ConRec: An Ontology-Based Recommender System for Concept Coverage in Education Enhanced with a Gamified Chatbot Interface

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Abstract. *This paper presents an improvement to ConRec, an ontology-based recommender system designed to personalize learning by ensuring concept-level coverage of educational content. The system models students and learning objects using an ontology enriched with pedagogical metadata and SWRL inference rules. To enhance usability and engagement, a gamified chatbot interface was integrated into the system. The solution was evaluated in a real classroom with Computer Science undergraduates, demonstrating high satisfaction levels, increased student engagement, and improved effectiveness in supporting learning and clarifying conceptual doubts.*

1. Introduction

In recent years, the increasing availability of digital learning resources has created new opportunities for personalized education through adaptive technologies. Among these, Recommender Systems (RS) have emerged as a promising solution to guide learners toward relevant educational content based on their profiles, preferences, and learning needs. In the educational context, recommending the right content at the right time is essential to optimize learning outcomes, particularly in environments where student support is limited or asynchronous.

Over the past few years, we have developed a recommendation system for personalized learning, which has progressively evolved in both recommendation quality and underlying ontological modeling [Belizário Júnior et al. 2023, Belizário Júnior et al. 2024]. The system models both learners and Learning Objects (LOs) using an educational ontology that incorporates pedagogical metadata, learning styles, and concept-based relationships. It addresses the Learning Object Recommendation Problem (LORP) by framing it as a Set Covering Problem (SCP), allowing for efficient selection of LOs that collectively cover all the concepts a learner needs to study.

Although previous computational evaluations have demonstrated the system's effectiveness in recommending concept-relevant resources, it lacked an interactive, user-

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facing interface and had not been tested with real students in authentic learning environments. As a result, its practical applicability and user acceptance remained unassessed.

To address these limitations, this study proposes the implementation of a chatbot-based interface module enhanced with gamification elements, aiming to make the interaction more engaging and motivating for students. The chatbot, named Anya, was integrated into the system as a natural communication channel to recommend LOs, collect user feedback, and guide learners through exercises and conceptual questions. Gamification was incorporated to encourage continued use and reduce the cold-start problem by incentivizing the completion of student profiles and interaction history.

Furthermore, we conducted a real-world classroom experiment with undergraduate Computer Science students to evaluate the system's usability, acceptance, and performance. The results indicate that the integration of the gamified chatbot significantly improves the educational experience, making the recommendation process more engaging and effective for learners. In particular, the recommended contents contributed to students' understanding of core course concepts and helped them resolve their questions more effectively, reinforcing the pedagogical alignment of the system's outputs. The system, along with its source code and ontology, is publicly available on GitHub, supporting further research and adaptation in other educational contexts. To guide this study, we address the following research question: RQ1: How does the integration of a gamified chatbot into an ontology-based recommender system influence learner engagement, satisfaction, and perceived learning support in real classroom settings?

The remainder of this paper is organized as follows. Section 2 presents the background concepts and related work on recommender systems, ontologies, and gamification. Section 3 describes the architecture of the ConRec system, while Section 4 details the new modules developed for chatbot interaction and gamification. Section 5 reports the experimental setup and results obtained in a real classroom scenario. Finally, Section 6 discusses the findings, limitations, and directions for future research.

2. Background and Related Work

Recommender systems (RS) in education often combine content-based, collaborative, and knowledge-based filtering techniques [Vanetti et al. 2010, De Medio et al. 2020, Tarus et al. 2017] to provide personalized recommendations of LOs for students. This recommendation process can be improved by using ontologies. Ontology-based approaches, supported by Semantic Web (SW) technologies such as OWL and SWRL [Berners-Lee et al. 2001, Horrocks et al. 2004], allow the representation of pedagogical metadata and reasoning rules, enabling concept-level recommendations aligned with learning objectives. Standards such as IEEE-LOM [LTSC 2002] and learning style models like FSLSM [Felder et al. 1988] further enhance personalization by describing LOs and student preferences.

Research in educational resource recommendation frequently integrates recommendation techniques with ontologies and the Web, including Wikipedia, as shown in Table 1. Wiki content can be recommended to teachers for course creation [Limongelli et al. 2015] or recommended to students [Belizário Júnior and Dorça 2018]. In this previous work, we defined LORP as an SCP and addressed it using a Genetic Algorithm (GA). Subsequently, in [Pereira et al. 2020], we also solved it using the Prey-

Predator Algorithm (PPA) [Tilahun and Ong 2015] and Particle Swarm Optimization (PSO). In [Falci et al. 2019], this problem was approached using a greedy heuristic algorithm that selects LOs based on the student's learning style while covering a broad range of concepts. The heuristic algorithm is faster than GA, particularly for larger instances with thousands of LOs. However, GA-based solutions, such as the Compatible Genetic Algorithm (CGA) proposed in [Christudas et al. 2018] for LO delivery, can be effective when LORP is not based on SCP.

Table 1. Comparison of related literature with the proposal of this work

Reference	A	B	C	D	E	F	G
[Limongelli et al. 2015]	x		x				x
[Graesser 2016]						x	x
[Christudas et al. 2018]	x		x				x
[Falci et al. 2019]	x	x	x				
[Ruan et al. 2019]						x	x
[Ayedoun et al. 2019]						x	x
[Mendes et al. 2019]					x		x
[Moreira et al. 2022]					x		x
[Belizário Júnior et al. 2023]	x	x	x	x		x	
[Kingchang et al. 2024]			x			x	x
[Gomaa et al. 2024]		x	x		x		
[Belizário Júnior et al. 2024]	x	x	x	x		x	
Our proposal	**x**	**x**	**x**	**x**	**x**	**x**	**x**

A - Web content reuse; B - Use of Semantic Web technologies; C - Personalized recommendation;
D - LOs coverage using fine-grained concepts from different areas of knowledge;
E - Gamification; F - Chatbot; G - Approach tested in a real scenario.

Beyond algorithmic improvements, enhancing learner engagement has become a key objective in modern RS research. Gamification and conversational agents have emerged as promising solutions. [Ruan et al. 2019] introduced QuizBot, a dialogue-based system delivering quiz-style questions, but with limited adaptability to different learner profiles or instructional paths. [Moreira et al. 2022] explored the use of badges and leaderboards to motivate learners in MOOCs, yet without connecting these elements to content recommendation.

[Kingchang et al. 2024] proposed an AI chatbot platform aimed at guiding prospective students in selecting suitable academic programs based on their aptitudes and interests. The system responds to user questions such as "What field should I study?" by applying topic modeling and machine learning to recommend areas of study aligned with student profiles. While effective for academic guidance at the institutional level, the system does not address conceptual learning needs or provide support for resolving course-related questions. In contrast, our approach focuses on concept-level recommendations tailored to individual learners' profiles and learning gaps, using ontological reasoning and interactive feedback through a gamified chatbot.

A different perspective was presented by [Gomaa et al. 2024], who proposed a teacher-centered RS to assist in the design of gamified activities using ontology-enhanced CF. While this supports content planning, it does not adapt to student feedback in real time or facilitate direct learner interaction. Our system fills this gap by introducing a gamified chatbot that responds to natural-language queries, identifies knowledge gaps through ontological inference, and delivers dynamically personalized LOs.

To test the quality and usability of our RS in a real scenario, with undergraduate Computer Science students, we implemented a chatbot called Anya. In the teaching-learning context, chatbots can simulate human tutoring [Graesser 2016], motivate students to learn about course content [Ruan et al. 2019] and increase students' willingness to communicate when they are learning a new language [Ayedoun et al. 2019]. Furthermore, we use gamification to increase student engagement. Several studies in the literature suggest that gamification increases student motivation and engagement [Mendes et al. 2019] and leads to increased interest and perceived competence among students, thus promoting a more engaging and effective learning environment [Moreira et al. 2022].

These studies illustrate the evolution from behavior-based and content-based recommender systems to more structured, explainable, and pedagogically aligned approaches. Building on our previous work, where the Learning Object Recommendation Problem (LORP) was modeled as a SCP [Belizário Júnior and Dorça 2018, Belizário 2018, Pereira et al. 2020, Belizário Júnior et al. 2020] and ontologies enriched with pedagogical metadata and learning styles were employed [Belizário Júnior et al. 2023, Belizário Júnior et al. 2024, Belizário 2024], we now extend this approach by implementing and evaluating a fully functional, interactive, and gamified chatbot interface. Tested in a real classroom setting, the system demonstrated usability, pedagogical relevance, and effectiveness, while its modular and low-cost design supports transparency, reproducibility, and potential scalability to diverse educational contexts.

3. ConRec: A Concept-Coverage Recommender System for Learning Objects

The ConRec system is a hybrid recommender system designed to personalize educational content based on learners' profiles and conceptual needs. Its architecture (Figure 1) integrates: (i) ontology-based modeling and reasoning, (ii) a recommendation engine formulated as a SCP, and (iii) an interactive interface module. The ontology describes both learning objects and student profiles using IEEE-LOM and FSLSM standards, with SWRL rules enabling concept-level reasoning and explainable recommendations.

When no suitable content is available in the internal repository, ConRec can generate LOs dynamically from Wikipedia, annotating them with pedagogical metadata before inclusion in the ontology. The SCP-based engine then selects the minimal set of LOs covering all required concepts while aligning with learner profiles. Further implementation details, including ontology structure and optimization strategies, can be found in [Belizário Júnior et al. 2023, Belizário Júnior et al. 2024].

The complete source code, including the ontology, optimization engine, and interface modules, is publicly available on GitHub (https://github.com/clarivando/conrec) to support transparency, reproducibility, and further research.

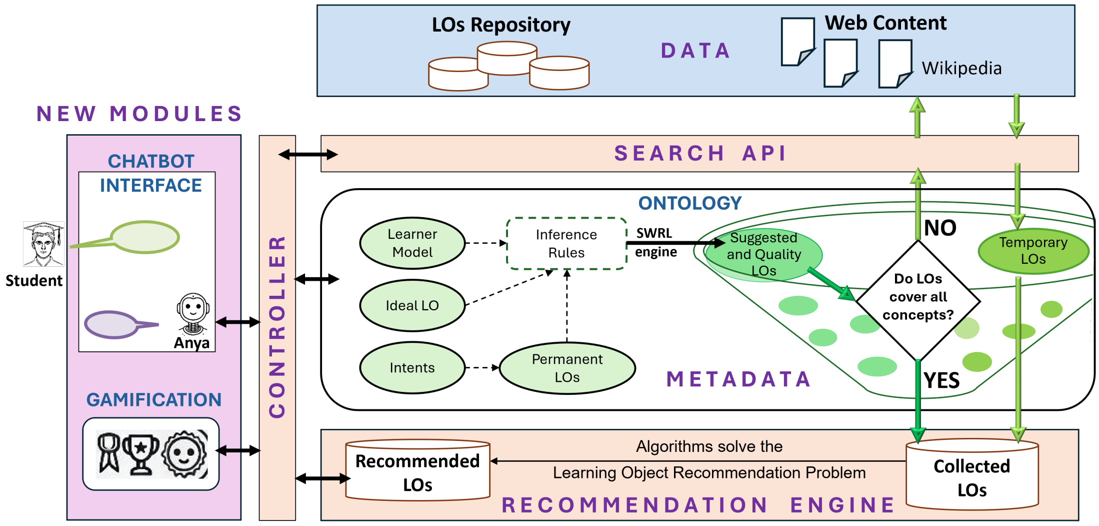

Figure 1. Overview of the proposed ConRec recommendation system

4. New Modules for ConRec: A Chatbot with Gamification for Real-World Use

To provide a user-friendly and engaging interface for the ConRec system, two integrated modules were developed: (i) a chatbot interface module, implemented in Python using the Microsoft Bot Framework, and (ii) a gamification module designed to enhance learner motivation through dynamic feedback and rewards. Both modules are coordinated by a central controller (see Fig. 1), which manages the recommendation workflow, user modeling, and the invocation of inference and optimization processes. This design ensures that recommendations are not only pedagogically aligned but also delivered in an interactive and motivating environment.

The chatbot, named Anya, was developed using the Microsoft Bot Framework and integrated into Moodle, enabling seamless communication between the learning management system and the ConRec backend. All requests made by students in natural language are processed by the chatbot and forwarded to the central controller, which queries the ontology and the SCP-based recommendation engine to generate learning object suggestions. This design ensures modularity: the chatbot is independent of the reasoning and recommendation layers, which facilitates future upgrades such as incorporating large language models (LLMs) for advanced natural language understanding.

The chatbot serves as the main access point for students. It mediates the communication between learners and the semantic reasoning engine, allowing users to request learning materials, clarify questions, and monitor their own progress. In the context of this work, Anya was trained in the domain of Procedural Programming (specifically, in the C language) and was integrated with Moodle, a widely adopted learning management system in universities.

The gamification module enhances the learning experience by awarding points, badges, and progress indicators based on the student's actions within the system. For example, when registering for the first time, the learner is prompted to answer at least 8 questions from the ILS questionnaire, which populates the user profile and mitigates the cold-start problem. Each answered question earns the student 1 point, encouraging them to gradually complete the full profile. Additionally, students also receive badges, for example, “Knows everything about you”, when they answer all ILS questions, which helps customize the recommended LOs according to each student’s learning style.

Students also accumulate points by interacting with content: 5, 10, or 15 points are awarded for correctly answering easy, medium, or difficult quiz questions, respectively; 3 points for clarifying a conceptual question or learning a new concept; and 2 points for evaluating recommended learning objects.

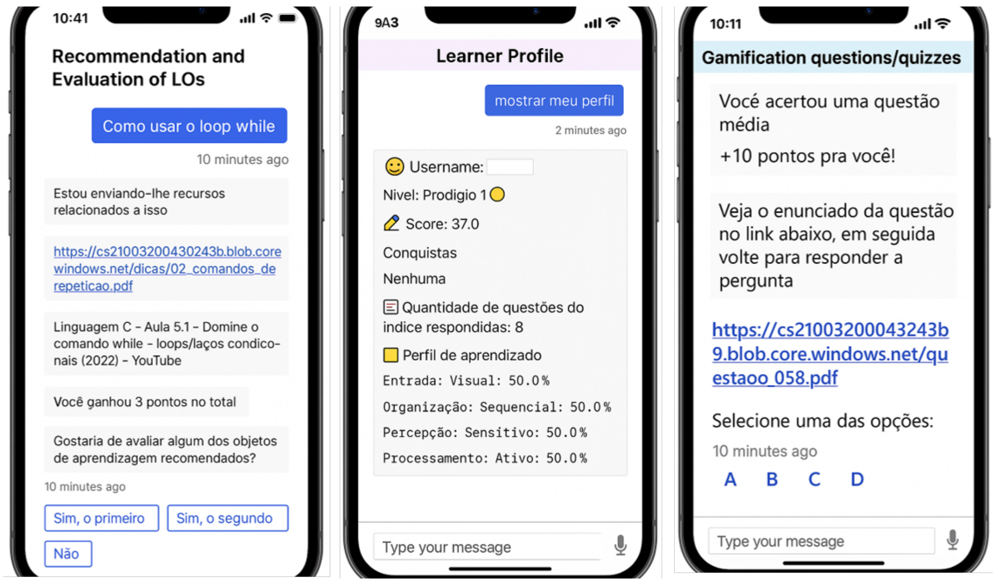

Figure 2. Anya chatbot interface with gamification

The gamification logic is deeply connected to the recommendation engine. For instance, when a student requests content by typing “how to use the while loop” (the first example in Fig. 2), the controller invokes the SCP-based recommendation algorithm, which selects three relevant LOs (e.g., two PDFs and one video) covering the target concept. The student can evaluate each LO on a scale from 1 to 5. This score is important to help filter quality LOs, especially for content derived from the Web with minimal human intervention. These evaluations are recorded and later used in collaborative filtering, influencing future recommendations for other learners with similar profiles.

In addition, Anya can present the student’s gamified profile, including their score, level, unlocked badges, learning style (as inferred from the ILS), and number of answered questions. By typing commands such as “I want to practice” students can interact with the system naturally while deepening their mastery of concepts. In practice mode, they may choose the number and difficulty of questions, receiving immediate feedback and additional points for each correct answer.

In the second example in Fig. 2, the student types: “show my profile” (in Portuguese), then Anya shows the student’s level, accumulated score and achievements, in addition to the number of ILS questions answered and their learning styles. Students are encouraged to put their acquired knowledge into practice by answering questions related to the subject (see the third example in Fig. 2). In this case, they type “I want to practice” and then select the level of difficulty and the number of questions they want to answer. Each correct answer increases their score and helps them earn badges.

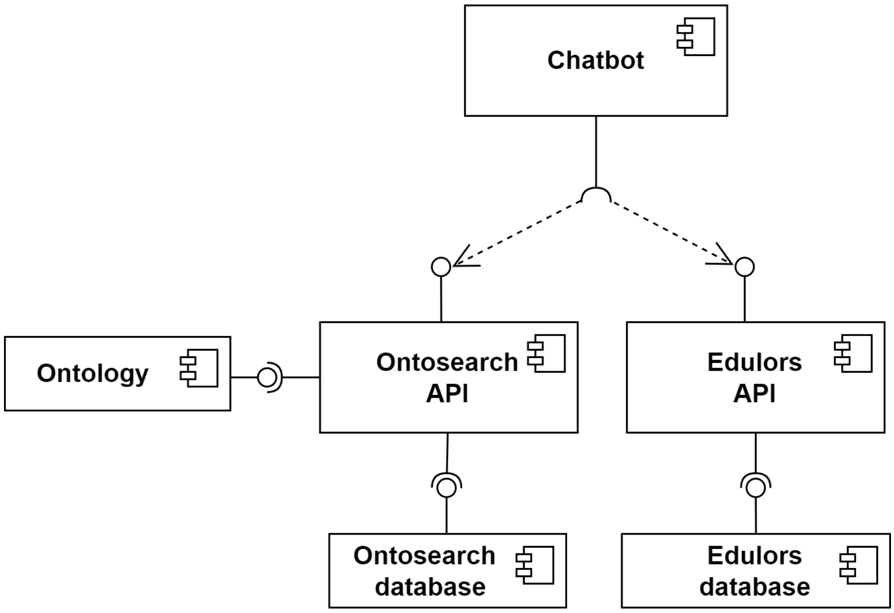

Figure 3. Component diagram of the recommender system

Fig. 3 illustrates the six main components of the system: Ontosearch API, Edulors API, Chatbot, Ontology, Ontosearch database, and Edulors database, all deployed on Microsoft Azure. Azure provides the infrastructure for managing, deploying, and scaling the system, while the ontology stores pedagogical metadata essential for inference-based recommendations. To improve efficiency, some information—such as learning object ratings and user interaction logs—is maintained in relational databases to reduce unnecessary ontology queries.

The Ontosearch API manages ontology-related operations, including retrieving LO metadata, capturing student profiles, saving ILS questionnaire responses, and performing web searches to augment LO coverage with external resources. The Edulors API handles LO recommendations, student evaluations, CRUD operations for LOs and concepts, and gamification data such as scores, levels, and achievements. Both APIs were documented using the Swagger toolkit, ensuring interactive documentation and robust endpoint testing for seamless integration.

The login workflow (Fig. 4) exemplifies the interaction flow: students provide their credentials to the chatbot, which forwards the request to the Ontosearch API for validation. The API queries the database and returns the result to the chatbot, which communicates the outcome to the user.

By combining conversational interaction, gamified incentives, and a modular API-based architecture, the new modules make the recommendation process more interactive, adaptive, and motivating. This integrated design ensures that LO recommendations are pedagogically aligned, technically scalable, and engaging for students, thus enhancing both the personalization and the effectiveness of the learning experience.

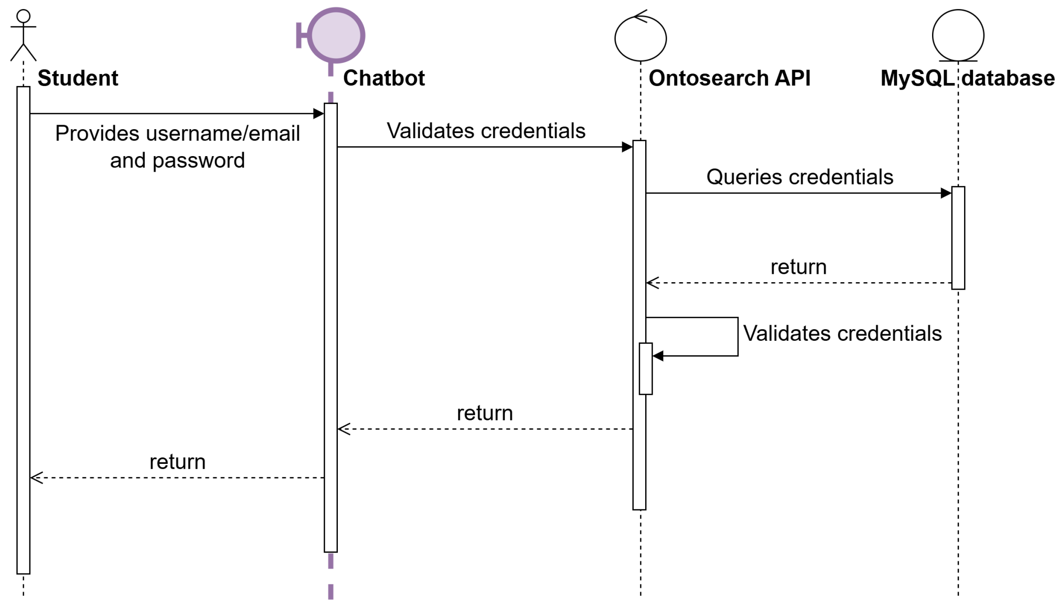

Figure 4. Sequence diagram of the login process

5. Experimental results: Learner satisfaction measure

The proposed recommendation system combined with the Anya chatbot was tested in a Procedural Programming class of the Computer Science course at the Federal University of Uberlândia. Thirty-two students agreed to participate in the research approved by the Ethics Committee (Protocol No. 57343822.0.0000.5152) and answered the Usability and Satisfaction questionnaire.

Fig. 5 shows the result of this evaluation on the Likert scale [Joshi et al. 2015] ranging from 1 (completely disagree) to 5 (completely agree). The height of the bars represents the average level of satisfaction of the class of 32 students in relation to each of the 16 statements. Most students expressed satisfaction with the system's usability, agreeing with 13 positive statements, while remaining neutral regarding three statements that pointed to some limitations of the system to clarify all student questions (Q3, Q4) and to present an attractive layout.

To better interpret the results, the questionnaire items were grouped into three thematic categories: Usability, Functionality, and Satisfaction & Engagement. This grouping allowed us to evaluate the system from multiple complementary dimensions, revealing how students interacted with it and perceived its pedagogical effectiveness.

The analysis of items related to Functionality, which assess whether the system effectively supports learning and helps clarify conceptual questions (e.g., Q3, Q4, Q5, Q7, Q8), showed the highest average score (M = 3.74). This indicates that students found the recommended content useful and aligned with their learning needs. High scores in Q5 ("The system provides reliable materials") and Q7 ("The recommended content was useful") further reinforce students' trust in the relevance and quality of the recommendations.

In the Usability category (e.g., Q2, Q12, Q13, Q14, Q15, Q16), which focuses on ease of use, clarity of recommendation logic, and interaction flow, the average score was also favorable (M = 3.62). Students considered the system intuitive, and items related to feedback interaction (Q13) and decision-making support (Q16) were particularly well rated. Lastly, the Satisfaction & Engagement category (Q1, Q9, Q11) presented positive results as well (M = 3.53), demonstrating general user satisfaction and willingness to continue using the system. The slightly lower score in Q11, regarding the chatbot's visual appeal, highlights an area for potential interface improvement. Overall, the findings validate the system's usability and pedagogical contribution within an authentic learning scenario.

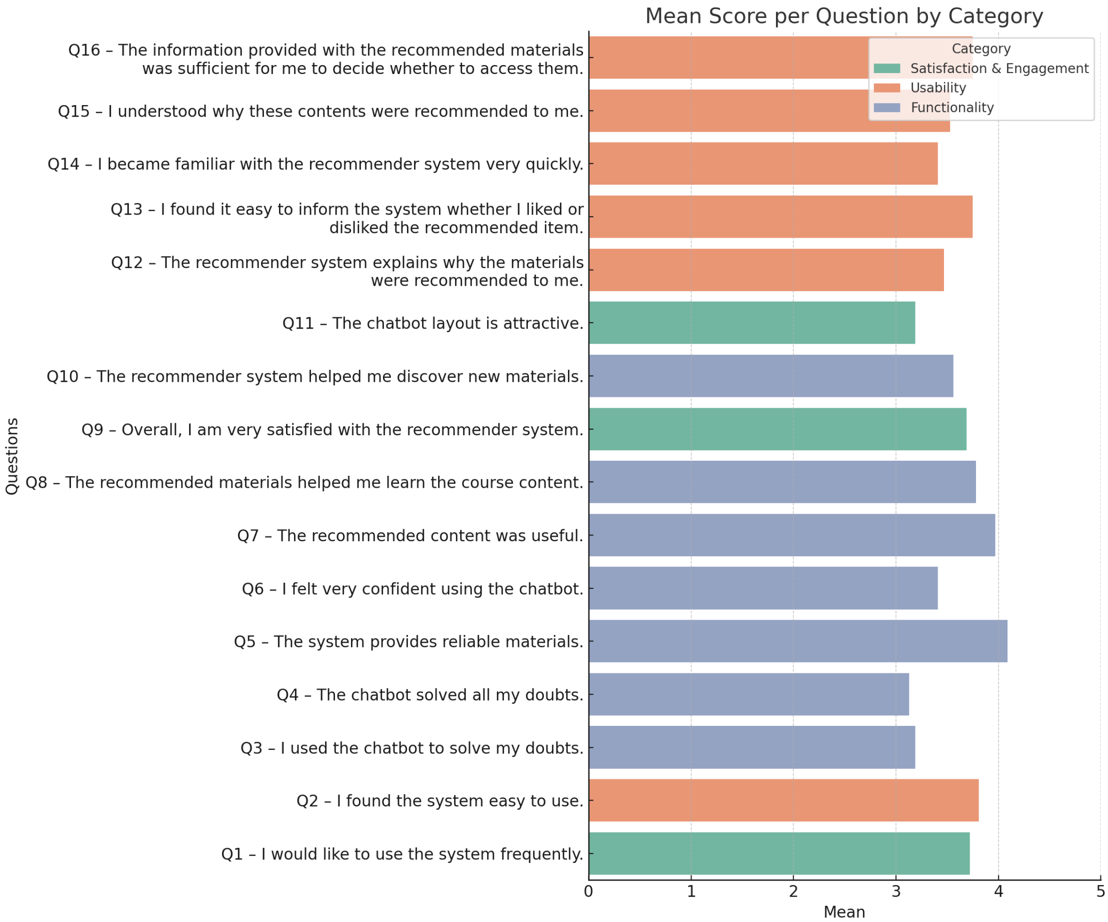

Figure 5. Learner feedback on ConRec by evaluation category

6. Discussion and Conclusions

This work presented ConRec, a concept-coverage recommender system that integrates ontological reasoning, optimization algorithms, and a gamified chatbot interface to support personalized learning. Unlike previous versions validated only through simulated experiments, the current system was tested with real students, demonstrating higher levels of engagement and satisfaction. The inclusion of chatbot and gamification modules fostered more frequent interaction with the platform, increased students' motivation to complete learning activities, and enhanced the perceived usefulness of the recommendations for clarifying conceptual doubts.

The system combines pedagogical modeling, semantic inference with SWRL rules, and a SCP formulation to generate LO recommendations tailored to learners' profiles and conceptual needs. Engagement and sustained use were further encouraged by introducing two user-facing modules—chatbot and gamification—coordinated by a central controller that manages system interactions and recommendation logic.

Evaluation in a real classroom with undergraduate Computer Science students confirmed the system's usability and pedagogical value. Results from the structured usability and satisfaction questionnaire indicated that students found the system intuitive, relevant, and helpful in understanding course topics. The Functionality category received the highest ratings, indicating that the recommended content effectively supported learning and conceptual clarification.

To answer RQ1, our findings demonstrate that integrating a gamified chatbot into the ontology-based recommender system significantly enhanced learner engagement and satisfaction while maintaining pedagogical alignment. Students valued the interactive features introduced by gamification, such as points, badges, and progress tracking, and reported that the recommendations effectively addressed their learning needs. These results suggest that combining semantic reasoning with conversational and motivational elements can create more engaging and effective learning experiences in real educational settings.

Despite these promising results, some limitations were identified. A few students remained neutral about the chatbot's ability to address all questions (Q3, Q4), highlighting the need for greater content diversity, response flexibility, and contextual adaptation. The interface's visual appeal also received lower scores, suggesting refinements to improve user experience. Additionally, potential response bias from the novelty effect or social desirability should be considered, and broader evaluations across diverse educational settings are needed to strengthen generalizability.

As future work, we will: (i) expand the recommendation domain beyond the C programming language to other subjects; (ii) enhance the chatbot's natural language processing capabilities using large language models (LLMs) to better handle open-ended questions; and (iii) integrate explainability features to help learners understand why specific objects were recommended. We also plan to deepen the integration with Moodle to support full-cycle adaptive learning experiences. The open-source availability of ConRec fosters reproducibility and invites collaboration from the educational technology community to scale and refine the solution across diverse contexts.

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References

Ayedoun, E., Hayashi, Y., and Seta, K. (2019). Adding communicative and affective strategies to an embodied conversational agent to enhance second language learners' willingness to communicate. *International Journal of Artificial Intelligence in Education*, 29(1):29–57.

Belizário, Júnior, C. F. (2018). Reúso de conteúdo da web na recomendação personalizada de objetos de aprendizagem: uma abordagem baseada em um algoritmo genético, tecnologias da web semântica e uma ontologia. Master's thesis, Universidade Federal de Uberlândia.

Belizário, Júnior, C. F. (2024). *An Approach to the Personalized Learning Objects Recommendation Problem as a Set Covering Problem Using Ontologies and Metaheuristics*. PhD thesis, Universidade Federal de Uberlândia.

Belizário Júnior, C. F. and Dorça, F. (2018). Uma abordagem para a criaçao e recomendaçao de objetos de aprendizagem usando um algoritmo genético, tecnologias da web semântica e uma ontologia. In *Brazilian Symposium on Computers in Education*, volume 29, pages 1533–1542, Fortaleza, CE. SBC.

Belizário Júnior, C. F., Dorça, F., Andrade, A. V., and Assis, L. P. (2020). Avanços na recomendação personalizada de objetos de aprendizagem através da utilização de meta-heurísticas clássicas associadas aos problemas de cobertura de conjuntos e de máxima cobertura: Uma análise experimental. In *Brazilian Symposium on Computers in Education*, volume 31, pages 1383–1392, Natal, RN. SBC.

Belizário Júnior, C. F., Dorça, F., Assis, L. P., and Andrade, A. V. (2024). Advances in personalised recommendation of learning objects based on the set covering problem using ontology. *International Journal of Learning Technology*, 19(1):25–57.

Belizário Júnior, C. F., Dorça, F. A., Assis, L., and Vivas, A. (2023). Solving the individualized instructional content delivery problem using ontology and metaheuristics on the set covering problem: An experimental analysis. In *Anais do XXXIV Simpósio Brasileiro de Informática na Educação*, pages 1202–1214. SBC.

Berners-Lee, T., Hendler, J., and Lassila, O. (2001). The semantic web. *Scientific american*, 284(5):34–43.

Christudas, B. C. L., Kirubakaran, E., and Thangaiah, P. R. J. (2018). An evolutionary approach for personalization of content delivery in e-learning systems based on learner behavior forcing compatibility of learning materials. *Tel. and Inf.*, 35(3):520–533.

De Medio, C., Limongelli, C., Sciarrone, F., and Temperini, M. (2020). Moodlerec: A recommendation system for creating courses using the moodle e-learning platform. *Computers in Human Behavior*, 104:106168.

Falci, S. H., Dorça, F. A., Falci, D. H. M., and Vivas, A. (2019). A low complexity heuristic to solve a learning objects recommendation problem. In *2019 IEEE 19th ICALT*, volume 19, pages 49–53. IEEE.

Felder, R. M., Silverman, L. K., et al. (1988). Learning and teaching styles in engineering education. *Engineering education*, 78(7):674–681.

Gomaa, Y., Moussa, S., Lahoud, C., and Abel, M.-H. (2024). Exploring recommender systems for assisting teachers in e-learning gamification. In *Procedia Computer Science*, volume 246, pages 2312–2321. Elsevier.

Graesser, A. C. (2016). Conversations with autotutor help students learn. *International Journal of Artificial Intelligence in Education*, 26(1):124–132.

Horrocks, I., Patel-Schneider, P. F., Boley, H., Tabet, S., Grosof, B., Dean, M., et al. (2004). Swrl: A semantic web rule language combining owl and ruleml. *W3C Member submission*, 21(79):1–31.

Joshi, A., Kale, S., Chandel, S., and Pal, D. K. (2015). Likert scale: Explored and explained. *British journal of applied science & technology*, 7(4):396–403.

Kingchang, T., Chatwattana, P., and Wannapiroon, P. (2024). Artificial intelligence chatbot platform: Ai chatbot platform for educational recommendations in higher education. *International Journal of Information and Education Technology*, 14(1):34–41.

Limongelli, C., Gasparetti, F., and Sciarrone, F. (2015). Wiki course builder: a system for retrieving and sequencing didactic materials from wikipedia. In *2015 Inter. Conf. on Inform. Tech. Based Higher Education and Training*, pages 1–6. IEEE.

LTSC (2002). Standard for learning object metadata (ieee 1484.12.1). *Learning Technology Standards Committee*.

Mendes, T., Pereira, L., Baranda, V. R., de Oliveira Julio, A. M., and da Silva, R. L. d. S. (2019). Uso de sistemas de gamificação no combate a evasão de cursos de graduação da área de exatas. In *Brazilian Symposium on Computers in Education-SBIE*, volume 30, page 733.

Moreira, S., Sousa, T., Silva, W., and Marques, A. B. (2022). Uma experiência de gamificação no ensino com o ambiente classcraft: análise da motivação dos estudantes. In *Simpósio Brasileiro de Informática na Educação (SBIE)*, pages 403–414. SBC.

Pereira, Júnior, C., Belizário, Júnior, C. F., Araújo, R. D., and Dorça, F. A. (2020). Personalized recommendation of learning objects through bio-inspired algorithms and semantic web technologies: an experimental analysis. In *Anais do XXXI Simpósio Brasileiro de Informática na Educação*, pages 1333–1342. SBC.

Ruan, S., Jiang, L., Xu, J., Tham, B. J.-K., Qiu, Z., Zhu, Y., Murnane, E. L., Brunskill, E., and Landay, J. A. (2019). Quizbot: A dialogue-based adaptive learning system for factual knowledge. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, pages 1–13.

Tarus, J. K., Niu, Z., and Yousif, A. (2017). A hybrid knowledge-based recommender system for e-learning based on ontology and sequential pattern mining. *Future Generation Computer Systems*, 72:37–48.

Tilahun, S. L. and Ong, H. C. (2015). Prey-predator algorithm: a new metaheuristic algorithm for optimization problems. *International Journal of Information Technology & Decision Making*, 14(06):1331–1352.

Vanetti, M., Binaghi, E., Carminati, B., Carullo, M., and Ferrari, E. (2010). Content-based filtering in on-line social networks. In *International Workshop on Privacy and Security Issues in Data Mining and Machine Learning*, pages 127–140. Springer.