Pisco Med Publishing

Human Resources Management and Services 2026, 8(4), 6772.
https://doi.org/10.18282/hrms6772

Article

An ontology-driven framework for competency-based job recommendation and career development

Fatima Zahra Abbadi[1*], Chahinaze Fikri Benbrahim[1], Mohamed Fourka[1]

[1]Faculty of Science and Technology of Tangier, Abdelmalek Essaâdi University, Tangier 90000, Morocco.

[*]**Corresponding author:** Fatima Zahra Abbadi, abbadi.fatimazahra@etu.uae.ac.ma

CITATION

Abbadi FZ, Benbrahim, CF, Fourka M. (2026). An ontology-driven framework for competency-based job recommendation and career development. Human Resources Management and Services. 8(4): 6772. https://doi.org/10.18282/hrms6772

COPYRIGHT

Copyright © 2026 by author(s). *Human Resources Management and Services* is published by Piscomed Publishing Pte. Ltd. This work is licensed under the Creative Commons Attribution (CC BY) license. https://creativecommons.org/licenses/by/4.0/

Abstract: Guiding school dropouts and job seekers towards high-demand careers is a complex task that requires intelligent, data-driven decision support. Most recruitment and career-guidance platforms publish job requirements without considering applicants who wish to retrain for a new field or who lack some of the required competencies. This paper proposes the conceptual framework of a Career Recommender System (CRS) that links competency-based job recommendation with gap-based training recommendation for high-demand sectors such as digital technologies, automotive and aeronautics. The framework is centered on an Web Ontology Language (OWL) with six core classes (applicants, assessments, job specification frameworks, competencies, training courses and jobs) and two association classes that make competency levels explicit (CompetencyRequirement and CompetencyAssessment), built with Protégé. Applicants' assessment results are converted into competency levels and compared with the importance and required level of each competency of a job. Two simple rules based on indispensable competencies decide whether a job is recommended directly or is reachable after training; the jobs are then ranked with a weighted scoring function, and training courses are recommended to close the gaps identified. SPARQL Protocol and RDF Query Language (SPARQL) queries and a hypothetical worked example illustrate the procedure. The ontology was validated for logical consistency with the HermiT reasoner; this validation does not measure recommendation accuracy or user satisfaction. The implementation of the full platform and its empirical evaluation with applicants, career counselors and human resources (HR) practitioners are left for future work.

Keywords: ontology-based recommendation; semantic web; competency modeling; career guidance; employability; job recommendation; knowledge representation; competency gap analysis

1. Introduction

Nowadays, organizations face new requirements when recruiting employees. Technological advances, the availability of data, new societal challenges and new types of jobs require competencies that current staff or available candidates may not possess. This rapid evolution has created a highly dynamic labor market (Bañeres and Conesa, 2017).

Finding the right applicant for a position among many applications requires considerable time and resources. Likewise, finding a job that matches a job seeker's aspirations and competencies is an equally tedious task. In this context, a decision-support system is a promising way to assist employers. Such a system can also help young job seekers, and people who need to change fields, to find suitable job offers and the specific training courses they need to enter the desired profession.

Many studies have applied recommender systems to education, while others

have focused on recruitment. On the one hand, several recommender systems suggest e-learning resources such as courses and training modules; on the other hand, job recommender systems compute the match between job seekers' profiles and the requirements of a position, using information extracted from curricula vitae (CVs), user preferences or user interactions with the system.

Our aim is to combine the benefits of these two types of system in a single framework. The framework recommends jobs and, when an applicant lacks some of the required competencies, suggests relevant training courses to improve the applicant's eligibility for the job.

The framework is also intended to highlight jobs that are in high demand on the labor market, pointing young people towards occupations that may be little known but are in high demand, together with the training needed to enter them.

Existing recommender systems rely on keyword search, users' prior knowledge or collaborative filtering, among other techniques. Our framework is instead based on the assessment of competencies, combined with several filtering techniques.

For these tasks to run smoothly, a suitable user model is needed that represents the most significant information about the applicant (Rodríguez et al. 2015).

Ideally, this model should also include mechanisms that reveal the applicant's actual level of competency. To improve personalization, we therefore propose a framework that uses semantic web technologies to model applicants, jobs, competencies and training courses, and to reason about the gaps between them.

The semantic web is an extension of the current web in which information is given explicit meaning, enabling better collaboration between machines and users (Obeid et al. 2018); machines thus become capable of processing and "understanding" data. Ontologies are the backbone of the semantic web. An ontology is a formal, explicit specification of a shared conceptualization (Guarino et al. 2009), made up of concepts, entities, attributes and properties related to a domain. The use of ontologies facilitates the analysis, reasoning, sharing and reuse of knowledge (Obeid et al. 2018; Urdaneta-Ponte et al. 2021). This work takes the first step towards building such a tool by presenting its conceptual framework.

In this paper, a skill denotes a specific, observable ability (e.g., writing a Structured Query Language (SQL) query), whereas a competency is a broader combination of knowledge, skills, abilities and other attributes (KSAOs) required to perform a job effectively, described with a proficiency level (Campion et al. 2011; Gagné et al. 2005). A competency can therefore include several skills. Jobs, assessments and training courses are expressed in terms of competencies throughout the framework, and the term "competency gap" denotes a required competency that an applicant does not hold at the required level.

This paper makes three contributions. First, it proposes an ontology that links applicants, assessments, job specification frameworks, competencies, training courses and jobs, together with the requirements of each job and the assessed level of each applicant, in a single model, so that job recommendations and training recommendations are derived from the same competency-gap analysis. Second, it specifies a transparent recommendation procedure, namely rule-based retrieval of jobs from explicit competency requirements (importance and required level), a weighted scoring function and gap-based training ranking, and illustrates it with a worked example. Third, it discusses how the framework can support applicants, career counselors and human resources (HR) practitioners, including the role of professional judgment, privacy and bias. By helping users become aware of their competencies and limitations, the framework aims to narrow the gap between

academic qualifications and labor market demands (Castillo et al. 2021) and to widen the pool of applicants for unfilled jobs.

The remainder of the paper is organized as follows. Section 2 reviews related work and presents the materials and methods: the design of the platform, its ontology and the consistency check of the ontology. Section 3 presents the results of the design work: the recommendation procedure (scoring function, SPARQL Protocol and RDF Query Language (SPARQL) queries and competency levels), a worked example and the system architecture. Section 4 discusses the implementation status of the framework, its practical use by HR practitioners, ethical considerations, limitations and future work, and Section 5 concludes the paper.

2. Materials and methods

Several studies have addressed e-recruitment and the automation of the recruitment process, while others have focused on recommending courses to students based on their preferences and interactions. Although several e-recruitment and educational recommender systems exist, our approach integrates job market needs with competency development pathways.

The subject requires an interdisciplinary approach that combines information and communication technologies with management sciences (adaptive hypermedia systems, online learning platforms, competency management, and career guidance and professional integration).

Given the large number of studies on online recruitment (e-recruitment) and course recommender systems, we selected about ten representative works, some focusing on the conceptualization of the recommendation process and others on the modeling and construction of the systems' ontologies. This section presents these works.

2.1. Synthesis of Core Findings from Related Literature

Table 1 compares several ontology-based systems discussed in this paper. Although most of them are ontology-based, none covers all the aspects required of a comprehensive support system. In particular, we did not find a system that uses semantic technologies to guide a broad population of applicants towards suitable job positions on the basis of a prior assessment of their competencies. Most available systems rely on users' prior knowledge of courses, their personal background or keyword search, without assessing applicants' abilities (Ibrahim ME, 2019). This study therefore proposes an ontology-based decision-support framework that helps different categories of people find jobs in high demand on the labor market, together with the training courses needed to acquire the competencies required for these positions.

Table 1. A comparative overview about ontology based recommender systems.

Title	Year	Authors	Strengths	Limitations
A proposal for an adaptive Recommender System based on competences and Ontologies	2022	Julia Clemente et al.	This work proposes a novel approach to develop an adaptive recommender system based on students' skills. This system helps identify students who need tutoring sessions so that they can overcome and correct their deficiencies. To promote personalized learning.	This work can be used in designing the student model.
Ontology-Based Personalized Job Recommendation Framework for Migrants and Refugees	2022	D. Ntioudis et al.	Rich ontology covering skills, experience, and preferences; semantic reasoning for explainable recommendations; real employability context	Domain-specific (migrants/refugees).

Continued table:

Title	Year	Authors	Strengths	Limitations
Ontology-Based System for Educational Program Counseling	2021	Majid et al.	The study developed an integrated system that efficiently extracts user-specific constraints into unambiguous queries and then retrieves more precise information about educational fields and associated university offerings.	Data collected from student queries, does not offer precise choices.
EduCOR: An Educational and Career-Oriented Recommendation Ontology	2021	Ilkou et al.	Comprehensive career-education ontology; links skills, learning paths, and labour-market needs; reusable semantic schema	Focuses on ontology design rather than full recommender implementation.
Diminishing the university drop-out rates in Romanian engineering programs by using a smart career path profiling system	2020	Dascălu et al.	A career recommendation system based on student interests; this data is extracted from several social networks as well as phycological tests. Structured by ontologies, the system will also offer virtual boardrooms.	Adapted to the Romanian system.
Ontology-Based Personalized Course Recommendation Framework	2019	Ibrahim et al.	The study proposes a Framework based on an ontological model, and using filtering methods to help students identify and choose courses that meet their expectations and interests.	No assessment of skills and interests.
Improving Job Recommendation Using Ontological Modeling and User Profiles	2019	Rimitha et al.	Explicit ontological modeling of user profiles and job offers; semantic matching improves recommendation precision; practical job-matching use case.	Limited scalability analysis.
Career Recommendation System for Scientific Students Based on Ontologies	2019	Abdellah et al.	This work is the basis of a professional and university guidance system. The proposed ontological model is based on the comparison of students' skills with those required in university courses.	Career Recommendation System for Scientific Students Based on Ontologies.
Ontology-based recommender system in higher education	2018	Charbel Obeid et al.	A hybrid recommendation system that helps high school students choose a college path. This system offers personalized recommendation based on student interests.	It does not offer a recommendation based on current market demands but only on predictions of student interests.
Ontologies to Model User Profiles in Personalized Job Recommendation	2018	Rimitha et al.	In this work the authors propose a user model for an employment recommendation system. The system offers a collection of jobs that may interest the user the most.	Model is not general.
A Life-long Learning Recommender System to Promote Employability	2017	Bañeres & Conesa	The proposal for an employability assistance system. This system helps people by showing what knowledge and skills a person lacks for a given position and which college courses they can take to gain the required skills and knowledge.	No assessment of user competencies.
A Research of Job Recommendation System Based on Collaborative Filtering	2014	Zhang et al.	This work presents the different data filtering techniques, namely content-based and collaboration-based filtering techniques for an online recruitment system as well as the comparison between these methods with the precision calculation of each method.	Does not consider user behavior and interaction.

Several of these works already connect career guidance, competencies and learning. The Educational and Career-Oriented Recommendation Ontology (EduCOR), Ilkou et al. (2021) provides a rich career- and education-oriented ontology but focuses on ontology design rather than on a recommendation procedure; Bañeres and Conesa (2017), identify missing knowledge and suggest courses, but do not assess users' competencies and do not use an ontology; Clemente et al. (2022) assess competencies to recommend tutoring, without career or job recommendation; and Ntioudis et al. (2022) recommend jobs semantically,

without linking unmet requirements to training. Compared with these approaches, the proposed framework adds three elements: (i) competency levels derived from structured assessments (diagnostic, competency and technical tests) rather than from declared skills or preferences; (ii) a single competency-gap analysis that produces both the job ranking and the training recommendations, so that a job that is not yet attainable is presented together with the training needed to reach it; and (iii) an explicit, explainable scoring and retrieval procedure grounded in official job specification frameworks and involving career counselors in the process.

2.2. Recruitment Recommender System

A recommender system is a mechanism that provides tailored recommendations based on users' interests and preferences to help them make relevant choices (Ibrahim et al. 2018). Recommender systems originate from information retrieval and use various intelligent techniques such as text analysis, text mining, semantic technologies, artificial intelligence and machine learning (Obeid C, 2021).

There is a semantic matching approach for recruitment (Fazel-Zarandi and Fox, 2009). The aim is to identify appropriate profiles for particular job advertisements. The goal of this approach is to present a hybrid ontology-based strategy to efficiently match job seekers with job vacancies. For each job ad, they distinguish between useful and indispensable skills and also define the level of mastery of each skill (Ntioudis et al. 2022).

Recommender systems have become a key means of filtering information and personalizing content on the basis of users' preferences and behavior. George and Lal (2019) distinguish several major categories. Domain-specific (context-aware) models take into account contextual information such as location, time or the user's current situation to adapt their recommendations (Ricci et al. 2015). Hybrid models combine different strategies to improve results; they include weighted, switching, feature-augmentation, cascade, meta-level and mixed hybrids (Burke, 2002). Collaborative filtering, one of the most common techniques, exploits patterns of user interactions or item similarities to predict user preferences; it can be divided into neighborhood-based models, which focus on users or items, and model-based approaches such as decision trees, rule-based systems or naive Bayes models (Adomavicius and Tuzhilin, 2005). Content-based systems compare the attributes of items with the user's profile (Pazzani, 1999). Knowledge-based systems rely on explicit domain knowledge, such as ontologies, rules or past cases, to ensure that recommendations are appropriate to the context (Burke, 2007). The fundamental models of recommender systems therefore rely on two categories of data: user–item interactions (such as ratings) and attribute information about users and items (such as profiles and preferences). Methods based on the first type are called collaborative filtering methods, and methods based on the second type are called content-based methods. In knowledge-based recommender systems, recommendations are derived from the user's explicitly stated needs; instead of relying on historical ratings or purchase data, these systems use external knowledge bases and predefined constraints. Hybrid systems combine these elements to exploit the strengths of the different types of recommender systems across a broader range of contexts (Aggarwal, 2016).

2.3. Ontology-based recommender system

The integration of the ontological domain in the recommendation process can help overcome the limitations of conventional recommender systems. Ontology-based recommender systems are knowledge-based recommender systems that use ontology to represent knowledge about items and users in the recommendation process (Tarus et al. 2018). Ontologies play an important role for the representation, sharing and reuse of knowledge in these systems (Joy e al.

2019). In this work, an ontology-driven model is proposed for online vocational guidance, aimed at recommending training modules or job advertisements by evaluating the competencies of the applicant.

2.4. Ontological construction

2.4.1. What is ontology?

There are several definitions of ontology in the literature of artificial intelligence. As one of the semantic web technologies, an ontology facilitates the sharing and reuse of knowledge. It is a solid base to construct intensive and rich knowledge for systems (Ge et al. 2012). According to the guide of Noy and McGuinness (2002), an ontology is a formal and explicit description of the concepts of a domain of discourse (classes (sometimes called concepts)), the properties of each concept describing various characteristics and attributes of the concept (Attributes (sometimes called roles or properties), and restrictions on properties (facets (sometimes called role restrictions)). An ontology as well as a set of individual instances of classes constitute a knowledge base. Furthermore, ontology provides a vocabulary of classes and properties that can be used to describe a domain and emphasize knowledge sharing (Ibrahim et al. 2018). This makes it possible to build automated reasoning engines using the relationships between entities that can make "intelligent" choices in different situations (Benbrahim et al. 2018).

2.4.2. Stage of an ontology construction

Several methods of ontology construction have been proposed; these methodologies define steps and guide domain experts, ontology engineers and pedagogues to build better models (Ahmed et al. 2016). According to Niles and Pease (2001) quoted by Ahmed et al. (2016), the general steps in the design and development of an ontology are as follows:

1. Define the domain, scope, and objective.
2. Review any pre-existing domain ontologies.
3. Identify key domain terms.
4. Define the concepts and their hierarchical relationships.
5. Establish properties to construct the internal structure.
6. Incorporate facets, constraints on allowed values, type constraints, and cardinalities into the ontology.
7. Create instances of entities/classes and establish connections between them through defined relationships.

2.5. The proposed Recommender System

2.5.1. Platform Presentation

The long-term aim of this research is to model and prototype an intelligent platform facilitating the assessment, orientation, support and training of people seeking employment in new professions sought by companies. The platform, to be designed with the various stakeholders, will be based on artificial intelligence techniques and will allow the evaluation of applicants (tests and levels of knowledge), the recommendation (guidance of applicants towards a profession and/or offers of employment), course management (creation of tailor-made training courses) as well as support for applicants in order to achieve their integration objectives. Platform users are:

Training establishments (such as universities, schools, and vocational institutions) are organizations that design and deliver educational programs to provide individuals with the skills, knowledge, and qualifications needed for specific careers or personal development. They propose a training offer by developing curricula and courses tailored to the needs of students and the job

market (Tight, 2012).

Applicants are individuals who seek employment, career guidance, or training opportunities. They actively engage in the job search process, applying for positions, seeking professional development, or pursuing education to enhance their competencies and qualifications (Saks and Uggerslev, 2010).

Career counselors or career guidance professionals: Career counselors are professionals who guide individuals in making informed decisions about their career paths by assessing personal interests, skills, values, and personality traits. They provide support in career exploration, job search strategies, skill development, and navigating career transitions (Gati and Asher, 2001).

Companies (HR departments): they are responsible for managing the recruitment process, which involves attracting, evaluating, and hiring applicants to fill job openings. They develop job descriptions, source applicants, conduct interviews, and manage the hiring logistics to ensure the organization has the right talent to meet its business needs (Stone, 2017). The basic functionalities offered by our platform for these users are:

Assessment:

Assess the potential and level of knowledge of applicants;

Continuously assess the acquisition of trainees' competencies.

Recommendation:

Direct applicants towards a profession;

Direct applicants towards additional training modules.

Confirm the orientation of trainees towards a profession, a market sector and/or a type of employer.

Design:

Create tailor-made training paths by assembling learning units based on job and competencies benchmarks.

2.5.2. Semantic Course Recommendation Design

The proposed solution is a new orientation and recommendation architecture for professions and adaptive training courses, while considering the profile of the users, the field of training and the competencies and motivation linked to a specific field. The proposed framework is based on an ontology model, orchestrated by a recommendation engine, and supported by a database that stores the data and user information. The ontological model is centered on developing dynamic ontologies customized for each user, along with the components that map these ontologies to provide a thorough understanding of the recommendations. After the ontologies are constructed and aligned, they are used as input data for the recommendation engine. The recommendation engine then uses this data to suggest items to users, using the ontologies with the aim of improving the relevance of the recommendations (Ibrahim et al. 2018). The architecture of the proposed CRS (Career Recommender System) platform is as follows in **Figure 1**.

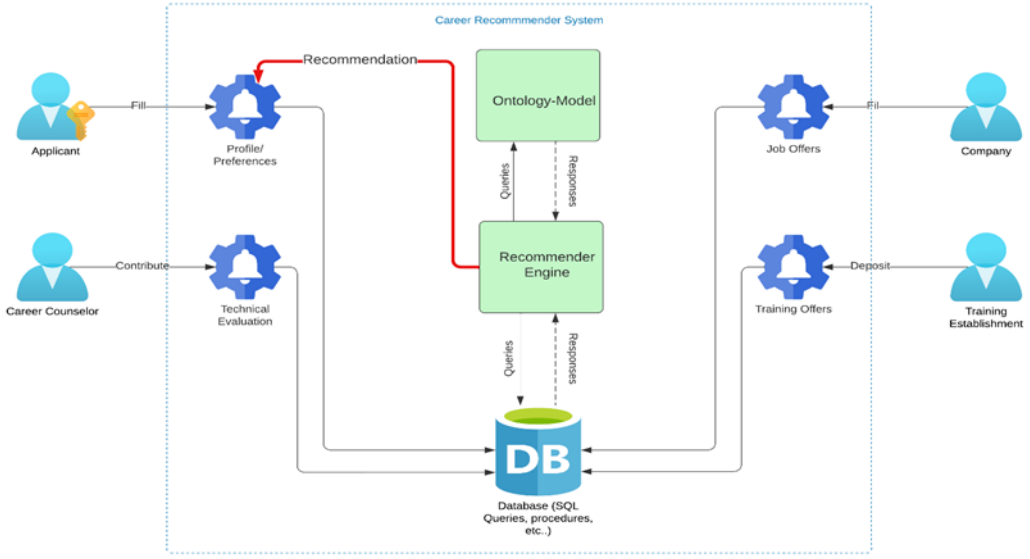

Figure 1. Architecture of the proposed Career Recommender System (CRS) platform.

2.5.3. The mechanism of generating job recommendations

The main objective for a recommender system is to generate recommendations. The design of this process shapes the overall architecture of the system. The recommender mechanism within the Career Recommender System executes the following steps:

The extraction of information from various sources (Interfaces, Web sources, Evaluation…): collection of the data about the user profile is the starting point. In our case we are going to use the static and dynamic profiling. Static profiling consists of demographic information provided by the user and through various tests on user's personality, IQ, and EQ (Dascălu et al. 2023).

Applying ontologies by using Protégé Tools: refers to the process of creating, managing, and utilizing structured knowledge representations (ontologies) with the help of Protégé, a widely-used open-source ontology editor. Protégé provides an intuitive platform to define concepts, relationships, and rules, enabling users to model complex domains and support applications in areas like semantic web, data integration, and artificial intelligence.

Semantic Calculation.

Refine the recommendation.

Based on these steps, personalized and complete guidance is offered to the applicant.

2.5.4. Dynamic ontological model

The difference between a static ontology and a dynamic ontology is that the latter depends on the modification of certain parameters which can be considered globally as situations (Ibrahim et al. 2018). In our case, occupations are recommended on the basis of the assessment of applicants' competencies; this assessment is based on the benchmark for the job requested, which is itself based on a benchmark of competencies necessary for the performance of this function, an official Job Specification Framework. If applicants meet the requirements of a profession, they are proposed for the position, otherwise they are redirected to additional training to strengthen their profile and apply again for this profession. The construction of ontologies is based on the ontological model **Figure 2**.

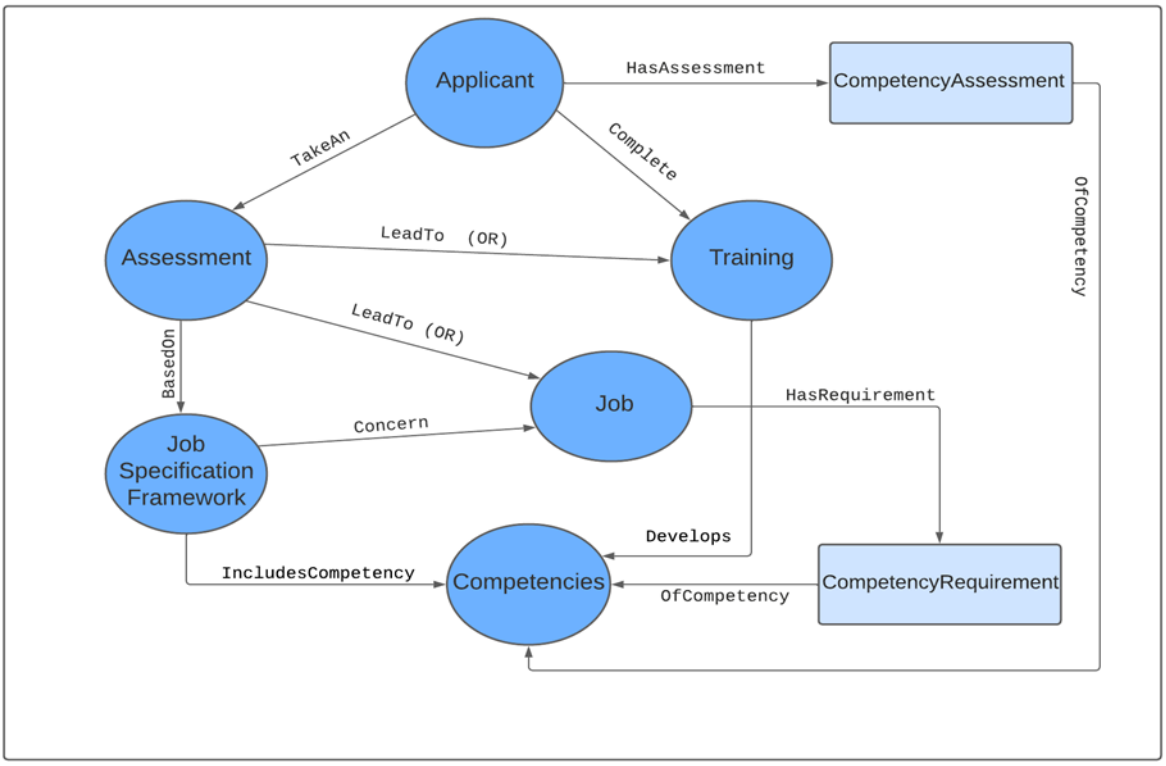

Figure 2. Conceptual model: main classes (ellipses) and association classes (rectangles).

Our ontological model contains six main classes which are the applicants, the evaluation, the Job Specification Framework which contains a professional Competencies repository, the training courses and the jobs (jobs in the field of new technologies and the Internet), completed by two association classes, CompetencyRequirement and CompetencyAssessment, that make the importance, the required level and the assessed level of competencies explicit. This division aims to facilitate interoperability with other ontologies. The class models are as follows:

Applicants: Contains personal information and information about their education as well as the preferences of any user.

Assessment: Contains tests and quizzes to validate applicant's competencies.

The Job Specification Framework: describes the competencies to be acquired for a job and the necessary resources.

Competencies: this is part of the job specification framework, which describes the competencies necessary for the exercise of a specific job and is also used to define the basic competencies of applicants. It is further divided into three subclasses (Knowledge, Skills and Attitudes).

Training: Contains the training courses and modules necessary to complete a specific profile.

The Job: a job offer published by a company for a specific position; it contains all the information about the position and its competency requirements (CompetencyRequirement).

CompetencyRequirement: An association class, attached to a job offer (Job), that records one requirement of the offer: the competency concerned, its importance (indispensable or useful) and the required level (1 to 3). Making the requirement an entity of its own allows the importance and the required level to be attached to each competency of a job, which a simple link between a job specification and a competency cannot express. The Job Specification Framework lists all the competencies of an occupation; each job offer selects among them and

sets their importance and required level according to the needs of the recruiting organization.

CompetencyAssessment: An association class, part of the applicant's profile, that records the result of the assessment of one competency: the competency concerned, the score, the resulting level (0 to 3) and the date of the assessment. It allows the level of each competency to be compared with the level required by a job and to be updated after training.

2.5.5. Use Case Diagram of the System

In this part of modeling, we present the vision of the system and the needs of the main users and their interactions with the system. CRS also used some of the information provided in the International Standard Classification of Occupations (ISCO) which is a global framework developed by the International Labor Organization (ILO) to classify and organize jobs and occupations into standardized categories based on the tasks and duties performed. It facilitates international comparison of occupational statistics and serves as a tool for job-related research, policy-making, and workforce planning (International Labor Organization (ILO)-ISCO Overview). The information, combined with the Requirements Model and Actors, facilitated the creation of a domain representation, offering an initial approximation of reality to depict the elements in the Business Use Cases Model. In **Figure 3**, two actors (the applicant and the orientation professional) are identified, each interacting with the system and its core processes.

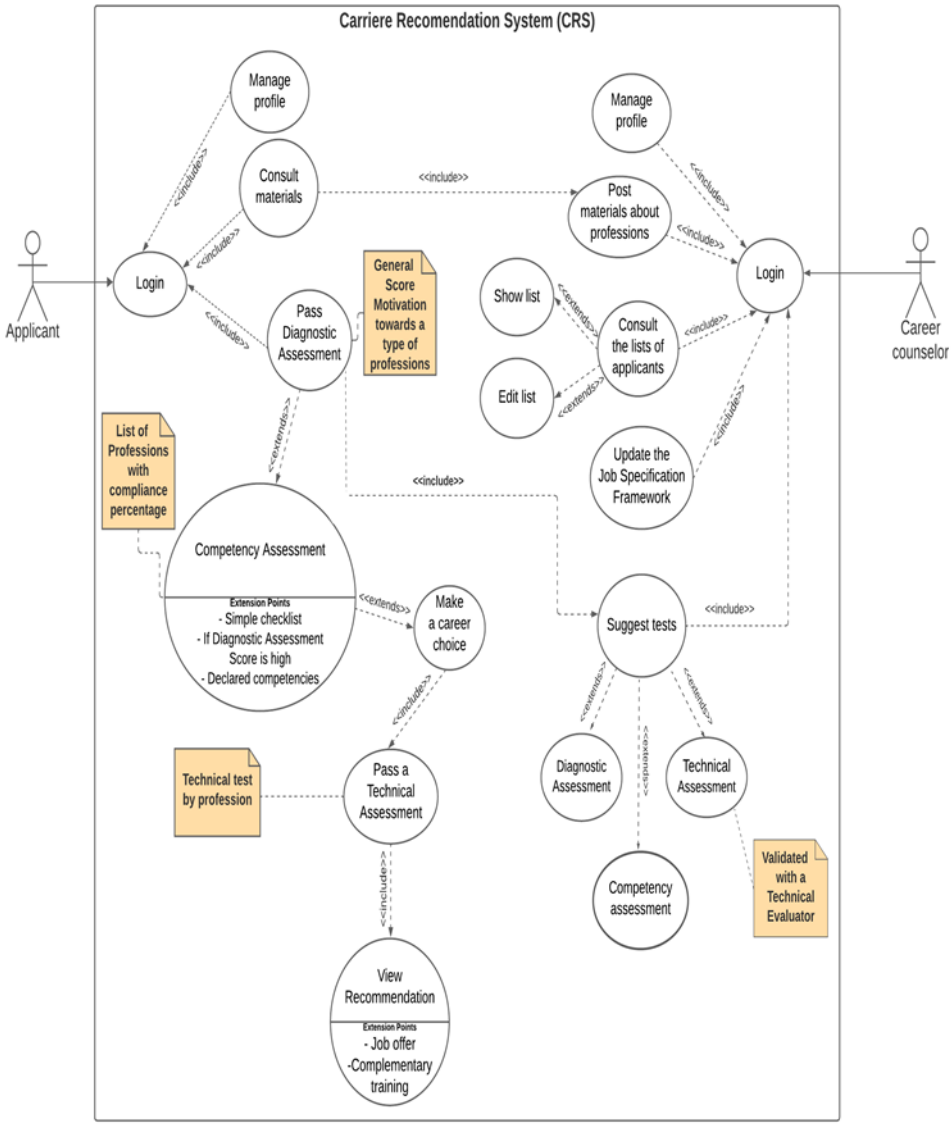

Figure 3: A use case model of the applicant and career counselor.

2.5.6. Description of the Use Cases of the System

Applicant: For an applicant, such a system could streamline the job search process by recommending job opportunities tailored to their competencies, experience, and career interests or training program to strengthen their competencies. By analyzing the applicant's profile, results of evaluation, and interactions, the system can identify the most relevant openings, save time and increase the chances of finding a perfect match. The use cases of the applicant are as follows:

Login: The applicant can access the platform with a username and password.

Manage profile: The applicant can add/update their personal and professional information.

Consult Materials: the applicant can check the materials (Documents, videos, testimonials…) that concerns the job concerned.

Pass Diagnostic Assessment: the applicant takes a preliminary test that checks their motivation for the job concerned. If the score is high enough, the applicant proceeds to the competency assessment.

Competency Assessment: In this stage the applicant takes a test of the competencies linked to the desired field of work. A score will be generated, and

will indicate, for every job position, the competencies that are met and those that are still missing.

Make a career choice: the applicant chooses the position that best matches their competencies.

Pass a technical assessment: Based on this choice, the applicant is redirected to a technical test that measures the technical skills of the applicant.

View recommendation: After passing all the tests, the applicant sees the recommendation proposed by the system; it can be a training course to improve their competencies in the field or a job offer that perfectly matches their profile.

Career Counselor: This part describes what a career counselor can do in the system to guide applicants in making informed decisions about their education, career paths, and professional goals. They provide the system with all the information needed to give a personalized recommendation.

Login: The Career Counselor can access the platform with a username and password.

Manage profile: The Career Counselor can add/update their personal and professional information.

Post Materials about professions: The Career Counselor can upload materials (Documents, videos, testimonials…) about the job concerned.

Consult the list of applicants: The Career Counselor can view and edit the list of applicants who have completed the first test, for example when a technical issue has occurred.

Update the Job Specification Framework: The Career Counselor can upgrade the job framework when changes occur.

Suggest tests: The Career Counselor can submit tests (skills tests and technical tests) that help to evaluate the applicant in the platform. For technical tests the Career Counselor can have the approval of a technical Evaluator.

2.6. General Ontology presentation

As mentioned, we used ontologies to model knowledge about our system, such as the applicant (information about the applicant), Course (training suggested), Job description, the domain knowledge (The specification Framework), and other different actors mentioned in the ontological model **Figure 2** above. This design facilitates the sharing of a unified understanding of the knowledge structure. According to Ibrahim et al. (2018), ontologies give the possibility to interpret the context of student profiles and course content features. In addition, they provide a conceptual basis for developers to reuse domain ontologies, or to develop a practical model. The general ontology of our system is shown below (**Figure 4**) with Protégé 5.6.7.

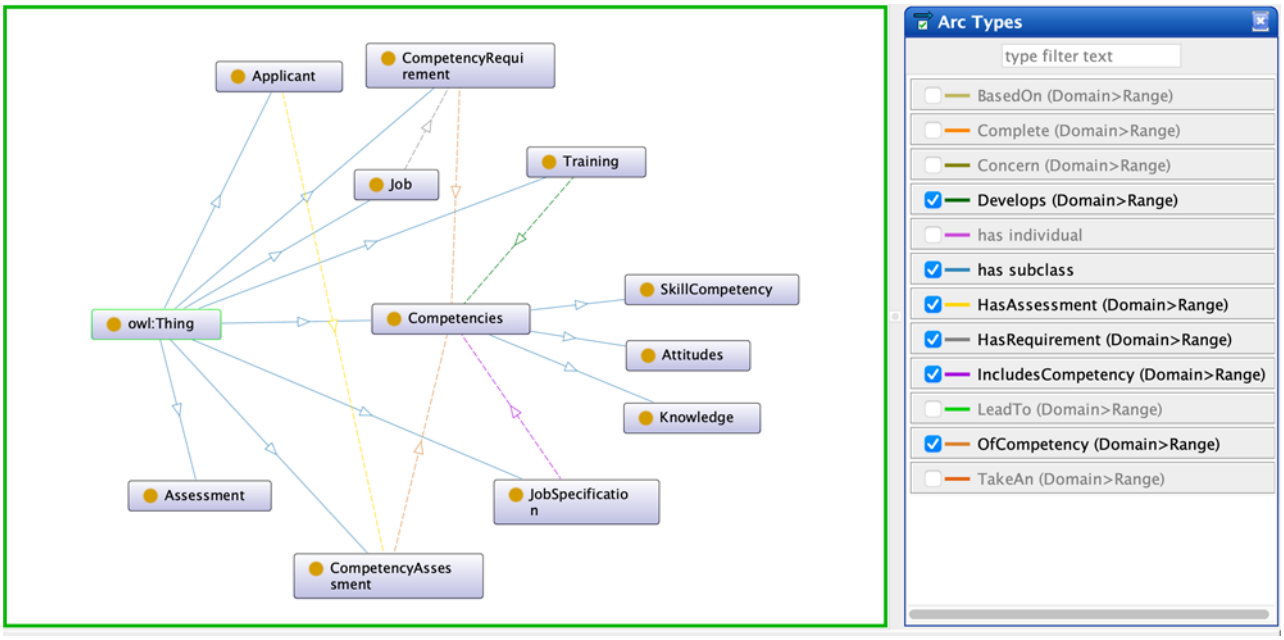

Figure 4. Main classes and selected relationships of the proposed ontology visualized in OntoGraf.

Table 2 shows examples of object properties and data properties of the CRS ontology.

Table 2. Examples of object and data properties from the CRS Ontology.

Property name	Class Relationship	Description
BasedOn	Assessment and JobSpecification	Shows tests about specific Domain.
Complete	Applicant and Training	Shows applicant who had complete a training.
Concern	JobSpecification and Job	Shows a job and Competencies about a specific job position.
IncludesCompetency	JobSpecification and Competencies	Lists all the competencies required to exercise a given occupation.
HasAssessment	Applicant and CompetencyAssessment	Shows the current assessed competencies of an applicant.
LeadTo	Assessment and Job/Assessment and Training	Shows the job offers for a specific Applicant/Shows a Training Program for Applicant.
HasRequirement	Job and CompetencyRequirement	Shows the requirements (competency, importance, required level) of a job offer, set according to the needs of the recruiting organization.
TakeAn	Applicant and Assessment	Shows the tests taken by Applicant.
Develops	Training and Competencies	Shows the competencies developed by a training course.
OfCompetency (object property)	CompetencyRequirement and Competencies/CompetencyAssessment and Competencies	Shows the competency concerned by a requirement or by an assessment result.
requiredLevel (data property)	CompetencyRequirement and integer (1–3)	Level of the competency required by the job.
importance (data property)	CompetencyRequirement and string	“Indispensable” or “Useful”.
level (data property)	CompetencyAssessment and integer (0–3)	Level reached by the applicant (Section 3.1.4).
score (data property)	CompetencyAssessment and integer (0–100)	Assessment score from which the level is derived.
assessmentDate (data property)	CompetencyAssessment and date	Date of the assessment; used to keep the history of levels.

The SPARQL queries in Section 3.1.3 use exactly these property names with the CRS namespace prefix “:” (e.g., : HasRequirement, :OfCompetency, :HasAssessment, :importance, :requiredLevel, :level and :Develops), and the class names of **Figure 4** (e.g., :Applicant, : Job and :Training). Competency levels and assessment scores are stored as data values of the

CompetencyAssessment individuals attached to the applicant (Section 3.1.4). The classes CompetencyRequirement and CompetencyAssessment and their properties are shown in **Figures 2** and **4**.

2.7. Ontology Evaluation

Logical Consistency Check: Consistency is the first property to check when evaluating an ontology. An inconsistent ontology contains contradictions that can lead to inference or reasoning errors. To check the consistency of our ontological model, we used the HermiT reasoner in the Protégé tool. This reasoner, which implements Description Logic (DL), tests the consistency of the ontology by identifying logical inconsistencies in the axioms and relationships defined between classes and individuals.

When the tool was run, the reasoner confirmed that the ontology was logically consistent and that no contradictions had been detected. No error messages were returned, indicating that classes, properties and relationships are compatible with each other. The results of the HerimT reasoner in Protégé 5.6.7 are shown below (**Figure 5**).

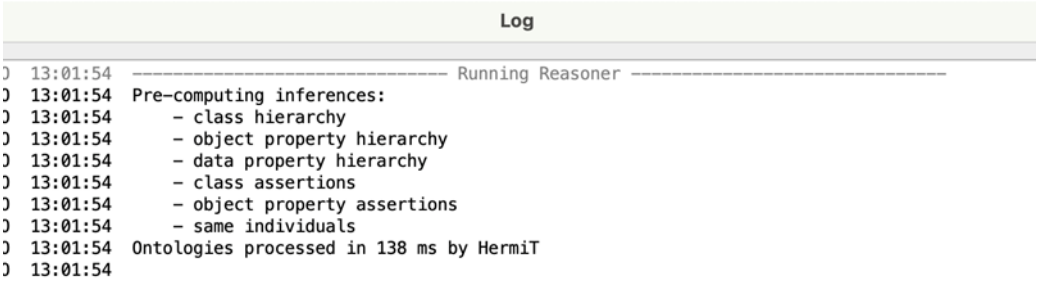

Figure 5. Results of HermiT reasoner by Protégé tool.

This check establishes only the logical coherence of the ontology. It does not measure the accuracy of the recommendations or user satisfaction, which require the empirical evaluation outlined in Section 4.4.

3. Results

3.1. Competency-Based Recommendation Procedure

This section presents the outcome of the design work: the recommendation procedure built on the ontology described in Section 2, a worked example and the overall system architecture. It specifies how recommendations are produced; it does not report an empirical evaluation, which is discussed in Section 4.

3.1.1. Positioning of the Recommendation Approach

As discussed in Section 2.2, recommender systems are commonly classified as collaborative filtering, content-based, knowledge-based, demographic and hybrid systems (Lahoud et al. 2022). CRS is primarily a knowledge-based recommender: recommendations are derived from the explicit, ontology-based representation of applicants' competencies, job requirements and training offers, rather than from historical ratings. Interaction data collected through the feedback loop (Section 3.3) could later be used to add a collaborative component and form a hybrid system.

3.1.2. Competency-Based Recommendation Algorithms

Instead of depending only on skills, recommendation engines are increasingly adopting a competency-based framework in contemporary talent and learning systems. It has been demonstrated that competency-based methods, which take into account knowledge, skills, and other attributes (KSAOs), provide greater predictive validity when it comes to hiring decisions (Campion et al. 2011; Spencer and Spencer, 1993). By integrating semantic relationships

and level-based reasoning, ontology-driven architectures that are in line with competency standards like ESCO can further increase matching accuracy.

Ontology-Based Filtering: Jobs are retrieved from the explicit requirements of the job offer, not from a similarity threshold. Each requirement (CompetencyRequirement) states the competency, its importance (indispensable or useful) and the required level, and is compared with the level of the same competency in the applicant's current assessment (CompetencyAssessment). A job is recommended directly when all its indispensable competencies are reached at the required level (Rule 1), and is presented as reachable after training when exactly one indispensable competency is missing or below the required level (Rule 2); SPARQL queries (Section 3.1.3) implement these rules. Semantic similarity based on ontology relations such as "broader" and "narrower" in competency taxonomies (e.g., ESCO) is not used at this stage and is left for future work (Section 4.4).

Competency Gap-Based Training Recommendation: Training pathways are recommended based on detected gaps in competencies rather than isolated skills. Programs are prioritized when they: - Address multiple missing competencies; - Align with the applicant's existing proficiency levels; - Fit the applicant's professional domain and experience background. This method supports progression planning based on competency frameworks (e.g., the European e-CF model).

Hybrid Scoring Algorithm Each job retained by the eligibility rules is ranked using a hybrid score that balances matching, experience fit, and penalty for unmet requirements. The score is computed with Equation (1); training courses are ranked separately by the number of gaps they cover (Section 3.1.3):

$$\text{Score}(j) = \alpha \times \text{CompetencyMatch}(j,a) + \beta \times \text{ExperienceFit}(j,a) - \gamma \times \text{GapPenalty}(j,a) \quad (1)$$

Where:

$\text{CompetencyMatch}(j,a) = \Sigma_{c \in R(j)} w_c \cdot \min(L_a(c), L_j(c)) / L_j(c) \div \Sigma_{c \in R(j)} w_c$: the level-aware match between applicant a and job j, where R(j) is the set of competencies required by job j, $L_j(c) \in \{1, 2, 3\}$ is the level required for competency c, $L_a(c) \in \{0, 1, 2, 3\}$ is the applicant's assessed level (0 when the competency is not held; Section 3.1.4), and w_c is the importance of the competency ($w_c = 2$ for indispensable and $w_c = 1$ for useful competencies, following the distinction made in (Fazel-Zarandi and Fox, 2009). $L_j(c)$ and w_c are read from the CompetencyRequirement of the job (properties: requiredLevel and: importance, **Table 2**) and $L_a(c)$ from the CompetencyAssessment of the applicant (property: level). This term ranges from 0 to 1;

$\text{ExperienceFit}(j,a) = \min(1, Y_a(j) / Y_j)$: the relevance of the applicant's work history, where $Y_a(j)$ is the applicant's years of experience in the professional domain of job j and Y_j is the experience required by the job (ExperienceFit $= 1$ when no experience is required). This term ranges from 0 to 1;

$\text{GapPenalty}(j,a) = |\{c \in I(j): L_a(c) < L_j(c)\}| / |I(j)|$: the proportion of the indispensable competencies I(j) of job j whose required level is not reached by the applicant (GapPenalty $= 0$ when the job has no indispensable competency). This term ranges from 0 to 1 and penalizes unmet mandatory requirements more strongly than CompetencyMatch alone.

Because the three terms are normalized to [0, 1], Score(j) ranges from $-\gamma$ to $\alpha + \beta$. In this framework paper, the weights have not yet been tested empirically. We propose $\alpha = 0.6$, $\beta = 0.2$ and $\gamma = 0.2$ ($\alpha + \beta + \gamma = 1$) as initial values, giving priority to the competency match, which is the core of the framework, while keeping experience and unmet mandatory requirements as secondary criteria. These values

are configurable design choices; in future work they will be calibrated with career counselors and HR experts (for example, through structured expert weighting) and validated on real recruitment and training data (Section 4.4). The eligibility rules of Section 3.1.3 decide how a job is presented: a job with GapPenalty(j,a) $= 0$ satisfies Rule 1 and is recommended directly; a job with exactly one unmet indispensable competency satisfies Rule 2 and is presented as reachable after training, together with the training recommendations described in Section 3.1.3; jobs with two or more unmet indispensable competencies are not recommended. Within each group, jobs are ranked by Score(j). Because each term can be reported to the user, the resulting recommendations remain explainable.

3.1.3. Semantic Reasoning for Competency-Based Job Matching and Training Recommendations

Competency-based systems have become central to modern intelligent decision-support frameworks, particularly in domains like recruitment and personalized learning. According to Gagné (2005), competencies represent measurable patterns of knowledge, skills, abilities, and behaviors essential for effective performance. Similarly, Boyatzis (2008) emphasizes the significance of aligning individual competencies with organizational roles to enhance performance outcomes. In semantic web technologies, reasoning engines such as Apache Jena or RDF4J play a critical role in facilitating this alignment through rule-based inference and semantic querying over ontologies.

In our framework, the reasoning engine queries the knowledge base with SPARQL to retrieve candidate jobs and training courses for a given applicant (here the individual: Applicant_A01). Eligibility is based on the indispensable competencies of each job, whose importance and required level are stored in its CompetencyRequirement individuals, and on the applicant's current CompetencyAssessment individuals. Two rules are applied. Rule 1 (recommended directly): every indispensable competency of the job is reached at the required level. Rule 2 (reachable after training): exactly one indispensable competency is missing or below the required level. Jobs that satisfy Rule 1 are retrieved by the following query, which returns the jobs for which no indispensable requirement is left unmet:

```
SELECT DISTINCT ?job
WHERE {
    ?job rdf:type :Job .
    FILTER NOT EXISTS {
        ?job :HasRequirement ?r .
        ?r :importance "Indispensable" ;
            :OfCompetency ?c ;
            :requiredLevel ?lj .
        FILTER NOT EXISTS {
            :Applicant_A01 :HasAssessment ?e .
            ?e :OfCompetency ?c ;
                :level ?la .
            FILTER (?la ≥ ?lj)
        }
    }
}
```

For each job, the inner FILTER NOT EXISTS checks whether the applicant has a current assessment of the required competency (:HasAssessment, :OfCompetency) at a level (: level) at least equal to the required level (:requiredLevel); the outer FILTER NOT EXISTS keeps the jobs for which no indispensable requirement

(:importance “Indispensable”) is unmet. Useful competencies do not affect eligibility; they are taken into account in the scoring step (Equation (1)). The jobs of Rule 2 are retrieved by counting the unmet indispensable requirements of each job:

```
SELECT ?job (COUNT(DISTINCT ?r) AS ?nUnmet)
WHERE {
    ?job rdf:type :Job ;
                :HasRequirement ?r .
    ?r :importance “Indispensable” ;
        :OfCompetency ?c ;
        :requiredLevel ?lj .
    FILTER NOT EXISTS {
        :Applicant_A01 :HasAssessment ?e .
        ?e :OfCompetency ?c ;
            :level ?la .
        FILTER (?la ≥ ?lj)
    }
}
GROUP BY ?job
HAVING (COUNT(DISTINCT ?r) ≤ 1)
```

Because only unmet indispensable requirements are counted, a job appears in the result only if at least one of them is unmet (jobs with none are returned by the first query); the HAVING clause therefore keeps the jobs with exactly one unmet indispensable requirement. Replacing 1 by a parameter k allows career counselors to accept up to k unmet indispensable competencies. Replacing a percentage threshold by these two rules makes eligibility depend on the importance of each competency: a high share of useful competencies cannot compensate for a missing indispensable one. The tolerance of one unmet indispensable competency is a design parameter rather than an empirically derived value. It was chosen because a single missing mandatory competency can generally be addressed by a limited number of targeted training modules, whereas two or more would imply an almost complete retraining. It will be calibrated during the empirical evaluation (Section 4.4).

Training courses are then retrieved for the set of competency gaps $G(j,a) = \{c \in R(j) : L_a(c) < L_j(c)\}$, which includes both competencies that are not held and those held below the required level. The gap set is computed in the scoring step and passed to the query (VALUES clause); training courses are ranked by the number of gaps they cover:

```
SELECT ?training (COUNT(DISTINCT ?gap) AS ?gapsCovered)
WHERE {
    VALUES ?gap { :SQL_Databases :Data_Visualization }
    ?training rdf:type :Training ;
        :Develops ?gap .
}
GROUP BY ?training
ORDER BY DESC(?gapsCovered)
```

Here, the query identifies the training courses (:Training) that develop (:Develops) one or more of the applicant’s competency gaps; the VALUES clause shows the gaps of the worked example in Section 3.2. When several courses cover the same number of gaps, they are further prioritized according to the criteria listed in Section 3.1.2 (alignment with the applicant’s current levels and professional domain). This guides applicants towards training that closes their competency gaps.

3.1.4. From Assessment Results to Competency Levels

Each competency is assessed by the tests that the career counselor associates with it (Section 2.5.6). The assessment score, expressed on a 0–100 scale, is converted into a competency level using the scale in **Table 3**. The thresholds in **Table 3** are proposed values that career counselors can adapt to each job specification framework. The level is stored in the property :level of a CompetencyAssessment individual, together with the score (:score) and the date of the assessment (:assessmentDate), and this individual is linked to the applicant by :HasAssessment. A competency that has not been assessed is treated as level 0.

Table 3. Proposed conversion of assessment scores into competency levels.

Assessment score	Competency level	Label
0–39	0	Not acquired
40–59	1	Basic
60–79	2	Intermediate
80–100	3	Advanced

Competency levels are updated after training. When an applicant completes a training course (: Complete), they take a post-training assessment of the competencies developed by that course (: Develops). The new level replaces the previous one, the previous CompetencyAssessment is moved to the applicant's history, where it keeps its: assessmentDate, so that only the current assessments are linked by: HasAssessment, and the gaps, scores and recommendations are recalculated. In this way, the applicant model is updated dynamically, as described in Section 2.5.4.

3.2. Worked Example (Hypothetical Data)

To link the ontology to the final recommendations, this section presents a worked example. All data in this example (applicant, job, scores and training courses) are hypothetical and are used for illustration only. A hypothetical applicant, A01, who left a bachelor's program in mathematics and completed a six-month internship in reporting, is matched against a hypothetical junior data analyst position whose job offer contains five competency requirements (each with an importance and a required level) and one year of experience in the data domain. **Table 4** shows the applicant's assessment results, the corresponding levels and the resulting gaps.

Table 4. Worked example (hypothetical data): competencies required for the junior data analyst position and assessment results of applicant A01.

Competency	Importance (w_c)	Required level L_j(c)	Assessment score	Applicant level L_a(c)	Gap
Python programming	Indispensable (2)	2	68	2	None
SQL and databases	Indispensable (2)	2	30	0	Not held (indispensable)
Data visualization	Useful (1)	2	52	1	Level gap ($1 \rightarrow 2$)
Statistical analysis	Indispensable (2)	2	74	2	None
Communication	Useful (1)	1	81	3	None

Step 1: retrieval. Three of the five requirements are indispensable (Python programming, SQL and databases, Statistical analysis). The applicant reaches the required level for two of them; SQL and databases (level $0 < 2$) is the only unmet indispensable competency. Rule 1 is therefore not satisfied and the first query does not return the job, whereas Rule 2 is satisfied: the second query returns the job with nUnmet $= 1$. The job is retained as reachable after training. The unmet

useful competency (data visualization) does not affect eligibility but is counted in the scoring step.

Step 2: scoring. CompetencyMatch $= (2\times1 + 2\times0 + 1\times0.5 + 2\times1 + 1\times1) / 8 = 5.5 / 8 \approx 0.69$; ExperienceFit $= \min(1, 0.5 / 1) = 0.50$; and GapPenalty $= 1/3 \approx 0.33$, because one of the three indispensable competencies (SQL and databases) is not reached. With the proposed weights, Score $= 0.6 \times 0.69 + 0.2 \times 0.50 - 0.2 \times 0.33 \approx 0.45$. Because exactly one indispensable competency is unmet (Rule 2), the job is presented as reachable after training and is ranked by this score among the other jobs of the same group.

Step 3: training recommendation. The gap set is G = {SQL and databases, Data visualization}. **Table 5** lists three hypothetical training courses retrieved by the training query (the third query in Section 3.1.3).

Table 5. Worked example (hypothetical data): training courses retrieved for the competency gaps of applicant A01.

Training course	Competencies developed	Gaps covered	Rank
T3 –Data analytics module: SQL and dashboards	SQL and databases; Data visualization	2	1
T1 –SQL for data analysis	SQL and databases	1	2
T2 –Data visualization with Power BI	Data visualization	1	3

T3 is recommended first because it covers both gaps.

Step 4: update. If, after completing T3, the applicant obtains post-training scores of 66 in SQL and databases and 71 in data visualization (level 2 for both), CompetencyMatch becomes 1.00 and GapPenalty becomes 0, giving Score $= 0.6 \times 1.00 + 0.2 \times 0.50 - 0.2 \times 0 = 0.70$; all indispensable competencies are then reached, the job satisfies Rule 1 and is recommended directly. The career counselor reviews these recommendations with the applicant before any application is made (Section 4.3). Here, the query identifies training programs that offer competencies the applicant currently lacks. It matches: TrainingProgram entities that provide (:offersSkill) one or more missing competencies recorded for the applicant (:missingSkill). This helps guide individuals toward educational opportunities that strategically close their competency gaps.

3.3. System Architecture and Workflow Integration

The overall architecture integrates the ontology with the application backend through a structured sequence of processes. The proposed workflow comprises the following steps:

1. Input Layer: Applicants provide their profiles, which include both manual data entry and results from various tests.

2. Semantic Annotation: Natural Language Processing (NLP) techniques will be used to map the user's data to the predefined ontology. This enables the extraction and categorization of competencies.

3. Reasoning Layer: An ontology reasoner evaluates competency gaps and assesses the fit of the user's profile to available job roles or training opportunities. This process helps to identify areas of improvement or necessary training.

4. Recommendation Engine: The system combines rule-based logic and hybrid scoring models to offer personalized job or training recommendations based on the user's profile, competencies, and identified gaps.

5. Feedback Loop: The system tracks user interactions with the provided recommendations. Based on this feedback, the system can refine future suggestions and, where necessary, update the underlying ontology to reflect changes in competencies or job market trends.

This architecture is designed to support continuous improvement and personalization through feedback. The flowchart below (**Figure 6**) visualizes the architecture and the integration of each stage in the system's process:

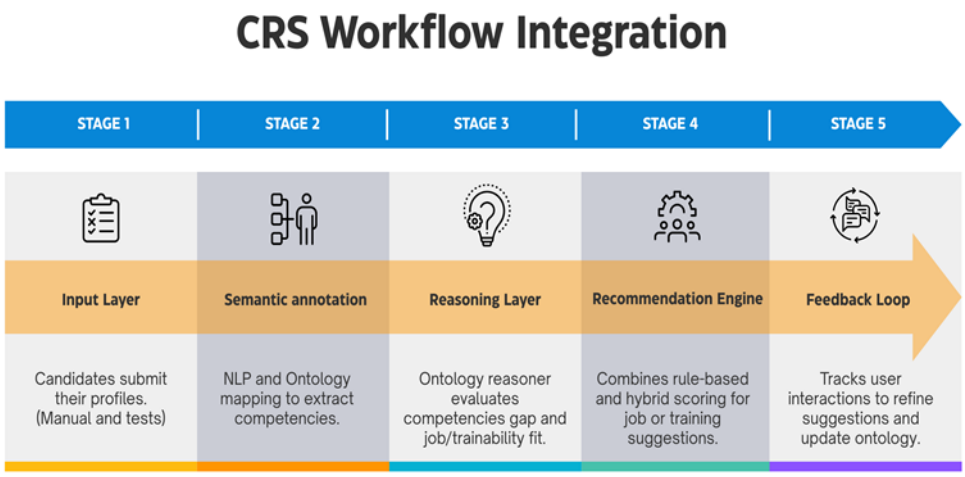

Figure 6. CRS Integration Workflow.

4. Discussion

Searching for relevant information can be very difficult for users, and for students and job seekers, choosing a career or a course of study is a major decision. Recommender systems can help to resolve information overload by assisting candidates and trainees in finding employment or further training in a particular field among the many online resources available. The main focus of this work is the design of a support and orientation platform for job seekers, people wishing to move into other professions and people wishing to enter a new field. Previous studies indicate that filtering approaches that exploit hierarchically related concepts can perform better than approaches based only on keyword similarity, and that ontological similarity between user profiles and items can improve recommendations (George and Lal ,2019; Tarus et al. 2018). The present paper, however, proposes and illustrates a framework; its practical effectiveness remains to be tested.

4.1. Implementation Status

Table 6 distinguishes the components that have been implemented from those that are proposed for future development. At this stage, the ontology has been built and validated for logical consistency, and the recommendation procedure has been specified and illustrated; the full platform is not yet operational.

Table 6. Implementation status of the CRS components.

Component	Status
CRS ontology (six core classes, the association classes CompetencyRequirement and CompetencyAssessment, and object and data properties) in Protégé 5.6.7	Implemented
Logical consistency check with the HermiT reasoner	Implemented
Scoring function, competency-level conversion and eligibility rules (Rules 1 and 2)	Specified (Sections 3.1.2–3.1.4); weights and thresholds not yet calibrated
SPARQL queries for job matching and training retrieval	Designed and illustrated (Section 3.1.3)
Assessment module (diagnostic, competency and technical tests)	Proposed
NLP-based semantic annotation of user data	Proposed
Web platform, user interfaces and feedback loop	Proposed
Empirical evaluation of recommendation quality and user satisfaction	Future work

4.2. Practical Use by HR Practitioners

In recruitment, HR practitioners could apply the same rules and score to all applicants for a given job offer to obtain a ranked list of applicants, together with each applicant's competency profile and gaps, to shortlist candidates, structure interviews around the competencies that are missing or uncertain, and justify decisions on the basis of the requirements of the job offer. In training and career development, the gap-based recommendations could help HR and training managers to plan individual development paths, select internal or external courses, and identify recurring gaps across applicants or employees that call for new training offers. The recommendations are intended as decision support only. Professional judgment remains necessary to validate the job specification framework, the requirements of each job offer and the weights used in the scoring function, to interpret borderline scores, to take into account factors that the system does not capture (such as motivation, organizational fit, interview performance and personal circumstances), and to make final hiring, promotion and training decisions.

4.3. Privacy, Bias and Human Oversight

Because the platform processes personal data on applicants, many of whom are young people, dropouts or job seekers, privacy must be protected by design: only data needed for the recommendations should be collected (data minimization), applicants should give informed consent and be able to view, correct and delete their data, and data should be stored securely in compliance with applicable data-protection legislation (e.g., the GDPR in Europe and Law 09-08 in Morocco). Bias may arise in assessments (e.g., tests that disadvantage some groups through language or cultural content), in job specification frameworks, and in the scoring weights. To mitigate this risk, sensitive attributes such as gender, age or origin should not be used in the scoring, assessment instruments should be validated, and the distribution of recommendations across groups of applicants should be audited regularly. Finally, recommendations should not lead to fully automated decisions: a career counselor reviews the recommendations with each applicant, explains the competency gaps and the suggested training, and can adjust or override the recommendations when necessary.

4.4. Limitations and Future Work

This study has several limitations. First, the evaluation is limited to the logical consistency of the ontology, which was verified with the HermiT reasoner; this check does not establish recommendation accuracy or user satisfaction. Second, the weights of the scoring function, the tolerance of one unmet indispensable competency and the score-to-level conversion are proposed values that have not yet been calibrated. Third, the worked example uses hypothetical data, and the full platform has not yet been implemented. Future work will implement the ontological model in a prototype focused on digital professions and new technologies, develop assessments and tests that comply with the requirements of official job specification repositories, and align the competency model with standard frameworks such as ESCO. The recommendations will then be evaluated offline on historical recruitment and training data (e.g., precision@k, recall@k and nDCG), through expert review by career counselors and HR practitioners, and through user studies measuring the satisfaction of applicants.

5. Conclusions

This paper has presented the conceptual framework of a Career Recommender System that links competency-based job recommendation with gap-based training recommendation. The framework is built on an OWL ontology in which each job offer states the importance and required level of its competencies

(CompetencyRequirement) and each applicant's assessed levels are recorded explicitly (CompetencyAssessment). On this basis, two transparent rules decide whether a job is recommended directly or is reachable after training, a weighted score ranks the jobs, and training courses are selected to close the identified gaps, as illustrated by a hypothetical worked example. The ontology has been validated for logical consistency only; the weights, the tolerance rule and the level scale remain to be calibrated, and the platform remains to be implemented. Future work will develop a prototype for digital professions, populate the ontology with real job offers and assessment data, and evaluate the recommendations with offline metrics, expert review by career counselors and HR practitioners, and user studies.

Author contributions: Conceptualization, FZA and CFB; methodology, FZA and CFB; software, FZA; validation, CFB and MF; formal analysis, FZA; investigation, FZA; writing—original draft preparation, FZA; writing—review and editing, FZA, CFB and MF; visualization, MF; supervision, CFB. All authors have read and agreed to the published version of the manuscript.

Funding: The author(s) received no financial support for the research, authorship, and/or publication of this article.

Acknowledgment: The authors declare that no external support, funding, or assistance was received for this study.

Conflict of interest: The authors declare no conflict of interest.

References

[1] Abdellah AM, Karim AM, Hamid S. (2019). Career recommendation system for scientific students based on ontologies. Advances in Science Technology and Engineering Systems Journal. 4(4): 29–41. https://doi.org/10.25046/aj040404

[2] Adomavicius G, Tuzhilin A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. IEEE Transactions on Knowledge and Data Engineering. 17(6): 734–749.

[3] Aggarwal CC. (2016). Recommender Systems. Springer eBooks. https://doi.org/10.1007/978-3-319-29659-3

[4] Ahmed N, Khan S, Latif K. (2016). Job description ontology. In: Proceedings of the International Conference on Frontiers of Information Technology (FIT); 2016. https://doi.org/10.1109/fit.2016.047

[5] Bañeres D, Conesa J. (2017). A life-long learning recommender system to promote employability. International Journal of Emerging Technologies in Learning (iJET). 12(06): 77. https://doi.org/10.3991/ijet.v12i06.7166

[6] Benbrahim Fikri C, Elbouhdidi J, Bakkali H, et al. (2018). Ontological model of competence management. In: Proceedings of the 11th International Colloquium of Logistics and Supply Chain Management LOGISTIQUA; April 2018; FSTT & ENSAT, Tangier, Morocco, pp. 26–27.

[7] Boyatzis RE. (2008). Competencies in the 21st century. Journal of Management Development. 27(1): 5–12. https://doi.org/10.1108/02621710810840730

[8] Burke R. (2002). Hybrid recommender systems: Survey and experiments. User Modeling and User-Adapted Interaction. 12(4): 331–370.

[9] Burke R. (2007). Knowledge-based recommender systems. In: Recommender Systems Handbook. Springer US, pp. 377–406.

[10] Campion MA, Fink AA, Ruggeberg BJ, et al. (2011). Doing competencies well: Best practices in competency modeling. Personnel Psychology. 64(1): 225–262. https://doi.org/10.1111/j.1744-6570.2010.01207.x

[11] Castillo A, Villarreal V, Mora D, et al. (2021). State of digital transformation in the Universities of Central America. In: Lecture Notes in Educational Technology, pp. 109–128. https://doi.org/10.1007/978-981-16-3941-8_7

[12] Clemente J, Yago H, De Pedro-Carracedo J, et al. (2022). A proposal for an adaptive Recommender System based on competences and ontologies. Expert Systems with Applications. 208(118171). https://doi.org/10.1016/j.eswa.2022.118171

[13] Dascălu M, Hang A, Puskás I, et al. (2023). CareProfSys: A job recommender system based on machine learning and ontology to support learners' employability at regional level. Issues in Information Systems. 24(3): 71–82.

[14] Dascălu MI, Stanica IC, Bodea C, et al. (2020). Diminishing the university drop-out rates in Romanian engineering programs by using a smart career path profiling system. ELearning and Software for Education. 2: 297–304. https://doi.org/10.12753/2066-026x-20-123

[15] Fazel-Zarandi M, Fox MS. (2009). Semantic matchmaking for job recruitment: An ontology-based hybrid approach. In: Proceedings of the 8th International Semantic Web Conference; 2009; Chantilly, VA, USA, 525:25–29.

[16] Gagné RM, Wager WW, Golas KC, et al. (2005). Principles of instructional design, 5th ed. Wadsworth: Thomson Learning. (Reviewed by Russell JD.)

[17] Gati I, Asher I. (2001). The decision-making model for career counseling. Journal of Career Assessment. 9(3): 273–289.

[18] Ge J, Chen Z, Peng J, et al. (2012). An ontology-based method for personalized recommendation. In: Proceedings of the 11th International Conference on Cognitive Informatics and Cognitive Computing; 2012; Kyoto, Japan, pp. 522–526. https://doi.org/10.1109/ICCI-CC.2012.6311204

[19] George G, Lal AM. (2019). Review of ontology-based recommender systems in e-learning. Computers & Education. 142:103642. https://doi.org/10.1016/j.compedu.2019.103642

[20] Guarino N, Oberle D, Staab S. (2009). What is an ontology? Springer-Verlag Berlin Heidelberg. https://doi.org/10.1007/978-3-540-92673-3_0
[21] Ibrahim ME. (2019). An ontology-based hybrid approach to course recommendation in higher education [PhD thesis]. University of Portsmouth.
[22] Ibrahim ME, Yang Y, Ndzi DL, et al. (2018). Ontology-based personalized course recommendation framework. IEEE Access. 7:5180–5199. https://doi.org/10.1109/ACCESS.2018.2889635
[23] Ilkou E, Abu-Rasheed H, Tavakoli M, et al. (2021). EDUCOR: An educational and career-oriented recommendation ontology. In: Lecture Notes in Computer Science, pp. 546–562. https://doi.org/10.1007/978-3-030-88361-4_32
[24] Joy J, Raj NS, Renumol VG. (2019). An ontology model for content recommendation in personalized learning environment. In: Proceedings of the Second International Conference on Data Science, E-Learning and Information Systems (DATA '19); 2019; New York, NY, USA. Association for Computing Machinery, Article 9, 1–6. https://doi.org/10.1145/3368691.3368700
[25] Lahoud C, Moussa S, Obeid C, et al. (2022). A comparative analysis of different recommender systems for university major and career domain guidance. Education and Information Technologies. 28(7): 8733–8759. https://doi.org/10.1007/s10639-022-11541-3
[26] Majid M, Hayat MF, Khan FZ, et al. (2021). Ontology-based system for educational program counseling. Intelligent Automation & Soft Computing. 29(3): 373–386. https://doi.org/10.32604/iasc.2021.017840
[27] McClelland DC. (1973). Testing for competence rather than 'intelligence'. American Psychologist. 28(1): 1–14. https://doi.org/10.1037/h0034092
[28] Niles I, Pease A. (2001). Towards a standard upper ontology. In: Proceedings of the International Conference on Formal Ontology in Information Systems; 2001, pp. 2–9.
[29] Noy NF, McGuinness DL. (2002). Ontology Development 101: A guide to creating your first ontology. Knowledge Systems Laboratory.
[30] Ntioudis D, Masa P, Karakostas A, et al. (2022). Ontology based personalized job recommendation framework for migrants and refugees. Big Data and Cognitive Computing. 6(4): 120. https://doi.org/10.3390/bdcc6040120
[31] Obeid C. (2021). A hybrid recommender system for student academic advising supported by case-based reasoning and ontology [PhD thesis]. University of Lyon, France.
[32] Obeid C, Lahoud I, El Khoury H, et al. (2018). Ontology-based recommender system in higher education. In: Proceedings of the Companion Proceedings of The Web Conference 2018 (WWW '18); 2018; Republic and Canton of Geneva, CHE. International World Wide Web Conferences Steering Committee, pp. 1031–1034. https://doi.org/10.1145/3184558.3191533
[33] Pazzani MJ. (1999). A framework for collaborative, content-based, and demographic filtering. Artificial Intelligence Review. 13(5–6): 393–408.
[34] Ricci F, Rokach L, Shapira B. (2015). In: Recommender Systems Handbook, 2nd ed. Springer.
[35] Rimitha S, Abburu V, Kiranmai A, et al. (2018). Ontologies to model user profiles in personalized job recommendation. In: Proceedings of the 2018 IEEE Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER); 2018; Mangalore, India, pp. 98–103. https://doi.org/10.1109/discover.2018.8674084
[36] Rimitha SR, Abburu V, Kiranmai A, et al. (2019). Improving job recommendation using ontological modeling and user profiles. In: Proceedings of the Fifteenth International Conference on Information Processing (ICINPRO); 2019; Bengaluru, India, pp. 1–8. https://doi.org/10.1109/ICInPro47689.2019.9092271
[37] Rodríguez PA, Ovalle DA, Duque ND. (2015). A student-centered hybrid recommender system to provide relevant learning objects from repositories. In: Lecture Notes in Computer Science, pp. 291–300. https://doi.org/10.1007/978-3-319-20609-7_28
[38] Saks AM, Uggerslev KL. (2010). Social influence and applicant attraction: A meta-analysis of the applicant attraction literature. Journal of Vocational Behavior. 76(2): 225–239.
[39] Spencer LM, Spencer SM. (1993). In: Competence at Work: Models for Superior Performance. John Wiley & Sons, New York.
[40] Stone RJ. (2017). In: Human Resource Management. John Wiley & Sons.
[41] Tarus JK, Niu Z, Mustafa G. (2018). Knowledge-based recommendation: A review of ontology-based recommender systems for e-learning. Artificial Intelligence Review. 50(1): 21–48. https://doi.org/10.1007/s10462-017-9539-5
[42] Tight M. (2012). The role of higher education in career development: A global perspective. Education + Training. 54(4): 268–285.
[43] Urdaneta-Ponte MC, Méndez-Zorrilla A, Oleagordia-Ruiz I. (2021). Lifelong learning courses recommendation system to improve professional skills using ontology and machine learning. Applied Sciences. 11(9): 3839. https://doi.org/10.3390/app11093839
[44] Zhang Y, Yang C, Niu Z. (2014). A research of job recommendation system based on collaborative filtering. In: Proceedings of the Seventh International Symposium on Computational Intelligence and Design; 2014; Hangzhou, China, pp. 533–538. https://doi.org/10.1109/iscid.2014.228