Automation of learning outcome generation using a Large Language Model

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Abstract. Learning Outcomes are clear and specific statements about what students should know, understand, and be able to do at the end of a learning process. They are a fundamental pillar in curriculum design and competency assessment, ensuring coherence between teaching, learning, and evaluation. Their proper formulation is key to constructive alignment and educational planning. Traditionally developed through manual writing, learning outcomes present challenges such as structural variability, the lack of standardized guidelines, and the workload for educators. To address these difficulties, methodologies based on competency matrices, cognitive taxonomies, and tools such as analytical rubrics have been developed, facilitating the connection between competencies, teaching strategies, and assessment. However, the increasing need for standardization and efficiency in their formulation highlights the necessity of automating their generation. This article analyzes the writing process of learning outcomes and the feasibility of automation to improve coherence and applicability in higher education.

Keywords: education; assessment; competencies; artificial intelligence

1 Introduction

In recent years, competency-based curriculum design has emerged in academic settings as a student-centered learning approach. Its goal is to ensure the development of transferable and applicable skills in professional contexts. As part of this approach, Learning Outcomes (LOs) play a key role, as they precisely define what a student should have achieved by the end of a learning unit, ensuring coherence between teaching, learning, and assessment (Neil et al., 2023). The creation of LOs requires careful consideration. It requires alignment with the competency matrix, the expected level of mastery, and the instructional and assessment strategies of the course. The lack of standardized guidelines and the subjectivity in their formulation can lead to inconsistencies in interpretation. To address these challenges, various strategies have been implemented, including the use of competency matrices—which link graduation competencies to course-specific LOs—and cognitive taxonomies to select verbs based on the required level of cognitive complexity (Neil et al., 2023). Despite these advances, manually drafting LOs remains a demanding task for educators or those responsible for their creation, as they must ensure that the outcomes are measurable, coherent, and aligned with the student's graduate profile. In this context, automating the generation of LOs emerges as a necessary step to improve both accuracy and efficiency. This article explores the importance of LOs, the writing process, and the associated challenges, as well as the potential for using automation tools to support their generation.

2 Learning Outcome Writing Process

Before addressing the automation of LOs, it is essential to understand the process by which they are manually constructed. A notable challenge in this area is the absence of clear standards or guidelines in academic literature. This study draws on the model proposed by Prieto J.H.P (2012), which defines an LO structure comprising four key elements: a verb, a knowledge object, one or more intended purposes, and one or more reference conditions. Figure 1, adapted from Neil et al. (2023), illustrates the sequential steps that can be followed for effective LO development.

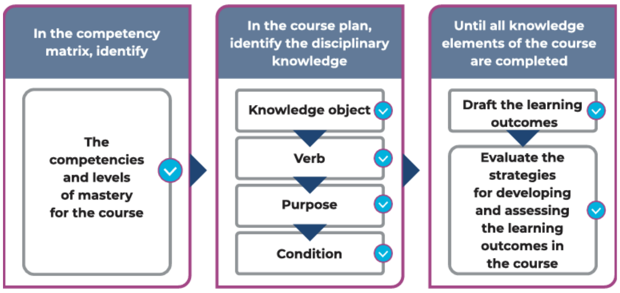

Fig. 1. Learning Outcome Writing Process (Neil et al., 2023).

The process is structured around five key steps. First, specific competencies and levels of mastery are identified using the course's competency matrix. Then, knowledge objects are defined by grouping the main topics of the course. Next, an appropriate verb is selected based on Bloom's taxonomy and the identified level of mastery. After that, the purpose of the LO is established, indicating its aim and application context. Finally, the conditions under which the LO will be assessed are defined, ensuring alignment with the course's methodologies and educational standards.

3 Need for Automation

The manual formulation of LOs involves multiple challenges. One of the main issues is the lack of uniformity in language and structure, which can lead to varied interpretations and complicate the assessment of learning. To address this difficulty, the use of competency matrices has proven to be an effective tool in the creation and evaluation of LOs. Nevertheless, automation emerges as a necessary solution to improve efficiency and precision in this process (Benites et al., 2023). In line with trends observed across multiple sectors, Large Language Models (LLMs) proven to be efficient tools for generating structured content. In the field of medicine, Li et al. (2023) developed a chatbot trained on clinical data and medical opinions, enhancing diagnostic accuracy. In the financial domain, Pavlyshenko (2023) implemented a news analysis model based on an LLM, enabling the extraction of key indicators and more accurate forecasting. Automating the writing of LOs using LLMs allows for greater time efficiency for instructors and improved alignment with competency frameworks. By leveraging databases containing validated LOs from the academic community, it is possible to generate new outcomes tailored to the objectives of each course. Furthermore, integration with dynamic knowledge bases facilitates continuous updates in response to curricular changes, thereby enhancing the overall quality of curriculum design in higher education.

4 Use of LLM and RAG for LO Generation

As previously mentioned, LLMs are a viable option for addressing the generation of LOs. These are artificial intelligence models trained on large volumes of data, enabling them to produce coherent and contextualized content. However, given the specialized nature of the LO, it is necessary to complement these models with additional information to ensure the accuracy of their responses. In this context, Retrieval-Augmented Generation (RAG) plays a key role. The RAG approach combines a generative model with a structured knowledge base, using specific data that allows the LLM to be more precisely contextualized. Although there are numerous proposals, this work is based on the study by Posedaru et al. (2024), who propose a text generation solution that applies fine-tuning to the response using the LangChain framework (Figure 2).

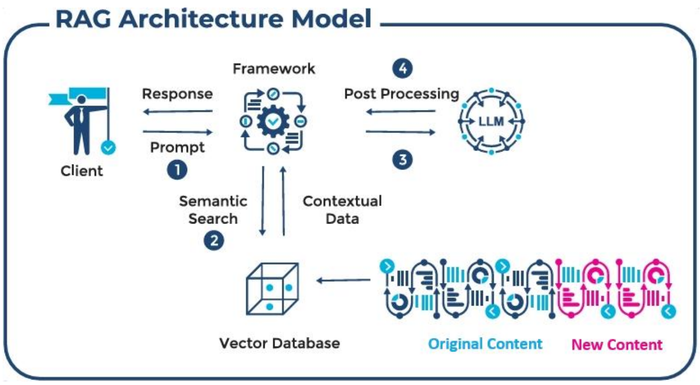

Fig. 2. Proposed model for LO generation using the RAG architecture. Based on Posedaru et al. (2024)

The main stages of the generation process are:

1) User query: A prompt is submitted for LO generation.

2) Semantic search: The query is converted into embeddings and relevant information is retrieved from a vector database.

3) Information retrieval: Relevant fragments are extracted and structured as context for the LLM.

4) LO generation: The LLM processes the retrieved information and generates an LO aligned with educational standards.

4.1 Model implementation

Preliminary results indicate a significant improvement in the coherence and accuracy of LO formulation, reducing the time required for manual writing while ensuring alignment with competency matrices and curriculum standards. Additionally, the combination of LLMs with RAG has proven effective in enhancing the contextualization of LOs, enabling the generation of more precise and relevant outcomes. These initial findings suggest that the model has the potential to optimize curriculum design and contribute to the standardization of LO writing across various academic disciplines.

Conclusion

The automation of LO creation using LLMs represents an innovative solution to the challenges of manual drafting. By integrating tools such as RAG and databases containing validated LOs, it is possible to enhance coherence, efficiency, and alignment with competency frameworks. Further exploration of its implementation and evaluation of its impact in educational settings represents a future line of research.

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