iModuleBuddy - A Hybrid AI-Based Academic Planning System

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Abstract

iModuleBuddy is a study planner that helps postgraduate students create personalized study plans. It combines course recommendation with long-term planning and considers students' professional background, career goals, and individual study preferences. The system integrates structured data from the ESCO ontology and course descriptions with vector-based similarity methods and retrieval-augmented generation (RAG). A key component is the JobRanking algorithm, which prioritizes courses based on the relevance of a student's career history. The system uses a multi-agent architecture: one agent aligns professional experience with suitable courses, while another organizes these into a multi-semester plan. Based on user input, iModuleBuddy generates different study plans—career-focused, balanced, and preference-based—along with explanations of how the recommended courses contribute to career development. The system is currently under development, with the career-focused plan already implemented and the other variants in progress.

Keywords

Academic Planning System, Study Planner, Course Recommendations, Multi-agent System

1. Introduction

The availability of flexible and part-time study programs reflects an institutional effort to attract students with professional backgrounds and support those who wish to continue working while earning a degree [1]. While universities provide flexible degree options, students are responsible for planning their studies and balancing academic requirements with personal and career interests [2, 3]. This planning involves both short-term course selection and long-term strategies to meet degree requirements while considering academic prerequisites and individual preferences. Challenges include limited personalized guidance, high student-to-advisor ratios [4], and frequent course updates [5]. Consequently, students often struggle to create study plans that align with their professional experience and aspirations, as current planning systems primarily focus on compliance with regulations rather than individual career goals [2, 6, 7, 8].

In prior works, we explored several approaches to support students in academic planning. [9] created a performance prediction model that uses course description embeddings and measures of student similarity to forecast academic outcomes. The model combines indicators based on students' academic interests and past grades. However, small datasets and varied course combinations limit prediction accuracy. [10] proposed a knowledge-based recommender system that links course learning objectives to job-related competencies using the European Skills, Competences, Qualifications and Occupations

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(ESCO)[1] ontology and a Large Language Model (LLM). This system ranks courses based on how well they support skills relevant to selected careers and explains each recommendation. ChatGPT was used to extract learning objectives and assign them to competencies, resulting in some inconsistencies. Different competencies were sometimes assigned to the same objectives, raising concerns about reliability and reproducibility. [11] developed an ontology-based recommendation system that uses semantic representations of course content and student preferences to generate personalized course suggestions. Although the ontology was designed to generate tailored recommendations, further refinement is necessary to improve the accuracy and relevance of these recommendations.

Building on these foundations, this position paper introduces *iModuleBuddy*, an academic planning system under active development. It is based on the assumption that academic planning should consider various individual and contextual factors. These include students' professional experience, personal interests, career goals, course content, learning objectives, and scheduling constraints. Grades and similarities to other students were not considered, as they are context-dependent and may not accurately reflect motivations or future potential. *iModuleBuddy* aims to improve how study plans are generated and builds on earlier research, addressing practical limitations such as reliance on historical data, limited adaptability, and lack of explanation in existing systems. A knowledge graph connects occupations, competencies, and courses through structured representations to address issues such as cold-start problems and shifting student goals, which are common in systems based on past behavior. A Retrieval-Augmented Generation (RAG) framework with a LLM accesses relevant course content and provides explanations. To align study recommendations with students' professional backgrounds, *iModuleBuddy* employs a JobRanking algorithm that sorts courses based on career relevance, extending earlier efforts to link academic content with job-related competencies. *iModuleBuddy* produces three study plans: career-focused, balanced, and preference-based. By synthesizing insights from our earlier data-driven, competency-oriented, and ontology-based approaches, *iModuleBuddy* aims to deliver a flexible and transparent planning experience that integrates students' career goals, professional backgrounds, and personal preferences. *iModuleBuddy* is still under active development; the career-focused study plan functionality is implemented, while the balanced and preference-based plans are currently in progress.

This paper is structured as follows: Section 2 overviews current research on study planning systems and identifies the research gap. Section 3 introduces the research methodology. Section 4 highlights the practical relevance of the *iModuleBuddy* study planner, and Section 5 describes the system architecture and the role of the different components. Finally, Section 7 concludes the paper and outlines the next steps.

2. Related Work

Study planning and course recommendation systems have been explored from various angles, including collaborative filtering, content-based methods, and hybrid approaches that combine machine learning and domain knowledge [12, 5, 6].

Content-based recommendation systems typically align course selection with career goals by analyzing job market data. [13, 14] developed a tool that maps course content to career-relevant skills extracted from job descriptions. In contrast,[15] introduced a system that utilizes LinkedIn profiles for course recommendations. Nonetheless, incomplete or biased data may limit the accuracy of such methods. Decision-support systems (DSS) such as IDiSC+ [8] enable students to create long-term academic plans based on constraints like graduation timelines and budgets but do not consider career relevance. Other DSS solutions [16, 17] focus on optimizing study duration rather than aligning courses with professional backgrounds. Beyond these approaches, social network-based systems attempt to enhance study planning through peer recommendations. [18] developed a model leveraging Facebook connections for course suggestions. These systems often fall short when students lack meaningful social connections or require personalized career-oriented recommendations.

[1]https://esco.ec.europa.eu/en/classification/occupation_main

Regarding applied techniques, AI-driven methods leverage knowledge graphs and machine learning to provide tailored course recommendations. [19] uses reinforcement learning and graph-based modeling to improve the selection of online courses and dynamically adapt recommendations to students' evolving learning behaviors. [20] proposes a hybrid model that constructs course knowledge graphs using rule-based and deep learning techniques, improving recommendation accuracy through structured dependency mapping. [21] explores using OpenAI's embedding models with LLMs to refine course suggestions through RAG, demonstrating improved contextual relevance.

Despite recent advancements, most existing systems generate a single study plan, making it difficult for students to assess how different course selections might align with their goals or constraints. In addition, there is insufficient integration between course recommendations and overall study planning, treating them as isolated decisions rather than part of a longer-term academic path. While factors such as past academic performance, career aspirations, and personal preferences are often included, students' professional experience is not considered. Although a considerable number of students with professional experience enrol in higher education. For example, [1] found that 38% of higher education graduates in a Swiss sample had completed vocational education and training (VET) before entering university, suggesting that these students possessed work experience. Similarly, [22] found that among an Australian university student sample, 53.6% were employed during their studies, and another 46.4% had worked previously, while only 3.2% had never worked. These findings demonstrate that many students, particularly those entering postgraduate programs, possess professional experience. These findings highlight that professional experience is part of many students' profiles.

Data-driven approaches that predict student performance using historical enrollment data may face challenges, particularly when dealing with sparse datasets or rapidly changing curricula [2, 7, 8]. These insights suggest that academic planning systems could benefit from expanding their focus beyond academic data by incorporating diverse student backgrounds, including professional experience.

In our earlier work, we explored how textual course descriptions could be coded to improve recommendations, although small data sets and different pathways remain a challenge [9]. Further, our research introduced ontology-based methods to represent academic knowledge, such as learning objectives, prerequisites, and competencies, enabling more powerful queries and structured reasoning [11]. Additionally, our earlier work demonstrated how linking learning objectives to job-related competencies could enable more targeted course choices [10]. However, purely knowledge-based solutions can be difficult to scale or maintain, whereas purely data-driven solutions fail to exploit domain knowledge and career-oriented constraints. *iModuleBuddy* addresses these issues by including professional background information through a *JobRanking* algorithm and offers multiple plan variations (career-focused, balanced, preference-based).

3. Methodology

The development of *iModuleBuddy* follows the Design Science Research (DSR) methodology, which offers a structured approach for designing and evaluating innovative information systems artifacts [23]. DSR involves iterative phases: problem awareness, suggestion, development, evaluation, and conclusion. During the problem awareness phase, challenges in course selection were explored through a literature review and World-Café workshops [24] conducted with postgraduate students from the MSc in Business Information Systems program at the University of Applied Sciences and Arts Northwestern Switzerland (FHNW). Students reported that they find it hard to select courses that will both qualify them for their desired future job and fulfill academic requirements. They also noted limited personalized guidance and a lack of consideration for professional experience. These findings reflect gaps identified in prior data-driven and ontology-based course recommendation research [9, 11, 10]. In the suggestion phase, key requirements for *iModuleBuddy* were derived from workshop insights, interviews with alumni, and a review of existing AI-driven study planning systems. Emphasis was placed on integrating professional experience, generating multiple personalized study plans, and clarifying the relevance of each recommended course for different career goals. During the development phase, *iModuleBuddy* was designed to link structured career information with flexible course recommendations. To achieve this, a knowledge graph based on the ESCO ontology is combined with a language model that retrieves and explains relevant courses using a Retrieval-Augmented Generation (RAG) approach. Course relevance is further refined through a custom *JobRanking* algorithm that takes the student's professional background into account. The system currently produces a *career-focused* study plan. Additional plan types—*balanced* and *preference-based*—are in development. Evaluation of *iModuleBuddy* will occur in future stages, assessing both individual components and overall performance once all plan variations are fully implemented.

4. Application Scenario

The MSc BIS study program at the FHNW provides a practical context for developing *iModuleBuddy*. As a Swiss postgraduate program, it reflects the characteristics of Switzerland's education system. Most students begin the study program in their late twenties, with a median starting age of 28 and an average of 29.5 years. A few students enter earlier, around age 21, mainly as exchange students from countries where postgraduate studies follow directly after a bachelor's degree. Admission typically requires at least one year of professional experience, with exceptions for exchange students under institutional agreements. To understand the professional backgrounds of students, 463 LinkedIn profiles from those enrolled between 2013 and the spring semester of 2023 were analyzed. This period includes a total of 1045 matriculated students. The analysis shows that students in their mid-twenties generally have 1–2 years of work experience, while those in their thirties or older often have significantly more. Older students (aged 39–42) report 3 to nearly 15 years of experience, while even younger students (around 24) may already have up to 5 years. This pattern reflects Switzerland's dual education system, where vocational training often starts at age 15, followed by early entry into the workforce around age 19 [25]. Figures 1 and 2 visualize the distribution of student age and professional experience.

Age at the Start of Their Studies	Number of Students	%
21	2	0.19%
22	8	0.77%
23	39	3.73%
24	73	6.99%
25	85	8.13%
26	117	11.20%
27	101	9.67%
28	112	10.72%
29	104	9.95%
30	73	6.99%
31	57	5.45%
32	50	4.78%
33	45	4.31%
34	26	2.49%
35	25	2.39%
36	26	2.49%
37	19	1.82%
38	11	1.05%
39	19	1.82%
40	9	0.86%
41	10	0.96%
42	9	0.86%
43	4	0.38%
44	5	0.48%
45	4	0.38%
46	6	0.57%
47	1	0.10%
48	3	0.29%
49	1	0.10%
50	1	0.10%
Total	**1045**	**100.00%**

Figure 1: Number of Students by Age at the Start of Their Studies

Age at the Start of Their Studies	Number of Students	max. Work Experience	avg. Work Experience
22	5	39	7.00
23	11	35	8.00
24	34	59	13.62
25	39	59	14.71
26	60	90	18.11
27	49	80	17.93
28	57	106	17.88
29	52	84	19.86
30	32	83	19.85
31	24	70	27.12
32	19	123	22.24
33	19	84	19.49
34	12	125	25.90
35	9	95	33.65
36	12	103	26.41
37	6	100	30.14
38	2	37	14.38
39	7	138	47.05
40	4	88	27.48
41	3	177	33.55
42	4	133	46.72
45	1	72	33.71
46	2	71	42.00
Total	**463**	**177**	**20.70**

Figure 2: Professional Experience in Months based on LinkedIn Profile

The MSc BIS curriculum consists of 90 ECTS credits. Of these, 36 ECTS are allocated to elective courses, which students choose from a pool of over 20 options. The study program is offered as full-time (1.5 years) and part-time (2.5 years) formats. Insights from World-Café workshops, together with an analysis of student enrollment event logs from FHNW's internal course registration system (2013–2023), show that students create individualized study plans, with few following the same combinations of courses per semester. While core courses are typically taken early in the program, elective course selection varies significantly. The workshops revealed that multiple factors influence course choices, including alignment with career goals, prior knowledge, relevance to professional experience, assessment format, scheduling flexibility, and lecturer reputation. Peer recommendations play a limited role and are typically only valued if they come from trusted individuals. Social influence from friends or former alumni in students' private networks has little impact on their final decisions. Many students work up to 80% alongside their studies and therefore, balance their workload across the semester. Figure 3 illustrates the course selection process as described by the students. Despite this structured approach,

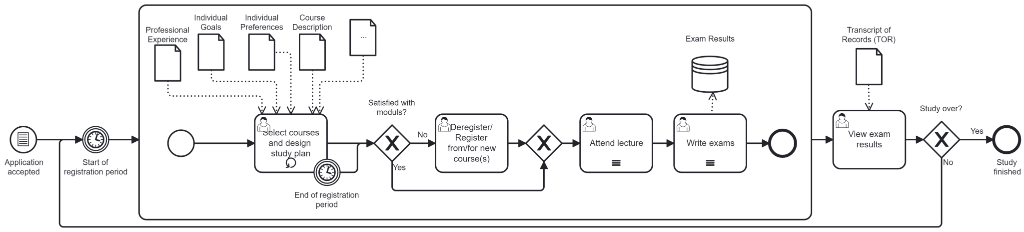

Figure 3: Simplified Course Selection and Study Plan Design Process

students struggle with the selection process. Many feel uncertain about choosing the right courses or course combinations. In the first two weeks of each semester, when course changes are still permitted, it is common for students to switch courses. Further, students often seek input from the head of the program or lecturers they trust, not only to confirm whether their course choices are appropriate, but also to explore alternative options and to discuss whether they should enrol in certain courses during the same semester or distribute them across different ones.

5. System Development and Architecture of iModuleBuddy

This section provides an overview of the *iModuleBuddy* architecture, describing the key components and processes involved in retrieving, ranking, and generating customized study plans.

5.1. System Architecture of iModuleBuddy

iModuleBuddy is designed as a multi-agent system with three layers — (1) data, (2) processing, and (3) application — which work together to generate personalized study plans. This architecture reflects the complexity of academic planning, where students must weigh multiple, and sometimes conflicting, factors such as career goals, professional experience, prior knowledge, personal interests, assessment formats, and scheduling constraints. To support this process, the system uses two specialized agents *careerAgent* and *scheduleAgent*, which operate collaboratively within a shared workflow. Each agent focuses on a distinct aspect of the planning task. The *careerAgent* receives student inputs, such as career goals and prior professional experience, and determines whether occupation-based recommendations are necessary. When required, the agent queries the Neo4j knowledge graph to retrieve relevant courses, considering metadata such as learning outcomes, required skills, and ECTS credits to ensure alignment with the student's target occupations. Once the relevant courses are identified, the *scheduleAgent* organizes them into a multi-semester plan, considering prerequisites, degree requirements, and previously completed credits. Finally, the agent refines the semester-level plan into a detailed weekly schedule, incorporating specific teaching sessions, locations, and times to provide students with a concrete academic roadmap.

The data layer holds both structured and unstructured information. This includes course details, professional roles, user profiles, and the ESCO ontology. At its core is a Neo4j knowledge graph that links occupations, skills, and courses. Each course entry includes metadata like learning objectives, prerequisites, and scheduling. The ESCO ontology helps map occupations to skills, supporting course recommendations based on career paths. User profiles store information on completed courses, earned credits, and personal preferences such as the planned study duration.

The processing layer is responsible for retrieving and ranking relevant data. To assess how well courses support specific skills, both course descriptions, including learning objectives, and ESCO skill descriptors are transformed into vector representations using the mxbai-embed-large model from

Ollama. Similarity scores are then calculated to evaluate the match between each course and the skills associated with both the student's target occupation and their past work experience. These scores help identify courses that are most relevant to the student's profile. A central component of this layer is the *JobRanking* algorithm [1], which evaluates job experiences based on duration, recency, and job type. When the *careerAgent* receives a student's background, it uses the algorithm to prioritize experiences that are most influential for course selection.

Algorithm 1 JobRanking Algorithm

Require: *jobs* (list of job records), *weights* (dictionary with weights for work period, recency, and job type), *max_experience_years* (integer)
Ensure: Ranked list of jobs with scores in descending order

Initialize an empty dictionary *merged_jobs* to aggregate experiences by job title.
Calculate the cutoff date based on *max_experience_years*.
Filter *jobs* to include only those with end dates after the cutoff date.
for each job in filtered *jobs* **do**
    Update *merged_jobs* with work periods, minimum recency, and the highest job type (full-time if applicable).
end for
for each job title in *merged_jobs* **do**
    Sort work periods by start date.
    Merge overlapping or contiguous work periods.
end for
Compute normalization factors for maximum duration and maximum recency across all jobs.
for each job title in *merged_jobs* **do**
    Calculate the normalized duration of work periods.
    Calculate the normalized recency of the job.
    Assign a score for job type (1.0 for full-time, 0.5 for part-time).
    Compute the total score using the weighted sum of duration, recency, and job type scores.
end for
Sort jobs by their scores in descending order.
return The sorted list of job titles with their corresponding scores.

The application layer uses RAG to generate personalized study plans in natural language. This approach allows the system to retrieve relevant course descriptions and align them with the student's professional background or career goals. It explains how each course supports students' goals and contributes to their development. The application layer coordinates two specialized agents that produce multi-semester plans based on user input and processed data. A LLM, Claude 3 Sonnet from Anthropic, is used to generate these explanations and assist in matching course content to student profiles. When activated, the *careerAgent* analyzes the student's professional background and aligns it with one or more ESCO occupations (e.g., "Enterprise Architect," "ICT Network Architect"). Using the similarity scores from the processing layer, it identifies courses whose learning outcomes best match the skills required by the selected occupations. It then retrieves relevant courses from the knowledge graph, considering completed credits and prior experience, and ranks them so that the most relevant options appear first. The *scheduleAgent* refines this ranked list by applying user-defined constraints, such as semester workload limits, scheduling preferences, and course availability (Spring or Autumn). It verifies prerequisite requirements and constructs a multi-semester plan. For instance, a foundational course like "Business Intelligence" might be scheduled before an advanced elective requiring analytical skills. The agent also generates a detailed weekly schedule for the upcoming semester, including specific days, times, and campus locations. Figure 4 illustrates the architecture of the *iModuleBuddy* study planners.

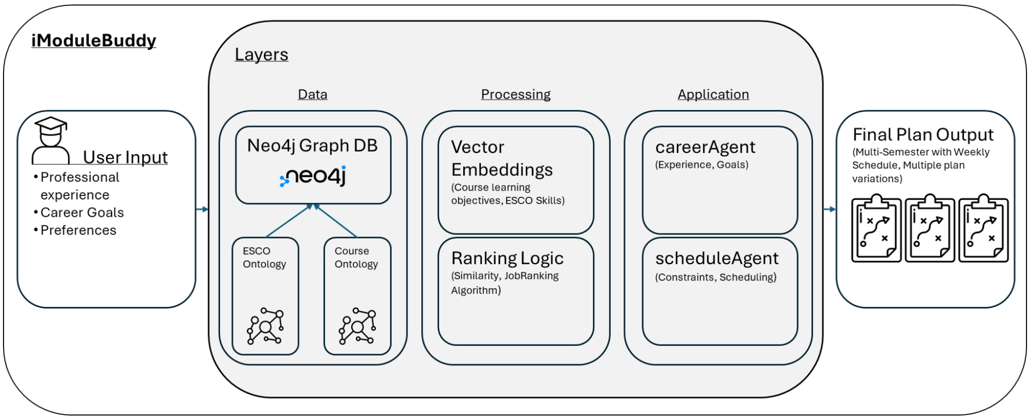

Figure 4: *iModuleBuddy* System Architecture

6. Data Flow and Execution Process

The process begins when the student provides their career goals, prior professional experience, and study preferences, such as the number of courses per semester. The system converts ESCO skills and course learning outcomes into vector embeddings, computing similarity scores to find the best matches for the student's target occupation. On the Application Layer, the *careerAgent* gathers all potentially relevant modules from the Data Layer, leveraging the embedding scores and factoring in partial completions or previously earned credits. The *scheduleAgent* takes the ranked list of modules, applies constraints (e.g., "no more than 12 ECTS in a single semester"), and distributes courses across the planned study duration. It also generates a week-by-week timetable for the following semester. A final multi-semester study plan and a detailed weekly schedule for the immediate term are produced. This plan highlights both mandatory and elective modules, alignment with the student's career goals, and a feasible timetable. To accommodate different student requirements, *iModuleBuddy* generates multiple study plans. The career-focused plan prioritizes courses essential for the student's professional aspirations, ensuring that their studies directly support career advancement. The balanced plan combines core and elective courses to foster academic breadth and career relevance. The preference-based plan tailors recommendations to personal interests while ensuring compliance with degree requirements. Each plan explains how the selected courses contribute to specific professional roles or competencies. Figure 5 illustrates how the system organizes courses over semesters and offers a weekly schedule.

Based on your desired occupations (enterprise architect and ICT network architect), the modules available, and your current progress, I've created a comprehensive study plan for your 5 semesters.
Semester-Wise Study Plan for 5 Semesters:
- **Spring 2025** (Total Credits: 12):
    - Business Process Management (Mandatory, Spring): Provides foundational knowledge in process modeling and workflow management, essential for enterprise architects to understand how business processes can be optimized and digitalized.
    - Cloud Computing (Elective, Spring): Covers different cloud service models, deployment strategies, and security challenges in hybrid environments - critical knowledge for both enterprise and network architects.
- **Autumn 2025** (Total Credits: 12):
    - IT Governance, Risk and Compliance (Elective, Autumn): Helps you understand IT governance principles, privacy requirements, and risk management strategies that are fundamental for enterprise architecture roles.
    - Data Governance and Information Management (Elective, Autumn): Teaches you to understand data as a strategic asset, including data protection regulations and quality management programs.
- **Spring 2026** (Total Credits: 12):
    - Business Intelligence (Mandatory, Spring): Focuses on data-driven decision making and eliciting analytical requirements from stakeholders, essential skills for architectural planning.
    - Cyber Security and Cyber Resilience (Elective, Spring): Provides comprehensive understanding of security risks and implementation of security mechanisms, critical for both enterprise and network architects.
- **Autumn 2026** (Total Credits: 12):
    - Strategic Business Innovation (Mandatory, Autumn): Develops strategic thinking for architectural decisions and helps you recognize future business opportunities in the digital economy.
    - Research Methods in Information Systems (Thesis-related): Introduces you to research methodologies necessary for your thesis work.
- **Spring 2027** (Total Credits: 24):
    - Master Thesis Proposal (Thesis-related): Helps you develop your thesis proposal based on your research interests in enterprise or network architecture.
    - Master Thesis (Thesis-related): The culmination of your studies where you'll apply your knowledge to solve a real-world problem in enterprise or network architecture.
Additional Notes:
- Total graduation requirement: 90 credits.
- Credits already completed: 6.
- Credits remaining: 84.
- Breakdown:
    - 54 credits from the Main Study Plan,
    - 6 credits from Research Methods,
    - 6 credits from Master Thesis Proposal,
    - 18 credits from Master Thesis.

Now, let me create a weekly study schedule for your upcoming semester (Spring 2025) based on the teaching sessions available for the modules in your first semester.
Weekly Lecture Schedule
Week Semester 1
- Business Process Management: Wednesday at 13:15-17:00 in Olten
- Cloud Computing: Thursday at 08:15-12:00 in Olten

This schedule gives you a balanced workload with classes on two different days of the week, allowing you ample time for self-study, assignments, and project work. The Business Process Management session is in the afternoon, while the Cloud Computing session is in the morning, providing a good distribution throughout the week.

Figure 5: Illustrative System Output of a career-focused Study Plan

By separating concerns into a Data Layer, a Processing Layer, and an Application Layer, *iModuleBuddy* combines different AI approaches through two specialized agents. The *careerAgent* combines professional experience and specific career goals to propose relevant courses. In contrast, the *scheduleAgent* converts this ranked list into a feasible multi-semester plan that adheres to user constraints and semester availability. This approach preserves the flexibility to accommodate various schedules and aspirations while adhering to academic prerequisites. Finally, *iModuleBuddy* delivers a transparent, career-oriented planning solution that supports postgraduate students in designing a personal study plan.

7. Conclusion

iModuleBuddy is a hybrid AI-based academic planning system that generates personalized study plans aligned with students' professional backgrounds and career goals. It combines sub-symbolic AI, such as Large Language Models, with symbolic AI methods like knowledge graphs and the ESCO ontology. By pairing the *careerAgent*, which aligns course recommendations with professional experience and career goals, with the *scheduleAgent*, which structures a multi-semester plan and weekly schedule, *iModuleBuddy* fills a gap in traditional course planning systems: recognizing the importance of students' professional experience and offering multiple study plans. The system's main features, such as vector embeddings for learning outcomes, the ESCO ontology for skill matching, and the *JobRanking* algorithm, ensure that recommended courses are aligned with the student's career path. Neo4j was chosen for its flexible data modeling and efficient retrieval capabilities. However, future versions may utilize ontology-driven graph databases for improved semantic reasoning and scalability. An upcoming evaluation phase will examine how effectively the system's *JobRanking* algorithm and skill-based course mapping perform in real-world postgraduate programs, using student interviews and surveys to gauge user acceptance and outcome quality. Overall, *iModuleBuddy* demonstrates a new approach to academic planning, merging AI-driven personalization with structured knowledge to better serve postgraduate students' career aspirations. The current development focuses on the MSc BIS program at FHNW. The next step will be to assess how well the approach generalizes to other academic contexts, including possible extensions to programs such as the FHNW School of Music or partner universities.

Declaration on Generative AI

While preparing this work, the author(s) used Grammarly to check grammar and spelling. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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