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# CAREPROFSYS – AN ONTOLOGY FOR CAREER DEVELOPMENT IN ENGINEERING DESIGNED FOR THE ROMANIAN JOB MARKET

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**Professionalization of work represents the process of transforming an occupation into a profession with a high degree of integrity and competence, requiring the existence of professional qualification frameworks, standards, and nomenclatures to describe the necessary skills, abilities, and education for an individual to have a fruitful career. The current study provides details on professions from the engineering domain that are modeled using a prototype ontology tailored to the context of Industry 4.0 in the Romanian landscape. Our ontology represents the foundations for providing personalized recommendations to find suitable professions in the Romanian job market while illustrating the importance of AI tools to support career development.**

## 1. INTRODUCTION

Major technological innovations applied to production systems represent the core industrial revolutions. Chronologically, the first three industrial revolutions mainly relied on steam-based machines, electrical energy-based mass production, and computer and Internet-based knowledge. The 4$^{th}$ industrial revolution, or Industry 4.0, is characterized by Artificial Intelligence (AI). Technological changes significantly impact other technical-economic elements (*i.e.*, processes/tasks, material, and financial metrics) and social aspects of the production systems, such as interpersonal relationships, organizational culture, competence profile of employees, coordination, and control practices. Industry 4.0 led to the emergence of the *digital transformation* concept, which implies modifications at operational and organizational levels, but also cultural changes through the integration of AI technologies in the production processes and competency profiles across all levels and functions of the organization [1–3].

AI led to new occupations (e.g., data manager, forensic analyst, carbon emission manager, industrial vision system operator, and cyber security specialist) and to reshaping existing ones (*e.g.*, quality assurance specialist, online instructor, and online consultant). Employees need to extend their knowledge, skills, and attitudes toward innovations in the context of radical and rapid changes in the workplace. However, practical experience accumulated at the workplace might not be enough to keep the job; a professional qualification is required. Occupations tend to transform into professions that require professional qualification, systematic evaluation of professional competencies, and compliance with the professional code of conduct requirements.

*Work professionalization represents* transforming an occupation into a profession with high integrity and competence [4]. Professionalization requires a) professional qualification frameworks, b) professional associations that define and recommend best practices to members of the represented professional community, c) a code of professional conduct, and d) professional certifications to differentiate between competent or less-competent professionals. Sometimes, professional associations create the so-called "professional closure" by limiting the rights of practice to amateurs or unqualified persons. Standards and regulations should be defined for all these processes to be aligned and properly performed, while the main actors in the labor market should adhere to them.

Entering a professional community requires a consistent long-term effort to get qualifications, apply for, and obtain a job related to the profession while properly performing the tasks associated with the job. Concurrently, communities ensure continuous professional development activities. Most people agreeing to go through all these *career development stages* are motivated by quick income opportunities associated with the profession. However, at the same time, an important percentage of people looking for a job have a genuine passion for the profession. The *professional identity* represents the common perception of opportunities for the associated profession beyond improving income levels.

This study addresses professionalization in the engineering domain and its connection with job performance, the associated engineering qualification frameworks, and competence standards. As such, this paper focuses on AI technologies that might support career development in engineering by providing a prototype version of our ontology of professions in the Romanian landscape.

The structure of the paper is further presented. After the introduction, section 2 addresses the state-of-the-art centered on the professionalization of engineering. Section 3 presents career development in engineering and the potential of AI technologies for career development in engineering, with examples. The final sections present the proposed ontology for career development in engineering in Romania, followed by conclusions and future work.

## 2. THE ENGINEERING PROFESSION. RELEVANT PROFESSIONAL BODIES, TAXONOMIES, AND STANDARDS

A profession requires an institutional framework that includes a) public institutions and professional bodies to organize and regulate that profession, b) specialized knowledge and skills acquired through academic education and professional training, c) competence certification,

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d) professional codes of conduct, and e) relevance for society. Occupations that do not fulfill these requirements are considered non-professionalized. Engineering, defined as the creative application of scientific principles to develop or design structures, apparatus, machines, and manufacturing processes [5] is a profession because it has all professional elements, namely: regulation and organization, competence, public relevance, code of ethics, responsibility, and accountability.

Systems such as engineering institutions (EI) or engineering societies (ES) for organizing and regulating the engineering profession have particularities in different countries [6], as seen in Table 1. The engineering profession has a long-standing tradition in Romania. The Technical Corps was founded in 1894, and the first engineering societies were established during the 19th century. The General Association of Engineers in Romania (A.G.I.R.) has several affiliated professional societies.

*Table 1*

Systems for organizing and regulating the engineering profession

| *Countries* | *Central body* | *Other bodies/ organizations* |
|---|---|---|
| UK | Engineering Council - EC | >40 EIs |
| Germany | Does not exist | Deutscher Verband Technisch-Wissenschaftlicher Vereine (DVT) with 95 societies, Zentralverband der Ingenieurvereine (ZBI), > 100 EIs |
| France | Commission des Titres d'Ingenieur (CTI), Conseil National des Ingenierus et Scientifiques de France (CNISF) | Several ESs |
| Italy | Consiglio Nazionale deli Ingegneri (CNI) | Ordine Provinciale degli Ingegneri (OPI) |
| USA | American Association of Engineering Societies (AAES) | 70 EIs and 30 ESs |
| Romania | General Association of Engineers in Romania (A.G.I.R) | Romanian Society of Energetics, Federation of Engineers in Metallurgy, Society of Engineers in Telecommunications, Society of Engineers in Transports |

The pillar for occupation regulation at an organizational level is the international or national classification of occupations that includes both professionalized and non-professionalized occupations. The International Standard Classification of Occupations (ISCO), with ISCO-08 as the latest edition, represents a system for classifying and aggregating information related to occupations present in the labor market. ISCO-08 is developed based on population censuses, other statistical surveys, and administrative information. ISCO-08 uses the concepts of *job* and *skill*. A job is a set of tasks executed by a person and a set of similar jobs represents an occupation. A skill is the capability to carry out the tasks associated with a given occupation. Considering the skill specialization (the field of required knowledge), four occupational levels were defined, like the ones of the *International Standard Classification of Education* (ISCED). The first ISCO skill level corresponds to ISCED category 1, the second ISCO skill level corresponds to ISCED categories 2 and 3, the third ISCO skill level corresponds to ISCED category 5, whereas the fourth ISCO skill level corresponds to ISCED categories 6 and 7.

ISCO-08 has a hierarchical structure consisting of ten major groups, subdivided into 28 sub-major, 116 minor, and 390-unit groups with more than one occupation. The skill level is not applied to major groups 0 and 1. All ISCO-08 elements have a code, a title, and a short content description. ISCO88 (COM) is the variant of the ISCO-08 provided by the European Union. The Romanian Occupational Classification (COR) is aligned with ISCO88 (COM) and ISCO-08 [7].

The Romanian COR first appeared in 1995 and represented a system of identification and coding of Romanian occupations regardless of their type and place. The COR defines a six-digit code mapped to each professional position in the Romanian job market. The COR is periodically revised and updated with occupations not yet included. The last revision and update were in 2022. Like many other national classifications of occupations, the Romanian classification also follows the structure of ISCO-08 [10].

Occupational standards have been developed for around 20 % of the total occupations included in COR. An occupational standard establishes the competencies and performance levels required for practicing that occupation. Occupational standards include the description of competence units that the employer can use to evaluate persons asking for employment or by the employees during their continual professional development. As tools for career development, *occupational profiles* are issued with a short description of occupations, including associated tasks and responsibilities, working environment characteristics, work schedule, wage, requirements for professional training, and promotion opportunities.

Skills represent an important factor in work performance. Different studies on productivity identified skills improvement as the key factor of productivity growth [8, 9]. The definition of skills taxonomies and their connections to the classifications of occupations might have many potential applications, such as career guidance (i.e., what skills are required for an occupation or what occupation is suitable to a particular skill set), education curriculum development, understanding occupations' dynamics, and identification of skills shortages or skills mismatches.

One of the most used skills taxonomies is the US Occupational Information Network *O*NET* [9] which includes skills, knowledge, abilities, job characteristics, and requirements for around 1,000 occupations. O*NET is the main source of information in the USA regarding competencies for the labor market. O*NET is widely used in the US and other countries due to its comprehensiveness and accessibility as an open-source resource. OECD, decision-makers, experts from academia, and society use *O*NET* in their studies and/or programs. O*NET includes 35 skill-type elements, grouped into basic skills, social skills, resource management, systems skills, complex problem-solving, and technical skills. O*NET includes 33 knowledge-type elements (sets of facts and principles across general domains), 52 ability-type elements (cognitive, psychomotor, physical, and sensorial abilities), 16 work style-type elements, and 41 work activities-type elements. All these elements are associated and scored to the occupations.

The European Skills, Competences, Qualifications, and Occupations (*ESCO*) is a taxonomy having separate 'pillars' for skills, occupations, and qualifications [10]. It is a classification of qualifications, skills, and occupations provided in multiple languages. The skills pillar includes knowledge, skills, and competencies. Skills are classified based on their generality as occupation-specific, sector-specific, cross-sector, or transversal skills. There are separate hierarchies for attitudes, knowledge, and language. Overall, the skills pillar of ESCO includes 13,500 elements. The occupation pillar refers to the occupations included in ISCO-08, while the qualification pillar includes the qualifications defined by the EQF (European Qualification Framework). There are multiple connections defined between the elements of these three pillars. ESCO data elements are in rich data format, being easy to be interrogated by APIs.

The Skills Framework for the Information Age (SFIA) describes competencies required by digital occupations. It includes 102 digital skills structured in a hierarchy with three layers. Software testing and data visualization are among the most important specialized areas covered by these skills. SFIA facilitates career development within organizations, being useful to support the education and training providers in the curricula and syllabi design.

## 3. CAREER GUIDANCE IN ENGINEERING. ARTIFICIAL INTELLIGENCE SOLUTIONS

According to several studies, engineering has steadily grown in the labor market across most countries [9, 10]. Romania might be considered an exception, with a high increase in the demand for engineers. This situation may be explained by Romania's major labor force crisis [12] that spans the last 15 years. The main reasons include the demographic crisis, emigration (approx. 200,000 engineers left the country after 1989), qualifications not aligned with the job requirements, and high expectations of people looking for jobs not fulfilled by the labor market. The estimations for demand are 600,000 engineers; in contrast, around 3,700 engineers graduate each year at the University POLITEHNICA of Bucharest, the largest supplier of engineers in Romania, while at other Romanian universities, there are around 8,000 engineering graduates per year. The workforce deficit registered in Romania has also been reflected in the many requests from employers to hire foreign citizens from outside Europe. Engineering is a creative and innovative profession related to state-of-the-art technologies, tools, and methods. Engineering education develops creative thinking, problem-solving, and communication skills, as well as psychomotor, physical, and sensorial abilities. Considering the alignment of engineers' skills required by employers in the labor market and engineering skills developed by academic programs, most studies have identified a significant gap to be covered by curricula restructuring and continual professional development [13].

A career in engineering is determined by the decision to start studying engineering disciplines, the so-called initial qualification in engineering. It is recommended that individuals to take personality tests, participate in evaluation discussions with family members, friends, and teachers, and assess their level of cognitive and social skills [14]. The main actors involved in this career development stage include counselors from career placement and counseling centers, family members, friends, or members of professional bodies. The employed tools consist of standardized tests, brochures with professional outlook figures, reports of the labor market survey, or job posts. The involved actors might also use or recommend specialized software tools assuring assistance in the career development process [14].

The next stage in career development is choosing the academic program to be followed based on the program curriculum, testimonials from graduates, academic rankings, or internship opportunities. Finding the first job is an important step for professionals. Career development also implies continual professional development, achieved through increasing work experience, professional training, continuing academic education, reading, participation in professional events, and involvement in activities organized by professional bodies. Sometimes, a re-skilling process might be necessary, leading to a new career path in a new discipline or specialization; nevertheless, another career development cycle might also be necessary.

AI technologies, especially ontologies and knowledge graphs [15] integrated into recommender systems, are useful for supporting the career development cycle, as the number of counselors is insufficient. Competence ontologies are formal, explicit specifications of competence profiles, with the links between competencies and an inference engine for identifying competence gaps, the most suitable job for job applicants, or the most suitable educational program/training for filling the competence gap. [16] developed an ontology-based system for recruitment, including the following ontologies: Job Requirements, Job Seekers/ applicants, and Skills. The Skill ontology was introduced to match the job requirements with applicants' profiles and obtain a ranked list of the most suitable applicants. Similar systems were introduced by [17,18]. [19] created an ontology for identifying employees to be assigned to specific company positions. [20] defined an ontology-enhanced specification of job-related knowledge with a reasoning tool for identifying skills' balance between the so-called "World of Work" and "World of Education" skills.

Recommender systems (RSs) may be actors that provide suggestions in each stage of career development in engineering. The most common RSs types are collaborative, content-based, knowledge-based, demographic-based, hybrid filter, and reclusive methods based; the main features of each type are presented by [21]. Ontologies and RSs may be combined in hybrid AI systems to support career development and guidance. [22] describes a hybrid system for knowledge access improvement in engineering projects. [23] presents a hybrid system using LinkedIn endorsements to reinforce an ontology-based recommender algorithm that improves professional skills.

## 4. CareProfSys ONTOLOGY FOR CAREER DEVELOPMENT IN ENGINEERING

We developed a prototype of an ontology reflecting a professional nomenclature to support implementing a recommender system for suitable professions. We have chosen as a reference the Romanian COR. Our taxonomy of occupations has 5 levels directly mapped to the COR digits as the first four digits model the hierarchy, and the last two are used together to ensure incremental unique IDs to each occupation. The classes of the first four levels have an ISCO code correspondence. The fifth level contains the occupations that are already in the COR. The occupations do not have an ISCO code correspondence, as they are specific to the Romanian job market. The topmost level is divided into nine main categories with the same names as in ISCO (without military-related occupations). The nine main groups can be seen in Fig. 1 below: their sizes are proportional to the number of subsequently included occupations. Figure 2 expands the hierarchy of occupations from the main group 2 – Professionals, subgroup 25 – Information and communications technology professionals.

The COR nomenclature contains all necessary details for all occupations, including general activities, the context of work, work style, needs, and values connected to the respective professional position. It also specifies all the skills, competencies, and knowledge required to fill that position. Many occupations also have a corresponding job description sheet that further details all necessary skills, knowledge, qualifications, and abilities needed from a candidate. In addition, the description sheet contains all activities required by the job, the context, and the work style. As much as possible, our ontology reflects all details from the COR.

Besides the occupation pillar, our ontology contains three more pillars: a) the first contains the domains of study, thus connecting education with professions; b) the second details all characteristics linked to the occupation (i.e., general activities, the context of work, work style, values, and requirements), and c) the thirds pillar contains all the required characteristics to fulfill a given position (*i.e.*, abilities, competencies, and interests). A description is provided for all characteristics as annotation in the ontology, and the importance of the linked characteristic or domain is given for all connections to an occupation.

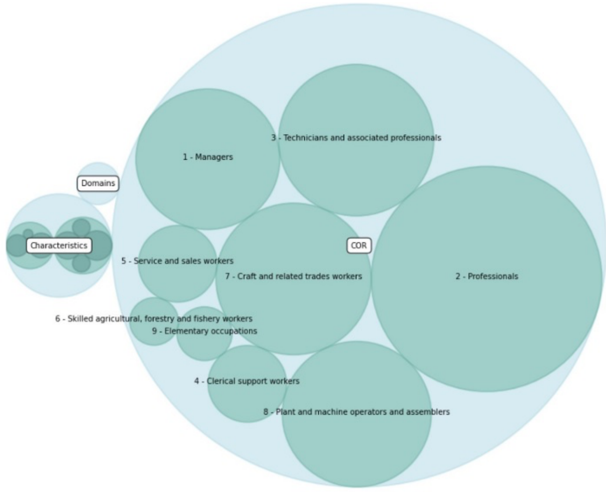


Fig. 1 – Principal groups of jobs in the prototype CareProfSys COR ontology exported from GraphDB.

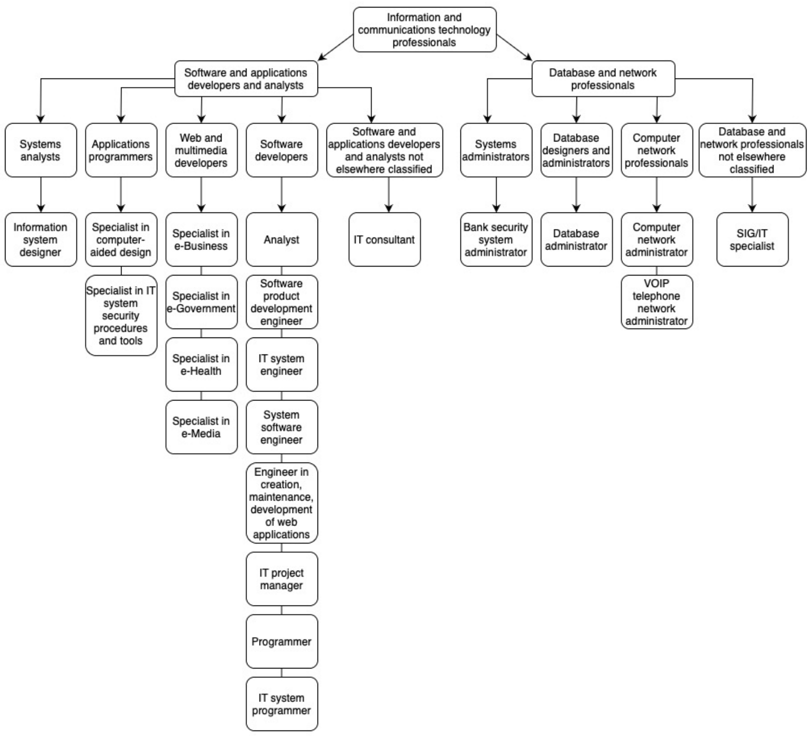


Fig. 2 – Hierarchy of occupations snippet in CareProfSys COR ontology from Protégé.

Ontological object properties were developed to connect domains, work styles, and interests to the requisites for a specific job. For example, we observe in Fig. 3 the connection between necessary knowledge from a specific domain and the COR professions, reflected in the property *hasCunostinteNecesare*, defined on the COR class with values in the *Domeniu* class.

Each occupation in COR has 8 characteristics: general activities, the context of work, working style, values and needs connected, necessary domains of knowledge, abilities, aptitudes, and interests. Every job has three connections to interests and four to every other characteristic. Through these connections, queries can be made to show the possibilities of a user in the Romanian job market, given his/her qualifications and interests. A Europass CV can also give the user's profile, and the recommendation considers all previous experiences and knowledge. On the other hand, the applicants can be filtered for someone hiring for a specific position based on the competencies and tasks needed to fulfill the position. Another scenario of usage is someone preparing for a position: someone aiming to work in a specific field can see what competencies she/he needs to get that job. A query can be made to see all the necessary conditions to fulfill the job. In Fig. 4, a SPARQL query is shown for the profession *'Controlor si reconditioner filme' (eng. Controller and film reconditioner).*

This definition of a profession contains all the necessary information that can link a person to a suitable job based on their profile which can be built from a CV, social network input, or any other suitable information. For example, knowledge of *Design* is indispensable for the previous occupation; candidates can be excluded from that position if they do not have any Design knowledge. Nevertheless, a person looking for a job with deep knowledge of the four listed domains (*Engineering and Technology, Computers and Electronics, Design,* and *Mathematics*) can be linked to this occupation.

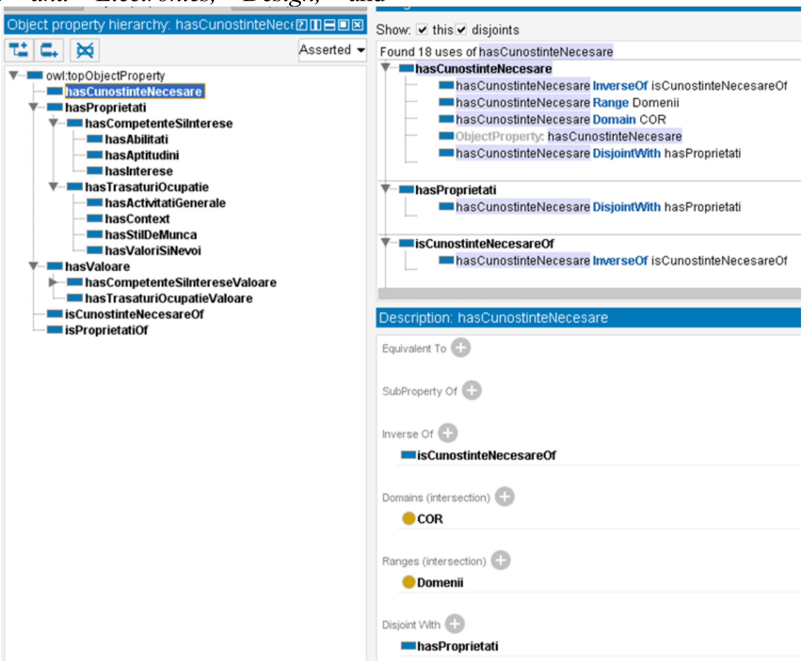


Fig. 3 – Relations between classes and concepts in CareProfSys COR ontology modeled using Protégé.

We also observe that this occupation requires high investigative and artistic interests and that all properties are required when connecting a professional profile and a user profile. In other cases, partial matching between a recommended professional profile and a user profile might be sufficient. Figure 5 introduces a comprehensive specification of the class corresponding to Electrical Engineers with all corresponding properties adequately set.

```
for a in list(default_world.sparql("""
PREFIX cor: <http://www.cor.ro#>
PREFIX job: <https://www.rubinian.com/cor_6_ocupatia_detalii.php?id=>
SELECT ?y
        { ?x rdfs:label "Controlor si reconditioner filme" .
          ?x rdfs:subClassOf* ?y
        }
    """)):
    if ('indispensabil' in str(a[0])):
        print(str(a[0])
```

Fig. 4 – Example of SPARQL Query for CareProfSys COR ontology.

```
Class expression editor
'Ingineri electronisti'
and (hasActivitatiGenerale some ('Actualizarea sau utilizarea cunoştinţelor relevante' and (hasValoareImportanta value indispensabil)))
and (hasActivitatiGenerale some ('Gandirea creativa' and (hasValoareImportanta value indispensabil)))
and (hasActivitatiGenerale some ('Luarea deciziilor sau rezolvarea problemelor' and (hasValoareImportanta value indispensabil)))
and (hasActivitatiGenerale some ('Utilizarea calculatoarelor' and (hasValoareImportanta value indispensabil)))

and (hasContextulMuncii some ('Comunicare fata in fata' and (hasValoareImportanta value indispensabil)))
and (hasContextulMuncii some ('Comunicare prin email' and (hasValoareImportanta value indispensabil)))
and (hasContextulMuncii some ('Comunicare prin telefon' and (hasValoareImportanta value indispensabil)))
and (hasContextulMuncii some ('Mediu interior, controlat'  and (hasValoareImportanta value indispensabil)))

and (hasAbilitati some ('Expresivitatea verbala' and (hasValoareImportanta value foarte_important)))
and (hasAbilitati some ('Intelegerea textelor scrise' and (hasValoareImportanta value foarte_important)))
and (hasAbilitati some ('Identificarea problemelor' and (hasValoareImportanta value foarte_important)))
and (hasAbilitati some ('Intelegerea verbala' and (hasValoareImportanta value foarte_important)))

and (hasAptitudini some ('Analiza sistemelor' and (hasValoareImportanta value foarte_important)))
and (hasAptitudini some ('Rezolvarea problemelor complexe' and (hasValoareImportanta value foarte_important)))
and (hasAptitudini some ('Intelegerea textelor citite' and (hasValoareImportanta value foarte_important)))
and (hasAptitudini some ('Gandirea critica' and (hasValoareImportanta value foarte_important)))

and (hasIntereseOcupationale some ('Interese artistice' and (hasValoareImportanta value destul_de_important)))
and (hasIntereseOcupationale some ('Interese investigative' and (hasValoareImportanta value indispensabil)))
and (hasIntereseOcupationale some ('Interese realiste' and (hasValoareImportanta value foarte_important)))

and (hasValoriSiNevoi some ('Conditii de munca' and (hasValoareImportanta value foarte_important)))
and (hasValoriSiNevoi some (Independenta and (hasValoareImportanta value foarte_important)))
and (hasValoriSiNevoi some (Realizarea and (hasValoareImportanta value foarte_important)))
and (hasValoriSiNevoi some (Recunoasterea and (hasValoareImportanta value destul_de_important)))

and (hasStilDeMunca some ('Gandirea analitica' and (hasValoareImportanta value foarte_important)))
and (hasStilDeMunca some ('Atentie la detalii' and (hasValoareImportanta value indispensabil)))
and (hasStilDeMunca some (Cooperare and (hasValoareImportanta value foarte_important)))
and (hasStilDeMunca some ('Respectarea obligatiilor' and (hasValoareImportanta value foarte_important)))

and (hasCunostinteNecesare some ('Inginerie si tehnologie' and (hasValoareImportanta value indispensabil)))
and (hasCunostinteNecesare some ('Calculatoare si eletronica' and (hasValoareImportanta value indispensabil)))
and (hasCunostinteNecesare some (Design and (hasValoareImportanta value indispensabil)))
and (hasCunostinteNecesare some (Matematica and (hasValoareImportanta value foarte_important)))
```

Fig. 5 – Definition of research engineer in applied electronics in COR ontology.

Besides performing SPARQL queries to retrieve relevant entries, similarities between profiles in our ontology can be computed using an adapted Wu-Palmer index [24]:

$$similarity(pp, up) = \frac{2 * depth(LCS(pp, up))}{depth(pp) + depth(up)} \quad (1)$$

where:

- *similarity(pp,up)* is the similarity between the ontological representations of the professional profile (pp) and user profile (up);
- *depth(pp)* represents the shortest path between *pp* and root in the ontology;
- *depth(up)* represents the shortest path between *up* and root in the ontology;

- *LCS(pp,up)* represents the least common subsummer or the most specific concept, which is an ancestor of both *pp* and *up*;
- *depth(LCS(pp,up))* represents the shortest path between the ontology root and the least common ancestor of both *pp* and *up*.

## 5. CONCLUSIONS AND FUTURE WORK

The current paper debates the topic of professionalization, and we propose an ontology-based recommender to find suitable professions in the Romanian job market. The proposed AI solution is especially useful to engineering students for whom there is an insufficient number of career counselors to provide guidance.

As future work, we envision implementing a recommendation mechanism consisting of the following steps: (1) identify the user's skills and interests; (2) map skills extracted in natural language to predefined properties from the ontology; (3) retrieve the possible matched professions using the ontology; (4) optimize the matches obtained from the ontology by implementing a collaborative filtering recommendation algorithm; (5) return the results to the user.

The candidate's skills and interests will be identified by parsing the CV and scrapping linked social media accounts. The mapping of skills extracted from various sources to standard skills will consider a machine learning model based on the Transformer architecture [25]; from all available models, we will consider experimenting with the Romanian BERT model [26]. Afterward, we will rely on our ontology to retrieve all jobs adequate for a candidate. An ontological class reflecting the candidate profile will be created for the specific example from the previous section. After starting the reasoning process from the ontology, that class will be automatically classified as a subclass of *Research engineer in applied electronics*, thus enabling the recommendation of that profession to our user. Further on, collaborative filtering algorithms [21] can be applied to identify similarities between the current user profile and other profiles when the user database is mature enough.

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