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Integrating FHIR and UMLS in an Intelligent Tutoring System

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Abstract. Our novel Intelligent Tutoring System (ITS) architecture integrates HL7 Fast Healthcare Interoperability Resources (FHIR) for data exchange and Unified Medical Language System (UMLS) codes for content mapping.

Keywords. Intelligent Tutoring System, Interoperability, Medical Education, FHIR

1. Introduction

ITS have evolved substantially to enhance educational quality [1]. Our study introduces a novel ITS architecture that integrates and repurposes HL7 FHIR and UMLS, examining the potential benefits of their combined use in enhancing the adaptability, scalability, and overall effectiveness of an ITS for medical education, ensuring seamless data exchange, precise content mapping, and enhanced personalized learning experiences.

2. Methods

Our ITS uses FHIR version R4. We used *Patient* resources for learner information, *Goal* resources from a knowledge map for learning goals, and *CarePlan* for recommended next steps, activities, and Questionnaires. *Questionnaires* capture learners' knowledge states, and *QuestionnaireResponse* records their answers. To align learning materials with learners' goals, we mapped resources with UMLS codes and a score that represents the similarity of the meaning of the code to the coded learning content, utilizing FHIR core extension *Ordinal Value*. We implemented the ITS as a microservice architecture, all four ITS components are microservices, that expose a REST API with endpoints accepting and exposing FHIR resources as JSON.

3. Results

Figure 1 shows the communication flow of posing new questions to a student. The recommender drives the system's communication flow, fetching FHIR resources from the

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knowledge base, presenting questions, goals and content to the user and requesting the learner model to gauge the learners' progress. This makes the whole system horizontally scalable; multiple instances of the recommender and learner model can be initiated.

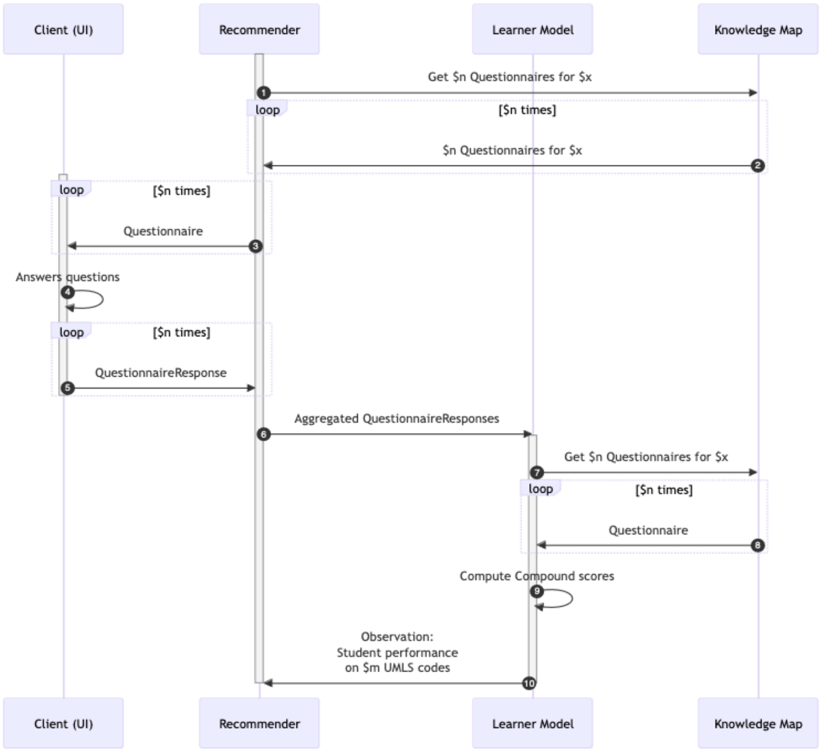

Figure 1. This sequence diagram illustrates the interaction between Client (UI), Recommender, Learner Model, and Knowledge Map. $n denotes aggregation count; $m signifies UMLS code count. It includes loops for questionnaire delivery and response collection, aggregated questionnaire responses, and the computation of compound scores based on UMLS codes. The Learner Model computes compound scores to assess student performance on $Sm-smoothed codes and sends these performance metrics back to the Recommender.

4. Conclusion

The implementation confirmed the use of FHIR and UMLS in an ITS beyond its initial scope. Next, we will evaluate the system's performance, create personalized learning paths with machine learning, and integrate the ITS into existing interoperable platforms to enhance learning environments.

References

[1] Alkhatlan A, Kalita J. Intelligent Tutoring Systems: A Comprehensive Historical Survey with Recent Developments. Int J Comput Appl. 2019 Mar 15;181(43):1–20.