LEVERAGING CHATGPT FOR AUTOMATED KNOWLEDGE CONCEPT GENERATION

Tianyuan Yang, Baofeng Ren, Chenghao Gu, Boxuan Ma and Shin'ichi Konomi
Kyushu University, Japan

ABSTRACT

As education increasingly shifts towards a technology-driven model, artificial intelligence systems like ChatGPT are gaining recognition for their potential to enhance educational support. In university education and MOOC environments, students often select courses that align with their specific needs. During this process, access to information about the knowledge concepts covered in a course can help students make more informed decisions. However, manually constructing this knowledge concept information is a labor-intensive and time-consuming task. In this paper, we explore the capability of ChatGPT in generating relevant knowledge concepts from course syllabi and evaluate the accuracy and consistency of these AI-generated concepts against course content using four assessment techniques at both the concept level and course level. We investigate the feasibility of using ChatGPT-generated concepts as a direct educational resource, as well as their potential integration into broader educational technologies, such as interpretable course recommendation systems.

KEYWORDS

Educational Data Mining, Large Language Models, Knowledge Concepts

1. INTRODUCTION

In university and MOOC environments, learners typically have the autonomy to select courses based on their interests and educational goals. The concepts covered within a course play a pivotal role in informing these decisions, as they provide learners with insights into the course content and any prerequisites required (Ma et al., 2024). Institutions often provide students with detailed information to facilitate informed decision-making to help learners, including course syllabi and the key concepts associated with each course. However, course syllabi are usually prepared by instructors or academic departments, which is time-consuming and labor-intensive (Pan et al., 2017).

As educational paradigms continue to advance and increasingly integrate technology-driven methodologies, the role of AI systems such as ChatGPT in augmenting educational practices has garnered significant attention. Within the educational sphere, ChatGPT has been employed for generating simple code snippets and brief texts (Ehara, 2023), with studies suggesting that it delivers surprisingly high-quality outputs across a variety of tasks. Recently, there have been attempts to generate course-related information using AI models like ChatGPT in research (Gupta et al., 2023). However, despite its promising capabilities, ChatGPT's responses may still harbor factual inaccuracies or logical inconsistencies. For tasks such as code generation, essay composition, and other extensive text-based projects, educators or subject matter experts can typically review and rectify these errors. Nevertheless, when it comes to more straightforward outputs, such as course syllabi or lists of related knowledge concepts, even experienced educators may find it challenging to identify subtle inaccuracies (Alexander et al., 2023; Perkins et al., 2024).

In response to these challenges, our research aims to explore the feasibility of using ChatGPT to automatically generate high-quality knowledge concepts. In this paper, we explore the feasibility of applying ChatGPT within the educational domain, with a particular focus on its ability to generate relevant concepts from course syllabi. Our objective is to automatically extract key concepts that a course is designed to cover by inputting the course syllabus into ChatGPT, employing carefully designed prompt. This approach not only saves time but also reduces the need for extensive data collection, providing students with a more efficient way to understand and choose courses. The concepts generated by ChatGPT are subsequently compared to manually extracted knowledge concepts in a multi-dimensional analysis of their relevance. This comparison aims to evaluate the potential of ChatGPT in autonomously generating course-specific knowledge concepts. To determine the feasibility of utilizing ChatGPT-generated concepts as a direct educational resource for students and as a foundation for further technology-driven educational strategies, we employed two distinct levels of assessment. Our study addresses several critical questions:

- RQ1: How closely do the ChatGPT-generated knowledge concepts from course syllabi align with those manually generated by academic departments?
- RQ2: Are the ChatGPT-generated concepts comprehensible from a human perspective?
- RQ3: Can the ChatGPT-generated concepts accurately represent the core content of the course?

By investigating these questions, we aim to contribute to the growing body of knowledge regarding the application of AI technologies in education. Our findings indicate that ChatGPT is capable of generating high-quality knowledge concepts that not only assist students in understanding course content but also provide valuable insights for the development of more effective AI-driven educational tools, such as course recommender systems. This approach offers significant time savings and reduces the effort required for the manual generation of knowledge concepts.

2. RELATED WORK

The emergence of large language models (LLMs) like ChatGPT has opened new possibilities in education, including generating educational content, providing personalized learning experiences, and enhancing educational tools. Research has increasingly explored LLMs in various educational applications, such as course recommendation, content generation, and addressing data sparsity (Wu et al., 2024). For example, Yang et al. (2024) used ChatGPT to expand course concepts, enhancing the transparency and explainability of course recommendations. Ehara (2023) investigated the effectiveness of GPT-generated concepts in enhancing the explainability of course recommendations. The study found that while these concepts generally align with recognized curricular content, further refinement is required due to inconsistencies in accuracy. Barany et al. (2024) examined ChatGPT's potential in qualitative codebook development, comparing manual, automated, and hybrid approaches to assess their impact on code quality, reliability, and coding efficiency in educational research. Castleman et al. (2023) explored how integrating domain knowledge bases into GPT-based intelligent tutoring systems affects their accuracy and pedagogical abilities, finding that enhanced knowledge base access improves these systems' comprehension and communication, though they still fall short of human experts. Lin et al. (2024) focused on using GPT models, specifically through prompting and fine-tuning, to automatically generate explanatory feedback in tutor responses, aiming to improve tutor training programs' quality and effectiveness. Beyond its direct application in educational scenarios, ChatGPT can also be integrated into a range of educational tools.

The use of ChatGPT in course recommendation systems has become increasingly popular. Course recommendation in educational environments poses a multifaceted challenge, influenced by diverse factors such as career aspirations, skill enhancement goals, and credit requirements (Ma et al., 2021). Previous research (Wagner et al., 2023; Jiang et al., 2023; Yang et al., 2023) has leveraged various types of information to improve recommendation accuracy, but these efforts often encounter the challenge of data sparsity in educational datasets. Our research addresses this issue by automatically generating supplementary information through ChatGPT.

Despite these advancements, challenges persist in the application of LLMs in education. As highlighted by our study and others, the uncertainty surrounding the accuracy and relevance of AI-generated content underscores the necessity for ongoing improvement. Ensuring that LLM-generated concepts accurately reflect course content and effectively meet students' learning needs remains a crucial focus for future research. Our work explores the usability of ChatGPT for generating course knowledge concepts, which could potentially address the issue of data sparsity in educational datasets and, accordingly, enhance the performance of course recommendation systems.

3. METHOD

3.1 Dataset

In this paper, we utilized a dataset collected from the XuetangX MOOC platform Yu et al. (2020). After preprocessing the dataset, it included 683 courses and 25,161 distinct knowledge concept entities. Each course in the dataset is associated with a course description and several related knowledge concepts. An illustrative example of course information in the dataset is shown in Table 1. Based on the course information provided, we prompted GPT to generate the corresponding knowledge concepts for each course.

Table 1. An example of course information in XuetangX dataset

Course Name	Manual Knowledge Concept	Course Description
Principles and Development of Database Systems	Minimum Spanning Tree; Database Technology; Shortest Path	Database technology is a core component of various information systems such as business processing systems, e-commerce systems, management information systems, office automation systems, and big data application systems. It is also a crucial technical means for efficiently managing and utilizing data resources in an information society, supporting business processing, data analysis, information services, scientific research, and decision-making management. The educational objectives of this course are to help learners grasp the principles and development techniques of database systems, and cultivate students' engineering abilities in database design, programming, and innovative applications, thereby establishing their competencies in database application system development.

3.2 Prompting Structure

We utilized ChatGPT-3.5 to generate relevant knowledge concept entities for each course. To ensure that the responses were both accurate and engaging, we prompted ChatGPT to "respond as a teacher." When generating the knowledge concepts, we provided ChatGPT with the course name, course description, and existing knowledge concepts. The prompt used in our experiments is presented in Table 2.

Table 2. Prompt for generating knowledge concepts for each course

Role	Content
System	You are responded as a teacher to output relevant knowledge concepts of each course. Your task is to analyze course information to generate appropriate knowledge concepts to help students understand course content based on the course name, course description, and the relevant concepts. Extract and generate keywords that summarize the knowledge concepts related to the course content. Respond with the keywords in Chinese, separated by spaces.
User	Continue extracting the relevant concepts for the following course by considering the course description, cour: name, and existing concepts from a similar perspective. Course Name: {course name} Existing Concepts: {existing concepts} Course Description: {desc}
Assistant	**Response of ChatGPT-generated course knowledge concepts**

After designing prompts to generate course knowledge concepts using ChatGPT, we successfully generated a total of 27,120 distinct knowledge concepts, a figure comparable to the number of manually generated concepts. This equivalence in quantity enables us to conduct a follow-up assessment without introducing bias related to discrepancies in the number of concepts, thereby ensuring a more accurate and fair evaluation. Since the dataset was entirely in Chinese, the knowledge concepts generated were also in Chinese. For readability in this paper, we have translated these concepts into English. We select some representative manual concepts and ChatGPT-generated concepts as shown in Table 3.

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Table 3. The examples of manual concepts and ChatGPT-generated concepts

Course Name	Manual Concepts	ChatGPT-generated Concepts
Calculus	Exponential; Median Theorem; Polynomials; Fourier Series	Functions; Closed Interval; Definite Integral; Limit; Calculus
Pathophysiology	Infectious Disease; Bronchial Asthma; Myocardial Infarction	Disease Process; Metabolism; Systemic Pathophysiology
Introduction to Logic	Formal System; Dialectics of Nature; Axiomatization; Classification	Formal System; Dialectics of Nature; Objective Law; Ambiguity
Big Data Machine Learning	Optimization; Decision Problem; Random Variable; Convolution	Statistical Learning; Image Segmentation; Decision Theory
Principles of Economics	Cash; Policy; Consumer; Entrepreneur; Inflation; Redistribution Policy	Cash; Psychology; Market; Resource Allocation; Government Intervention
Principles and Development of Database Systems	Minimum Spanning Tree; Database Technology; Shortest Path	Database Technology; Big data application system; Database design

3.3 Evaluation

After generating the knowledge concepts for each course using ChatGPT, we evaluated the quality of the concepts generated by ChatGPT both at the conceptual level and the course level to determine their usability. While previous research (Ehara, 2024) has predominantly focused on concept-level assessment, and overlooking course-level evaluation, we contend that course-level assessment is equally critical. When selecting courses, students typically consider the overall knowledge offered by the course rather than focusing on individual concepts in isolation. Our concept-level assessments concentrated on the semantic similarities between individual concepts, whereas our course-level assessments examined the coherence and relevance of the concepts generated for the course as a whole. Specifically, we utilized a pre-trained term embedding corpus provided by Song et al. (2018). This corpus enabled us to obtain embeddings for each concept. By calculating the spatial distance between the embeddings of different concepts, specifically using cosine similarity, we were able to identify similar concepts.

4. RESULT

4.1 Concept-Level Similarity (RQ1 & RQ2)

In the first evaluation, we assessed the quality of the concepts generated by GPT at the concept level. We calculated each ChatGPT-generated concept's similarity to all other concepts in the dataset and identified the Top-K most similar concepts. We then determined how many of these similar concepts belonged to the same course as the GPT-generated concept. The underlying assumption is that concepts belonging to the same course are inherently more similar. This evaluation provided insight into the semantic coherence of the GPT-generated concepts within the context of each course.

The result of concept-level similarity is shown in Figure 1, which presents four histograms showing the distribution of match ratios for the Top-K similar concepts generated by GPT, where K is set to 10, 20, 50, and 100. The match ratio represents the proportion of similar concepts generated by GPT that also belong to the same course as the manual course concept. We can observe that (1) Across all four histograms, the majority of concepts have a low match ratio, concentrated between 0.1 and 0.3. This suggests that most of the top K similar concepts generated by GPT are only moderately aligned with the manual course concepts in the same course. (2) The concept-level evaluation shows that while GPT can generate related concepts, the relevance to the original course decreases as more similar concepts are considered. This could reflect the challenge GPT faces in accurately capturing the specific context or nuances of the course content.

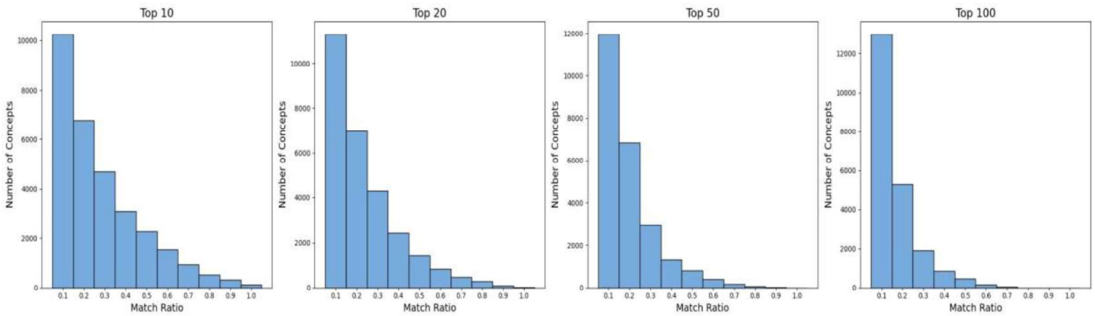

Figure 1. The distribution between match ratio and the number of concepts under different Top-K similar concepts

Given the challenges associated with accurately assessing the quality of concepts using only existing NLP techniques, we employed expert scoring to evaluate the knowledge concepts generated by GPT, thereby enhancing the credibility of our assessment. The evaluation process involved two experts independently scoring each automatically generated knowledge concept based on their expertise. To ensure the fairness of the assessment, we randomly selected 10,000 concepts across various domains due to the large volume of generated concepts. A 5-point scale was utilized, where higher scores indicated greater alignment of the generated concepts with the curriculum content. Given the diverse range of concepts sampled, the expert evaluation was informed by a combination of course descriptions, manually generated concepts, and ChatGPT-generated advice.

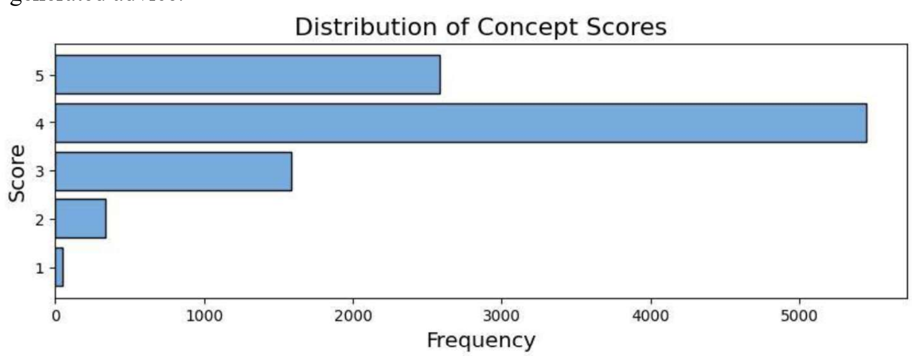

Figure 2. The distribution between expert scoring evaluation

The result of expert scoring is shown in Figure 2, which illustrates the distribution of expert scoring evaluation for 10,000 GPT-generated concepts, evaluated on a 5-point scale based on their relevance to the corresponding course. We can observe that (1) Only a small number of concepts received a score of 1 or 2, indicating minimal or no relevance to the course. Conversely, the majority of concepts were scored as 4, reflecting significant relevance and alignment within the same domain as the course. (2) The results from this expert evaluation indicate that GPT is largely capable of generating course knowledge concepts with high relevance, as evidenced by the concentration of scores at 4 and 5. However, the presence of a notable portion of mid-range scores indicates that there are still inconsistencies in concept relevance. These findings support the feasibility of using GPT-generated concepts in educational contexts, but they also highlight the need for further refinement to consistently achieve the highest levels of relevance and alignment.

Notably, the expert scoring evaluation experiment demonstrates that the GPT-generated concepts are indeed usable at the concept level, as evidenced by the high relevance scores assigned by experts. However, these findings present a contrast to the results from the earlier similarity-based evaluation. The discrepancy between the two outcomes suggests that the similarity experiment might be constrained by the limitations of similarity calculations, which rely heavily on embedding-based methods. These methods may not fully capture the nuanced and context-specific relationships between concepts, leading to lower similarity scores despite the expert evaluations indicating strong relevance. This highlights the importance of incorporating multiple evaluation approaches to fully understand the utility of AI-generated content in educational applications.

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4.2 Course-Level Consistency Evaluation (RQ3)

Next, we evaluated the generated concepts at the course level. Using pre-trained word embeddings, we computed the embeddings for both the manual course concepts and the GPT-generated concepts. For each course, we aggregated the embeddings of the manual concepts and the GPT-generated concepts separately. We then calculated the Top-K most similar courses for each course, based on both the manually generated and GPT-generated concept embeddings. By comparing the overlap between the two Top-K lists, we assessed the consistency of similar courses identified by the manually generated and ChatGPT-generated concepts. The manual course concept-based similarity was treated as the ground truth, providing a benchmark to evaluate the utility of the GPT-generated concepts.

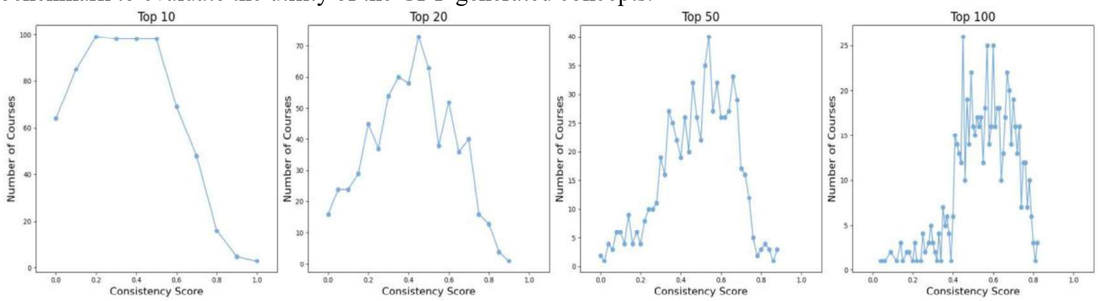

Figure 3. The distribution of consistency scores across different Top-K values (10, 20, 50, 100)

Figure 3 presents the distribution of consistency scores across different Top-K values (10, 20, 50, 100). The consistency score reflects the overlap between the lists of similar courses generated based on the manual course concepts and those generated using GPT-generated concepts. We can observe that the course-level evaluation results suggest that GPT-generated concepts are generally consistent with the manual course concepts when identifying similar courses. The high consistency scores across various K values indicate that the GPT-generated concepts can reliably represent the course content, making them useful for educational purposes.

We conducted a further course-level evaluation to determine whether the Top-K similar courses identified by GPT-generated concept embeddings corresponded with those identified by embeddings derived from manually created course concepts. Specifically, we calculated the cosine similarity between the embeddings derived from the GPT-generated concepts and those from the manually generated concepts, recording whether the original course was among the Top-K similar courses. A hit was recorded as 1, and a miss as 0. Hit Ratio (HR) analysis to further assess the effectiveness of GPT-generated concepts at the course level. The hit ratio measures the proportion of cases where the Top-K similar courses identified using GPT-generated concepts include the course identified using the manual concepts as a ground truth. This provides a direct measure of the alignment between the two sets of similar courses.

Table 4. The result of hit ratio (HR@K) analysis in different K values

Top-K	10	20	50	100
HR (%)	42.6061	48.6091	56.9546	63.9824

The result is shown in Table 4, we observe that (1) The hit ratio analysis supports the findings from the consistency score evaluation, demonstrating that GPT-generated concepts exhibit a high degree of alignment with manually generated course concepts. Therefore, GPT-generated concepts hold significant potential for enhancing course recommendation systems, especially when used in conjunction with a broader analysis that includes more similar courses. (2) As the value of K increases from 10 to 100, there is a steady improvement in the Hit Ratio, rising from approximately 42.6% at K=10 to 63.9% at K=100. This trend indicates that the GPT-generated concepts increasingly align with the original course content as a larger set of similar courses is considered. The growing Hit Ratio suggests that GPT-generated concepts become more reliable and consistent when the comparison includes more courses, demonstrating their potential to effectively capture the essential features of course content.

4.3 Discussion

The comprehensive evaluation of GPT-generated concepts involved four distinct yet complementary analyses: the concept-level similarity, expert scoring evaluation, the consistency score and the hit ratio. These analyses collectively provide a comprehensive understanding of the alignment and reliability of GPT-generated concepts concerning the manually generated course concepts.

The results from these four analyses suggest that GPT-generated concepts are generally effective in representing the content and context of courses, particularly at a broader, thematic level. While there may be some limitations in capturing finer details or specific nuances, the overall alignment with manual concepts reflected in both the consistency scores and hit ratios supports the use of GPT-generated concepts in educational applications. This result aligns with the previous research (Ehara, 2023). These concepts can reliably identify courses with similar content, making them a valuable tool for tasks such as course recommendation, curriculum development, and personalized learning pathways.

The evaluations indicate that GPT-generated concepts can serve as a useful complement to traditional concept-generation methods, particularly in large-scale educational environments where the need for automated, scalable solutions is paramount. However, for applications requiring high precision and specificity, further refinement of the GPT model's output may be necessary to ensure closer alignment with course-specific details.

We note that several researchers have attempted to leverage ChatGPT to address issues related to data sparsity in education, particularly in the context of interpretable course recommendation systems. Yang et al. (2024) have utilized ChatGPT to expand course concepts, aiming to enhance the transparency and interpretability of these systems. We argue that by providing well-defined and contextually relevant concepts to describe course content, AI-generated concepts can significantly aid students in understanding why certain courses are recommended to them. However, as observed in our evaluation, variations in the accuracy and relevance of these concepts indicate that further refinement is necessary to ensure that these systems can reliably recommend courses that genuinely meet students' learning needs and goals.

5. CONCLUSION

This study investigated the potential of GPT to generate knowledge concepts for educational purposes, evaluating the generated concepts through both concept-level and course-level analyses. The results indicate that GPT-generated concepts are generally of high quality, with expert evaluations confirming their relevance and utility at the concept level. However, the similarity-based evaluation revealed some discrepancies, likely due to the limitations of embedding-based similarity calculations, which may not fully capture the nuanced relationships between concepts. Despite these challenges, our findings suggest that GPT-generated concepts offer a promising solution for automating the time-consuming task of manual concept generation, holding significant potential for enhancing educational practices. As educational paradigms increasingly embrace personalized and technology-driven approaches, GPT-generated concepts could play a vital role in supporting direct teaching applications, potentially streamlining content creation and improving learning outcomes.

While our results are encouraging, it is important to note that GPT-generated concepts are not yet ready for direct implementation without further refinement. The variability in accuracy and relevance observed in our evaluations indicates that additional optimization is needed to ensure these concepts consistently meet the high standards required for educational use.

This study acknowledges some limitations, notably the lack of an efficient solution to the variability in the quality of ChatGPT-generated concepts. Although the generated concepts were validated through four assessment strategies, we did not conduct sufficient user studies to determine if students find these concepts reasonable. Future work will involve user evaluations to assess the applicability of these concepts in educational settings. Additionally, we aim to leverage this information to enhance digital education, such as by constructing a more informative knowledge graph for improving course recommendation systems to better guide student course selection.

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