

Personalized Course Recommender: Linking Learning Objectives and Career Goals through Competencies

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Abstract

This paper presents a Knowledge-Based Recommender System (KBRS) that aims to align course recommendations with students' career goals in the field of information systems. The developed KBRS uses the European Skills, Competences, qualifications, and Occupations (ESCO) ontology, course descriptions, and a Large Language Model (LLM) such as ChatGPT 3.5 to bridge course content with the skills required for specific careers in information systems. In this context, no reference is made to the previous behavior of students. The system links course content to the skills required for different careers, adapts to students' changing interests, and provides clear reasoning for the courses proposed. An LLM is used to extract learning objectives from course descriptions and to map the promoted competency. The system evaluates the degree of relevance of courses based on the number of job-related skills supported by the learning objectives. This recommendation is supported by information that facilitates decision-making. The paper describes the system's development, methodology and evaluation and highlights its flexibility, user orientation and adaptability. It also discusses the challenges that arose during the development and evaluation of the system.

Introduction

Higher education aims to provide students with skills for their professional careers, but the plethora of courses and learning objectives makes course selection challenging. While some universities offer a wide range of electives, students only need a fraction of the available credits, so they must prioritize. The overabundance of information and limited time to make decisions, especially for new students who do not receive advice from peers or lecturers, can lead to suboptimal decisions (Fernandez 2017). Moreover, disenrollment from courses requires further effort – both for the students and the university. Recommender systems (RS) in higher education, such as those used for online shopping or media platforms, can simplify these decisions (Wakil et al. 2015).

Primarily, students enroll in degree programs to acquire the necessary skills for their future careers (Lynn and

Emanuel 2021). Therefore, course recommendations should focus on what students will learn in these courses and how this aligns with their career goals. An RS should match course suggestions with the skills required for different careers without being influenced by other factors. It should also be flexible, adapting to students' changing interests and allowing them to consider different career options throughout their studies. Further, an RS should provide clear justifications and explanations for its suggestions, which helps build confidence in the system's reliability and validity (Swearingen and Sinha 2001).

Current RS in higher education, which rely primarily on collaborative or content-based filtering, are often insufficient to match course recommendations optimally to students' career aspirations. These systems, which depend heavily on students' past behaviors and characteristics, struggle, especially when relevant historical data is lacking. However, they tend to overlook that past behaviors may not accurately reflect current career goals (Guruge, Kadel, and Halder 2021; Maphosa, Doorsamy, and Paul 2020). Therefore, such systems face challenges like the cold-start problem (Gunawardana, Shani, and Yogev 2022), changing preferences (Mishra et al. 2021), and data bias (Chen et al. 2023).

This paper addresses the discussed gap by proposing a Knowledge-Based Recommender System (KBRS) that aligns course recommendations with students' evolving career goals, focusing on domain knowledge rather than solely past behaviors or performance data. This approach aims to enhance the adaptability of RS, considering students' changing preferences and the evolving curriculum, particularly beneficial for new students. The Master of Science in Business Information Systems (BIS) program at the FHNW University of Applied Sciences and Arts Northwestern Switzerland (FHNW) is a case study for developing this recommendation system. For this reason, the system is primarily oriented towards career profiles in business information systems. Students trigger the system by indicating their desired job in the information systems domain and receive a list of BIS courses ranked by usefulness for their career goal. This usefulness is calculated upon the number of job-related competencies a course promotes with its learning objectives. The recommendation is accompanied by information that creates a common ground regarding the job and makes the recommendation easier to understand. The RS's knowledge base

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is built using the course descriptions by the FHNW and European Skills, Competences, qualifications, and Occupations (ESCO) as reliable external knowledge sources and employing the Large Language Model (LLM) ChatGPT 3.5 (ChatGPT) to create the bridging knowledge between those sources.

This paper is structured as follows: First, different recommendation techniques and the current state of the research in recommendation systems for education are discussed. Secondly, the methodology used is described, and its application is justified. Thirdly, the case study used as the basis for developing the recommendation system is addressed. Following, the development steps of the recommendation system are described. Finally, the evaluation process is outlined, and the results are presented. The conclusion is given at the end, and further research options are outlined.

Recommender Systems

Selecting the proper courses is important for a student to complete a degree program successfully. However, many students struggle with their course choices when enrolling at a higher education institution. Many choices can negatively impact users' well-being and decision-making, leading to overwhelming and lower satisfaction (Fernandez 2017). To address users' challenges in making informed decisions due to limited knowledge and the difficulty of evaluating options, as a solution, RS have been developed (Ricci, Rokach, and Shapira 2022; Wakil et al. 2015).

Recommendation Techniques

RS are software tools and techniques designed to make user recommendations based on their preferences and interests (Resnick and Varian 1997). These systems are designed to help users navigate through information overload by providing tailored recommendations.

Ricci, Rokach, and Shapira (2022) describe RS as tools that suggest items to users by predicting their utility or comparing them with other items. These systems gather information about users either explicitly through ratings or implicitly through interaction analysis. RS data encompasses items (the objects recommended), users (the recipients), and interactions (the data generated from user-item engagement). The effectiveness of an RS depends on the recommendation technique and computational resources available, utilizing various data and knowledge sources. Burke (2007) classifies five categories of recommendation techniques: Collaborative-filtering (CFRS), Content-based (CBRS), Demographic, Knowledge-based (KBRS), and Hybrid.

CBRS estimate an item's utility for a user based on their past preferences for similar items, determining item similarity through associated features (Ricci, Rokach, and Shapira 2022). CBRS advantages include user independence (using only the active user's ratings), transparency (explaining recommendations by listing influencing features), and the ability to recommend new, unrated items (Musto et al. 2022). However, they face challenges like limited content analysis (relying on item features for recommendations), overspecialization (leading to a lack of novelty in suggestions),

and the new user cold start problem (requiring sufficient user ratings for accurate recommendations) (Musto et al. 2022). Integrating features from a student's LinkedIn profile has been proposed as a solution to the new user problem, but this is limited by the availability of such profiles (Lessa and Brandão 2018). Unlike CBRS, which rely on item features, CFRS recommend items based on user rating similarities, (Ricci, Rokach, and Shapira 2022). CFRS advantages include suggesting novel and serendipitous items, recommending content-limited items through user feedback, and relying on peer evaluations for recommendation quality (Burke 2007). However, challenges include the cold start problem for new items and users, the sparsity problem due to insufficient user ratings, reduced explainability due to implicit data collection, and the 'grey sheep' problem, where a user's similarity to multiple groups complicates accurate recommendations (Burke 2007; Guruge, Kadel, and Halder 2021; Mishra et al. 2021). KBRS use domain-specific knowledge and case-based reasoning to recommend items based on how well they meet users' needs (Ricci, Rokach, and Shapira 2022). These systems rely on rules or similarity metrics to determine the utility of recommendations (Felfernig et al. 2014). Advantages of KBRS include offering novel and unexpected recommendations, providing personalized explanations, and better initial performance due to avoidance of the cold start problem (Burke 2007; Lynn and Emanuel 2021). They also exhibit higher reliability using domain-specific, noise-free knowledge (Bouraga et al. 2014). However, KBRS face challenges such as the knowledge engineering bottleneck, requiring substantial effort and expertise to set up and maintain the knowledge base, making them costly and less prevalent in certain applications like course recommendation systems (Burke 2007; Felfernig et al. 2014). Therefore, hybrid RS blend various recommendation approaches to overcome the limitations of individual methods, thereby enhancing recommendation quality (Guruge, Kadel, and Halder 2021). These techniques can function independently and in conjunction (Puntheeranurak and Chaiwitooanukool 2011). Burke (2007) notes that some of the most effective RS use knowledge-based components as supportive elements. Guruge, Kadel, and Halder (2021) highlight the challenge of recommending for new students without a user profile and suggest that hybrid approaches combining CBRS and CFRS can effectively address this issue, improving recommendation quality and tackling problems like the new user problem, item sparsity, and scalability. While hybrid systems offer the primary benefit of mitigating individual method weaknesses, such as the cold start problem, they require more development effort due to integrating multiple techniques (Guruge, Kadel, and Halder 2021).

RS face several challenges in providing recommendations, and the relevance of these challenges depends on the specific application of the RS. Key challenges include the changing preferences, where past course choices may not accurately reflect current student preferences, and the cold start problem, where new students or courses lack historical data (Guruge, Kadel, and Halder 2021; Maphosa, Doorsamy, and Paul 2020).

Recommender Systems in Education

In an educational environment, RS typically target students or lecturers. Student-directed systems offer the advantage of direct interaction but may lead to a loss of control over the recommendations (Yago, Clemente, and Rodriguez 2018). RS for course selection in higher education can be distinguished based on several factors, including the techniques used, input data, recommendation goals, and target recipients.

Guruge, Kadel, and Halder (2021) performed a systematic literature review by including papers from 2016 to June 2020 and identified the following six primary techniques for course recommendation: CBRS, CFRS, KBRS, data mining (DM), hybrid, and others like conversational or statistical RS. The most common were hybrid and DM approaches. However, knowledge-based and content-based techniques were less common. The evaluated systems' primary focus was recommending offline courses to university students or online courses to new students, using data sources ranging from student enrollment to LinkedIn profiles and surveys. In addition, Lynn and Emanuel (2021) also reviewed RS in higher education, emphasizing the importance of course selection for students' future skills and career prospects. They noted that RS help students make informed decisions and benefit institutions and lecturers. While CBRS and CFRS were commonly used, the hybrid approach was deemed the most effective. Similarly, Maphosa, Doorsamy, and Paul (2020) reviewed RS for elective courses, noting an increasing interest and varied methods like considering student backgrounds and providing course descriptions. CFRS was the most used technique, with no KBRS-specific work identified. The study underlined the need to overcome limitations related to structured data and the assumption that past performance reliably predicts future success, which external factors can influence.

While KBRS for course selection is rare, other applications like college or learning object recommendations have been developed. For instance, Saraswathi et al. (2014) developed a rule-based KBRS to suggest the most suitable colleges for students, using an automatically generated ontology about colleges in Pondicherry. The system considers various student parameters, such as interests, field of study, financial situation, and required facilities, with career goals not being the primary factor for choosing an institution. Alternatively, Abech et al. (2016) created an ontology-based KBRS that recommends learning objects tailored to students' specific contexts and learning styles to enhance user satisfaction. Whereas the work of Saraswathi et al. (2014) suggests a university and includes other factors besides professional interests, the system of Abech et al. (2016) only evaluates the individual learning objects of a course regarding the context. Hence, previous work did not examine a KBRS for recommending courses based on subject knowledge.

In contrast, Ibrahim, Yang, and Ndzi (2017) and Ibrahim et al. (2019) created RS using course, student, and job ontologies, aligning recommendations with career goals through hybrid models that blend CBRS and CFRS techniques. These models rely on patterns from similar students

and require detailed student profiles. Additionally, Obeid et al. (2018) used an ontology and past student behavior to recommend majors and universities. Chen et al. (2023) tested five approaches for course recommendations based on student interests, finding content-based methods (focused on course content) the most effective. However, reliance on past behavior limits adaptability to changing preferences, and implementing multiple approaches is resource-intensive. Vo et al. (2022) proposed a context-aware hybrid RS for students, faculty, and tech universities, offering suggestions for courses, careers, jobs, and skills, along with learning materials and analysis dashboards. This system provides course recommendations based on chosen careers and job suggestions based on enrollment history. In addition, Nguyen, Vu, and Ly (2022) developed a knowledge graph architecture for recommending learning paths in IT aligned with career goals, using competencies to connect courses and careers. This architecture supports RS for course recommendations based on IT career goals. Ilkou et al. (2021) built the EduCOR ontology to link education, the labor market, and user profiles for personalized online learning course recommendations. EduCOR encompasses various patterns and classes but does not provide specific domain knowledge.

Existing research in the field of RS for course selection in higher education does not sufficiently address the alignment of course recommendations with students' career goals through knowledge of common competencies between jobs and courses. Current knowledge-based RS focus on recommending institutions, majors, or learning objects rather than individual courses. Other studies that make course recommendations often rely on past behaviors and profiles of students that take into account interests, contexts, or patterns of behavior. This approach assumes that past behaviors also represent current interests, not considering the possibility of changing preferences and other influencing factors. As a result, these systems lack the ability to make course recommendations based solely on a student's current career goals. Thus, there is potential for improvement in using knowledge-based methods to recommend courses that align with individual career goals.

Methodology

Design Science Research (DSR) was chosen as the research strategy since it emphasizes the importance of practical outcomes and focuses on developing an artifact (Vaishnavi and Kuechler 2015). The literature review raised awareness of the problem to provide an understanding of the current state of the research and identify the gaps in the field of RS in higher education. Subsequently, a case study involving interviews with BIS students was conducted. These interviews aimed to gather insights into the course selection process from the students' perspectives and collect specific requirements for an RS. During the suggestion phase, methods for representing domain knowledge were identified. This involved utilizing the ESCO ontology, which covers three taxonomies – Occupation, Skill (and Competencies), and Qualification – for more than 3,000 occupations. ESCO is integral to Europe 2020's strategy. It identifies and categorizes skills, competencies, qualifications, and occupations perti-

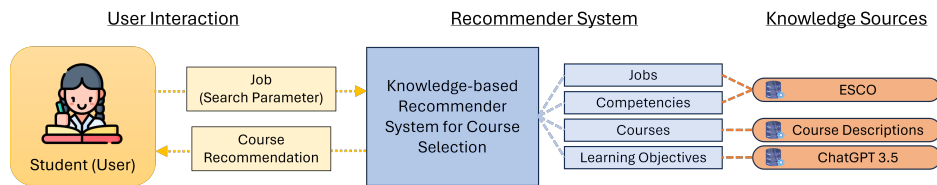


Figure 1: Suggested Knowledge-based Recommender System

ment to the EU labor market and education sectors, systematically delineating the relationships among these various concepts. Furthermore, course descriptions from the BIS program were encapsulated into an OWL ontology, following the method for creating ontologies described by Noy and McGuinness (2001). The decision to use an ontology to capture information from course descriptions is based on its strengths in systematically organizing and structuring complex knowledge, its ability to model semantic relationships between concepts, and its ability to facilitate data interoperability (Noy and McGuinness 2001). A recommender system was created in the development phase, utilizing an LLM to align occupation competencies with course descriptions. This system was designed to recommend courses that support and correspond with specific occupations. The system was tested during and after its development in the evaluation phase, based on the criteria defined in the problem awareness phase. This evaluation included user-centered criteria such as user satisfaction and perceived usefulness, which were determined through interviews with students (as recipients of the recommendations) and faculty members (as contributors to the knowledge base). As primary end users, students were tasked with evaluating the practicality of the system by directly testing the prototype and evaluating the job-related knowledge resource in their professional capacity. In addition, a qualitative analysis was conducted to cover criteria not directly related to the users, comparing the performance of the artifact with the findings from the literature review. Finally, in the conclusion, the insights gained were summarised. In addition, the limitations of the artifact are pointed out, and further research directions are identified.

Case Study: Master of Science in Business Information Systems

The FHNW Master’s degree program BIS offers students a high degree of flexibility in curriculum design. This flexible choice of courses makes the program ideally suited for developing an RS. Around 80 new students start each semester and are confronted with deciding which courses to take. To graduate from the BIS program at the FHNW, students need to acquire 90 ECTS points. The program structure includes Core Courses, Electives, and Research and Innovation Projects. Students must complete the four Core Courses (each worth 6 ECTS points), three Research and Innovation Projects (a total of 30 ECTS points, including the Master Thesis), and choose from 20 elective courses (6 ECTS points each) for the remaining 36 points. The program offers flexibility in scheduling, allowing full-time completion in 1.5

years or part-time over an extended period. The majority of students study part-time and work up to 80%. Students can select courses each semester with schedules published in advance. However, some courses have prerequisites, like the Master’s thesis, typically completed in the last semester. The MSc BIS program also offers exchange opportunities with universities in South Africa and Italy, and credits can be transferred from another program, Master of Science in International Management, at the FHNW. Course descriptions detailing prerequisites, competencies, content, and assessment methods are available on the FHNW website before the semester starts ¹. While students receive structured information for course planning, personalized course recommendations are not provided.

Key requirements for the RS were defined based on the case study. Those include aiding students in course selection aligned with career goals, recommending courses based on job-related competencies, and focusing on new students using domain knowledge and explicit career goals. The RS addresses critical issues such as minimizing the knowledge engineering bottleneck, ensuring user orientation, accuracy, and adaptability, and includes features for explainability and user feedback. The case study with BIS students refines these requirements to include specific aspects like international job profiles while informing course prerequisites and distinguishing between mandatory and elective courses. This streamlined requirements analysis ensures the relevance and practicality of the RS, particularly in the context of the BIS program.

Development of the Recommender System

The design of the knowledge-based recommendation systems is approached from the student’s perspective. A student should be able to specify a job and receive corresponding course recommendations. To achieve this, a knowledge-based recommender system has to possess domain knowledge about different professions and their required competencies. In addition, detailed information about courses and their learning objectives is relevant. Figure 1 provides a naive overview of the artifact.

The student selects a desired job role from a predefined list within the system. This choice acts as the query parameter. Once a job role is selected, the student receives details about that job and a list of recommended courses tailored to that specific role as visualized in Figure 2. These recommendations include courses that best match the job’s requirements and explain why each course is suggested, as

¹See <https://modulbeschreibungen.webapps.fhnw.ch>

Course	Type	Course Prerequisite	Promoted Job Competencies	Sum of Competencies
Business Intelligence	mandatory	none	interview people market research perform business analysis business intelligence conduct qualitative research seek innovation in current practices liaise with managers scientific research methodology	8
Alignment of Business and IT	mandatory	none	interview people scientific research methodology define organisational standards align efforts towards business development business strategy concepts market research	6

Figure 2: Recommendation for the Job Business Analyst

Course	Type	Taught Learning Objective	Promoted Job Competency	Importance for Job	Competency Description
Business Intelligence	mandatory	Derive multidimensional models from a description of business information needs.	scientific research methodology	Essential	The theoretical methodology used in scientific research involving doing background research, constructing an hypothesis, testing it, analysing data and concluding the results.
Business Intelligence	mandatory	Judge the potential that predictive analytics techniques have for improving effectiveness and efficiency of decision making.	market research	Essential	The processes, techniques, and purposes comprised in the first step for developing marketing strategies such as the collection of information about customers and the definition of segments and targets.

Figure 3: Explaining the Logic for the Recommendation for the Job Business Analyst

illustrated in Figure 3. The system incorporates a predefined list of job roles, with alternative titles available for each to account for variations in job naming. These job roles are accompanied by descriptions and links to detailed job profiles, fostering a clear understanding of each role. The job profiles reveal the specific competencies required for each job, ensuring transparency about the system's basis. The system presents course recommendations in descending order of relevance to the chosen job. This relevance, or usefulness, is determined by the number of unique competencies each course develops that align with the job's requirements. Thus, competencies serve as the connecting factor between the job and the course. Each recommended course includes its title, type (mandatory or elective), prerequisite details, the job competencies it addresses, and a cumulative count of these competencies. This format highlights how each mandatory or elective course contributes to career goals, enhancing the system's explainability. Detailed prerequisite information for each course helps students make informed decisions, considering necessary skills or previous courses. Additionally, by displaying the job-specific competencies each course supports, the system justifies its recommendations and aids in ranking courses effectively.

Conceptualizing Domain Knowledge

The success of a KBRs hinges on its knowledge base, yet creating this base often encounters the challenge of the knowledge engineering bottleneck. To mitigate this, the system design incorporates external knowledge sources and automates processes where possible. The approach to gathering and using knowledge for the KBRs includes external sources and internally generated information as needed.

Within the proposed KBRs, the ontology acts as a central repository, organizing and categorizing information about BIS courses, information systems job roles, and the competencies these jobs require. This structured format of ontology aids in clearly understanding the interconnections between these elements, forming the basis for tailored course recommendations for BIS students.

The ontology is a critical component in the KBRs framework. Noy and McGuinness (2001) recommend seven steps when developing an ontology: (1) Determine the domain and scope of the ontology, (2) Consider reusing existing ontologies, (3) Enumerate important terms in the ontology, (4) Define the classes and the class hierarchy, (5) Define the properties of classes—slots, (6) Define the facets of the slots and (7) Create instances.

To determine the scope, the following competency questions were formulated:

- What are the available job options within the information systems domain?
- What specific competencies are essential for a particular job?
- Which courses are designed to promote the competencies required for job [...]?
- How do these courses promote the competencies?

Furthermore, it was examined whether existing ontologies that could be reused are available. Job profiles and competencies are sourced from ESCO². ESCO offers detailed information on 3,007 occupations and 13,890 skills and competencies. Additionally, it provides job profiles with alterna-

²See https://esco.ec.europa.eu/en/classification/occupation_main

tive titles, descriptions, and competencies categorized as essential or optional. As an example of the role of an ICT business analyst, the following essential skills and competencies are defined: analyze business processes, analyze business requirements, analyze the context of an organization, apply change management, create business process models, define technical requirements, identify customer requirements, identify legal requirements, implement strategic planning, interact with users to gather requirements, propose ICT solutions to business problems, provide cost-benefit analysis reports and translate requirement concepts into visual design.

To recommend courses that develop competencies for specific jobs by linking them to course learning objectives, the following key concepts were defined in the ontology:

- **Course:** Representing BIS program courses, these are the items the system recommends. Defined as conceptual teaching units with specific thematic focus and competencies, these courses are linked to the learning objectives they cover and prerequisite courses.
- **Learning Objective:** This concept outlines the competencies students can acquire through each course, serving as a bridge between course content and job-related competencies.
- **Job:** This concept encapsulates various roles in the information systems domain, targeting entities for which the RS will recommend courses. A job is defined as the regular work a person does for earnings, with each job having a relationship with the competencies it requires.
- **Competency:** Encompassing the skills, knowledge, and competencies necessary for a job, this concept is broad and includes any skill or knowledge linked to jobs, as opposed to learning objectives specific to courses. Competencies are linked to the jobs they are associated with and the learning objectives that promote them.

This structure aims to create a shared understanding of the domain and provides a common vocabulary for the system. Figure 4 illustrates the ontology structure.

The ontology presents a hierarchical structure that categorizes and links various concepts essential for the BIS program’s recommender system. It details courses in the program, including their titles, descriptions, prerequisites, and learning outcomes. Additionally, it identifies competencies associated with different job roles and aligns them with the courses that develop relevant skills and knowledge through their learning objectives. This organized ontology structure is critical for the system’s recommendation logic, enabling information retrieval through SPARQL queries. Beyond its role in the KBRS, the ontology’s logical setup, scalability, and SPARQL’s advanced search capabilities make it versatile for various academic and professional applications. Thus, ontology is a key component of the KBRS and a versatile knowledge framework applicable in various educational and professional contexts.

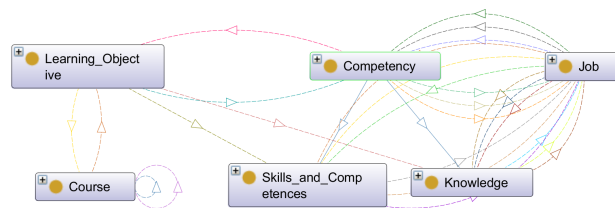


Figure 4: Structure of the Developed Ontology with its Classes and Object Properties

Linking Learning Objectives with Career Goals Using LLM


The ‘Learning Objective’ class in the ontology captures the competencies students are expected to gain from each course, as outlined in the FHNW’s course descriptions. Since these learning objectives are not explicitly itemized in the descriptions, LLM ChatGPT is used for extraction. Additionally, ChatGPT assists in aligning these learning objectives with relevant competencies by comparing course descriptions with a list of competencies. The list comprising essential and optional competencies and knowledge was extracted from the ESCO ontology. Each item in this list has been assigned a unique identifier to facilitate specific referencing.

The fields ‘Module Title’, ‘Leading Principle / Short Description’, ‘Competencies to be Achieved’, and ‘Module Content’ from the course descriptions are inputted into ChatGPT to facilitate extracting learning objectives. Additionally, a list detailing the designations of all individuals in the Knowledge, Skills, and Competences classes is provided for aligning these learning objectives with the corresponding competencies. ChatGPT processes these inputs to extract learning objectives from the course descriptions and to match them with the relevant competencies listed.

Extracting and aligning learning objectives with competencies for each course involves a structured approach using ChatGPT. The analysis is executed with a distinct prompt for every course. Initially, the first prompt outlines the task of creating a table detailing the learning objectives students can acquire from the course and the competencies these objectives support. The second prompt introduces a list of 342 competencies, each uniquely identified by a combination of a letter and a number (e.g., S008 for advising on personnel management, K013 for business intelligence).

For each course, the relevant fields are inputted into ChatGPT, resulting in a table that pairs learning objectives with their corresponding competencies, as demonstrated in Figure 5. This procedure is repeated for each course, with instructions to ChatGPT to disregard the descriptions of previous courses, ensuring distinct and accurate analysis for each one.

Creating effective prompts for ChatGPT to link learning objectives with competencies required numerous trials, with approximately 40 initial prompt versions tested. Simpler prompts often led to better results, but challenges arose with the response format, such as unexpected columns, con-

 **ChatGPT**

I've analyzed the module description for "Cloud Computing" and identified the learning outcomes along with the corresponding promoted skills and knowledge concepts. Here's a table summarizing the information as per your instructions:

Module Title	Learning Outcomes	Promoted Skills and Knowledge	Explanation
Cloud Computing	1. Understand different cloud service and deployment models.	Skills: S039 (Create flowchart diagram), S118 (Oversee quality control) Knowledge: K004 (Agile project management), K017 (Business strategy concepts)	Students gain an understanding of cloud service and deployment models, complemented by the ability to create flowchart diagrams and oversee quality control, with knowledge in agile project management and business strategy concepts.

Figure 5: Example Result of the Analysis with ChatGPT

tinuous text, or missing information. Additionally, ChatGPT exhibited inconsistency, assigning varying competencies to the same learning objectives in different attempts, indicating a lack of reliability. This inconsistency affected the quality of competency allocations and raised concerns about the process's replicability, as emphasized by Sikorski and Andreoletti (2023). The most successful prompt was chosen based on the lowest error rate, although some manual correction of minor errors was necessary. Overall, the use of ChatGPT for this task highlighted challenges in consistency and reliability, suggesting the need for alternative approaches or system refinements for more dependable outcomes in recommendation scenarios.

Recommender System

As a result, a functional KBRS was developed, specifically tailored to the context of the BIS program, as depicted in Figure 6. The developed knowledge base includes information on nine jobs common in information systems, 342 competencies, all 27 courses offered in the BIS program in 2023, and 83 learning objectives across 11 courses. The resulting ontology contains 3285 axioms, six classes, 26 object properties, 19 data properties, and 461 individuals. For evaluation, a simple prototype of the user interface was also created. Figure 6 highlights the components of the knowledge base, including its sources, and illustrates the interaction with the user.

The artifact developed is an RS designed to assist BIS students at FHNW select courses. The system activates when students specify their desired job in the information systems field, prompting it to generate a list of BIS courses ranked according to their relevance to the chosen career path. This relevance is determined by the number of job-related competencies each course addresses through its learning ob-

jectives. The recommendations are supplemented with detailed job information, enhancing understanding and aiding decision-making. The RS's knowledge base is constructed using FHNW course descriptions and ESCO, serving as reliable external sources, along with the LLM ChatGPT, which synthesizes the connecting knowledge between these sources. However, due to resource constraints, the scope of the artifact was narrowed. It primarily focuses on the methodology for storing and retrieving information for personalized course recommendations without incorporating a user interface or a systematic feedback mechanism.

Evaluation

The evaluation of the artifact follows the Framework for Evaluating Recommender Systems (FEVR), developed by Zangerle and Bauer (2023). FEVR provides a structured approach for thorough RS assessments, covering four key components: evaluation objectives, principles, aspects and experiment type. Evaluation objectives include determining what aspects to assess and how to measure them, influencing the overall evaluation design. These objectives cover the system's overall goal, aligning it with business or research objectives, the diverse stakeholders involved beyond RS users, and specific properties like prediction accuracy and privacy levels. Evaluating these aspects helps identify potential areas for improvement in the RS. Evaluation principles are closely linked to the evaluation objectives. Key elements include formulating hypotheses or research questions aligned with the objectives, controlling variables to minimize external influences on results, assessing the generalisability of conclusions, and ensuring reliability for consistent and accurate data and measurements. These components ensure a focused evaluation, enhance external validity, and maintain the integrity and trustworthiness of the evaluation outcomes.

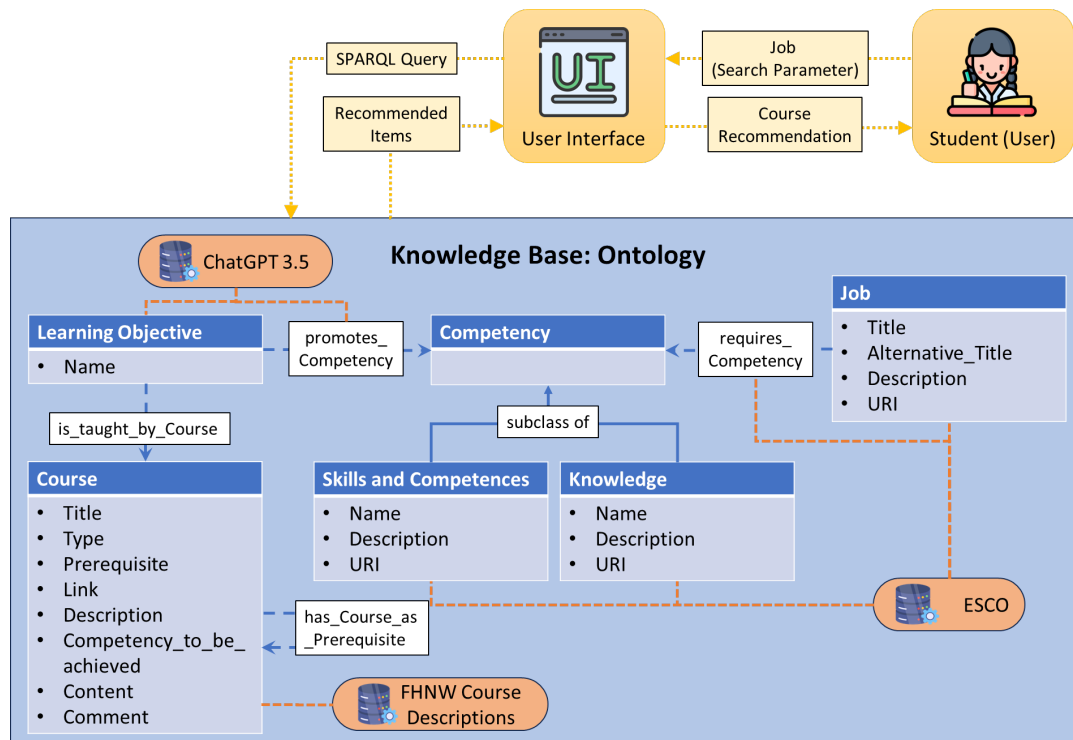


Figure 6: Detailed Visualisation of the Knowledge-Based Recommender System

The types of experiments are categorized into three main groups: offline evaluation, user study, and online evaluation. The choice among these depends on the evaluation’s specific goals, guiding principles, and nature. Lastly, evaluation aspects include the types of data used and their sources, the methods of data collection, the quality of data and biases, the choice of evaluation metrics specific to the RS context, and the incorporation of users into evaluations. The accuracy and reliability of evaluations depend on data quality and bias mitigation. Additionally, integrating the system into real-world settings and designing user interfaces are crucial for effective user involvement in the evaluation process.

The KBRS artifact includes several key elements for evaluation:

- A knowledge-based system for generating course recommendations, with students assessing the recommendation quality based on user-centric aspects.
- An LLM-based approach to address the knowledge engineering bottleneck in KBRS, evaluated by lecturers regarding effectiveness in deriving learning objectives and matching them with competencies.
- Integration of ESCO for job profiles and competencies, evaluated for suitability by students with relevant professional experience.

The stakeholder-involved evaluation of the contributions follows FEVR, detailing the consideration of individual components.

Evaluation Objective: The goal is to evaluate whether the KBRS effectively aids BIS students in course selec-

tion, aligning with the requirements and design principles. The evaluation focuses on two main stakeholders: students and lecturers. Students, as end-users, require a user-centric KBRS that meets their course selection needs. Lecturers, providing course descriptions and representing FHNW, seek accurate course representation in the KBRS. Evaluation properties are based on the requirements identified during the ‘Problem Awareness’ phase and cover various aspects. User-centric properties include the RS’s goal, item suitability, user needs, utility, accuracy, and trustworthiness. ChatGPT is evaluated for accuracy, while ESCO’s effectiveness as a job profile and competency source addresses the international context. Other evaluation aspects include recommended item type, input data, target users, technique-related weaknesses, adaptivity, recommended items, domain, language, prerequisites, and course type.

Evaluation Principles: Derived from its evaluation objectives, the KBRS evaluation is guided by the hypothesis ‘The developed KBRS facilitates the course selection process of students’. Control variables are carefully managed to minimize external influences, ensuring consistent evaluations across different artifact iterations with the same participants. The generalization potential of the study is significant, focusing on BIS courses and information systems jobs but applicable to a broader range of higher education contexts. Insights from using ESCO as a knowledge source and the LLM have implications beyond this specific application. Despite the reliability of the evaluation being constrained by a limited number of participants and reliance on qualitative methods, the use of structured interviews aids in maintaining

Student	Job	Experience	Semester
A	ICT Consultant	8 years	5th
B	ICT Product Manager	3 years	4th
C	ICT Consultant	2,5 years	3rd
D	Business Analyst	1,5 years	3rd
E	ICT Project Manager	4 years	6th

Table 1: Participating Students Profiles

consistency in data collection.

Experiment Type: A user study is selected as the experiment type for involving stakeholders in the evaluation, where participants complete a task and provide qualitative feedback on various properties through an interview.

Evaluation Aspects: Interviews are the primary method for gathering student and lecturer feedback, ensuring user-centricity and provider insights. The artifact assumes domain knowledge is noise-free, and biases like popularity bias in RS are not applicable. Participant feedback may be influenced by individual factors but is considered acceptable for exploratory work. Evaluation metrics are primarily qualitative, with participants rating properties on a scale of 1 to 5, and accuracy is measured by the percentage of correctly generated learning objectives and matched competencies by ChatGPT.

Interviews are conducted with five BIS students, each possessing at least one year of professional experience in one of the integrated jobs within the knowledge base. These participants serve a dual purpose, representing end users in the application context and providing expertise for evaluating recommendation accuracy and ESCO database validity. The students, summarised in Table 1, cover four distinct jobs and are currently in the 3rd to 6th semesters of their studies, providing a combination of academic knowledge and professional experience for a useful interview perspective. Additionally, structured interviews are conducted with three lecturers to evaluate the correctness and comprehensiveness of the extracted learning objectives and the precision of the assigned competencies.

The artifact’s recommendation received positive feedback for user satisfaction and meeting user needs, enhancing course selection aligned with career goals. However, trustworthiness was moderate, and improving accuracy and providing clearer explanations could enhance trust. Despite high utility ratings, competency assignment accuracy remained a concern, suggesting a nuanced ranking mechanism was needed. The knowledge-based technique showed high adaptivity and minimal user effort. Future research should focus on improving accuracy and introducing a feedback mechanism for real-world implementation.

ChatGPT successfully extracted learning objectives from course descriptions but struggled with accurately matching them to competencies, lacking replicability. Future research should seek alternative methods for reliable and replicable competency assignments to enhance recommendation precision.

The evaluation showed positive student feedback on using ESCO for job profiles but highlighted minor discrepancies

in essential and optional competencies. Insights from user evaluations led to artifact enhancements, improving competency relevance displays and explanations for usability. In summary, the KBRS supports course selection but partially fulfills some requirements. The design adheres to principles, but automation can enhance efficiency. The knowledge-based approach and ESCO demonstrate practicality; however, ChatGPT has shown to be less effective and would require targeted training to meet the necessary criteria.

Conclusion

This research introduces a novel KBRS for course selection in higher education, shifting from data-centric to knowledge-based approaches. It demonstrates the effectiveness of this approach, contributing to the understanding of course recommendations in higher education. This development has highlighted several areas for potential improvements in future work. Future research should refine KBRS techniques to overcome limitations, explore alternative methods for linking learning objectives to competencies, investigate advanced LLM models, and offer a fine-grained rationale for personalized recommendations. Furthermore, the focus should also be on streamlining the knowledge base creation, exploring innovative tools to integrate external domain knowledge, developing mechanisms to incorporate external ontologies like ESCO, and standardizing course descriptions for improved knowledge base creation and comparison among courses. Besides, efforts should be directed towards expanding the applicability of KBRS to various academic domains, conducting comparative studies with other recommendation techniques, and evaluating KBRS against other RS in higher education settings to enhance its development and impact. Moreover, to enhance its precision in aligning courses with competencies, ChatGPT requires specialized training. Additionally, deploying the KBRS at another university would be beneficial for evaluating its broader applicability and promoting its generalization.

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