LD-EnactAI: Towards Generative AI-Enabled Smart Enactment of Learning Designs*

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Abstract

Generative AI (GenAI) tools are increasingly used by educators to plan and adapt educational resources. However, enacting learning designs (LDs) authored in dedicated LD authoring tools into deployable courses in virtual learning environments (VLEs) such as Moodle remains time-consuming and technically demanding, revealing a persistent translation gap. This paper introduces LD-EnactAI, a first version of a GenAI-enabled smart adapter architecture that aims to help educators enact their LDs in a VLE in a way that better addresses learners' and educators' needs through smart learning environment (SLE)-like, context-aware capabilities. LD-EnactAI combines educator preferences with an LLM-based transformation and preview loop to preserve the pedagogical intent of the original design while supporting human-centered decision-making before deployment. We also introduce LD-EnactAI within ABPxODS (an LD authoring tool), as an initial proof of concept, to translate the structured LDs into Moodle by exporting them in a Moodle-ready backup file format.

Keywords

Generative AI, Learning Design (LD), Moodle, Learning Analytics (LA)

1. Introduction

Educators spend a considerable amount of time on lesson preparation, as an OECD report indicates that full-time educators in Spain spend 7.7 hours per week in 2024, which is 1.3 hours more than in 2018 and slightly above the OECD average of 7.4 hours [1]. To manage their own time effectively in lesson planning, advances in educational technology have offered educators authoring tools, teacher community platforms with features to co-create and share Open Educational Resources (OERs), so they can adapt them to fit their own teaching needs [2]. However, such resources often are limited in terms of their interoperable support for their implementation or enactment in learning management systems or other virtual learning environments (VLEs) [3]. Although authoring tools use computational representations for the created learning design and, thus, offer potential to address transferable lesson plans, LD tools alone have remained limited adoption by educators, as they are hard to deploy LDs in VLEs, such as Moodle [1], where educators implement their courses [3, 4].

This highlights a translation gap between LDs and VLEs. To mitigate this challenge, GLUE!-PS offered a multi-tier architecture and data model that introduce adapter patterns, which allow contextual customization and are designed to deploy LDs in different VLEs with minimal software development costs and changes to existing platforms [3]. Although GLUE!-PS provided an important architectural advance to reconsider LD-to-VLE translation, how to align educators' LDs with learners' needs remains a gap, since educators often create pedagogical designs without information relevant to learners' performance [5]. Beyond the translation gap, there is also growing interest in evolving VLEs towards Smart Learning Environments (SLEs) [6], which are defined as technology-enhanced learning environments that can sense relevant context by collecting and analyzing data, then provide adaptive and personalized

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[1]An open-source learning management system (LMS) widely used to support online and blended learning in education: https://moodle.org/

support to enhance learners' experiences. This implies that addressing the LD-to-VLE translation gap is not only a matter of interoperability, but also a prerequisite for enabling VLEs to incorporate smarter SLE-like, context-aware capabilities. Learning Analytics (LA), which enables the analysis of learners' actions, helps educators improve their LDs in a context-aware manner incorporating learners' academic performance and demographic data [7, 8]. Although recent work enables informed decision-making in the enactment of LDs based on learners' data, educators still need to analyze these data on their own, often without guidance and sufficient information to determine whether the LD is suitable for learners' characteristics [5, 8].

To address the aforementioned gaps, Generative AI (GenAI) offers a promising bridging role between LA, LD and VLE, as it has begun transforming the sector including healthcare, media, finance and education by providing insights, improving work quality and saving time [9, 10, 11]. Research shows that GenAI tools are regarded by educators, particularly those who regularly use this technology, as a supportive tool for planning and managing their educational activities rather than as a threat that could replace them [12, 13, 14]. A high level of knowledge about these tools encourages educators to adopt them in their educational practices, whereas limited understanding hinders their adoption or leads to counterproductive implications [15].

Building on this perspective, this study leverages GenAI to address three needs that support advancing LD into VLE enactment toward SLE-like capabilities: (i) saving educators time by translating their educational designs for use in a VLE, (ii) supporting educators across all levels of technological expertise in transferring their pedagogical designs to another platform, and (iii) enhancing personalized introductions and activities to better suit learners' needs. To address these needs, the main objective of this paper is defined as follows: To introduce a first version of GenAI-enabled smart adapter architecture that helps educators enact their LDs a VLE, in a way that addresses learners' and educators' needs, and its initial proof of concept implementation.

The rest of the paper is structured as follows: In Section 2, we present our conceptual architecture (LD-EnactAI) for building a smart adapter that incorporates LA. Section 3 then describes, as a proof of concept, a first implementation of LD-EnactAI for the cases of the ABPxODS LD platform with Moodle VLE, whereas Section 4 presents the discussion and conclusions, reflecting on how the architecture addresses the stated objective, outlining limitations, and indicating directions for future work.

2. LD-EnactAI Conceptual Architecture

We aimed to address the translation gap by building LD-EnactAI as a connection layer that enables contextual customization based on educators' preferences and the target learners' data, in line with prior work on adapter patterns for deploying LDs across VLEs [3].

LD-EnactAI takes as input a structured LD authored in an LD tool, a set of educator's preferences to configure how the design should be deployed in the target VLE, and learners' data, such as demographic, and academic, as shown in Figure 1. After an LLM-Based Learners' Data Analyzer extracts insights to be used as LA indicators from the learners' data (e.g. reflecting prior knowledge and engagement patterns in the VLE), these insights are fed to an LLM-Based Implementation Generator. The LLM-Based Implementation Generator transforms these inputs while maintaining the pedagogical intent with suggested adaptations (e.g. difficulty level, engagement supports) of the original LD, and the resulting draft is displayed through an editable preview, using a Preview Generator, to keep educators in the decision loop. Once confirmed, a Computational Representation Mapper encodes the translated LD in a machine-operational format compatible with the target VLE.

Finally, the target VLE uses this format to deploy the course/project properly. When it is deployed, the target VLE can also provide qualitative and quantitative indicators to identify patterns in learners' knowledge and engagement [16, 17]. These indicators can also be leveraged as LA inputs in subsequent iterations (in aggregated ways or as suitable depending on ethical and institutional policies), enabling LD-EnactAI to improve the current LD during the course/project duration.

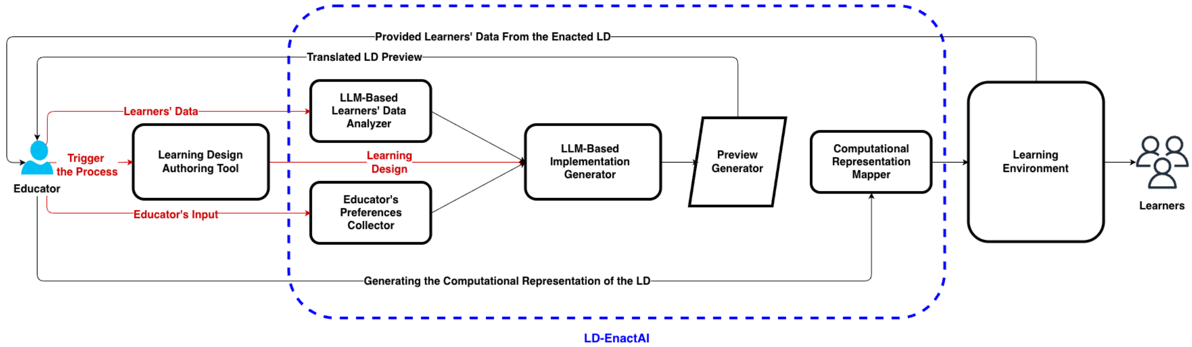

Figure 1: Overview of LD-EnactAI conceptual architecture.

3. Towards a Proof of Concept: From ABPxODS to Moodle

3.1. Implementation of LD-EnactAI

To implement the first prototype of LD-EnactAI, we used ABPxODS [18], which is a digital authoring tool that enables educators to create their LDs including activities or projects to develop learners' key competencies for the Sustainable Development Goals (SDGs) following the Project-Based Learning (PBL) methodology, as it is pedagogically rich and relevant. An LD structure in ABPxODS includes three main components: Description, Design, and Reflection. These components contain information that identifies the learning plan aligned with PBL that allows learners to explore real-world problems through collaborative projects [11]. We also chose Moodle as the target VLE for the study, because it is a widely used online teaching and learning platform that enables educators to measure learners' engagement with the learning plan and analyze their performance by providing not only quantitative but also qualitative insights [16, 17].

First, the components in both platforms were mapped, as shown in Figure 2, to provide an appropriate computational representation of the original LD in a deployable Moodle-ready format. For example, the Description components in ABPxODS were mapped to the Course component in Moodle, whereas the Design components were mapped to the Activities component to maintain the section-based structure in ABPxODS. The Forum component in Moodle, which enables educators to post general announcements about their LDs, was kept as a default section once the LD was deployed in Moodle. Moreover, the

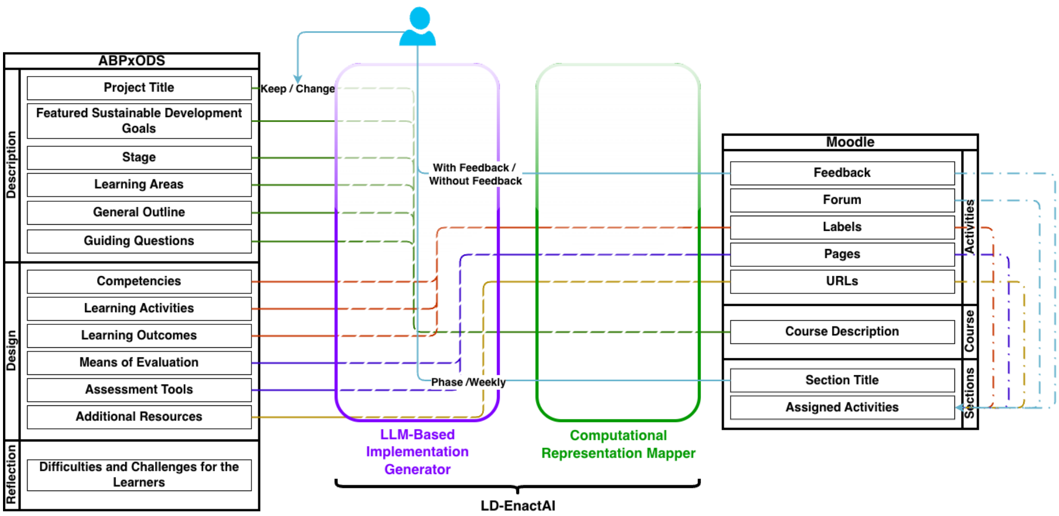

Figure 2: Overview of the structure of the LD-EnactAI adapter and the mapping elements between ABPxODS and Moodle.

Feedback component, which allows educators to gather learners' feedback, was made optional based on educators' preferences.

To manage educator's preferences in a structural robust way, a workflow acting as an Educator's Preferences Collector that includes four nodes (Section Router, Week Generator, Project Title Updater, Content Language Mapper), was implemented using LangChain [2] and LangGraph [3]. Figure 3 illustrates the detailed structure of the implementation. The Section Router routes requests depending on whether the educator selects weekly or phase-based sections. In the weekly case, a planned start date of the course/project is requested and used by the Week Generator to create section titles based on weekly dates, otherwise default phase labels are assigned. The Project Title Updater adjusts the title according to the educator's preference, and the Content Language Mapper converts ISO 639-1 language codes in ABPxODS into their natural language names.

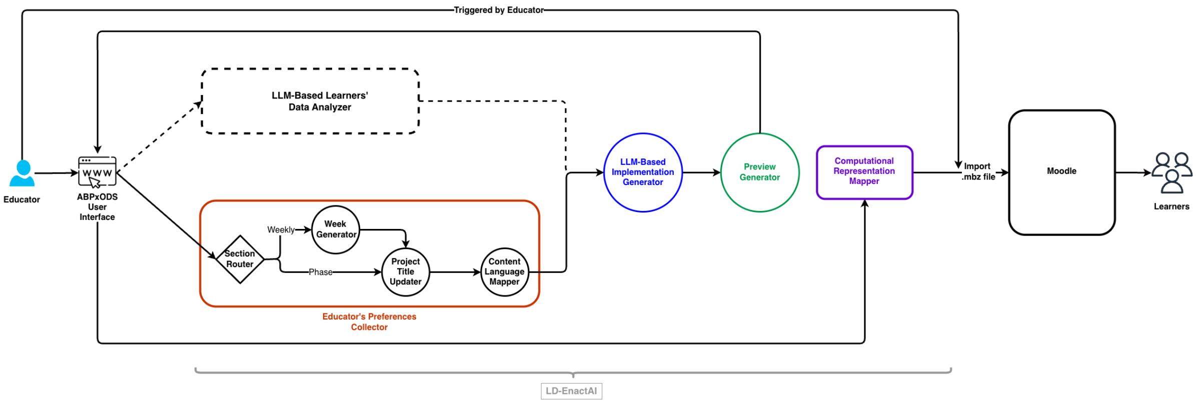

Figure 3: Detailed illustration of the LD-EnactAI architecture. The dashed circle and dashed line indicate the extended architecture for future implementations of the adapter, while the remaining elements depict the current first prototype architecture.

In the following component of the architecture (the LLM-Based Implementation Generator), we leveraged human-oriented instruction prompting, which is widely applicable to complex tasks [19], as illustrated in Figure 4 and utilized Llama 3.3 70B Versatile developed by Meta [4], as an LLM. The prompt specifies the LLM's role and tone, describes the steps to follow, and defines the required output format based on the provided LD, transforming the inputs in a way that addresses learners. This translated LD is then conveyed to ABPxODS user interface, through the Preview Generator, to be displayed to the educator.

In Moodle, translated LDs can be imported either via .csv files or .mbz backup files. We chose to create .mbz backup files because they provide more flexibility for reflecting a detailed course/project structure, whereas .csv files are mainly limited to tabular data. We performed a reverse-engineering process on sample courses exported from Moodle 3.11+ to infer the required .mbz structure. Then, a code pipeline was built acting as a Computational Representation Mapper based on the mapping process described above, using the Python programming language. This pipeline automatically creates .mbz backup files, which are used to import the translated LDs into Moodle, and allows educators to download them. The files keep metadata of the translated LD, and folders such as activities, course, and sections, stores the corresponding components such as, feedback, forum, course description in XML format, and assigns unique IDs to link each activity to its section as shown in Figure 2.

Additionally, we explored how LA can be integrated into LD-EnactAI for the future implementations of the architecture. As Moodle offers both qualitative and quantitative insights, such as grades, the total number of views and clicks, these indicators help identify patterns in learners' knowledge and engagement [16]. Thus, the LLM-Based Learners' Data Analyzer can analyze learners' knowledge and engagement level from tabular data (e.g., .csv or Excel files) and feed them into the LLM-Based

[2] An open source framework developers use to build AI agents. : https://www.langchain.com.
[3] An open source framework developers use to build AI agents with low-level control : https://www.langchain.com/langgraph.
[4] An AI research and technology company: https://about.meta.com/

ROLE & TONE

```
You are a helpful tutor that creates a learning content based on the given learning design, addressing the students. This learning design should be created based on the given user's instructions.
Your tone should be friendly, explicit, and kind, and it should address the students in a way that aligns with their age range.
```

INPUT CONTEXT

```
Here is the learning design JSON you should reference when answering the user:
        <learning_design>{learning_design}</learning_design>
```

RULES

```
**RULES**
Here are the rules you must follow:
1. Always replace learning areas (if any) in the given learning design with the following values in the learning areas dictionary;
<learning_areas_dictionary>
{{
    "f1": "Languages", "f2": "Mathematics",
    "f3": "Natural, social and cultural environment",
    "f4": "The arts", "f5": "Physical education",
    "f6": "Values education", "f7": "Digital technologies",
    "f8": "Learning to learn", "f9": "Autonomy and personal initiative"
  }}
</learning_areas_dictionary>

2. Always replace Sustainable Development Goals (SDGs) (if any) in the given learning design with the following values in the SDGs dictionary;
<sdgs_dictionary>
{{
    'ODS 1':'SDG 1: No Poverty','ODS 2':'SDG 2: Zero Hunger',
    'ODS 3':'SDG 3: Good Health and Well-Being','ODS 4':'SDG 4: Quality Education',
    'ODS 5':'SDG 5: Gender Equality','ODS 6':'SDG 6: Clean Water and Sanitation',
    'ODS 7':'SDG 7: Affordable and Clean Energy','ODS 8':'SDG 8: Decent Work and Economic Growth',
    'ODS 9':'SDG 9: Industry, Innovation and Infrastructure','ODS 10':'SDG 10: Reduced Inequalities',
    'ODS 11':'SDG 11: Sustainable Cities and Communities','ODS 12':'SDG 12: Responsible Consumption and Production',
    'ODS 13':'SDG 13: Climate Action','ODS 14':'SDG 14: Life Below Water',
    'ODS 15':'SDG 15: Life on Land','ODS 16':'SDG 16: Peace, Justice and Strong Institutions',
    'ODS 17':'SDG 17: Partnerships for the Goals'
  }}
</sdgs_dictionary>

3. Keep the course format as it is in the given learning design above and DO NOT translate it to any language. Just copy the current course format as <course_format>{course_format}</course_format>
and the urls in the given learning design above as they are.

4. Translate the given sections in the given order <sections>{sections}</sections> to <language>{language}</language>.

5. Keep the exact meaning of the title in the given learning design above <title>{title}</title>, ONLY translate it to <language>{language}</language>.

6. Create a Course Description using HTML elements to serve it in a premium look in a way that **addresses the students** in <language>{language}</language>
involving the following parts; **General Outline**, **Guiding Question**, **Learning Outcomes**, **Sustainable Development Goals**, **Learning Areas**, and **Age**.

7. List the reflection items <reflection_items>{reflection_items}</reflection_items> in <language>{language}</language> WHEN reflection is enabled.
Current reflection status is: <reflection_enabled>{reflection_enabled}</reflection_enabled>.

8. Create Course Description Title, Assessment Title, Feedback Title, Competencies Title, Learning Activities Title, Learning Outcomes Title, Assessment Tools Title, Means of Evaluation Title,
 and Phase Title in <language>{language}</language> using the following expressions in the given order; <course_description_title>Course Description</course_description_title>,
<assessment_title>Assessment</assessment_title>, <feedback_title>Add your reflections</feedback_title>, <competencies_title>Competencies</competencies_title>,
<learning_activities_title>Learning Activities</learning_activities_title>, <learning_outcomes_title>Learning Outcomes</learning_outcomes_title>,
<assessment_tools_title>Assessment Tools</assessment_tools_title>, <moe_title>Means of Evaluation</moe_title>, <phase_title>Phase</phase_title>.

9. Use also these exact titles, that are translated in rule 8, as sub-titles (using h3 heading) at the beginning of ONLY each corresponding entity as follows; competencies_N, learning_activities_N,
learning_outcomes_N, assessment_tools_N, and means_of_eval_N. And list their contents using HTML elements to serve them in a premium look.
```

REMINDER

```
NOTE: Think about your answer first before you respond. Answer only when it is very confident in your response.
```

OUTPUT FORMAT

```
**OUTPUT FORMAT**
Return ONLY a JSON object nothing else, with EXACTLY the same keys below and their values in <language>{language}</language>:
        <output_format>{{
          "course_description": "...", "course_description_title": "...", "assessment_title": "...", "feedback_title": "...", "competencies_title": "...",
          "learning_activities_title": "...", "learning_outcomes_title": "...", "assessment_tools_title": "...", "moe_title": "...", "phase_title": "...",
          "competencies_1": "...", "competencies_2": "...", "competencies_3": "...", "competencies_4": "...",
          "learning_activities_1": "...", "learning_activities_2": "...", "learning_activities_3": "...", "learning_activities_4": "...",
          "learning_outcomes_1": "...", "learning_outcomes_2": "...", "learning_outcomes_3": "...", "learning_outcomes_4": "...",
          "assessment_tools_1": "...", "assessment_tools_2": "...", "assessment_tools_3": "...", "assessment_tools_4": "...",
          "means_of_eval_1": "...", "means_of_eval_2": "...", "means_of_eval_3": "...", "means_of_eval_4": "...",
          "url_1": "...", "url_2": "...", "url_3": "...", "url_4": "...",
          "title": "...",
          "course_format": "...",
          "sections": [...],
          "reflection_enabled": ...,
          "reflection_items": [...]
        }}</output_format>
```

Figure 4: Human-oriented instruction prompt structure used in the LLM-Based Implementation Generator.

Implementation Generator [20]. This future implementation aims to help educators develop context-aware LDs tailored to learners' performance, rather than enacting LDs that are not aligned with the target learners' knowledge and engagement levels.

3.2. User Interface of LD-EnactAI

Educators can access LD-EnactAI from the ABPxODS repository interface (Figure 5) and select a small set of enactment preferences, such as the title, language, and course format. Once all preferences have been specified, educators view the translated LD preview. When educators approve the preview, they click "Create the Moodle file" and the backup file, that includes the structure of the translated LD, is downloaded. The file can then be uploaded to Moodle, where educators can continue editing their LDs. Thus, this workflow illustrates how LD-EnactAI puts LD-to-VLE translation into practice.

4. Discussion and Conclusions

This paper presented LD-EnactAI as a GenAI-enabled smart adapter architecture intended to mitigate the LD-to-VLE translation gap and support more human-centered enactment of pedagogical designs toward SLE-like capabilities. By combining educators' preferences with an LLM-based generation and preview workflow, LD-EnactAI aims to reduce the technical effort of deploying LDs in the target VLE while keeping educators in the loop to validate and refine the translated design prior to export. We also described an LA-aware loop in which learners' data can be analyzed to provide learners'

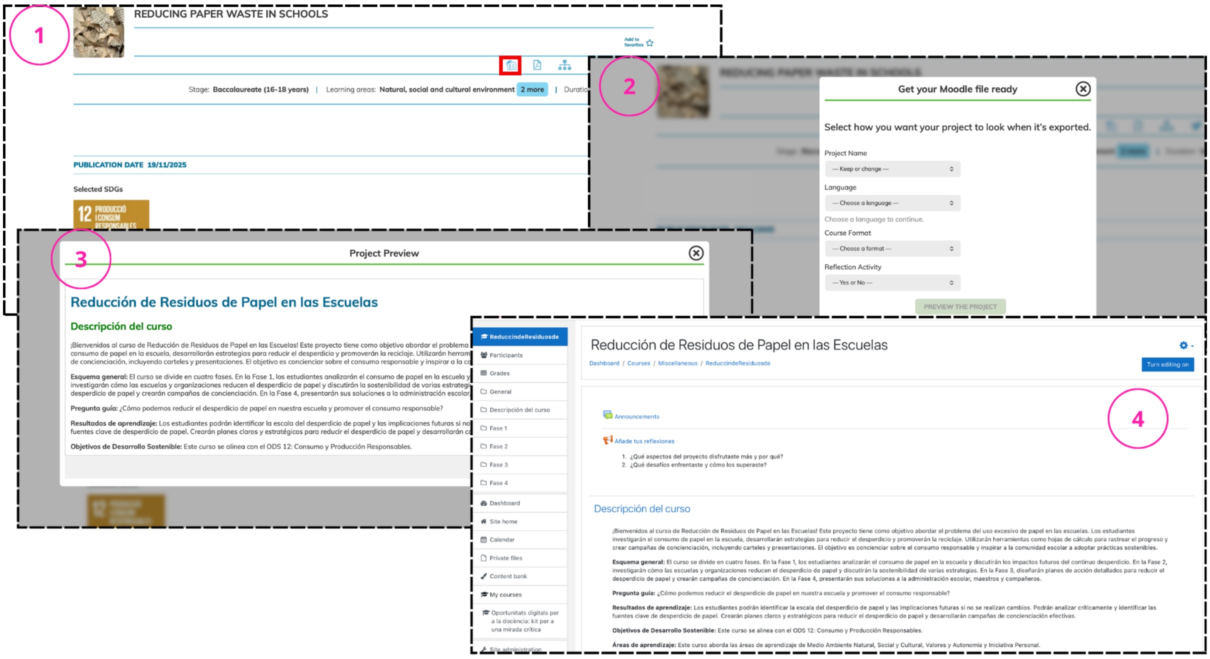

Figure 5: LD-EnactAI translation workflow: (top left, 1) LD-EnactAI icon highlighted in red box in ABPxODS; (top right, 2) pop-up window through which educators interact with the adapter; (bottom left, 3) the preview of the translated LD; (bottom right, 4) the corresponding course uploaded to Moodle.

insights that inform more context-aware introductions or activities, while acknowledging the need for privacy-preserving use of learner data.

As a proof of concept, we implemented LD-EnactAI in ABPxODS by performing a mapping process from ABPxODS components (Description, Design, Reflection) to Moodle elements, to obtain their appropriate computational representations to the target VLE. The prototype generates Moodle-ready .mbz backup files by encoding the translated structure into the required computational representations, enabling import and subsequent editing in Moodle. However, as this is an initial prototype, several limitations remain, including the use of a text-only LLM, the lack of empirical evaluation with practitioners, and the need to manually upload some resources (PDFs, Word documents, and images) after uploading the backup file to Moodle.

Future work will engage in further implementation considering other authoring tools and VLEs, in addition to focus on empirical studies with educators, implementing the LA-enhanced layer, and exploring privacy-aware mechanisms for analyzing learners' data without compromising pedagogical coherence or data protection.

5. Declaration of Generative AI Use

In this study, ChatGPT-5.4 was leveraged to assist in grammar correction and sentence refinement.

6. Acknowledgments

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