemporal analysis based on contexts history. *IEEE Latin America Transactions*, 19(9):1478–1485.

Gratch, I., Choo, T.-H., Galfalvy, H., Keilp, J. G., Itzhaky, L., Mann, J. J., Oquendo, M. A., and Stanley, B. (2021). Detecting suicidal thoughts: The power of ecological momentary assessment. *Depression and anxiety*, 38(1):8–16.

Gruninger, M. and Fox, M. S. (1995). Methodology for the design and evaluation of ontologies.

Horwood, S. and Anglim, J. (2018). Personality and problematic smartphone use: A facet-level analysis using the five factor model and HEXACO frameworks. *Computers in Human Behavior*, 85:349–359.

King, D. L., Delfabbro, P. H., Billieux, J., and Potenza, M. N. (2020). Problematic online gaming and the covid-19 pandemic. *Journal of Behavioral Addictions*, 9(2):184–186.

Kwon, M., Lee, J.-Y., Won, W.-Y., Park, J.-W., Min, J.-A., Hahn, C., Gu, X., Choi, J.-H., and Kim, D.-J. (2013). Development and Validation of a Smartphone Addiction Scale (SAS). *PLOS ONE*, 8(2):1–7.

Li, T., Zhang, M., Li, Y., Lagerspetz, E., Tarkoma, S., and Hui, P. (2021). The impact of covid-19 on smartphone usage. *IEEE Internet of Things Journal*, pages 1–1.

Norris, G. A. (2001). The requirement for congruence in normalization. *The International Journal of Life Cycle Assessment*, 6(2).

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

O'Dea, S. (2021). Number of smartphone users worldwide from 2016 to 2021. statista. Accessed: 2021-07-11.

Padgham, L. and Winikoff, M. (2003). Prometheus: A methodology for developing intelligent agents. In Giunchiglia, F., Odell, J., and Weiß, G., editors, *Agent-Oriented Software Engineering III*, pages 174–185, Berlin, Heidelberg. Springer Berlin Heidelberg.

Patel, V. R. and Mehta, R. G. (2011). Impact of outlier removal and normalization approach in modified k-means clustering algorithm. *International Journal of Computer Science Issues (IJCSI)*, 8(5):331.

Pérez, J., Arenas, M., and Gutierrez, C. (2006). Semantics and complexity of SPARQL. In *Lecture Notes in Computer Science*, pages 30–43. Springer Berlin Heidelberg.

Poznyak, V. (2018). Public health implications of excessive use of the internet and other communication and gaming platforms. Accessed: 2021-07-11.

Schroeder, G. L., Heckler, W., Francisco, R., and Barbosa, J. L. V. (2022). Problematic smartphone use on mental health: a systematic mapping study and taxonomy. *Behaviour &amp Information Technology*, pages 1–24.

Shouman, M., Turner, T., and Stocker, R. (2011). Using decision tree for diagnosing heart disease patients. In *Proceedings of the Ninth Australasian Data Mining Conference - Volume 121*, AusDM '11, page 23–30, AUS. Australian Computer Society, Inc.

Turner, A. (2021). How many smartphones are in the world?. bankmycell. Accessed: 2021-07-11.

Volungis, A. M., Kalpidou, M., Popores, C., and Joyce, M. (2020). Smartphone Addiction and Its Relationship with Indices of Social-Emotional Distress and Personality. *International Journal of Mental Health and Addiction*, 18(5):1209–1225.

Wagner, A., Barbosa, J. L. V., and Barbosa, D. N. F. (2014). A model for profile management applied to ubiquitous learning environments. *Expert Systems with Applications*, 41(4, Part 2):2023–2034.

Wang, R., Chen, F., Chen, Z., Li, T., Harari, G., Tignor, S., Zhou, X., Ben-Zeev, D., and Campbell, A. T. (2014). StudentLife. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM.

Yang, X., Zhou, Z., Liu, Q., and Fan, C. (2019). Mobile Phone Addiction and Adolescents' Anxiety and Depression: The Moderating Role of Mindfulness. *Journal of Child and Family Studies*, 28(3):822–830.

Yu, J., Amores, J., Sebe, N., Radeva, P., and Tian, Q. (2008). Distance learning for similarity estimation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 30(3):451–462.

Yuan, G., Elhai, J. D., and Hall, B. J. (2021). The influence of depressive symptoms and fear of missing out on severity of problematic smartphone use and Internet gaming disorder among Chinese young adults: A three-wave mediation model. *Addictive Behaviors*, 112.

Yue, H., Zhang, X., Sun, J., Liu, M., Li, C., and Bao, H. (2021). The relationships between negative emotions and latent classes of smartphone addiction. *PLoS ONE*, 16(3 March):1–13.