Human-Centered Ontological Work Environment Framework: a Focus on Motivational Factors

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Abstract. This paper addresses the complexities of conceptualizing and improving work environments, focusing particularly on employee motivation. We introduce the ENT (fr. Environnement de Travail, or Workplace Environment) Ontology, a new framework devised to structure work environments by prioritizing employee well-being. Grounded in an extensive review of public HR (human resources) data, our comprehensive ontology-based analysis illuminates the limitations of traditional simplifications of motivational factors, which often reduce them to mere 'Satisfaction'. The ENT Ontology overcomes these limitations by offering a detailed and scalable model that captures a broad spectrum of motivational factors, providing organizations with a robust tool to foster a conducive work environment. We highlight the imperative need for enhanced data collection and analytical frameworks to better understand and improve employee motivation.

Keywords: Work environment · Ontology · Well-being · Motivation.

1 Introduction

Improving the work environment holds significant advantages for organizations, encompassing reduced turnover, heightened employee loyalty, increased productivity, and enhanced team dynamics. This multifaceted endeavor also contributes to attracting talent, fostering innovation, improving customer satisfaction, bolstering reputation, and adapting to change. From an individual standpoint, a conducive work environment correlates with improved health, motivation, and overall well-being. Despite its paramount importance, this topic remains under-researched, primarily due to two major challenges: the absence of robust structures for analyzing work environments and a dearth of available data on employee well-being.

Conceptualizing the work environment proves to be intricate and inherently subjective, intertwined with the diverse perspectives of individuals within an organization. The essential role of human interpretation in delineating variables for defining the work environment introduces a significant challenge in studying this multifaceted concept. The exploration of work environments often aligns with the broader study of human behavior, with sectors like healthcare, known for high employee burnout rates, serving as prominent examples [25]. Consequently, existing approaches frequently adopt a psychological perspective [22], but they often inadequately link the work environment definition to that of the organization itself, resulting in shortcomings such as a lack of quality structures and insufficient variables related to employee motivation.

In the realm of machine learning approaches to work environment research and employee well-being, turnover prediction emerges as a commonly studied problem. These approaches leverage basic employee data and follow the traditional machine learning pipeline, achieving high performance [28]. However, they fall short in providing a comprehensive understanding of the myriad factors influencing employee motivation, a key factor in turnover.

Motivation has been relatively neglected in research, partly due to the scarcity of data. Organizations typically rely on traditional systems for collecting basic employee data, and the perception of AI, in particular, raises concerns, hindering the collection and analysis of relevant data [32]. Addressing this challenge involves changing employee perceptions of AI through education and emphasizing the ethical and effective application of these technologies. Despite the challenges, AI solutions can optimize the search for optimal improvement strategies within organizations.

Against this backdrop, our work seeks to redefine the study of motivation in work environments by proposing a more human-centered ontological framework. By integrating employee perspectives, we aim to offer organizations a robust framework to analyze motivation factors, opening new avenues for developing strategies to improve both individual well-being and organizational performance.

2 Related Work

Numerous studies have delved into the analysis of work environments, aiming to comprehend employee interactions, behaviors, and their evolution within organizations. Primarily rooted in psychology [17], this research spans various contexts, such as education [14,9] and medicine [19,11]. While the psychological perspective has dominated, quantitative approaches, particularly in machine learning, have gained prominence, primarily focusing on employee turnover, also known as attrition. In this section, we present key works in this domain and those associated with employee motivation.

2.1 Turnover Prediction

Addressing turnover, or attrition, has predominantly been a predictive challenge. The target variable often signifies whether an employee remains with or departs from the company. Traditional methods involve training supervised machine learning models, such as Support Vector Machines (SVM) and various random forest (RF) variations, on public human resources databases. Noteworthy studies report performances exceeding 80% [18,31,33,20,28,7]. Recent endeavors extend beyond turnover prediction, addressing the critical aspect of analyzing its root causes [27]. While experiments utilize databases with conventional variables like profile, salary, department, and projects, efforts focus on interpreting results to elucidate reasons behind employee departures. This understanding serves as a valuable incentive for companies to implement strategies that enhance working environments and promote employee retention.

2.2 Works on Matters Related to Employee Motivation

Beyond turnover, related studies explore predicting churn in sectors with high turnover rates like healthcare [12], human behavior prediction [24,5,25], influencing human behavior [16], job performance analysis [23], and representations of the work environment concept [15,10,8,13,6]. However, these structures often lack variables associated with motivational factors, such as fairness, team dynamics, workspace, conflict resolution, and access to information. Understanding employee motivation proves challenging, requiring analysis of various influencing variables, and the absence of suitable structures and public databases remains a hurdle for further research in this domain.

3 Human-Centered Ontological Work Environment Framework

3.1 Ontology Construction

This paper endeavors to develop an ontology that illuminates the intricate dynamics of work environments, focusing on factors shaping employee motivation and well-being. For this purpose, we adopt the Graphical Ontology Design Methodology (GODeM) due to its didactic simplicity and effectiveness in ontology development [29]. The key steps in our methodology are illustrated in Figure 1.

Approach Details: Our methodology unfolds through a series of well-defined steps:

- **Domain Precision and Expertise:** Commencing with a precise definition of the primary domain (work environments) and specifying expertise areas (employee well-being — motivation in consulting companies). Actions include gathering individual perspectives, conducting surveys on motivational factors, and analyzing public resources.
- **Terminology Definition:** Establishing a comprehensive glossary of terms related to work environments, informed by research, employee well-being surveys, participant feedback, and analysis of relevant databases and ontologies.
- **Competency Questions:** Formulating 18 competency questions that intricately address essential ontology requirements, ensuring a holistic coverage of work environment and motivation concepts.

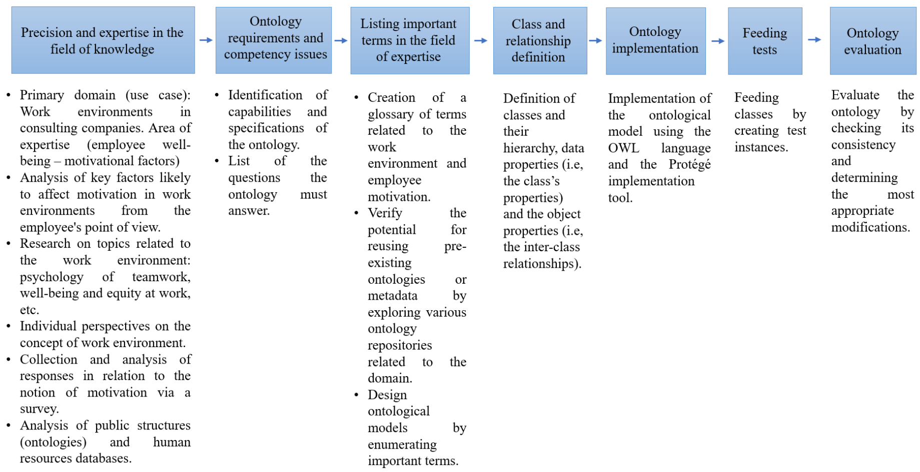

Fig. 1: Methodology for Work Environment Ontology Development.

- **Class and Relationship Definition:** Precision in defining ontology classes, hierarchy, data properties (attributes), and object properties (relationships) in alignment with established guidelines [30].
- **Ontology Implementation:** Selecting OWL as the ontology language and Protégé as the implementation tool for their completeness and adaptability[3][4].
- **Feeding Tests and Evaluation:** Iterative testing and evaluation of the ontology's composition, ensuring consistency, and confirming compatibility with the domain of expertise.

Iterative Evaluation Points Throughout multiple iterations, the ontology undergoes evaluations focusing on:

- **Syntactic and Logical Consistency:** Confirming adherence to OWL syntax and logical principles.
- **Clarity:** Emphasizing clear definitions for concepts, relationships, and axioms within the ontology documentation.
- **Relevance:** Ensuring alignment with intended purposes and fulfillment of specific requirements.
- **Maintainability:** Assessing the ontology's adaptability to changes, examining its feasibility for updates and long-term maintenance.
- **Validation and Scalability:** Examining performance, problem-solving potential, and scalability as data or complexity increases.

[3] OWL, `https://www.w3.org/TR/owl-ref/`
[4] Protégé, version 5.5, `https://protege.stanford.edu/software.php`

3.2 The ENT Ontology

In this section, we introduce the "ENT Ontology," our proposed work environment ontology, which will be publicly released upon publication. In summary, the ENT ontology comprises 57 classes, 29 data properties, and 29 object properties (relations). The class interaction graph, illustrated in Figure 2, provides a visual representation of the ontology's structure.

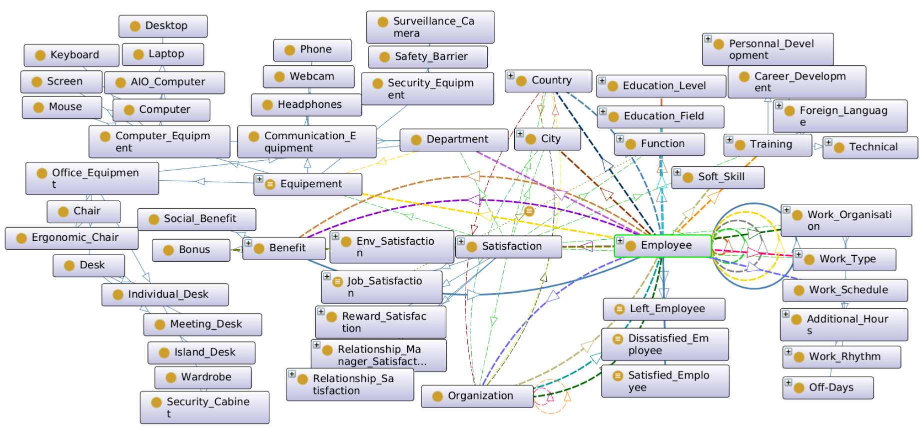

Fig. 2: ENT Ontology - Class interaction graph.

Table 1 offers examples from the set of classes, data properties, and object properties associated with the concept of motivation in the ENT Ontology. This set exemplifies how various factors can be evaluated when analyzing motivation in work environments, moving beyond the traditional and simplistic "Satisfaction" variable. Understanding specific issues at the root of dissatisfaction is crucial for companies seeking to enhance their working environments.

Classes	Properties	Relations
- Employee		
- Benefit		
- Equipment	- Distance from home	- hasBenefit
* Communication, computational resources, office, security	- Performance	- hasBonus
- Satisfaction	- Salary increases	- hasSatisfaction
* Environment, job, team, rewards	- Promotions	- hasWorkType
- Trainings	- Recognitions	- hasEquipment
* Career development, technical trainings, interdisciplinary trainings	- CSE existence	- hasTraining
- Work organization		
* Work schedules, work type		

Table 1: Examples of classes, data properties, and relations associated with the notion of motivation in the ENT Ontology.

3.3 A More In-depth Look at the Notion of Motivation in the ENT Ontology

Employee motivation in work environments is pivotal for both well-being and performance within a company. In a broad sense, employee satisfaction encompasses their contentment and fulfillment in their work and work environment, considering factors like tasks, relationships, physical space, career development, and remuneration. This comprehensive understanding of satisfaction contributes to an individual's overall well-being and, consequently, influences their motivation.

To delve into the notion of motivation in our ENT Ontology, we define it as *"The feeling of contentment or fulfillment experienced by an employee in their work environment in response to various factors"*. To achieve this, we conducted research and organized meetings with diverse employee profiles, gathering insights on their views regarding their work environment and how they define satisfaction.

While individual motivation is inherently complex to express objectively, we aimed to capture its meaning in the context of the work environment. The ENT Ontology reflects this effort by defining a "Satisfaction" class with five sub-classes, namely:

- **Env_Satisfaction:** General variable representing Work Environment Employee Satisfaction.
- **Job_Satisfaction:** Employee satisfaction with their position, function, and tasks.
- **Relationship_Manager_Satisfaction:** Employee satisfaction with their relationship with their manager.
- **Relationship_Satisfaction:** Employee satisfaction with relationships with colleagues.
- **Reward_Satisfaction:** Employee satisfaction with salary and any bonuses received from the organization.

The class graph associated with the "Satisfaction" class, depicted in Figure 3, illustrates relationships, including its sub-classes and linked classes through the object property "hasCause."

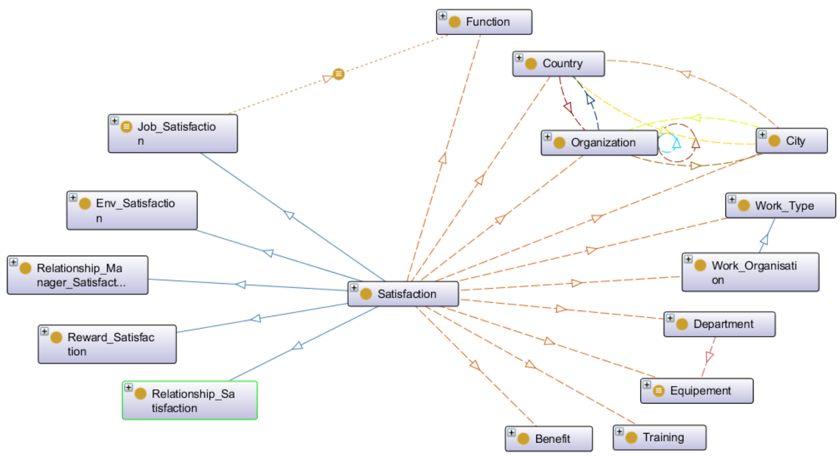

Fig. 3: The 'Satisfaction' Class Graph.

4 Analysis and State-of-the-Art Comparison

4.1 Existing Ontologies Related to Work Environments

Our ENT Ontology sets itself apart by its unique capability to comprehensively describe and encapsulate information related to employee satisfaction. With 57 classes, 29 data properties, and 29 object properties, the ENT Ontology serves as a robust framework derived directly from the employee's perspective, covering various concepts and objects within a work environment.

In contrast to the ENT Ontology's explicit focus on employee well-being, existing organizational and work environment ontologies often emphasize an organizational perspective, lacking detailed variables crucial for a comprehensive understanding of employee motivation. We scrutinized several ontologies, presenting three notable examples that approach the work environment concept, although from a predominantly organizational viewpoint.

– **FOAF Ontology (Friend Of A Friend):** Initially designed for social networks, FOAF has been extended to incorporate information about people, organizations, and their relationships, making it relevant to work environments[5]. Despite covering valuable variables related to social interactions, its

[5] FOAF Ontology, `http://xmlns.com/foaf/spec/`

primary focus on the social dimension may overlook crucial organizational aspects. The ontology comprises 19 classes, 44 data properties, and 27 object properties, yet lacks variables conducive to motivational analysis.
- **OntoHR Ontology (Human Resources Ontology):** Serving as a framework for representing human resources information, OntoHR aims to capture concepts related to job roles, competencies, and employee relationships within an organizational context [21]. This ontology, designed predominantly from an organizational perspective, lacks easily accessible statistical information.
- **SUMO Ontology (Suggested Upper Merged Ontology):** A large, general-purpose ontology encompassing around 48 domains, including work environments[6]. While it provides a foundational structure extendable for specific applications [26], its extensive and generic dimensionality may demand considerable effort for organizational adaptation. Additionally, it lacks variables associated with motivation, making it less useful in this context.

4.2 Existing Databases Related to Work Environments

The current challenge in research aimed at enhancing well-being in work environments lies in the limited availability of data directly associated with the concept of motivation. To address this gap, we compiled public databases containing human resources data and conducted machine learning experiments to analyze motivational factors. These databases encompass diverse facets of the work environment, including organizational practices, profile data such as age, department, and salary, alongside occasional employee satisfaction levels reported as a global variable. Target variables indicating whether an employee stays with or leaves the company were also included.

However, existing structures fall short in revealing the underlying factors influencing employee motivation, hindering the effective proposal of actions to address these issues. Most data has been predominantly analyzed with the singular objective of predicting attrition rather than comprehensively understanding the reasons behind employee departures.

From over 20 HR databases studied, three were selected for fair analysis based on the number of observations, variables, and their relevance to the concept of motivation. These databases include HR Analytics (14999 samples, 12 variables, approximately 7 motivation-related variables) [2], IBM HR Analytics (1470 samples, 35 variables, approximately 9 motivation-related variables) [3], and Human Resources Dataset (311 samples, 36 variables, approximately 6 motivation-related variables) [4]. While other databases, like Federal Data Turnover[1], contain interesting examples, they lack variables directly linked to motivation.

The experiments primarily focused on turnover analysis, a common variable across all three databases, with the specific aim of understanding factors related to motivation. Despite a significant imbalance in the target variable (attrition),

[6] SUMO Ontology, `https://www.ontologyportal.org/`

with employees leaving being the least represented class, the predictive models, including Support Vector Machine (SVM), Random Forest, and Logistic Regression, exhibited over 90% accuracy. However, our emphasis shifted from attrition prediction to the analysis of variables associated with motivation.

Our analyses on the three databases reveal several key conclusions. First, the task of predicting attrition stands apart from the more intricate analysis of motivation, limiting its efficacy in addressing the underlying causes of staff turnover. Additionally, the omission of the "satisfaction" variable during model training across most databases did not impact performance, indicating its current state provides limited useful information. The concept of workload requires further exploration, encompassing aspects such as under-appreciation or burnout, with current databases representing it simplistically as the "Number of projects." Understanding workload necessitates a deeper examination of its type and magnitude. Furthermore, the impact of benefits (promotions, pay raises, etc.) on motivation is acknowledged, but a lack of detailed information on their timing and specific effects hinders comprehensive analysis. Traditional methods of evaluating employee performance appear insufficient, highlighting the need for a shift in mindset and increased research into factors influencing performance. Inconsistent results within the databases raise concerns, such as burnout-affected employees appearing as motivated as those with low workloads, emphasizing the necessity for more accurate data. Notably, crucial variables affecting employee motivation, including those linked to work teams, communication, and well-being, are conspicuously absent in these databases.

5 Conclusion

Current databases face a fundamental challenge with their flat representation, lacking the depth needed to capture the complexities of factors influencing employee motivation. Our proposed ENT Ontology addresses this limitation and advances research in understanding employee motivation in two key ways. Firstly, it introduces a comprehensive framework by providing a structured data schema derived directly from the employee well-being perspective, offering a more profound understanding of motivational factors and overcoming the limitations of existing databases. Secondly, it enables more precise methodologies, allowing researchers to delve into the intricacies of employee motivation, aligning with various objectives. This facilitates the development of targeted strategies for improving work environments and informed decision-making.

Further enhancing the ontology's capability, the incorporation of fuzzy logic, as discussed by Martínez-Miranda et al. [24], offers a substantial improvement. Fuzzy logic provides a robust framework for handling the ambiguity and partial truths that characterize human emotional states and motivational drives. By integrating this approach, the ENT Ontology could accurately model the nuanced variations in employee satisfaction and motivation, allowing for more dynamic and granular analysis. This adaptation enhances the ontology's ability to move beyond binary classifications, presenting a richer, more adaptable tool for organizational analysis.

In embracing these developments, the ENT Ontology not only advances beyond traditional models but also unlocks deeper insights into employee motivation. This fosters a holistic understanding and enables more effective interventions to enhance workplace dynamics, promising significant improvements in how organizations approach employee motivation and well-being.

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