GENERATING EXPLANATORY TEXTS ON RELATIONSHIPS BETWEEN SUBJECTS AND THEIR POSITIONS IN A CURRICULUM USING GENERATIVE AI

Ryusei Munemura[1], Fumiya Okubo[2], Tsubasa Minematsu[3], Yuta Taniguchi[4] and Atsushi Shimada[2]
[1]*Graduate School of Information Science and Electrical Engineering, Kyushu University, 744, Motooka, Nishi-ku, Fukuoka 819-0395, Japan*
[2]*Faculty of Information Science and Electrical Engineering, Kyushu University, 744, Motooka, Nishi-ku, Fukuoka 819-0395, Japan*
[3]*Promotion Office for Data-Driven Innovation, Kyushu University, 744, Motooka, Nishi-ku, Fukuoka 819-0395, Japan*
[4]*Section of Educational Information Research Institute for Information Technology, Kyushu University, 744, Motooka, Nishi-ku, Fukuoka 819-0395, Japan*

ABSTRACT

Course planning is essential for academic success and the achievement of personal goals. Although universities provide course syllabi and curriculum maps for course planning, integrating and understanding these resources by the learners themselves for effective course planning is time-consuming and difficult. To address this issue, this study proposes a method that uses generative AI to classify relationships between subjects and generate explanatory texts describing the connections of subjects and positions of subjects within the curriculum based on subject and curriculum information. An evaluation experiment involving learners demonstrated a classification accuracy of approximately 70% for inter-subject relationships. Furthermore, our experimental results confirm that that the generated explanatory texts significantly enhance the understanding of relationships between subjects, and are thus effective for course planning.

KEYWORDS

Course Planning, Syllabus, Curriculum, Generative AI, Classification of Course Relationships, Text Generation

1. INTRODUCTION

Course planning, which involves the selection of subjects from a wide range of options based on one's interests and concerns, is important because it facilitates personal achievement for the learner. As the number of subjects that students can take in higher education has been increasing, students may find it more complex to decide on courses that align with their goals and interests (Farzan and Brusilovsky, 2007). Furthermore, it has been suggested that similar course titles can lead to different career paths, making it essential to grasp the content and objectives of the courses in the course planning process.

To mitigate these challenges, higher educational institutions such as universities provide information on subjects and curricula. For instance, detailed information on each subject is recorded in the syllabus, whereas curricular structures – including learning outcomes, learning opportunities, assessments, and teaching methods – are visualized on a curriculum map (Harden, 2001). However, integrating and understanding multiple educational resources by the learners themselves for appropriate course selection is tedious (Apaza et al., 2014). Additionally, because the curriculum map does not contain subject details, it must be cross-referenced with the syllabus to understand the educational relationships between subjects and curricula. Thus, providing explicit inter-subject information is meaningful from the perspective of supporting course planning.

Moreover, course planning is also important from the perspective of self-regulated learning (SRL). SRL refers to learners' abilities to plan, monitor, evaluate, and adjust their learning processes as needed to acquire academic skills or achieve personal goals, leading to a more effective and efficient learning experience (Zimmerman, 1998). Research shows that students with SRL skills tend to improve their academic performance, as well as maintain self-efficacy and motivation, throughout the learning process (Zimmerman, 2002). By planning their coursework, these students find it easier to achieve their academic goals (Cho, Tao, Yeomans, Tingley, and Kizilcec, 2024). Moreover, it has been reported that planning is positively associated to course completion and other personal learning objectives (Kizilcec, Pérez-Sanagustín and Maldonado, 2017). Thus, course planning represents an important activity in the context of SRL. However, many learners are yet to acquire sufficient SRL skills. In fact, approximately 75% of students were found to be undecided about career choices at the time of entering university (Cuseo, 2003).

To address these issues, this study proposes a method that uses generative AI to classify relationships between subjects and generate explanatory texts for these relationships. Specific types of relationships can provide useful information to foster a clearer perception of the subjects for learners, while explanatory texts vividly express the connections between subjects. Overall, this information can enable learners to understand connections with future subjects while reflecting on their current course enrollment status, thereby supporting learners with course planning and self-regulation.

2. RELATED WORK

2.1 Course Recommendation

Course recommendation has been widely researched as a common approach to academic planning, including methods using Latent Dirichlet Allocation (LDA) and regression models based on past academic performance (Apaza et al., 2014). LDA extracts latent topics from students' course histories and inputs them into a regression model to recommend the most suitable courses for individual students. This approach allows for more personalized recommendations by considering students' past performance patterns.

In addition, there are methods that create ontologies based on course information, such as syllabi, and use these ontologies to recommend courses (Jing and Tang, 2017; Ibrahim et al., 2018). Ontologies help clarify the relationships and prerequisites associated with courses, effectively aiding in the recommendation of courses that align with students' academic goals and interests. This makes it easier for students to select courses that are optimal for their educational objectives, while also facilitating smooth academic progress.

2.2 Syllabi and Curriculum Analysis

MIMA Search is a system that targets syllabi to search for and structure curricula, calculating subject similarities according to terms in syllabus documents and structured knowledge (MIMA, 2006). The processes of visualizing curricular structures and searching syllabi based on relatedness support course planning. The Curriculum Information System integrates subject information and learning management systems into a curriculum map to support inter-subject understanding, displaying keywords and links based on subject similarities (Yamamoto et al., 2021).

Some methods have been proposed to represent the relationships between subjects, or those between subjects and the curricula using graphs and keywords. However, these methods often fail to provide a detailed understanding of relationships and points of connection. Therefore, the present study was conducted to increase the specificity of inter-subject relationships and thus promote inter-subject understanding. The method proposed herein uses generative AI to classify inter-subject relationships into specific categories and explain these relationships in text form.

3. PROPOSED METHOD

The overall structure of the proposed method is illustrated in Figure 1, following the outlined steps.

(1) Collect subject and curriculum information from web syllabi and curriculum maps.
(2) Extract learning terms from subject information and calculate subject feature vectors using TF-IDF, then determine inter-subject similarities via cosine similarity.
(3) Use GPT to classify inter-subject relationships, as well as generate explanatory texts on these. relationships and the positioning of selected subjects within the curriculum.

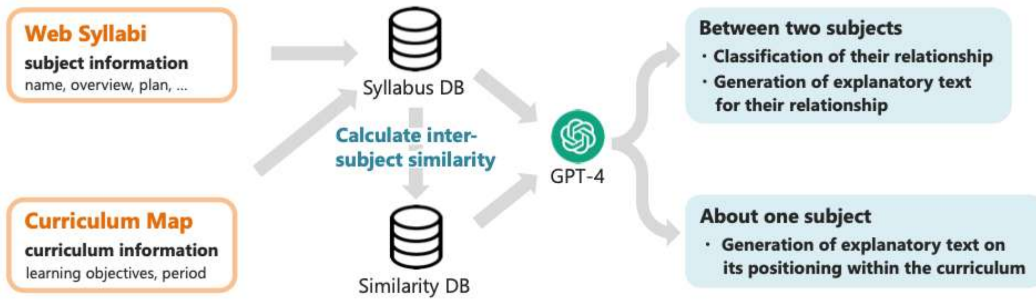

Figure 1. Overall workflow of proposed method

3.1 Collecting Subject and Curriculum Information

First, subject information was collected from Kyushu University's web syllabi, which contain basic information such as subject names and instructors, as well as subject descriptions and plans. Subject information was extracted from these syllabi to create a syllabus database. The curriculum map at our university visualizes the structure of the curriculum, direction and purpose of educational content, and learning objectives for each subject. We specifically collected the learning objectives and added them to the database.

3.2 Extracting Keywords and Calculating Inter-Subject Similarity

To capture the degrees of content-related relationships between subjects, the inter-subject similarity is calculated based on subject information. Initially, learning terms are extracted by analyzing the descriptions in the "subject description" and "subject plan" sections of the syllabus database. In the proposed system, text segmentation and morphological analysis are applied to extract only nouns and proper nouns as learning terms. Next, the TF-IDF (Ramos, 2003) values are calculated for each learning term. Feature vectors are created for each subject by arranging TF-IDF values for all terms represented in the subject information. Cosine similarity is then calculated between the feature vectors to determine inter-subject similarity. Similarity calculations are performed for all subject pairs, and the results are stored in a similarity database.

3.3 Classifying Inter-Subject Relationships and Generating Explanatory Texts

An overview of inter-subject relationship classification and explanatory text generation using GPT-4 is shown in Figure 2. Explanatory texts are generated using the following steps:

(1) Subject and curriculum information is described for two given subjects in the GPT prompt, including the overall ranking of inter-subject similarities. The types of relationships are defined in the prompt, enabling the GPT to select the appropriate relationship type.

(2) Based on the selected relationship type, a description is added to the prompt, and the subject information, curriculum information, and similarity ranking are re-entered to the prompt. Using this information, the GPT provides a detailed explanation of the relationship between the two subjects.

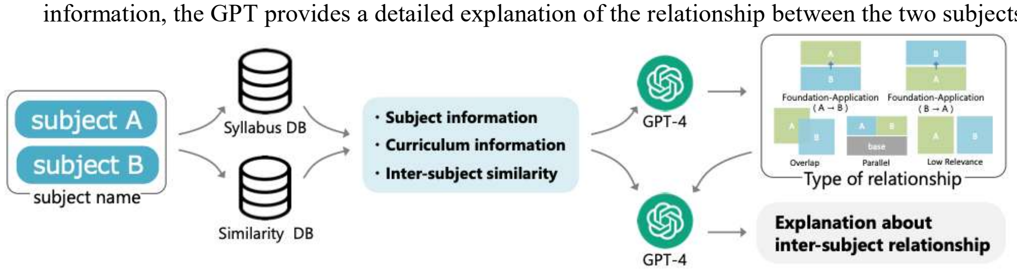

Figure 2. Overview chart of classifying inter-subject relationships and generating explanatory texts

ISBN: 978-989-8704-61-0 © 2024

3.3.1 Classifying Inter-Subject Relationships

First, the GPT is used to determine the types of relationships between two subjects. If the relationship type can be automatically determined, it will enhance the resolution of the generated text and potentially leads to a further examination of syllabi. The types of relationships between two subjects are defined as follows:

・ Foundation-Application (A → B): Subject A is foundational, and Subject B is an application of Subject A.
・ Foundation-Application (B → A): Subject B is foundational, and Subject A is an application of Subject B.
・ Overlap: Both subjects cover the same content but are not in a foundational-application relationship.
・ Parallel: Both subjects belong to the same field but have little direct connection.
・ Low-Relevance: The two subjects have little direct connection.

The descriptions and plans of two subjects and learning objectives are extracted from the syllabus database and included in the GPT prompt. The ranking of their inter-subject similarity from the similarity database is also included. The defined relationship types and their definitions are entered into the prompt, and the GPT generates the appropriate relationship type and reason in JSON format.

3.3.2 Generating Explanatory Texts on Inter-Subject Relationships

Next, based on the relationship type and reason obtained in the previous step, the descriptions of the two subjects, curriculum plans, learning objectives, and similarity ranking are included in the GPT prompt, which describes the selected relationship type and corresponding reasoning. The GPT then provides a detailed explanation of the relationship between the two subjects that encompasses their mutual commonalities, differences, overall relationships, and application techniques. Text generation follows a one-shot approach, wherein a template is provided to guide the text structure. An example of the explanatory text is presented in Figure 3.

共通点
オペレーティングシステムⅠと分散システムの講義は、両方とも情報工学の一部であり、コンピュータシステムの運用に関する知識を提供します。具体的には、両方の講義でプロセス管理、通信処理、同期処理などのトピックをカバーしています。また、学修目標も共通しており、実験や数値実験を適切に設計し、得られたデータを解釈して結論を導く能力や、電気情報工学分野における理論的、実験的、数値的な解析とモデリングの方法を理解し実行する能力を育成することを目指しています。

相違点
オペレーティングシステムⅠは、計算機を動作させる基盤ソフトウェアであるオペレーティングシステムの基本的な機能や構造に焦点を当てています。一方、分散システムは、IoTやクラウドサービスの基本となる分散処理の基本構成と要素技術について学びます。つまり、オペレーティングシステムⅠは一つのコンピュータシステムに焦点を当て、分散システムは複数のコンピュータシステムが連携して動作するシステムに焦点を当てています。

総合的な関連性
オペレーティングシステムⅠと分散システムの講義は「**基礎応用関係**」にあります。オペレーティングシステムⅠで学んだ知識は、分散システムの講義で学ぶ分散処理の基本構成や要素技術を理解するための基礎となります。例えば、オペレーティングシステムⅠで学んだプロセス管理や通信処理、同期処理などの知識は、分散システムで学ぶ分散処理の理解に直接役立ちます。したがって、オペレーティングシステムⅠは基礎となる講義であり、分散システムはその応用となる講義と言えます。

応用技術
例えば、オペレーティングシステムⅠで学んだプロセス管理の知識は、分散システムでの複数のコンピュータ間でのプロセスの分散管理に応用されます。また、通信処理や同期処理の知識は、分散システムでのコンピュータ間の通信や同期の管理に直接応用されます。これらの知識を組み合わせることで、効率的な分散システムの設計や運用が可能となります。

Commonalities
The courses "Operating Systems I" and "Distributed Systems" are both part of information engineering and provide knowledge about the operation of computer systems. Specifically, both courses cover topics such as process management, communication processing, and synchronization. They also share common learning objectives, aiming to develop the ability to design appropriate experiments and numerical experiments, interpret the obtained data to draw conclusions, and understand and execute theoretical, experimental, and numerical analysis and modeling methods in the field of electrical and information engineering.

Differences
"Operating Systems I" focuses on the basic functions and structures of operating systems, which are the foundational software that operate computers. In contrast, "Distributed Systems" focuses on the basic configuration and elemental technologies of distributed processing, which are fundamental to IoT and cloud services. In other words, "Operating Systems I" focuses on a single computer system, whereas "Distributed Systems" focuses on systems where multiple computer systems work together.

Overall Relationship
The courses "Operating Systems I" and "Distributed Systems" have a "fundamental and applied relationship." The knowledge learned in "Operating Systems I" forms the foundation for understanding the basic configuration and elemental technologies of distributed processing taught in "Distributed Systems." For example, knowledge of process management, communication processing, and synchronization learned in "Operating Systems I" is directly useful in understanding distributed processing in "Distributed Systems." Therefore, "Operating Systems I" can be considered a foundational course, while "Distributed Systems" can be seen as an applied course.

Applied Technologies
For instance, the knowledge of process management learned in "Operating Systems I" can be applied to the distributed management of processes across multiple computers in "Distributed Systems." Additionally, knowledge of communication processing and synchronization can be directly applied to the management of communication and synchronization between computers in "Distributed Systems." Combining this knowledge allows for the efficient design and operation of distributed systems.

Figure 3. Sample explanatory texts on inter-subject relationships. Left: Japanese original, Right: English translation

3.4 Generating Explanatory Texts on the Positioning of a Selected Subject Within the Curriculum

The generation of generating explanatory texts for the positioning of a selected subject within a curriculum is outlined in Figure 4. First, the year and the selected subject are given. Based on the year, the three subjects with the highest similarity are extracted from the similarity database and assumed to be related, representing a previously taken, currently taken, and future subject. Descriptions of the selected subject, as well as nine additional related subjects, are extracted from the syllabus database and included in the GPT prompt. By providing a prompt template and adopting a one-shot approach, the GPT generates explanations of relationships between the selected and related subjects, the flow of coursework, and the positioning of selected subject within the curriculum.

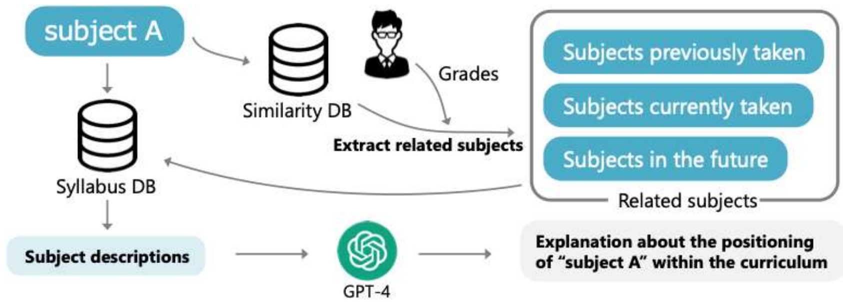

Figure 4. Overview of explanatory text generation on positioning within the curriculum

4. EXPERIMENTAL RESULTS & DISCUSSION

Experiments were conducted to evaluate the proposed method using subjects from the Computer Engineering Course of the Department of Electrical and Information Engineering at Kyushu University. The evaluation involved 43 third- and fourth-year students and course graduates. The evaluation aimed to determine the accuracy of classifying inter-subject relationships (Section 4.1), the effectiveness of generated explanatory texts in enhancing learners' understanding of these relationships (Section 4.2), and learners' preference for texts including the chronological positioning of subjects (Section 4.3).

4.1 Classification Accuracy of Inter-Subject Relationships

An evaluation questionnaire was administered to assess the classification accuracy of the five relationship types defined in Section 3.3.1. The evaluation targeted the eight subjects from the CM course curriculum listed in Table 1, with relationship types generated for the 28 pairs of subjects. Participants were presented with the "subject description" and "subject plan" from the syllabi, and asked to compare the learning content and select one relationship type for each subject pair. Based on the participants' responses, the most frequent relationship type selected for each subject pair was considered to be the ground truth.

Table 1. Courses to be evaluated for inter-subject relationships

Category	Subject name
system design	Operating system Ⅰ
	Computer system Ⅱ A
	Distributed system
signal processing	Digital signal processing
	Signals and Systems Ⅰ
foundation	Complex function theory
	Electro-informatics mathematics Ⅰ
exercises	Experiments in electrical and information engineering Ⅲ

Based on the ground-truth data obtained from the student responses, the accuracy of relationship classification was evaluated using the method described in Section 3.3.1. Because the GPT may generate somewhat inconsistent results, the classification of relationship types was performed 10 times for each of the 28 subject pairs, resulting in 280 classifications. The accuracy of these classifications was verified, and the results are presented in Table 2. The weighted average, which is the average of the product of each evaluation value and the amount of correct data, showed an accuracy of approximately 70%. Moreover, it was found that including the ranking of the subject similarity in the prompt improved accuracy for most metrics, demonstrating that the GPT can effectively consider the degree of relevance. Overall, these results confirm that the classification of inter-subject relationships can be performed with a reasonable level of accuracy.

Table 2. The evaluation of classification of relationship types

Type of relationships	Number in correct data	without inter-subject similarity				with inter-subject similarity			
		precision	recall	f1-score	accuracy	precision	recall	f1-score	accuracy
Foundation-Application(A → B)	30	0.52	0.77	0.62	0.77	0.52	**0.83**	**0.64**	**0.83**
Foundation-Application(B → A)	40	0.00	0.00	0.00	0.00	**0.25**	**0.07**	**0.12**	**0.07**
Overlap	30	0.28	0.37	0.31	0.37	0.28	0.37	0.31	0.37
Parallel	20	0.00	0.00	0.00	0.00	**0.30**	**0.15**	**0.20**	**0.15**
Low-Relevance	160	0.84	**0.98**	0.91	**0.98**	**0.88**	0.94	0.91	0.94
Weighted average	280	0.57	0.68	0.62	0.68	**0.65**	**0.69**	**0.65**	**0.69**

4.2 Evaluation of Explanatory Texts on Inter-Subject Relationships

We evaluated the explanatory texts generated for inter-subject relationships generated using the method described in Section 3.3.2 was conducted. Thurstone's paired comparison method (Thurstone, 1927) was adopted to assess the inclusion of subject information, response templates, learning objectives, and relationship types. Additionally, a five-point scale was used to determine whether the texts provided useful information to the students. The subjects targeted here were Operating system I, Distributed system, Signals and Systems I, and Electro-informatics mathematics I from Table 1.

4.2.1 Pair Comparison Method

The details of the paired comparison method used in this study are described here. This questionnaire was designed to analyze students' preferences for texts generated from five types of prompts.

Prompt A: Subject Description + Subject Plan
Prompt B: Subject Description + Subject Plan + Response Template
Prompt C: Subject Description + Subject Plan + Response Template + Learning Objectives
Prompt D: Subject Description + Subject Plan + Response Template + Relationship Type
Prompt E (Proposed Method): Subject Description + Subject Plan + Response Template + Learning Objectives + Relationship Type

For paired comparisons, students were shown all ten combinations of generated texts from the five prompts and asked to select the text they preferred. The questionnaire targeted four subjects, and six pairs of subjects were selected. Students compared 60 pairs in total, ensuring a random order and placement to avoid bias.

Responses from the paired comparisons were subjected to a consistency test. Combined with the agreement test described in the next section, the Bonferroni method was used to adjust the significance level from 5% to 2.5%, with responses not rejected at a 2.5% significance level considered inconsistent and excluded from further analysis. The percentage of inconsistent responses ranged from 21% to 42%.

For students whose responses were deemed consistent, an agreement test was conducted to verify whether their judgments of the generated texts were sufficiently consistent. If the judgments were found to be probabilistically consistent, the total rankings derived from these judgments were considered meaningful. The test results showed that for all subject pairs, the hypothesis stating that the students' judgments were consistent was supported at a significance level of 1.0%. Thus, low variability was observed in the ranking of generated sentences that students found desirable, and the calculated scale values can be considered reliable.

4.2.2 Scaling Preferences for Generated Texts:

The students' preferences for the generated texts were scaled using Thurstone's method, which calculates interval scale values from relative frequencies by applying a standard normal distribution to the data. The average scale values for the texts generated from the five prompts are listed in Table 3. Prompt E, the proposed method, was most preferred. This validates the proposed method, confirming that including subject description, plan, response template, learning objectives, and relationship type in explanatory texts is most effective.

Based on the proposed method, students rated a randomly selected description on a five-point scale. As described in Table 4, all students understood the relationship between the two subjects. Additionally, more 70% of the participants found the information useful for course planning. Thus, this method was found to effectively enhance inter-subject comprehension.

Table 3. Means of scaled preference values for generative sentences.

Prompt	A	B	C	D	E (Proposed method)
Average	-0.747	0.266	-0.041	0.202	0.320

Table 4. Ratings of the generated sentences explaining relationship between the two subjects (unit: %).
5: very much agree, 4: agree, 3: undecided, 2: disagree, 1: not at all agree

Evaluation item	Evaluation value				
	5	4	3	2	1
The relevance of the two subjects can be ascertained.	44.2	55.8	0.0	0.0	0.0
The information is useful for course planning.	23.3	53.5	16.3	7.0	0.0

4.3 Evaluation of Explanatory Texts on the Positioning of a Selected Subject

This evaluation targeted the explanatory texts generated using the method described in Section 3.4. Students assessed their text preferences using the subjects from Section 4.2, comparing texts with and without chronological context, with the results shown in Table 5. The proportion of texts generated by the proposed method ranged from approximately 40% to 80%. When the proposed method's texts did not clearly explain the relationships between subjects, texts without chronological context were generally preferred. Overall, considering the total percentage of responses, it was found that approximately 60% of students preferred the texts generated by the proposed method, indicating a preference for understanding subject positioning in line with the chronological order of their coursework. Moreover, Table 6 shows that more than 80% of participants found the randomly selected text useful for understanding subject relationships and positioning.

Table 5. Which generative statement is better for the selected one course and related courses (unit: %)

Subject name	Only related subject	Proposed method
Operating system Ⅰ	37.2	62.8
Computer system Ⅱ A	20.9	79.1
Distributed system	53.5	46.5
Digital signal processing	60.5	39.5
Signals and Systems Ⅰ	30.2	69.8
Complex function theory	44.2	55.8
Electro-informatics mathematics Ⅰ	37.2	62.8
Experiments in electrical and information engineering Ⅲ	34.9	65.1
Total Percentage of Responses	39.8	60.2

Table 6. Ratings of generative statements describing the position of one selected subject in the curriculum (unit: %).
5: very much agree, 4: agree, 3: undecided, 2: disagree, 1: not at all agree

Evaluation item	Evaluation value				
	5	4	3	2	1
Understand the relationship between courses already taken.	53.5	44.2	2.3	0.0	0.0
Understand the relationship between the course and the subject under study.	39.5	44.2	11.6	4.7	0.0
Understand the relationship between the course and future courses.	51.2	41.9	7.0	0.0	0.0
Understand the position of the subject in the curriculum.	44.2	44.2	9.3	2.3	0.0
The information is useful for course planning.	34.9	46.5	16.3	2.3	0.0

5. CONCLUSION & FUTURE WORK

We aim to support learners' course planning by clarifying relationships between subjects based on subject and curriculum information, using GPT-4. Our method involves three primary approaches. Firstly, relationships between pairs of subjects are classified to elucidate their connections and foster clearer perceptions of subjects, achieving an accuracy of approximately 70%. Second, explanatory texts are generated to help learners understand inter-subject relationships more concretely. The experimental results confirm that our method is most preferred through paired comparison, as it helps learners understand these relationships. Third, explanatory texts are generated to position a selected subject in the curriculum, allowing learners to understand its position in the curriculum. The results indicates that students generally prefer to understand the positioning of subjects in line with the chronological order of their coursework. Through these approaches, learners can understand connections with future subjects while reflecting on their current course enrollment status.

However, this study has several limitations. First, we used a one-shot approach without testing few-shot, leaving its reliability unverified. Second, we only used GPT-4, lacking comparisons with other models. Lastly, focusing on Computer Engineering Courses excluded humanities, leaving interdisciplinary use untested.

In future studies, we must verify the validity of the types of relationships defined between subjects. Furthermore, learners may have different evaluation criteria and information requirements, making it necessary to improve the system to present individually optimized information to learners, thereby enhancing interactivity.

ACKNOWLEDGEMENT

This work was supported by JST CREST Grant Number JPMJCR22D1, JSPS KAKENHI Grand Number JP22H00551 and JP22K19835, and Initiative for Life Design Innovation, Osaka University, Japan.

REFERENCES

Apaza, R. G., Cervantes, E. V., Quispe, L. V., and Luna, J. E. (2014). Online Courses Recommendation based on LDA. *Symposium on Information Management and Big Data*.

Cho, J. Y., Tao, Y., Yeomans, M., Tingley, D., and Kizilcec, R. F. (2024). Which Planning Tactics Predict Online Course Completion? *In Proceedings of the 14th Learning Analytics and Knowledge Conference (LAK '24). Association for Computing Machinery*, New York, NY, USA, pp. 360-370.

Cuseo, J. (2003). Academic advisement and student retention: Empirical connections and systemic interventions. *National Academic Advising Association*, pp. 2019-01.

Farzan, R. and Brusilovsky, P. (2006). Social Navigation Support in a Course Recommendation System. *International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems*. Berlin, Germany, pp. 91-100.

Harden, R. M. (2001). AMEE Guide No. 21: Curriculum mapping: a tool for transparent and authentic teaching and learning. *Medical teacher*, 23(2), pp. 123-137.

Ibrahim, M. E., Yang, Y., Ndzi, D. L., Yang, G., and Al-Maliki, M. (2018). Ontology-based personalized course recommendation framework. *IEEE Access*, vol.7, pp. 5180-5199.

Jing, X. and Tang, J. (2017). Guess you like: course recommendation in MOOCs. *Proceedings of the international conference on web intelligence*. New York, USA, pp. 783-789.

Kizilcec, R. F., Pérez-Sanagustín, M., and Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & education*, vol.104, pp. 18-33.

Mima, H. (2006). MIMA search: a structuring knowledge system towards innovation for engineering education. *Proceedings of the COLING/ACL 2006 Interactive Presentation Sessions*. Sydney, Australia, pp. 21-24.

Ramos, J. (2003). Using tf-idf to determine word relevance in document queries, *Proceedings of the first instructional conference on machine learning*, Vol. 242, No. 1, pp. 29-48.

Thurstone, L. L. (1927). A Law of Comparative Judgement, *Psychological Review*, Vol. 34, pp. 278-286.

Yamamoto, Y. [山本雄介], Minematsu, T. [峰松翼], Naganuma, S. [長沼祥太郎], Taniguchi, Y. [谷口雄太], Okubo, F. [大久保文哉], and Shimada, A. [島田敬士] (2021). Kamoku no kanrenseijouhou wo hukashita karikyuramujouhou etsurannsisutemu no kaihatsu [科目の関連性情報を付加したカリキュラム情報閲覧システムの開発. Development of a curriculum information browsing system with subject relevance information]， *IPSJ SIG Technical Report*, Vol. 2021, No. 9, pp. 1-8.

Zimmerman, B. J. (1998). Developing self-fulfilling cycles of academic regulation: An analysis of exemplary instructional models. In: Schunk, D. H., and Zimmerman, B. J. (eds.), *Self-Regulated Learning: From Teaching to Self-Reflective Practice, Guilford Press*, New York, USA.

Zimmerman, B. J. (2002). Becoming a Self-Regulated Learner: An Overview, *Theory into Practic*e, Vol. 41, No. 2, pp. 64-70.