Measuring the Matches Between University Courses: Ontological Comparison-Based Approach

Shahd Hamdan
Computer Science Dept.
An-Najah N. University
Nablus, Palestine, P.O.Box:7
www.najah.edu
s11924003@stu.najah.edu

Salma Ibrahim
Computer Science Dept.
An-Najah N. University
Nablus, Palestine, P.O.Box:7
www.najah.edu
salma.ibrahim@stu.najah.edu

Amjad Hawash*
Computer Science Dept.
An-Najah N. University
Nablus, Palestine, P.O.Box:7
www.najah.edu
amjad@najah.edu

***Abstract*—This study introduces an Ontological Comparison Approach that addresses the difficulties in finding appropriate substitute courses for graduating students if their first choices are not offered. Department heads have always had to manually compare courses across different departments, which is time-consuming and error-prone. Our method allows customers to specify desired matching percentages by measuring the degree of matching between course descriptions using sophisticated algorithms. This approach greatly simplifies the procedure and improves the speed and accuracy of finding suitable course substitutes. Additionally, the strategy is enhanced by an intuitive user interface that helps make well-informed decisions, addressing the challenges of choosing courses in the pivotal last stages of academic programs.**

***Index Terms*—Ontological Comparison, Semantic Similarity, Educational Technology, Course Matching, Knowledge Management, Database Schema, Algorithm Design.**

I. Introduction

Effective knowledge implementation in an organization or practice involves several strategies [1]. These include continuous learning, knowledge sharing, practical implementation, knowledge retention, technology utilization, culture and leadership, and monitoring and evaluation. Knowledge acquisition involves continuous learning through workshops, seminars, and online courses, networking with industry experts, investing in research and development, and using collaborative tools like Slack [1], Microsoft Teams [2], or Trello [3] [2]. Knowledge application involves real-world projects and problem-solving tasks, starting with small-scale implementations and establishing feedback loops. Knowledge retention involves strategies like mentorship programs, knowledge transfer sessions, and archiving. Technology utilization includes Knowledge Management Systems (KMS), Artificial Intelligence (AI), and automation tools. Culture and leadership should foster a supportive culture that values knowledge-sharing and continuous improvement, with leadership involvement and incentives for employees to engage in knowledge-sharing activities and continuous learning. Monitoring and evaluation should involve establishing key performance indicators (KPIs) to measure the effectiveness of knowledge implementation strategies, conducting regular reviews to assess progress, identify challenges, and make necessary adjustments, and benchmarking performance against industry standards to identify areas for improvement and best practices [3]. By integrating these strategies, organizations and individuals can effectively implement knowledge, driving innovation, efficiency, and competitive advantage. Knowledge representation is a crucial aspect of artificial intelligence (AI) and cognitive sciences, involving the structuring of information for effective processing [4]. Key strategies include logical representation, semantic networks, frames, rule-based systems, ontologies, conceptual graphs, Bayesian networks, neural networks, case-based reasoning, symbolic vs. sub-symbolic representation, and hybrid approaches. The logical representation uses propositional logic, which is suitable for simple sentences and complex relationships, while predicate logic extends it to include predicates and quantifiers [5]. Semantic networks use graph structures with nodes and links, inheritance, and frames for hierarchical information. Frames represent stereotypical situations using slots and fillers, while defaults and overrides allow for flexibility in representation.

Rule-based systems use production rules and expert systems to emulate human decision-making abilities in specific domains [6]. Ontologies represent knowledge as a set of concepts within a domain and their relationships, while description logic provides formal semantics for concepts and relationships. Conceptual graphs use graphs to represent logical structures and facilitate reasoning [7]. Bayesian networks represent knowledge in a directed acyclic graph, allowing for probabilistic inference and learning from data. Neural networks use connectionist models and deep learning to represent complex patterns and relationships in data. Case-based reasoning uses past cases to represent knowledge through specific instances or experiences, and adaptation and

Corresponding Author: amjad@najah.edu
[1]https://slack.com/
[2]https://www.microsoft.com/en-us/microsoft-teams/log-in
[3]https://trello.com/

retrieval involve retrieving relevant cases and adapting their solutions to fit new problem contexts. Symbolic vs. sub-symbolic representation involves explicit, discrete symbols, while sub-symbolic representations capture patterns and associations without explicit symbols. Hybrid approaches combine different knowledge representation strategies to leverage their strengths, such as integrating rule-based systems with neural networks for interpretability and learning capabilities. The choice of knowledge representation strategy depends on the application's complexity, need for reasoning and inference, and data nature. By selecting appropriate strategies, systems can become more intelligent, adaptable, and capable of solving complex problems.

Information is officially and methodically ordered when using ontology to describe knowledge; this usually involves employing a set of concepts, categories, and links that encapsulate the essence of a particular subject. Ontologies are semantic frameworks that make knowledge interchange, organization, and retrieval easier across a wide range of systems and applications [8]. Ontologies aid in more lucid thinking and communication about complicated subjects by describing items and their interactions within a particular domain. To facilitate consistency and interoperability as well as collaboration and integration across various disciplines and technologies, they offer a common vocabulary and structure. Information management is facilitated and a greater understanding and study of domain-specific phenomena are encouraged by ontology-based knowledge representation. As a result, advances are made in several domains, including artificial intelligence, bioinformatics, and semantic web technologies [9].

Semantically-based comparisons evaluate and analyze the content based on its meaning and context rather than just its syntactical structure [10]. This technique understands the relationships and nuances between different data sets by using complex algorithms and natural language processing (NLP) techniques. Particularly in fields as complex as information retrieval, data integration, and machine learning [11], semantic analysis improves the significance and accuracy of comparisons. For example, semantic comparison can improve search engine accuracy by considering the context of the query and returning results that are more in line with the user's intent. In contrast, understanding the underlying meaning even in situations where several terminologies are used facilitates the recognition and fusion of data from remote sources during data integration. This strategy promotes more careful analysis and improved decision-making by increasing the comparability and accuracy of comparisons [12].

Comparing ontologies involves examining and evaluating the structure, content, and semantics of different ontological frameworks to identify similarities, differences, and potential integrations [13]. In fields like knowledge management, data integration, and artificial intelligence, ontologies are crucial. They are formal depictions of a group of ideas within a field and the connections between those ideas. When comparing ontologies, it is crucial to take into account the alignment of classes, attributes, and hierarchies as well as the compatibility and equivalence of definitions. To map entities between ontologies and identify overlaps and differences, automated tools and algorithms are often used in this process. Effective ontology comparison can facilitate the merging of disparate information, enhance semantic search capabilities, and facilitate cross-system interoperability, hence improving the coherence and use of integrated knowledge bases [14]. By carefully comparing them, organizations can ensure that their ontological frameworks are robust, complete, and capable of handling sophisticated data-driven applications.

Bachelor students may think about alternative courses, independent study, cross-enrollment, summer/winter sessions, course rescheduling, curriculum adjustments, online courses, internships, or practical experience, directed study groups, or an extended graduation timeline when a core course is not available to them to finish their studies and graduate. If there is sufficient demand for the course, these solutions may be taken during a summer or winter session with approval from their department or academic advisor. A temporary modification of the curriculum requirements may be requested by the student if extraordinary circumstances prevent them from enrolling in the course. One flexible alternative for education is to take online classes, and academic coursework can be replaced with internships or real-world experience. If none of these options work, the student might have to wait until the next graduation period to enroll in the course. All of the previous options—aside from considering enrolling in a different course—cause delays in students' graduation. Selecting a suitable substitute course is considered to be a challenging task, especially when searching for one that doesn't conflict with the study schedule or deprives students of the knowledge and/or abilities they had hoped to acquire during their studies. Still, this might be the best choice.

We contribute to this effort by automating the process of comparing course descriptions once they have been represented in ontologies to determine which alternative courses are the most appropriate for a given course. In summary, we took the following actions:

- Manual study of a series of computer science course descriptions to become familiar with the terminology.
- We created an ontology for every course, consisting of a collection of related concepts with appropriate relations.
- We created a tool that compares the descriptions of each specific course with the descriptions of all other courses, which are all ontologies.
- The comparison result was presented to the users as a list of courses that were ranked and arranged in descending order according to the similarity values between the related ontologies.

The rest of this paper is organized as follows: Related Works is proposed in SectionII. Section III discusses the system architecture of the implemented work while Section IV illustrates the ontology-based mathematical computations used in the recommendation process. Section V discusses the conducted experimental tests and achieved results. Finally, Section VI concludes this paper.

II. Related Works

A rising number of approaches have been investigated to measure the matches between university courses, which is in line with the growing interest in promoting academic mobility, guaranteeing curriculum alignment, and easing student transfers across educational institutions. This section examines previous research and methods pertinent to the ontological comparison-based method of course matching.

Regarding computer science and information systems, ontology is a formal representation of knowledge that includes a set of ideas inside a domain and their relationships [14]. To build organized frameworks that facilitate more accurate and insightful comparisons between various educational entities, ontological techniques in education have been used.

This paper [15] presents an ontology-based approach for curriculum mapping in higher education, focusing on creating a core curriculum ontology for effective knowledge representation and discovery. The research demonstrates ontology reuse for micro-credentials and presents a conceptual framework for knowledge discovery, supporting various business use case scenarios based on ontology inferencing and querying operations.

The review paper presented in [16] analyzes the semantic web and its technologies, including RDF schema, OWL, and SPARQL, to help various domains resolve problems. It covers 10 related domains and focuses on growth, vital roles, and areas that go hand in hand with semantic web technologies. The paper serves as an unbiased direction for researchers.

Course matching uses manual reviews and subjective judgment to compare course content, structure, and outcomes. Modern advancements introduce systematic, automated methods for compatibility [17].

The work of [18] discusses text similarity measurement, a crucial aspect of natural language processing, and its current research status. It analyzes current methods, develops a comprehensive classification system, and discusses future development directions. The technique is described by text distance and representation, and the development of text similarity is summarized.

Authors of the work presented in [19] explore the benefits and challenges of concept mapping in undergraduate education. It highlights its potential to develop critical thinking, problem-solving, and understanding of concepts. Concept maps facilitate integration between theory and practice, promote technology inclusion, and enhance academic performance. However, challenges include difficulty in concept selection, resistance, and software issues.

An ontology is the "explicit, formal specification of a shared conceptualization of a domain of interest," according to a later expansion of the term's definition [20]. Formal ontologies are those that are represented in a language that is readable by machines. "Shared" is a reflection of the notion that an ontology includes collective knowledge that is not personal. "Shared" refers to the acceptance of a set of interpretations for the concepts given in the ontology rather than necessarily implying worldwide sharing. When it comes to domain ontologies, the reference to a domain of interest suggests that the goal is to represent only the portions of a given domain that are pertinent to it.

Several tools and platforms related to matching the similarity between university courses exist. Curriculum Analytics [4] allows institutions to align and compare course content to identify overlaps and gaps. Open Syllabus Project [5] is a resource that provides access to millions of syllabi from universities, allowing you to compare the content and structure of courses across institutions. Other tools are related to Natural Language Processing techniques like Word2Vec/Doc2Vec algorithms [6] that can convert course descriptions into vector representations and help measure the semantic similarity between them. However, SpaCy or NLTK [7] are Python libraries that provide pre-built tools for processing and comparing course descriptions, such as entity recognition and text similarity scoring. Machine Learning and Deep Learning Tools also have their contribution concerning course matching. BERT [8], A deep learning model that can be fine-tuned for text similarity tasks. You can apply it to measure the match between course descriptions or learning outcomes. Finally, Siamese Networks [9] are deep learning architecture that can be used to train models to compare pairs of courses and learn to determine their level of similarity.

Our tool is different from the previous tools in that it is an Ontological-based approach to measuring the similarity between courses. It relies on computing the similarity between the concepts of ontologies corresponding to courses.

In this work, we are comparing the course's knowledge represented as ontologies to measure the amount of similarity between a set of computer-related courses to suggest the best alternative courses for a given course.

III. System Architecture

This section describes the architecture of the tool, including the different structural components and their purposes. The

[4]https://curricularanalytics.org/home

[5]https://www.opensyllabus.org/

[6]https://shuzhanfan.github.io/2018/08/understanding-word2vec-and-doc2vec/

[7]https://dev.to/krishnaa192/spacy-vs-nltk-12e5

[8]https://www.techtarget.com/searchenterpriseai/definition/BERT-language-model

[9]https://en.wikipedia.org/wiki/Siamese_neural_network#Learning

client side, server side, and database layers comprise the tool's representation of a client/server architecture. Every layer has a distinct role in the system's overall operation. By clearly defining these levels in the tool's architecture, we ensure a division of duties, which facilitates future system upgrades, scalability, and maintenance.

A. *User Side*

Comprising client-side scripts that manage user-system interaction, this tier represents the tool's user interface. It operates via a standard request-reply protocol, where users submit requests via an online form, and the server responds with a new page that has the information they requested. Client-side development uses JavaScript to allow dynamic updating of the course selection options based on the user's chosen specialization. In a PHP-based server-side architecture, this offers a seamless and intuitive selection process, enabling productive and fruitful interaction.

B. *Server Side*

The server-side PHP implementation in our system serves as the primary engine that drives the application's functionality. This layer serves as the system's framework, enabling critical operations including processing user requests, applying logic, accessing and changing data, and generating dynamic responses by establishing a connection between the user interface and the backend database. The following components and functionalities are crucial to the server-side architecture:

1) Form Handling And User Input Processing: When the form is submitted, the server-side software saves user inputs such as the preferred similarity and course selection. It uses the $_POST method to ensure that user preferences are carried over into the subsequent processing phases. This approach lays the groundwork for personalized search results while also increasing user interaction.

2) Stop Words Removal: One important feature that was added early in the system's development process was the ability to remove stop words—common phrases that don't really offer anything to the semantic analysis—from course descriptions. This preprocessing step is crucial in order to clean up the data and ensure that subsequent analyses focus on the most important elements of the course material. The initial step of the function is to establish a connection to the local server database. A database query is then used to obtain the courseID, courseName, and courseDescription from the course table. The following two steps are used by the function each time a course description is retrieved:

1) Tokenization: The course description is divided into distinct words, or tokens, using a space delimiter. This tokenization process enables the function to independently assess each word in the context of the course description. The item Don't Filter Words: Subsequently, each token is compared against a predetermined list of stop words. Tokens that match a single character or any stop word in the array are excluded from the final keyword list for each course description. Tokens that remain are severely condensed into phrases with more semantic importance, strung together, and punctuated with commas. This list, which emphasizes terms that are more likely to be significant when comparing and analyzing the course material, is a shortened version of the course description.

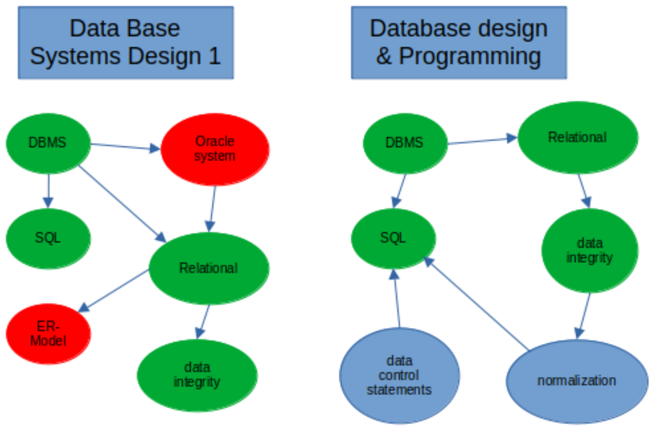

Fig. 1. Edges Comparison.

3) Term Extraction And Stemming: We choose key terms and leave out stop words from each subject's course description. In order to standardize variations and facilitate more accurate word comparisons, some terms have been stemmed, which is a lexical reduction to their root form. The ability of our algorithm to identify conceptual relationships and course-to-course analogies depends on this step.

4) Term Comparison: Our approach uses an ontological comparison-based methodology to determine course similarities, and two key components are the word comparison and matching percentage computation. Each "term Y," which we will call a "Edge" from now on, represents a conceptual relationship or link in the course content and represents the ontological structure that underpins the knowledge domain covered in the course.

Initially, the database is queried to retrieve every Edge for the selected course. Then, these Edges are compared to the Edges of every other course in the system. Rather than being a simple term-matching exercise, this comparison is an ontological analysis that searches for conceptual and thematic similarities between the courses. It examines the "termIn" and "termOut" of every Edge, where "termIn" denotes the concept of an Edge's beginning and "termOut" denotes its conclusion. This illustrates how the course material has directed relationships or knowledge transitions.

5) Matching Percentage Calculation: The function "calculateMatchingPercentage" is essential to this comparison to ascertain the percentage of matching Edges between the selected course and the other courses. The matching percentage is obtained by dividing the number of matching Edges by the total number of Edges in the selected course. This number is then multiplied by 100 to provide the percentage value. This provides a solid basis for finding alternative courses that have content that is significantly similar to the course the user has selected. It does this by quantifying the degree of ontological similarity between courses.

Our system emphasizes the ontological linkages contained by the Edges, ensuring that course comparisons are based on the intellectual underpinnings and deeper structure of the course content, rather than just keyword similarities. The algorithm may find more notable and educationally beneficial parallels between courses by employing an ontological comparison technique, which raises the standard and relevance of the alternative course recommendations that are provided to consumers.

6) Filtering Based On Matching Percentage: The matching percentage filtering process is a fundamental component of our system's functionality that gives the user relevant options for alternative courses. This step, which comes after a thorough analysis of the course material, compares each course in the database to the selected course to determine how similar they are to each other based on shared ontological edges.

We employ a custom filtering function named "filterBySimilarity" to analyze each course's matching % about the user-specified similarity threshold once all courses' word comparisons and matching percentages have been computed. The user can choose this criterion and determine how specific the search for alternative courses is by submitting a form. The selectable levels of 100%, 70%, 50%, and 30% offer a choice of granularity to satisfy varying user preferences for course similarity.

The filtering mechanism works as follows:

- The user selects a desired similarity threshold through the web interface, which our PHP script subsequently records and processes upon form submission.
- Every course's calculated matching
- If a course meets or exceeds the required level of similarity, it remains in the pool of potential selections. Only courses with subjects closely connected to the one you have chosen are included in this carefully curated list, which is a part of the entire course catalog.
- The user is presented with the filtered courses dynamically in the form of an ordered table with matching percentages. This presentation provides transparent information on the degree of similarity between each alternative route and the selected course, enabling the viewer to make an informed decision.

  Our method ensures that users are presented with alternative courses that satisfy their own standards for content similarity and aren't just connected arbitrarily by employing this screening process. This customized approach enhances user experience and streamlines the course selection process by correlating recommended courses with individual preferences and academic goals.

C. Database Side

Our system's database is designed to make it simple and quick to access and compare course data. It consists of two tables: "course," which contains the "courseID," "courseName," and "courseDescription," and "ontology," which has the "termIn" and "termOut" for each course, which denote the start and end of a knowledge transfer. The relational structure optimizes for queries that get the edges needed by the comparison algorithm, which speeds up the matching percentage computation.

IV. Matching Computations

The matching percentage is a crucial parameter in our course comparison approach. It assesses the degree of semantic alignment between the ontology of the selected route and every feasible alternative. Specifically, the matching percentage is calculated using the fraction of common ontological edges, which represent the conceptual connections present in the course material. The matching percentage is computed as follows: The number of edges in $O1$ is given by $N(O1)$, while the matching edges between two ontologies $O1$ and $O2$ are given by $M(O1, O2)$.

$$MatchingPercentage = \frac{M(O1, O2)}{N(O1)} \times 100\% \quad (1)$$

where:

- **Number of Matching Edges** indicates the number of ontological links that the chosen course and the alternate course have in common.
- **Total Number of Edges in the Selected Course** is the total number of distinct ontological links found in the chosen course.

A. Example On Two Courses Based On The Formula:

The matching percentage is one of the key performance indicators in our course comparison system. It gauges how closely each workable option and the selected course's ontology match semantically. More specifically, the matching percentage is calculated by counting the number of shared ontological edges, which serve as a metaphor for the conceptual links in the course content. The matching percentage can be computed using the following formula:

When "Multimedia Systems & Applications" is selected, the system first looks up all ontological linkages associated with this course. Next, a comparison is made between them and "Multimedia Technology" in terms of their linkages (edges). In this case, three common edges are seen. Given

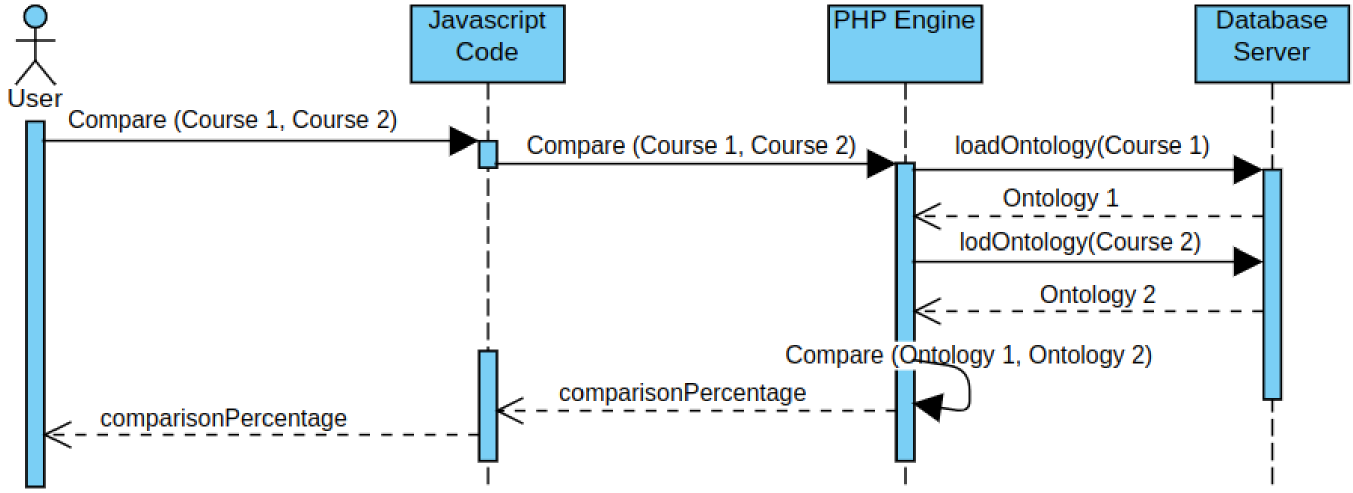

Fig. 2. Courses' Ontologies Comparison.

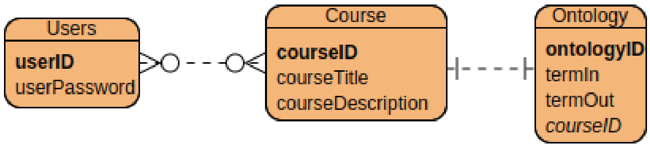

Fig. 3. Entity Relationship Diagram.

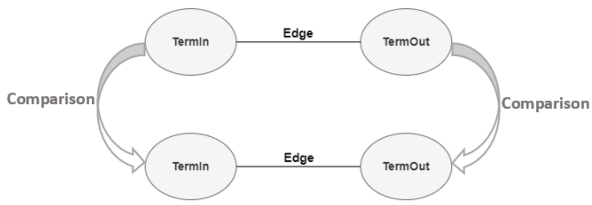

Fig. 4. Comparison Between Two Edges.

that "Multimedia Systems & Applications" has nine different edges overall, the similarity percentage can be calculated using the formula below:

Matching Percentage = (Number of Matching Edges / Total Number of Edges in the Selected Course) * 100

For "Multimedia Systems & Applications", this calculation would be:

$MatchingPercentage = \frac{3}{9} * 100 = 33.33\%$

This means that, based on the ontological connections, "Multimedia Systems & Applications" shares 33.33% similarity with "Multimedia Technology".

On the other hand, if the course "Multimedia Technology" is chosen, the same procedure is followed, but this time it starts with this course. It is discovered that "Multimedia Technology" has a total of 8 distinct edges, although there are still 3 matching edges. Therefore, the percentage of similarity is:

$MatchingPercentage = \frac{3}{8} * 100 = 37.50\%$ This indicates that "Multimedia Technology" has a 37.50% similarity with "Multimedia Systems & Applications", based on their shared ontological connections.

In summary, by evaluating the ontological connections between courses, the Matching Percentage formula helps students choose the most relevant alternative courses by quantifying how similar the courses are to one another.

Course ID	Course Name	Course Description
10672309	Multimedia Technology	This course has been designed to provide students with the knowledge and skills in multimedia domain. Coloring systems will be emphasized. Various types of images, videos and audio will be discussed. Create multimedia application using multimedia authoring tools.

Fig. 5. Multimedia Technology Course Description.

B. *Difficulties encountered*

- Some course descriptions did not express the course topics clearly and explicitly but were rather vague.

Course ID	Course Name	Course Description
10676332	Multimedia Systems & Applicati	This course gives an introduction to multimedia (MM) contents and the tools that produce MM contents. It also covers the design of a MM system considering the necessary resources in the form of CPU power, memory, bandwidth and storage system. The students will be able to produce multimedia applications that can run locally and over a network.

Fig. 6. Multimedia System & Application Course Description.

termID 1	courseID	termIn	termOut	relation
201	10676332	Coloring Systems	Audio	part of
200	10676332	Coloring Systems	Videos	part of
199	10676332	Coloring Systems	Images	part of
198	10676332	Multimedia	Coloring Systems	essential for
197	10676332	Multimedia Application	Multimedia Authoring Tools	used to
196	10676332	multimedia	Tools	Has A
195	10676332	Multimedia	Application	Has A
194	10676332	Multimedia Application	Tools	used in

Fig. 7. Multimedia Technology Terms.

- Some of the course descriptions were short and I was unable to extract various terms from them.
- Some course descriptions were full of stop words.

V. Experimental Tests

We created a list of courses and their accompanying descriptions gathered from a set of universities. The chosen courses are all related to computer science disciplines and are all saved in the database of the system with their descriptions. We took 7 courses out of the list to be fed to the system to suggest alternative courses for them other than the ones on the list to gauge how accurate our system was in suggesting the most relevant courses as alternatives. Additionally, to compare the system's results with those of the experts, 15 faculty members were requested to recommend courses in addition to those that were already on the list.

termID 1	courseID	termIn	termOut	relation
101	10671358	bandwidth	network	part of
100	10671358	multimedia applications	network	run on
99	10671358	Multimedia Applications	System	run on
98	10671358	System	Memory	used in
97	10671358	Memory	CPU Power	require
96	10671358	CPU Power	Tools	require
95	10671358	multimedia	Tools	Has A
94	10671358	Multimedia	Application	Has A
93	10671358	Multimedia Application	Tools	used in

Fig. 8. Multimedia System & Application Terms.

Table II reflects the results of the test. The amounts of percentages with the amounts of precision and recall reflect promising results.

To quantify the user's satisfaction with the tool, the testing participants are asked to fill out a questionnaire with the following questions (answers to the questions are on scales from 1 -the lowest- to 5):

1) How familiar are you with the course content and structure before using the system?
2) Did the system accurately reflect the courses' subject matter and complexity?
3) How easy was it to use the course comparison tool?
4) Were the recommendations or matches between courses clear and understandable?
5) Did the system provide accurate matches for the courses you were familiar with?
6) How much did using the system help you understand the similarities or differences between courses?
7) Would you recommend this tool to other students or educators for course comparison?

Table I reflects the answers scales of the test participants answers.

TABLE I
Percentages of scales for the participants' answers.

Questions #	Scale 1	Scale 2	Scale 3	Scale 4	Scale 5
Q1	0%	3%	5%	18%	74%
Q2	0%	2%	2%	20%	76%
Q3	1%	0%	6%	18%	75%
Q4	2%	10%	2%	15%	71%
Q5	0%	0%	12%	12%	76%
Q6	0%	0%	10%	25%	65%
Q7	2%	2%	0%	5%	91%

VI. Conclusion

Ultimately, we show that the process of identifying alternative academic courses is much enhanced by our Ontological Comparison Based Approach. By applying a methodical algorithm to compare ontological edges in course descriptions, our technology offers an informed and sophisticated tool for course selection. This streamlines a labor-intensive process by providing users with an easy-to-use interface and a useful method of filtering courses based on predetermined similarity levels. By using machine learning approaches, the system's capacity to adjust to evolving educational environments may be increased in the future, and similarity metrics may be improved.

For future works, expanding the ontology to cover a broader range of disciplines will make the approach more universally applicable. Additional ontologies will be added to cover all of the universities' majors. Moreover, further improvements could include methods for handling incomplete or vague descriptions. Ontology creation for each course is effort and time-consuming, we could rely on some work

TABLE II
A LIST OF COURSES AND THEIR ALTERNATIVES WITH THE AMOUNTS OF SIMILARITY PERCENTAGES AND THE VALUES OF PRECISION AND RECALL.

Course Name	**Alternatives**	**Similarity Percentage**	**Precision**	**Recall**
Internet Programming	Web Programming	89%	0.91	0.92
	Full-Stack Development	62%	0.84	0.89
	Web Application Development	86%	0.89	0.81
Data Structures	Data Structures and Algorithms	91%	0.92	0.93
	Advanced Data Structures	75%	0.78	0.81
	Programming and Problem Solving	54%	0.61	0.71
Digital Design	Digital Circuits Design 1	93%	0.96	0.99
	Computer Architecture	82%	0.86	0.85
Database System Design	Database Systems	95%	0.85	0.82
	Data Modeling	64%	0.62	0.71
	Data Warehousing	45%	0.96	0.95
Introduction in Compiler Design	Computer Architecture	91%	0.85	0.81
	Microprocessor Design	65%	0.84	0.89
Cryptography and Computer Security	Cryptography and Network Security	86%	0.96	0.94
	Cybersecurity Fundamentals	65%	0.84	0.78
Image Processing	Computer Vision	84%	0.93	0.96
	Digital Signal Processing	74%	0.93	0.89
	Pattern Recognition	85%	0.91	0.96
Average:			0.86	0.87

related to automating the creation of ontologies to speed up the ontologies-building process so that the system embeds them in its courses matching process in which we plan to involve NLP techniques to extract the important ontology concepts.

REFERENCES

[1] S. Hayaeian and R. Hesarzadeh, "Knowledge management strategies, intellectual capital, and ambidextrous innovation capability in smes: Are they relevant?" *Journal of the Knowledge Economy*, vol. 15, no. 2, pp. 6832–6859, 2024.

[2] M. Malkawi, "Knowledge acquisition base learning: An interactive learning approach," *The Eurasia Proceedings of Science Technology Engineering and Mathematics*, vol. 16, pp. 132–139, 12 2021.

[3] S. Govender and O. A. Ajani, "Monitoring and evaluation of teacher professional development for resourceful classroom practices," *Universal Journal of Educational Research*, vol. 9, no. 4, pp. 870–879, 2021.

[4] Y. Yang, Y. Zhuang, and Y. Pan, "Multiple knowledge representation for big data artificial intelligence: framework, applications, and case studies," *Frontiers of Information Technology & Electronic Engineering*, vol. 22, no. 12, pp. 1551–1558, 2021.

[5] M. Console, P. Guagliardo, and L. Libkin, "Propositional and predicate logics of incomplete information," *Artificial Intelligence*, vol. 302, p. 103603, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0004370221001545

[6] I. Mikulić, D. Lisjak, and N. Štefanić, "A rule-based system for human performance evaluation: A case study," *Applied Sciences*, vol. 11, no. 7, 2021. [Online]. Available: https://www.mdpi.com/2076-3417/11/7/2904

[7] K. W. Fung and O. Bodenreider, *Knowledge Representation and Ontologies*. Cham: Springer International Publishing, 2023, pp. 367–388. [Online]. Available: https://doi.org/10.1007/978-3-031-27173-1-18

[8] A. Patel and N. C. Debnath, "A comprehensive overview of ontology: Fundamental and research directions," *Current Materials Science: Formerly: Recent Patents on Materials Science*, vol. 17, no. 1, pp. 2–20, 2024.

[9] R. Bernardo, J. M. Sousa, and P. J. Gonçalves, "A novel framework to improve motion planning of robotic systems through semantic knowledge-based reasoning," *Computers & Industrial Engineering*, vol. 182, p. 109345, 2023.

[10] L. Addazi, A. Cicchetti, J. D. Rocco, D. D. Ruscio, L. Iovino, and A. Pierantonio, "Semantic-based model matching with emfcompare," in *Proceedings of the 10th Workshop on Models and Evolution co-located with ACM/IEEE 19th International Conference on Model Driven Engineering Languages and Systems (MODELS 2016), Saint-Malo, France, October 2, 2016*, ser. CEUR Workshop Proceedings, T. Mayerhofer, A. Pierantonio, B. Schätz, and D. Tamzalit, Eds., vol. 1706. CEUR-WS.org, 2016, pp. 40–49. [Online]. Available: https://ceur-ws.org/Vol-1706/paper6.pdf

[11] X. Xue, W. Zhang, and A. Fan, "Comparative analysis of gene ontology-based semantic similarity measurements for the application of identifying essential proteins," *Plos one*, vol. 18, no. 4, p. e0284274, 2023.

[12] S. Mhatre, S. Satre, M. Hajare, A. Hire, A. Itankar, and S. Patil, "Text comparison based on semantic similarity," in *2023 3rd International Conference on Intelligent Technologies (CONIT)*, 2023, pp. 1–5.

[13] A. Maedche and S. Staab, *Comparing ontologies-similarity measures and a comparison study*. AIFB, 2001, vol. 6.

[14] Z. Cui, E. Damiani, and M. Leida, "Benefits of ontologies in real time data access," in *2007 Inaugural IEEE-IES Digital EcoSystems and Technologies Conference*, 2007, pp. 392–397.

[15] M. A. Osman, S. A. Mohd Noah, and S. Saad, "Ontology-based knowledge management tools for knowledge sharing in organization—a review," *IEEE Access*, vol. 10, pp. 43 267–43 283, 2022.

[16] A. Patel and S. Jain, "Present and future of semantic web technologies: a research statement," *International Journal of Computers and Applications*, vol. 43, no. 5, pp. 413–422, 2021. [Online]. Available: https://doi.org/10.1080/1206212X.2019.1570666

[17] X. Chen, D. Zou, G. Cheng, and H. Xie, "Deep neural networks for the automatic understanding of the semantic content of online course reviews," *Education and Information Technologies*, vol. 29, no. 4, p. 3953–3991, jun 2023. [Online]. Available: https://doi.org/10.1007/s10639-023-11980-6

[18] J. Wang and Y. Dong, "Measurement of text similarity: A survey," *Information*, vol. 11, no. 9, 2020. [Online]. Available: https://www.mdpi.com/2078-2489/11/9/421

[19] C. T. Machado and A. A. Carvalho, "Concept mapping: Benefits and challenges in higher education," *The Journal of Continuing Higher Education*, vol. 68, no. 1, pp. 38–53, 2020. [Online]. Available: https://doi.org/10.1080/07377363.2020.1712579

[20] M. Cristani and R. Cuel, "A survey on ontology creation methodologies," *International Journal on Semantic Web and Information Systems (IJSWIS)*, vol. 1, no. 2, pp. 49–69, 2005.