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OntoKaire: an ontology-based reasoning for work-related stressors in industrial settings

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Abstract: Stress is a mental disorder responsible for impacting the industry through psychosomatic illnesses, loss of productivity, and accidents caused by stressful workplaces. Conversely, the literature indicates that fostering mental well-being among workers can boost motivation and performance while alleviating symptoms of stress. The fourth industrial revolution incorporated technologies into work that allowed the automation of processes and control of environments. The fifth revolution introduced the application of research and innovation aimed at a human-centered consciousness, enabling the advancement of mental health through sensors and wearables. Despite advancements in stress classification technologies, there remain opportunities for further research into identifying stress motivators within industrial work environments. In this sense, this paper proposes an ontology to identify stressors considering personal and environmental data, allowing knowledge generation related to work stressors for mitigating the problem. The methodology utilized in this ontology development consisted of seven stages and two evaluation phases. The findings addressed four key questions related to competency as outlined in the model. The results revealed potential stressful scenarios, including the timing of occurrence, shared locations, environmental factors, and identifying groups experiencing moments of stress. This study presents as a scientific contribution the first ontology to address the identification of work-related stressors in the industrial environment.

Keywords: Industry 5.0, Mental Health, Ontology, Stress, Workplace Mental Health

Categories: D.0, D.2.13, H.3.4, M.8
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1 Introduction

According to the National Health Service of the United Kingdom (NHS) [National Health Service, 2019], stress is usually a reaction to mental or emotional pressure, which can also cause behavior changes like becoming more aggressive. Stressors refer to physical or psychological triggers eliciting a stress response, with individual variations based on personal perception [Mifsud and Reul, 2018]. Factors such as intensity, frequency, duration, or past exposure to stressors can induce physiological harm and contribute to the development of chronic illnesses [Ketchesin et al., 2017]. Individuals under stress may undergo emotional fluctuations, such as feelings of anger, depression, or frustration [Behere and Yadav, 2011]. Additionally, individuals may experience physical symptoms such as headaches, nausea, or indigestion, which, in more severe cases, can progress to conditions like stomach ulcers or cardiovascular diseases [Goetz et al., 2022].

Stress diminishes professionals' quality of life and is associated with an increase in domestic violence. Specifically, occupational stressors are more strongly linked to violent behavior in men, while a broader range of stressors tends to influence violent behavior in women [Caño and Vivian, 2003, Bromley et al, 2023]. Furthermore, studies indicate that workplace and domestic harassment significantly elevate stress levels in men, resulting in negative impacts on cardiovascular health, mental well-being, job satisfaction, and an increased risk of problematic alcohol consumption [Willness et al., 2007, Rospenda et al., 2008, Rasool et al, 2020]. Numerous studies have highlighted the implications of stress in various contexts. For instance, [Teixeira et al, 2024] proposed a reference ontology that connects pregnancy and mental health. Additionally, [Abbas et al., 2023] investigated the effects of technostress in educational settings, while [Mahrishi et al, 2024] addressed the regulatory frameworks necessary for artificial intelligence in higher education.

The detrimental consequences of workplace stress can heavily influence the well-being and productivity of employees [Eddy et al., 2023], generating a loss of US$ 1 trillion each year [World Health Organization, 2024)]. The COVID-19 pandemic has also been a source of mental health problems [Bhaik et al., 2022]. This crisis has collapsed health systems around the world, causing negative psychological effects due to fear, insecurity, and social isolation [Rossi et al., 2023]. [Srivastava, 2009] addressed perspectives and dynamics between industry and mental health. Based on the research results, the author linked workers' mental well-being with physical conditions and motivations and recommended that employers consider the productivity losses associated with mental health. In this context, researchers have long been concerned with mental health in the workplace. For example, [Wright and Cropanzano, 2000] presented studies showing the positive reflection of psychological well-being in worker performance ratings. [Liona et al., 2020] highlighted the importance of work engagement and job satisfaction in enhancing workers' psychological well-being, consequently leading to improved performance. These results showed that the new environment proposal provided an increase in job satisfaction, an improvement in communication between colleagues, and a decrease in work-related stress symptoms.

The industry has undergone a technological revolution in the past few years, resulting in economic and social impacts [Sarfraz et al., 2021, Ghaithan et al., 2023]. The employment of the Internet and other emerging technologies broke the paradigm in industrial production with automated and integrated processes, leading to a new moment called Industry 4.0 [Bavaresco et al., 2021]. The application of research and innovation heralded the advent of Industry 5.0, aimed at fostering a sustainable and human-centric ethos [Broo et al., 2022]. The competitiveness between humans and machines promoted by these new technologies generated the need for efforts to create collaboration between these parties emphasized in the fifth revolution [Noble et al., 2022]. [Velasco et al., 2022] highlighted the importance of balancing productivity and human well-being to maintain the ergonomics of the worker's cognitive dimension, recommending principles for developing human-system interactions. [Mody and Mody, 2019] suggested some mental care alternatives using artificial intelligence: virtual counseling, precision therapy, and diagnostic systems. While the research community has made advancements in stress classification technologies, particularly through the use of physiological data [Iqbal2023 et al. 2023] and machine learning [Priyadarshini et al., 2020], the identification of specific stress motivators within industrial settings remains largely unexplored [Lukan et al., 2022, Awada et al., 2024].

Considering this scenario, this paper presents OntoKaire, an ontology that aligns technology with knowledge modeling. Ontologies can be efficient means to semantically represent knowledge allowing people and software to share a common understanding of a given domain [Ouatiq et al., 2022]. Furthermore, the use of ontologies for health care systems is emerging among researchers and involving collaborative development efforts [Larentis et al., 2021]. The OntoKaire objective is to identify stressors by incorporating personal and environmental data. This paper aims to foster an understanding of the impacts of repeated or prolonged exposure to stressors, thereby providing industry stakeholders with insights into the mental well-being of workers. Such insights can facilitate the development of targeted interventions to alleviate stress-related problems in the industry. The application of ontology enhances human-machine interaction and expands knowledge for future contributions. The findings revealed stressful situations by detailing the frequency and duration of incidents. Previous research did not uncover studies specifically aimed at identifying work-related stressors, thus highlighting the significance of these results within the research community.

Although existing models address mental health through discrete physiological markers or environmental elements [Dias et al, 2020, Paula et al., 2022], the integration of these components remains an area for further exploration. Current techniques face challenges in identifying subtle workplace stressors arising from the complex interactions between context, environment, and human factors. OntoKaire introduces a novel approach by combining physiological data with environmental factors, leveraging context histories to forecast stressors in industrial settings. OntoKaire offers a comprehensive approach to understanding workplace stressors, focusing on identifying present stressors and predicting future patterns using historical data, providing a proactive solution for managing workplace mental health.

The remainder of this paper is structured as follows. Section 2 addresses the related works. Section 3 describes the seven steps used in modeling the ontology, while Section 4 presents the evaluation results. Finally, Section 5 discusses the results of the OntoKaire, and Section 6 presents the study conclusions.

2 Related Works

This section examines studies that employed ontologies within the domain of mental stress. This analysis aimed to uncover opportunities within this area of research.

[Bavaresco et al., 2020] described a model to predict persons' stress states in their daily routines through mobile apps and unobtrusively physiological sensors. The authors designed an ontology using low-level and high-level contexts. In a low-level context, the authors considered raw data, such as physiological data and location, and information activity to achieve high-level context interpretations, such as psychological states and semantic location.

[Khoozani and Hadzic, 2019] introduced an ontology model that contained information related to stress, such as causes, effects, treatments, mediators, and measurements. This framework can help researchers and therapists evaluate stress and facilitate communication between the research community and clinical spaces. Moreover, the study also enables large-scale sharing to support data mining software.

[Yamada et al., 2018] developed an ontology capable of inferring about treatments and diagnoses related to mental health, including stress, helping professionals in clinical decisions, and serving as a knowledge base. The authors pointed out that the error rate in clinical diagnoses can reach 24.4%, and this work can help to minimize this percentage. This domain encompassed 361 classes, 37 relationships, and 72 individuals.

Table 1 compares the related works identified in this study and the OntoKaire. *Class modeling* informs whether the ontology was developed to be used as a basis for coding a computational model. *Reuse* describes whether authors considered another ontology to extend or leverage the knowledge, partially using the structure or concepts. *Reasoning* represents whether the studies apply class restrictions or semantic rules to generate new definitions through a reasoning engine. *Queries* column points to papers that adopted data extraction and manipulation via SPARQL queries. At last, *Evaluation* describes the type of dataset used to assess the ontology developed in the study.

Paper	**Class modeling**	**Reuse**	**Reasoning**	**Queries**	**Evaluation**
[Bavaresco et al., 2020]	Yes	No	No	No	Real environment
[Khoozani and Hadzic, 2019]	No	Yes	No	No	Article abstracts
[Yamada et al., 2018]	No	No	Yes	Yes	Public database
This study	Yes	Yes	Yes	Yes	Public dataset

Table 1: Comparison of related works.

Although prior research has explored the stress domain, none has proposed an ontology targeting stressors within industrial environments. Therefore, this study provides information to identify possible stress sources through personal and environmental data.

3 Ontology Modeling

Noy and McGuinness [Noy and McGuinness, 2001] explained that several viable modeling alternatives exist, depending on the application and extensibility. Furthermore, the authors emphasize the necessity of an interactive development process that can be adjusted throughout activities. The steps outlined for the design of OntoKaire were derived from the methodology proposed by Noy and McGuinness [Noy and McGuinness, 2001]. Figure 1 illustrates the steps utilized in this study.

Noy and McGuinness [Noy and McGuinness, 2001] suggested creating individuals as a last step. However, using semantic rules for inferences of instances demanded the anticipation of the creation of individuals to be used in the rules and restrictions step.

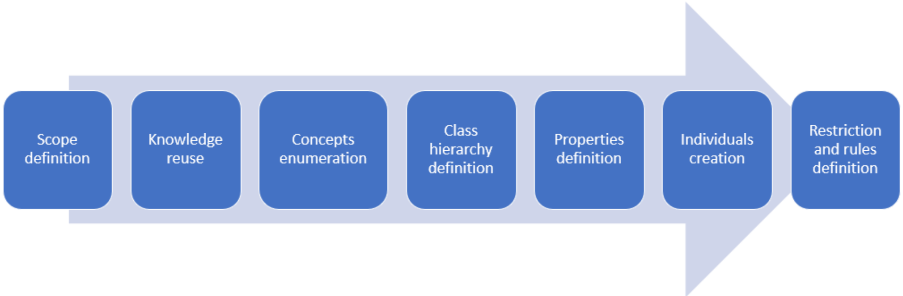


Figure 1: Steps for developing an ontology.

Therefore, the inversion of the sixth and seventh steps was an adaptation of the proposed methodology. The following sections outline each step of the OntoKaire construction process.

3.1 Scope definition

The initial phase in ontology development involves delineating its scope, specifying the domain knowledge organization, and defining which aspects will not be addressed. One common approach addresses key questions such as: What constitutes the domain? What is the intended purpose? And who will benefit from this knowledge?

In this regard, the knowledge domain of this study addresses work-related stress in industrial settings identified as 4.0 environments capable of monitoring the workplace. The purpose is the identification of stressors in the workplace and the environmental conditions. Thus, the ontology can be used by industries that seek to identify possible stressors within work routines to improve workers' mental health and productivity.

Furthermore, Noy and McGuinness [Noy and McGuinness, 2001] recommended elaborating questions about what the ontology should be able to answer. This task aims to prepare Competence Questions (CQs) to expand the scope through purpose assumptions. Table 2 lists these questions elaborated in this step.

ID	Question
CQ1	Which possible stressors are identified for each location and time?
CQ2	How long do the stressors keep in contact with the worker during their activities?
CQ3	How often are environmental conditions present in stressful situations?
CQ4	Who is present in the workgroups in stressful situations?

Table 2: Competence questions.

The first competence question (CQ1) refers to environments where stressors vary by shift or work area. In industrial manufacturing plants, night shifts often experience higher noise levels and reduced lighting, contributing to worker fatigue and decreased productivity [Åkerstedt and Landström, 1998, Cho et al, 2023]. CQ2 helps to quantify exposure to harmful conditions like loud machinery noise, which can lead to negative health consequences like hearing impairment and musculoskeletal problems [Themann and Masterson, 2019]. CQ3 addresses the association between extreme environmental stressors, such as heat or poor lighting, and stress-related incidents. Studies have identified these factors as determinants of occupational injuries [Lamb and Kwok, 2016]. Finally, CQ4 helps to identify teams or individuals involved in high-stress situations, enabling interventions such as improved communication or team-building [Sorensen et al., 2023]. These questions offer valuable insights into workplace stressors, enabling targeted strategies to enhance worker safety and performance.

3.2 Knowledge Reuse

This stage involves analyzing existing ontologies to adapt and extend knowledge already created by other authors [Noy and McGuinness, 2001]. Adapting entails crafting a new ontology by leveraging previously established components or knowledge structures while extending involves augmenting the original ontology with additional elements.

Authors have previously delved into stress classification. Although predicting stress levels is not the primary focus of this study, the domain knowledge within this realm holds significant relevance. Thus, this research acknowledges the insights outlined in the *RevitalMe* model [Bavaresco et al., 2020] as foundational, aiming to explore a distinct scope and enhance the modeling approach. Figure 2 depicts the *RevitalMe* ontology with the modifications considered in this study. The OntoKaire modeling process omitted the utilization of red classes, while the green classes were transformed into properties.

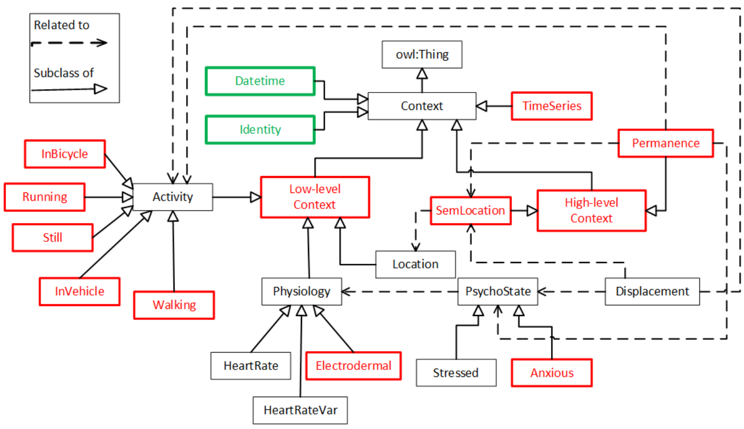


Figure 2: Modifications to the RevitalMe ontology.

In addition, this study took advantage of the previous ontology, using the knowledge of context and specializations of physiological data and psychological state, as well as the concepts of activity, location, and identity. However, adjustments were made to the class hierarchy, as the high and low levels of context did not fully align with the proposed modeling. Additionally, activity, location, and identity were integrated as separate entities, rather than specializing within contexts. Furthermore, time information transitioned from being a class to becoming a context attribute. Moreover, the introduction of new concepts occurred, addressing aspects pertinent to the industrial environment.

3.3 Concepts Enumeration

Enumerating terms facilitates a comprehensive understanding and conceptualization within a given domain. The enumerated terms create a large pool of concepts, without worrying about overlapping information [Kamel et al., 2007]. Not every item listed needs to be directly translated into classes or relationships, as these items do not need a place within the ontology structure. Instead, the compilation of terms serves the purpose of enriching the understanding of the domain under consideration.

The systematic review by [Goetz et al., 2022] addressed the concepts around stress, being the basis to enumerate the terms for this step. The studies showed psychological trial approaches to induce mental reactions through different *stressors*, for example, virtual simulations of *social interactions*, such as presentations or meetings [Gaggioli et al., 2014], *faulty equipment* [Liapis et al., 2015], or *activities* with different levels of concentration [Attallah et al., 2020, Ding et al., 2020]. *Humidity* and *temperature* measurements were gathered to assess thermal stress within *environments* posing potential risks to workers [Sandulescu et al., 2015]. This analysis demonstrated that *work conditions* can influence mental states. Additionally, variations in *light* and *noise* levels can impact cognitive workload during *tasks*, potentially heightening susceptibility to emotional responses like *stress* [Wang et al., 2013].

Finally, the list of terms was defined as follows: activity, environment, faulty equipment, humidity, light, noise, social interactions, stress, stressor, task, temperature, and work condition.

3.4 Class Hierarchy Definition

This step structures the terms listed in Subsection 3.1. The class hierarchy helps to organize knowledge as a basis for building the ontology. This task used the top-down methodology consisting of starting the hierarchy with the most general term and specializing the entities to the most specific. Figure 3 illustrates the structured class hierarchy.

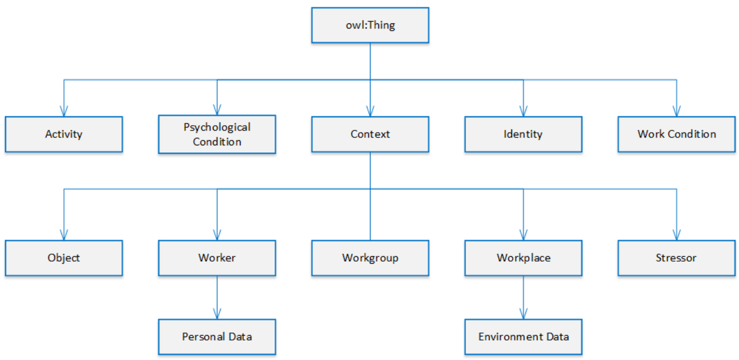


Figure 3: Class hierarchy

In OWL notation, the root class of the hierarchy is *Thing*, from which all other classes extend. The class hierarchy is premised on inheritance behavior. In this sense, subclasses will carry the same information as the superclasses to which they are connected, in addition to specific characteristics.

The *Context* class embodies dynamic temporal information, encompassing data that fluctuates throughout the day, such as location, stress levels, heart rate variations, and environmental temperatures. This class specializes in five possible types of contexts in this ontology: *Worker*, *Workplace*, *Object*, *Workgroup*, and *Stressor*. The *Worker* class references the data linked to a particular person mapped by the domain, specializing the context for the *Personal Data* class where the information collected at a given moment in time is recorded. Likewise, the *Workplace* class instantiates the workplace and specializes *Environmental Data* such as *Temperature, Humidity, Noise, and Light*. Also, the inheritance of the context class encompasses the *Object*, *Stressor*, and *Workgroup* classes. The *Object* class encompasses anything within the domain that can influence an individual's stress levels, such as malfunctioning equipment tailored to a particular task or an outdated machine failing to meet the worker's expectations. The *Workgroup* class represents the collective context, where workers from the same sector are identified. The last *Context* subclass is *Stressor*, which constitutes the instances present in the same location of other contexts identified as stressed.

The *Activity* class represents the kinds of activities a worker can perform within a given context. The *Identity* class illustrates in this hierarchy the unique identification of a given instance. The *Psychological Condition* class portrays the classification of stress-related mental health according to context information. Similarly, the *Work condition* class classifies the environment according to standards recognized in the scientific community.

Concepts with a specific definition were not used in the hierarchy of classes, being considered in the definition of properties and instances. For example, *meeting* is understood as an instance of the *Activity* class and *stressed* as a *Psychological Condition* instance.

3.5 Properties definition

The properties of an ontology represent how classes relate within the domain. Object properties demonstrate how classes behave with each other and they are usually expressed by a verb, for example, a *ClassA targets ClassB*. Data properties indicate the relationship between classes and literal values, such as *integers*, *strings*, and so on. Data properties commonly represent attributes of a class, for example, *ClassA hasId 1*.

Table 3 presents the object property, noting that subclasses inherit the relationship of superclasses. Furthermore, the fourth column encompasses the inverse property, which reverses the function of the primary relationship and aids in inferring additional information. The *Worker* and *Workplace* classes are related to their respective inferred conditions: *PsychoCondition* and *WorkCondition*. *Context* relates to the *Identity* and the *Location* where the information was collected.

Domain (Class)	Property	Range (Class)	Inverse
Worker	feels	PsychoCondition	N/A
Workplace	hasCondition	WorkCondition	N/A
Context	targets	Identity	targetedBy
Context	locationAt	Location	locationOf

Table 3: Object properties.

Table 4 demonstrates the data properties in OntoKaire. *Temperature, Noise, Humidity,* and *Light* are classes with properties related to the data collected from the environment, which are *hasCelsius* (degrees celsius), *hasDecibels* (decibels), *hasHumPercent* (humidity percentage), and *hasLux* (lux), respectively. This information is regarded for analyzing environmental conditions and was stored as type *xsd:unsignedInt* representing an integer between 0 and 4294967295. The *hasId* property relates to *Identity* for identifying the instance of the referenced entity and to *Context* for linking the information owner.

Domain (Class)	Property	Range (datatype)
Temperature	hasCelsius	xsd:unsignedInt
Noise	hasDecibels	xsd:unsignedInt
Humidity	hasHumPercent	xsd:unsignedInt
Light	hasLux	xsd:unsignedInt
Context OR Identity	hasId	xsd:unsignedInt
Context OR Location	hasLocationId	xsd:unsignedInt
Identity	hasWorkplaceId	xsd:unsignedInt
StressLevel	hasStressIndex	xsd:unsignedInt
Context	hasTimestamp	xsd:unsignedInt
Context	hasTsMin	xsd:unsignedInt
Context	hasHour	xsd:unsignedInt
Context	hasDayOfWeek	xsd:unsignedInt

Table 4: Data properties.

The *hasLocationId* and *hasWorkplaceId* are related to the worker's current location at the time of inference and the default location for working. The stress value inferred by the stress classifier or the group stress index calculation is recorded in the *hasStressIndex* context property. The *hasTimestamp* stores the time information when the measurement was performed. Another three properties were created for handling time data. A tolerance of one minute was considered to record the information without the seconds in *hasTsMin*, while *hasDayOfWeek* and *hasHour* calculate the day of the week and the time of collection procedure respectively.

3.6 Individuals creation

The next step in the development of the ontology is the creation of individuals. Individuals are instances of classes and represent a concrete reality in knowledge, with no extension or duplication of them. For example, *Activity* has no subclasses, and this class creates instances to apply the rules of the ontology, such as *WorkTask*, *Meeting*, and *Displacement*. Figure 4 presents the final result of the ontology.

The class *Activity* encompasses the actions performed by workers during their shifts, categorized into subclasses such as *Displacement*, *WorkTask*, and *Meeting*. The class *PsychoCondition* defines the psychological state of the worker. The *PsychoCondition* has two individuals: *Normal*, indicating no stress, and *Stressed*, signifying the presence of stress. This relationship between activities and psychological conditions highlights the dynamic nature of stress as workers transition between tasks.

The *Worker* class represents the workers responsible for the activities. Workers are modeled as entities interacting with their tasks and the surrounding context. The *Worker* is linked to the *PersonalData* class, which records physiological indicators such as *StressLevel*, *HeartRateVar* (heart rate variability), and *HeartRate*, providing data for

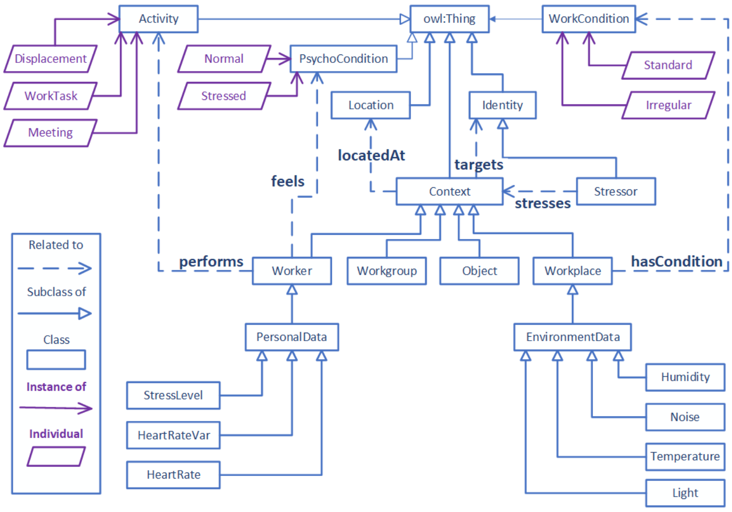


Figure 4: OntoKaire: an ontology to assist in stressors identification

inferring the worker's stress state. This integration of physiological data is essential for monitoring worker well-being in real-time.

The Context class captures the circumstances in which the worker operates. Contextual elements include *Location*, *Identity*, *Workgroup*, *Object*, and *Workplace*. The *Context* is stressed by various *Stressors*, a class that models the external and internal factors contributing to worker stress. The ontology specifies that these stressors target the Context, emphasizing the multifactorial nature of stress in work environments.

The *WorkCondition* class defines the nature of the work environment, categorizing it as *Standard* or *Irregular*. These conditions impact the *Workplace* and the tasks performed by the worker. The relationship between *WorkCondition* and *Workplace* is denoted by the *hasCondition* property, which links the environment with the current work conditions.

Environmental factors are captured in the *EnvironmentData* class, which includes critical metrics such as *Humidity*, *Noise*, *Temperature*, and *Light*. These environmental variables are known to affect worker stress and are modeled as attributes of the *Workplace*. The ontology enables the evaluation of real-time environmental data to determine how workplace conditions may intensify or mitigate stress.

The class *Stressor* models the specific elements within the work context that contribute to psychological strain on the worker. Stressors can derive from personal and environmental sources, including high temperatures, excessive noise, or irregular work conditions. These stressors interact with the *Context*, shaping the psycho-physiological response of the worker.

The *Workplace* class captures the physical condition of the worker environment. The association with environmental data may influence the worker's stress levels. The *Workplace* also plays a role in the *Context*, as the location and environmental conditions of the workplace significantly impact the overall work experience.

The ontology illustrates the interactions between the worker, the environment, and the tasks performed. The *Worker* class is linked to the *Activity* class through the *performs* relationship, while the worker's physiological and emotional responses to tasks are modeled by the *feels* relationship. Stress is a result of external environmental factors and the psychological conditions experienced during task performance.

3.7 Restrictions and rules definition

Semantic Web Rule Language (SWRL) allows expanding ontology constraints and classifications through a high-level abstract language. Two parts make up SWRL rules: body and head. The body encompasses all conditions to infer a piece of information. SWRL logic only allows conjunctions ($\wedge$) and does not admit negations, so when all conditions are true it implies ($\implies$) the result, represented by the head. Table 5 displays the expressions used to identify activities, locations, and time manipulation.

ID	Rule Name	SWRL expression
1	R_Displacement	$Context(?c), hasLocationId(?c, 0)- > performs(?c, Displacement)$
2	R_Meeting	$Context(?c) \wedge hasLocationId(?c, ?x) \wedge targetedBy(?i, ?c) \wedge hasWorkplaceId(?i, ?y) \wedge notEqual(?x, ?y) \wedge greaterThan(?x, 0) \implies performs(?c, Meeting)$
3	R_WorkTask	$Context(?c) \wedge hasLocationId(?c, ?x) \wedge targetedBy(?i, ?c) \wedge hasWorkplaceId(?i, ?y) \wedge equal(?x, ?y) \wedge greaterThan(?x, 0) \implies performs(?c, WorkTask)$
4	R_Location	$Context(?c) \wedge hasLocationId(?c, ?lid) \wedge Location(?l) \wedge hasLocationId(?l, ?lid) \implies locatedAt(?c, ?l)$
5	R_Min	$Context(?c) \wedge hasTimestamp(?c, ?ts) \wedge mod(?m, ?ts, 60) \wedge subtract(?h, ?ts, ?m) \implies hasTs5min(?c, ?h)$
6	R_Hour	$Context(?c) \wedge hasTimestamp(?c, ?ts) \wedge mod(?m, ?ts, 86400) \wedge integerDivide(?h, ?m, 3600) \implies hasHour(?c, ?h)$
7	R_DayOfWeek	$Context(?c) \wedge hasTimestamp(?c, ?ts) \wedge divide(?r, ?ts, 86400) \wedge floor(?f, ?r) \wedge add(?a, ?f, 4) \wedge mod(?d, ?a, 7) \implies hasDayOfWeek(?d, ?h)$

Table 5: Semantic rules to identify activities, locations, and time manipulation.

The *R_Displacement* (Rule 1), *R_Meeting* (Rule 2), and *R_WorkTask* (Rule 3) define the worker's activity type through their location, as defined in the individual creation step. When the worker is not tracked, the *hasLocationId* property receives the value 0, and the activity is considered as *Displacement*. In case the same values are found for *hasLocationId* and *hasWorkplaceId*, it is inferred as *WorkTask*; otherwise, it is classified as *Meeting*. *R_Location* (Rule 4) relates individuals of the *Context* and *Location* by comparing the *hasLocationId* to identify the current position of the context. *R_Min* (Rule 5), *R_Hour* (Rule 6), and *R_DayOfWeek* (Rule 7) are rules of time manipulation that respectively infer the *hasTsMin*, *hasHour*, and *hasDayofWeek* properties based on calculations using the *hasTimestamp* values. The equation for the day of the week returns an integer value from 0 to 6, representing respectively the days from Sunday to Saturday, and the equation for the hour returns an integer value on a 24-hour basis.

Appropriate environmental conditions can improve work performance and cognitive capacity due to psycho-physiological human processes [Taylor et al., 2016]. Also, the predominant climate is a variable to be considered when defining ideal limits, for example, regions with a temperate or cold climate should consider a temperature between 22°C and 26°C, and relative humidity between 40% and 60% for good results [Wolkoff et al., 2021]. Table 6 presents the rules for defining an environment condition.

ID	Rule Name	SWRL expression
8	R_Hum_Low	$hasHumPercent(?c, ?h) \wedge lessThan(?h, 40) \implies Irregular(?c)$
9	R_Hum_High	$hasHumPercent(?c, ?h) \wedge greaterThan(?h, 60) \implies Irregular(?c)$
10	R_Light_Low	$hasLux(?c, ?l) \wedge lessThan(?l, 50) \implies Irregular(?c)$
11	R_Light_High	$hasLux(?c, ?l) \wedge greaterThan(?l, 500) \implies Irregular(?c)$
12	R_Noise_High	$hasDecibels(?c, ?d) \wedge greaterThan(?d, 50) \implies Irregular(?c)$
13	R_Temp_Low	$hasCelsius(?c, ?t) \wedge lessThan(?t, 22) \implies Irregular(?c)$
14	R_Temp_High	$hasCelsius(?c, ?t) \wedge greaterThan(?t, 26) \implies Irregular(?c)$
15	R_Std_Env	$hasCelsius(?c, ?t) \wedge greaterThanOrEqual(?t, 22) \wedge lessThanOrEqual(?t, 26) \wedge hasHumPercent(?c, ?h) \wedge greaterThanOrEqual(?t, 40) \wedge lessThanOrEqual(?h, 60) \wedge hasDecibels(?c, ?t) \wedge lessThanOrEqual(?t, 85) \wedge hasLux(?c, ?l) \wedge greaterThanOrEqual(?l, 50) \wedge lessThanOrEqual(?l, 500) \implies Standard(?c)$

Table 6: Semantic rules to infer environment conditions.

The rules for *PsychoCondition* consider *hasStressIndex* and the predefined value for stress. This study uses a classification of 5 levels, assuming an index greater than or equal to 3 as *Stressed* and a lower value as *Normal*. However, other reference values can be defined based on the incorporated classifier. *R_Stressor* (Rule 18) uses *hasLocationId* and *hasTsMin* to identify instances that share the location and time in the moment of the identification of a *Stressed Context*. This outcome showcases potential stress-inducing factors, providing insight into various stressful events. Table 7 details the rules related to psychological conditions and stressors.

Rule	Name	SWRL Expression
16	R_Normal	$Worker(?c) \wedge hasStressIndex(?c, ?s) \wedge lessThan(?s, 3) \implies Normal(?c)$
17	R_Stressed	$Worker(?c) \wedge hasStressIndex(?c, ?s) \wedge greaterThanOrEqual(?s, 3) \implies Stressed(?c)$
18	R_Stressor	$Stressed(?c) \wedge hasId(?c, ?x) \wedge hasId(?s, ?y) \wedge notEqual(?x, ?y) \wedge hasLocationId(?c, ?l) \wedge hasLocationId(?s, ?l) \wedge hasTs5min(?c, ?ts) \wedge hasTs5min(?s, ?ts) \wedge greaterThan(?l, 0) \wedge targets(?s, ?z) \implies stressedBy(?c, ?z)$

Table 7: Semantic rules to infer psychological conditions and identify possible stressors.

The verification of consistency and inference in complex domains can be performed using a reasoner [Kamel et al., 2007]. Considering that the semantic rules adopted for this ontology expect property inferences, the choice of the reasoner tool pointed to the Pellet, an engine capable of performing these types of deductions.

4 Evaluation and Results

The ontology evaluation needs to consider two aspects: structure and content. In order to meet these two points, [Gangemi et al., 2006] suggested the steps as follows:

- Verification is the process that considers the semantic and logical construction, aiming at correct functioning through definitions without redundancy, free from restriction errors, and ensuring the consistency of relationships;
- Validation is the process that aims to demonstrate that the ontology achieves its proposal by relating the formal modeling created with the real world;

In this sense, no public dataset was found with all the information expected to evaluate OntoKaire. Thus, a stress-related public dataset served as the foundation for constructing the contexts of the workers. The following subsections detail the building of the dataset and the two evaluation steps.

4.1 Dataset

The context creation used the public dataset known as *Wearable Stress and Affect Detection* (WESAD)[1]. Although the dataset is not directly related to industrial settings, the selection was based on a comprehensive representation of stress-related factors applicable across various environments, including industrial contexts. The raw sensor data employed in the model evaluation were collected with a wrist-worn device (Empatica E4). This dataset presents physiological and movement data from 15 participants during a controlled study. The sensor modalities include blood volume pulse, electrocardiogram, electrodermal activity, electromyogram, respiration, body temperature, and three-axis acceleration.

[Schmidt et al., 2018] described the study protocol of this dataset in five distinct moments. The first moment is the Baseline, when the participant is equipped and induced to a neutral state. The next moments have different orders in the protocol and different objectives. The moments of stress and amusement aim to stimulate different reactions, such as stress, frustration, irritation, interest, joy, and others. Meditation and recovery times aim to reduce physiological changes. The self-report answers allowed the model evaluation, considering the assessments for the stressed condition.

The OntoKaire evaluation extracted a record from each of the 15 participants in 6 moments defined in the study protocol, totaling 90 *Contexts*. The created instances considered from *Worker1* to *Worker15* for the participants, and a room for each moment, i.e., *Baseline Room, Stress Room, Amusement Room, Relaxing Room, and Recovery Room*, assigning values from 1 to 5 respectively. Also, information recorded outside of each of the controlled moments received *hasLocationId* equal to 0 (zero), being considered by the ontology as *Displacement*. Still, a *Television* used in the amusement moment and a *Trier Social Stress Test (TSST)* applied in the stress moment instantiated objects in their respective rooms.

Table 8 depicts the first 12 rows of the dataset for workers. The *hasHRV* column has the calculated heart rate variation value from the interbeat interval data, and *hasStressIndex* has the value assigned through the Positive and Negative Affect Schedule (PANAS) questionnaire.

4.2 Verification

The verification step occurred through the reasoner incorporated into Protégé software[2] called Pellet. The reasoning tool analyzes all properties, rules, and restrictions, accusing

[1] https://ubicomp.eti.uni-siegen.de/home/datasets/icmi18/
[2] https://protege.stanford.edu/

Individual	Type	hasId	hasTimestamp	hasHRV	hasLocationId	hasStressIndex
Context1	Worker	1	1495437465	95	0	0
Context2	Worker	1	1495437863	60	1	2
Context3	Worker	1	1495439988	53	2	3
Context4	Worker	1	1495441853	96	4	1
Context5	Worker	1	1495442565	123	3	1
Context6	Worker	1	1495443063	93	5	1
Context7	Worker	2	1495624370	94	0	0
Context8	Worker	2	1495624613	102	1	1
Context9	Worker	2	1495626677	63	2	4
Context10	Worker	2	1495628678	123	4	1
Context11	Worker	2	1495629266	137	3	1
Context12	Worker	2	1495630158	89	5	2

Table 8: Fragment of the dataset for creating Worker class individuals.

errors and inconsistencies, or making inferences from the data model. Figure 5 illustrates the reasoner execution's result without any errors, which means that the data model is logically correct. Moreover, Figure 6 depicts the ontology metrics presented in Protégé. The axiom count represents statements held to be true in the domain through direct declarations or logical implications. The number of classes, properties, and individuals also demonstrate the ontology relevance.

```
INFO  12:46:36  ------------------------------ Running Reasoner ------------------------------
INFO  12:46:36  Pre-computing inferences:
INFO  12:46:36      - class hierarchy
INFO  12:46:36      - object property hierarchy
INFO  12:46:36      - data property hierarchy
INFO  12:46:36      - class assertions
INFO  12:46:36      - object property assertions
INFO  12:46:36      - data property assertions
INFO  12:46:36      - same individuals
INFO  12:46:36  Ontologies processed in 624 ms by Pellet
INFO  12:46:36
```

Figure 5: Reasoner execution result log.

Figure 7 shows the result of the reasoner's inferences for the *Context3* of the worker dataset. Flag 1 indicates the information loaded from the dataset, while flag 2 presents data inferred through defined restrictions and rules. In the loaded data, it is possible to visualize the worker identifier (*1*), the location identifier (*2*), Heart Rate Variability (HRV) (*53ms*), the context timestamp (1495439988), and the stress index (*3*). The inferred object properties comprise how the worker is feeling (*Stressed*), the location instance (*Stress Room*), the performed activity (*Meeting*), the identified stressor (*TSST*), and the worker instance (*Worker 1*). The data properties display the day of the week (*1 - Monday*), the context time (*7 a.m.*), and the timestamp without seconds (*1495439940*).

Figure 8 displays the result of inferences for the *EnvContext14*. Flags 1 and 2 have the same meaning previously described, addressing workplace information. The properties of data collected from the environment inform the location identifier (*2*), the context timestamp (*1497347105*), the temperature in degrees Celsius (*27°C*), the percentage of air humidity (*34%*), the brightness intensity (*147 lux*), and the amount of noise (*87 dB*). The inferred object properties describe the instance of the workplace (*Stress Room*), and the ambient conditions informing low percentage of relative humidity (*LowHumidity*),

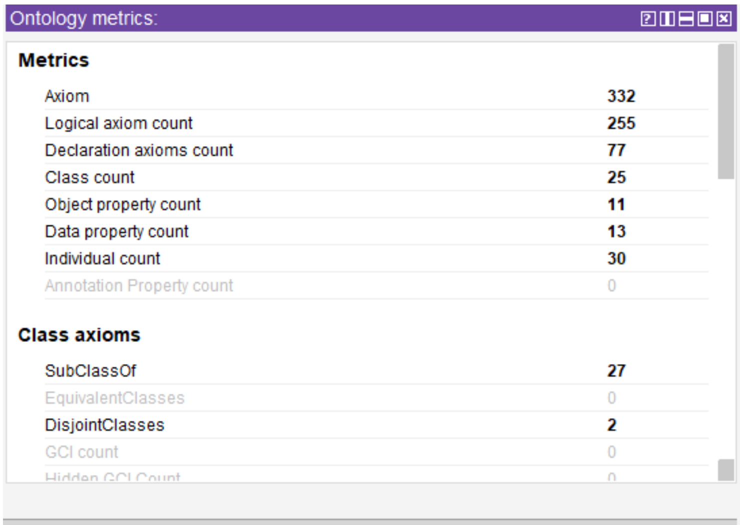


Figure 6: Ontology metrics.

high noise (*HighNoise*), and high temperature (*HighTemperature*). The inferred data properties display the day of the week (*2 - Tuesday*), the context time (*9 a.m.*), and the timestamp without seconds (*1497347100*).

4.3 Validation

The validation step evaluates how well the ontology meets the intended domain. The validation procedures employed in this study consist of applying the CQs defined in Subsection 3.1 to analyze the completeness of the ontology using Simple Protocol and RDF Query Language (SPARQL). SPARQL allows OWL to retrieve structured values, performing complex joins on the dataset. Figure 9 depicts the query for CQ1 (*Which possible stressors are identified for each location and time?*) used in the Protégé tool and the result set.

The elaborated SPARQL queries consist of 2 blocks that structure the request. The *SELECT* block informs the returned data through variables. The *CQ1* query presents the variables *?worker, ?psychoCondition, ?location, ?day, ?hour, and ?stressor*, which respectively represent the target worker, the psychological condition if stressed or not, the location of the context, and the identified stressor. The *WHERE* block informs the search criteria to limit data return through clauses expressed by ontology's classes and properties, using the dot operator (.) to concatenate semantic triples. The first record of the result informs that *Worker1* was stressed in the *StressRoom* on Monday at 7 am, with the *TSST* as a possible stressor. This question helps to find possible stressors for each worker, identifying contexts at a given moment in time and space.

Figure 10 responds to *CQ2*, presenting the duration in seconds of a stress context and how long the respective stressor has been sharing the same time and space with another context. *Worker1* was stressed for 560 seconds during a *StressRoom Meeting* with *TSST* who was present the entire time of the context.

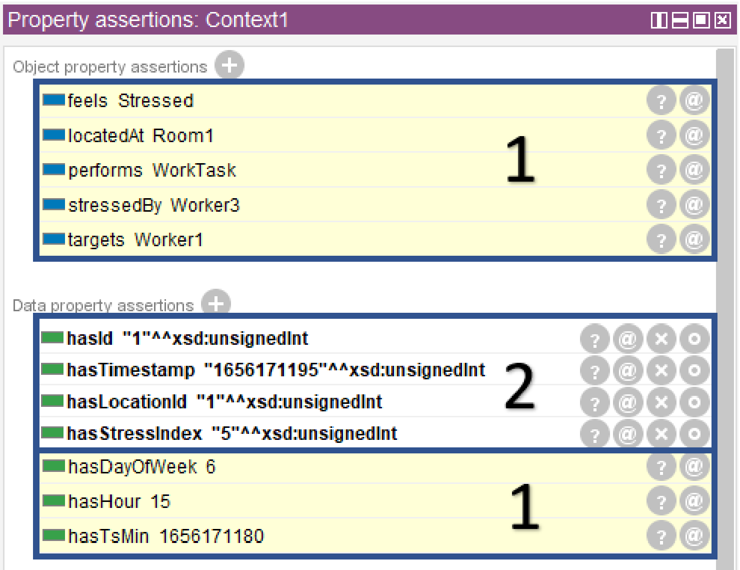


Figure 7: Property inferences for workers.

In addition, the ontology aims to compare worker and environment contexts to identify the workspace conditions. Figure 11 meets *CQ3* by showing the amount of stress recorded in a given location with irregular working conditions. For example, *StressRoom* had 16 stress records while in a low humidity condition. Furthermore, *CQ4* meets the possibility of stressors in a group of workers. Figure 12 presents the query and lists eight workers present in the *StressRoom* in two moments of identified stress.

The results presented in the validation demonstrate that the ontology can answer the Competence Questions proposed. These questions intend to identify possible stressors based on context history. Nonetheless, the domain knowledge derived from these inquiries is consolidated into a unified query, merging worker and environment data, and sending a single context to the stressor identifier for individual analysis.

5 Discussion

This section presents an analysis of the OntoKaire ontology, designed to identify work-related stressors in industrial settings. The ontology addressed the CQs posed in this study, showcasing its efficacy in capturing the complexities of stress in workplace environments.

The results from CQ1 focus on identifying contexts that share the environment with a stressed worker. Although shared environments do not inherently classify specific stressors, repeated exposure to similar situations can provide valuable insights into temporal relationships between contexts. This temporal analysis can reveal patterns of prolonged exposure, highlighting situations where workers are at risk of experiencing stress. Understanding these contextual relationships is crucial for developing targeted interventions to mitigate stress in the workplace.

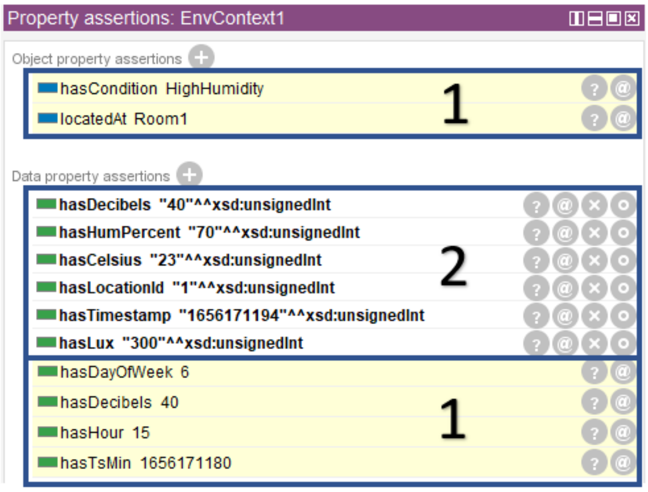
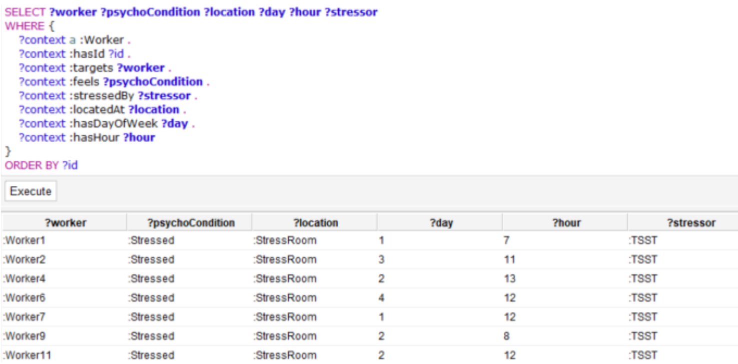


Figure 8: Property inferences for workers.



```
SELECT ?worker ?psychoCondition ?location ?day ?hour ?stressor
WHERE {
  ?context a :Worker .
  ?context :hasId ?id .
  ?context :targets ?worker .
  ?context :feels ?psychoCondition .
  ?context :stressedBy ?stressor .
  ?context :locatedAt ?location .
  ?context :hasDayOfWeek ?day .
  ?context :hasHour ?hour
}
ORDER BY ?id
```

Execute

?worker	?psychoCondition	?location	?day	?hour	?stressor
:Worker1	:Stressed	:StressRoom	1	7	:TSST
:Worker2	:Stressed	:StressRoom	3	11	:TSST
:Worker4	:Stressed	:StressRoom	2	13	:TSST
:Worker6	:Stressed	:StressRoom	4	12	:TSST
:Worker7	:Stressed	:StressRoom	1	12	:TSST
:Worker9	:Stressed	:StressRoom	2	8	:TSST
:Worker11	:Stressed	:StressRoom	2	12	:TSST

Figure 9: SPARQL query and result set for CQ1.

CQ2 examines the duration that stressors impacted workers during tasks and activities. This data enabled the assessment of the cumulative effects and intensity of stressors over time. The evaluation of the exposure to specific stressors allows to better understand the burnout occurrence and other health outcomes. The insights gained from this analysis can inform organizational strategies aimed at reducing stress exposure and promoting worker well-being.

In CQ3, we presented a list of environments of irregular conditions alongside the corresponding number of stress incidents. This information is pivotal in understanding how specific situations influence workers' mental health. The identification of environments that are consistently linked to higher stress incidents, organizations can take proactive measures to modify these conditions.

CQ4 quantifies the moments of stress experienced by each worker, allowing the identification of groups with a higher incidence of stress. This analysis highlights individual workers who may be at risk and sheds light on the compatibility of different workers

```
SELECT
  ?worker ?psychoCondition ?location ?activity ?duration ?stressor ?shared_time
WHERE {
  ?context a :Worker .
  ?context :hasId ?id .
  ?context :targets ?worker .
  ?context :feels ?psychoCondition .
  ?context :hasDuration ?duration .
  ?context :hasTsMin ?timestamp .
  ?context :hasTsMax ?tsMax .
  ?context :performs ?activity .
  ?context :locatedAt ?location .
  ?context :stressedBy ?stressor .
  ?context :stressedByContext ?contextStressor .
  ?contextStressor :hasTsMin ?tsMinStressor .
  ?contextStressor :hasTsMax ?tsMaxStressor .
        BIND (
          (IF(?tsMaxStressor < ?tsMax, ?tsMaxStressor - ?timestamp,
              IF(?tsMaxStressor > ?tsMax, ?tsMax - ?timestamp,?tsMax-?timestamp))
          ) AS ?shared_time
        )
}
ORDER BY ?id
```

Execute

?worker	?psychoCondition	?location	?activity	?duration	?stressor	?shared_time
:Worker1	:Stressed	:StressRoom	:Meeting	560	:TSST	560
:Worker2	:Stressed	:StressRoom	:Meeting	609	:TSST	609
:Worker4	:Stressed	:StressRoom	:Meeting	614	:TSST	614
:Worker6	:Stressed	:StressRoom	:Meeting	524	:TSST	524
:Worker7	:Stressed	:StressRoom	:Meeting	684	:TSST	684
:Worker9	:Stressed	:StressRoom	:Meeting	720	:TSST	720
:Worker11	:Stressed	:StressRoom	:Meeting	642	:TSST	642

Figure 10: SPARQL query and result set for CQ2.

```
SELECT ?location ?workCondition (count(?stressed) AS ?stressedTimes)
WHERE {
  ?context a :Worker .
  ?context :locatedAt ?location .
  ?context :hasEnvContext ?envContext .
  ?envContext :hasCondition ?workCondition
  OPTIONAL {
    ?context :feels :Stressed .
    ?context :targets ?stressed .
  }
}
GROUP BY ?location ?workCondition
ORDER BY ?location
```

Execute

?location	?workCondition	?stressedTimes
:AmusementRoom	:LowHumidity	0
:AmusementRoom	:HighNoise	0
:BaselineRoom	:LowHumidity	0
:StressRoom	:LowHumidity	16
:StressRoom	:HighNoise	4

Figure 11: SPARQL query and result set for CQ3.

with their respective groups. Understanding these dynamics can aid in developing team-building strategies and stress management programs tailored to the specific needs of different groups.

The OntoKaire ontology manages intricate environments by incorporating environmental control and location-tracking capabilities. The more workers and objects monitored within a workspace, the more effective the conditions become for inferring stressors. This capability allows for a nuanced understanding of stress dynamics in diverse industrial environments. However, it is important to note that the current study presents preliminary results based on a dataset of 15 participants. The ontology's performance and applicability require further validation with larger datasets to confirm its effectiveness and generalizability.

The primary contribution of this paper is the development of the OntoKaire, which serves as a tool for identifying workers' stressors in controlled industrial environments. This research represents a novel approach to stress prediction through physiological

```
SELECT ?workgroup ?worker (count(?env) AS ?stressedTimes)
WHERE {
   ?context a :Worker .
   ?context :hasId ?id .
   ?context :targets ?worker .
   ?context :locatedAt ?workgroup .
   ?context :hasEnvContext ?env .
   ?context :feels :Stressed .
   ?context :targets ?stressed .
}
GROUP BY ?worker ?workgroup
ORDER BY ?workgroup ?id
```

Execute

?workgroup	?worker	?stressedTimes
:RecoveryRoom	:Worker15	1
:StressRoom	:Worker13	2
:StressRoom	:Worker9	2
:StressRoom	:Worker6	2
:StressRoom	:Worker4	2

Figure 12: SPARQL query and result set for CQ4.

data, a topic that has not been extensively covered in existing literature. Additionally, the examination of group stress dynamics is an area that remains under-explored in the research community, underscoring the relevance and timeliness of this study.

6 Conclusion

This study presented OntoKaire, an ontology to identify work-related stressors, detailing its design process. Previous literature explored ontologies within the realm of stress but none specifically tackled stressor identification, highlighting an untouched frontier within the research community.

The ontology modeling elucidated the development from its conception to the creation of instances. The ontology construction consisted of seven development stages: scope definition, knowledge reuse, concept enumeration, class hierarchy definition, properties definition, creation of individuals, and restriction and rules definition.

The evaluation demonstrated that OntoKaire is assessable from the structural and conceptual aspects. The results obtained from the verification process evidenced the correctness of the semantic and logical construction. The validation process sought to illustrate that the ontology fulfills its intended purpose. This assessment used the reasoning process and data extraction with SPARQL queries to answer four competency questions. The results reached the expected answers, showing possible stressful contexts, the times of sharing location, environmental conditions, and identified groups with stress cases.

Even though Protégé is a widely used tool for ontology construction, this study presents innovations that increase the study's impact and uniqueness. The OntoKaire addresses the complexities of workplace stressors in industrial environments, incorporating novel concepts and relationships that extend beyond conventional frameworks. Additionally, the innovative application of context histories allows for a more accurate prediction of stressors, enabling the identification and anticipation of patterns often overlooked in existing methodologies. Furthermore, a more precise prediction of stressors is possible by the application of context histories, which also helps the model recognize and anticipate patterns missed by other approaches. Moreover, specialized assessment methods were created to evaluate OntoKaire efficacy. These enhancements showcase how OntoKaire established tools and contributes to advancing the understanding and management of workplace mental health.

However, a limitation of this study is that the information obtained by the dataset does not represent a real-world environment, allowing opportunities for future work using controlled experiments. In addition, there are many challenges in identifying stressors in the industry that can interfere with results. For further analysis, social interaction, environmental conditions, and workload must be considered. Another limitation is that the ontology cannot forecast stress, depending on the classified data to perform stressor inferences. Furthermore, the database size can interfere with the quality of the inferred data, where the collection of information over a long period and a greater number of individuals can generate meaningful results. In future work, collaboration with industrial partners will be pursued to validate the model using real-world data, addressing this limitation and further enhancing the study's credibility. Additionally, future studies can explore stress in students resulting from factors such as ineffective teaching pedagogy, bullying, and other school-related stressors, broadening the scope of the model's application.

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