Support Learning Design and Analytics with EduP Knowledge Model

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Abstract: Learning design (LD) have been a prominent topic in the academic community for many years. It aims at planning and organizing learning activities and resources to promote learning process and engage students in achieving learning outcomes. Learning analytics (LA) has matured in the education field and developed a strong connection with learning design. Learning analytics provides valuable insights to inform learning design decisions, while learning design serves as a means to turn learning analytics results into actionable strategies. Their alignment completes the big picture for enhancing teaching and learning. Despite numerous studies proposing means to support LD/LA and their alignment, both fields still face many challenges due to the lack of a consolidated framework for reflecting on the various types of knowledge essential for LD/LA. This paper aims at proposing a comprehensive framework, named EduP (Education-Domain-User-Pedagogy), that supports LD/LA by leveraging different types of knowledge. The main contributions of the framework include a knowledge model and an insight engine. The knowledge model helps clarify essential components for LD/LA and their relationships, while the insight engine addresses how this knowledge is accessible to teachers in the context of LD/LA. A brief discussion on the implications and future research is also presented.

1 INTRODUCTION

Our research focuses on the multidisciplinary aspects of learning design and learning analytics, and their alignment within a framework that supports them by leveraging knowledge-based solutions.

Learning Design (LD) has been a prominent topic in the academic community for many years. LD focuses on creating and refining learning scenarios, i.e., which consist of a sequence of learning activities and resources to engage learners in achieving specific learning outcomes (Koper & Bennett, 2008).

The creation of these scenarios is based on various pedagogical strategies (e.g., preparing activities and resources for problem-based learning differs from those used in inquiry-based learning). Many studies have been conducted to assist teachers in creating effective learning scenarios through various means, such as editing tools (Celik & Magoulas, 2016; Pozzi et al., 2020), modeling languages for specifying learning scenario elements (Botturi & Stubbs, 2008), or pedagogical design patterns (Eyal & Gil, 2020).

Learning Analytics (LA) is another area of interest in educational science, focusing on collecting, processing, and mining educational data to generate insights that support educational decision-making (Hernández-de-Menéndez et al., 2022; C. Romero & Ventura, 2020). With the advent of advanced data analytics tools and methods, learning analytics (LA) has emerged as a powerful tool for analyzing educational data to enhance learning and teaching (Mangaroska & Giannakos, 2019).

Many researchers in the analytics field focus on developing learning analytics dashboards to visualize learner performance and progression (Susnjak et al., 2022). Others concentrate on identifying associations within learning data to discover new insights, such as predicting dropout rates or identifying at-risk learners (Ouyang et al., 2023; Ramaswami et al., 2023). Another area of interest is personalization, which aims to provide learners with appropriate activities and resources based on their learning contexts (Chatti & Muslim, 2019; Romero et al., 2019).

Learning design and analytics have matured in their respective fields. However, these two topics

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have a strong convergence. Learning analytics provides valuable insights to inform learning design decisions. On the other hand, learning design serves as a means to turn learning analytics results into actionable strategies (Mangaroska & Giannakos, 2019). Together, these two fields offer a comprehensive approach to improving teaching and learning activities. As a result, a significant number of studies focus on the alignment of learning design and learning analytics (Ahmad et al., 2022; Bakharia et al., 2016).

Despite the numerous studies on proposing means to support LD/LA and their alignment, both fields still faces many challenges. The first challenge involves elaborating learning scenarios, which requires teachers to have a strong understanding of both pedagogical principles and learning domains, as well as how to integrate them effectively (Schmitz et al., 2017). A significant number of teachers lack this knowledge, which limits their ability to design effective learning scenarios (Lui & Bonner, 2016; Tatto et al., 2020). Therefore, developing learning scenarios remains a challenging task for teachers that requires additional support (Vu & Tchounikine, 2021). The second challenge involves the lack of a consolidated framework for learning analytics, which prevents data from being interpreted meaningfully. This makes it difficult to derive actionable insights from the data, thereby complicating their effective application to enhance teaching and learning (Ahmad et al., 2022).

To address these challenges, this study aims to propose a comprehensive framework, named **EduP** (**E**ducation-**D**omain-**U**ser-**P**edagogy), that supports learning design and analytics by leveraging different types of knowledge, such as pedagogical knowledge and learning domain knowledge. The framework also focuses on ensuring that this knowledge is accessible to teachers in the context of learning design and learning analytics.

To propose such supportive tools, knowledge should be clarified and structured efficiently. Additionally, to provide a consolidated framework, all stages—from collecting and organizing data to importing it into the knowledge base, to exploiting and disseminating the knowledge to teachers—should be well-defined. Ontologies, which provide formal representations of domain concepts and serve as powerful reasoning tools, are essential for structuring knowledge (Vu et al., 2023). The state-of-the-art reveals numerous types of ontologies for modeling learning activities, learning outcomes, learning domain knowledge, learner profiles, or generic ontologies that can be applied across various domains (Rahayu et al., 2022; Wang & Wang, 2021).

In the subsequent sections, the paper presents in more detail an ontology-based framework for LD/LA. These sections are organized as follows. Section 2 presents the methodology adopted to target the objectives of this study. Section 3 introduces related works by first providing a brief summary of essential topics on knowledge modeling and exploiting in education, followed by a review of the state-of-the-art research in these areas. Section 4 clarifies the first output of the paper, which is the definition of essential knowledge types that assist in LD/LA. Section 5 introduces a knowledge structure to organize these knowledge types as the second output of the paper. Subsequently, Section 6 provides a method/process for discovering this knowledge through the use of a reasoning engine as the last output of the paper. Section 7 focuses on the validation of the propsed framework through some real-world scenarios in higher education. Finally, Section 8 concludes by the implications and limitations of the study and suggests directions for future research.

2 METHODOLOGY

This section outlines a methodology based on the Design Science Research (DSR) methodology to conduct the research presented in this paper (Dresch et al., 2015). DSR emphasizes the creation of innovative artifacts to solve specific problems.

DSR's artifacts can be: *constructs* providing fundamental concepts for describing a specific problem and its solutions; *models* linking the constructs in a real-world situation; *methods* providing guidelines/processes for solving problems; and *instantiations* demonstrating how the theoretical constructs, models, and methods can be applied in practice (Peffers et al., 2007).

This research aims at proposing a knowledge-based framework for enhancing learning design and analytics (**EduP** Framework). The artifacts for the framework are created through the following phases.

Problem Identification. This phase focuses on identifying the research questions to be addressed for building EduP framework. Two key questions are identified: RQ#1: *What types of essential knowledge can support learning design and analytics*? And RQ#2: *How can the knowledge be elaborated and used effectively*?

Solution Definition. This phase defines the objectives of a solution to solve the identified problem, which requires the EduP framework: define essential knowledge types in LD/LA and determine effective methods for reasoning and disseminating this knowledge. To define these objectives, a brief literature review is conducted to summarize the current state-of-the art in knowledge modeling and reasoning for the education sector.

Design and Development. This phase involves creating EduP artifacts. These artifacts are classified in constructs, models, methods, and instantiation, according to DSR methodology (Peffers et al., 2007).

- EduP **Constructs** and EduP **knowledge model** are proposed to address RQ#1. The constructs define key knowledge components in LD/LA, while the knowledge model outlines how these components are related to one another.
- EduP **Insight Engine** is proposed as a method/process within the framework to response to RQ#2. The method defines multiple modules for representing, elaborating, and reasoning about knowledge, aiming to generate insights in LD/LA.
- Two **Instantiations** are also created to validate the framework in a subsequent phase. The first one is an ontology based on EduP knowledge model. The second one is a web-based reasoner built upon EduP insight engine. The reasoner serves as a prototype for reasoning with the created ontology through a simple interface.

Demonstration and Evaluation. This phase involves validating the proposed framework in real-world situations. The ontology and web-based reasoner developed in the previous phase are used to address various case studies in the higher education context.

3 RELATED WORKS

This section provides an overview of current research on ontology-based solutions for knowledge modeling and reasoning in education, addressing both the structural and behavioral aspects of these solutions.

3.1 Structural Aspect

The structural aspect focuses on the types of knowledge represented in ontologies. An ontology is a specification that defines concepts within a domain and their relationships in a structured, formal, and explicit manner (Gruber, 1993). In education, an ontology is defined as "a system of primitive vocabularies/concepts for constructing a tutoring system" (Mizoguchi et al., 1996). In technology-enhanced learning, ontologies are considered effective tools for modeling the learning and teaching domain due to their formal expressiveness, support for sharing, and reasoning capabilities.

In General, ontologies can be used to model a wide variety of information types. The classification of these ontologies can follow different criteria, such as their levels of abstraction (domain-independent and domain-specific ontologies) (Guarino et al., 2009), their intentions (domain ontologies modeling a target domain, task ontologies modeling generic problems and their solutions, and application ontologies dedicated to activities within a specific application), (Al-Yahya et al., 2015; Mizoguchi et al., 1996). From the perspective of smart systems, ontologies can be classified in five major types: ontologies for modeling generic concepts across domains, domain ontologies, user ontologies, context ontologies, and merged ontologies combining multiple ontology types to provide a comprehensive reasoning (Chimalakonda & Nori, 2020; Vu et al., 2023).

In Education, most ontologies are *domain ontologies*, which are used to describe the concepts of specific learning domains such as mathematics, physics, and programming (e.g., Iatrellis et al., 2019; Lalingkar et al., 2014; Ramesh et al., 2016). Other research also focuses on modeling *pedagogical elements* such as curriculum/syllabus, learning scenarios, learning activities, and outcomes (Hyunsook & Jeongmin, 2016; Katis et al., 2018; Reynolds et al., 2023). *Learner profiles* specifies user data such as user profiles, interest, needs; which is typically employed for learning recommendations and personalization (e.g., Pelap et al., 2023; Romero et al., 2019). *Context ontologies* are another type that emerged with the evolution of smart systems, supporting retrieving the most relevant knowledge, according to a specific learning context (Aguilar et al., 2018; Cabrera et al., 2017; Ouissem et al., 2021; Perera et al., 2014).

3.2 Behavioral Aspect

The behavioral aspect examines the processes and methods used to develop and reason with knowledge. This involves two key components: elaboration and reasoning.

Elaboration, also known as ontology building, involves the extraction of data and its integration into a predefined knowledge model or ontology structure, as outlined in the structural aspect. which can be done manually, semi-automatically, and automatically.

Manual approaches are performed by domain experts who analyze the specific domain, annotate data, and manually integrate it into an ontology structure (e.g., Verdú et al., 2017). This method is costly and prone to errors, especially with large datasets. However, human interaction and expert domain analysis can ensure the rationality of the extracted data, which is essential for complex domains such as education.

Automatic approaches employ natural language processing (NLP), data mining, or machine learning algorithms to extract information from unstructured data, such as text, and integrate it into an ontology structure without human intervention (e.g., Aguilar et al., 2018; Lacasta et al., 2018; Wei & Shao, 2022). These methods facilitate efficient and cost-effective knowledge extraction from large datasets. However, the absence of expert monitoring can lead to the generation of knowledge that may be unreasonable or inaccurate within the domain.

Semi-automatic approaches involve both domain experts and algorithms (e.g., (Cano-Benito et al., 2021; Chang et al., 2020; Ghazal et al., 2020; T. M. H. Vu & Tchounikine, 2021)). Several parts of the process are performed or supervised by experts, while others are carried out by algorithms. These approaches benefit from AI techniques to automate part of the extraction process, while also leveraging the collaboration with domain experts to minimize the risk of constructing an incomplete or potentially incorrect knowledge base

The second key component of the behavioral aspect is **reasoning**. The purpose of reasoning is to derive insights, make inferences, and effectively utilize the knowledge within ontologies to address issues and answer questions. This can be done through various methods such as query languages, built-in reasoners, and user-defined inference rules and algorithms.

Ontology query languages and built-in reasoners are typical solutions for *ontology-based reasoning*. The most widely used ontology query language is SPARQL, which provides a formal syntax for extracting and manipulating data within ontologies (e.g., Lacasta et al., 2018; LeClair et al., 2022; Wen et al., 2022). Another solution involves using built-in reasoners such as HermiT and Pellet, which are integrated into ontology editors like Protégé (e.g., Andrade et al., 2019). The reasoners enable automatic deduction and consistency checking. However, these approaches have a limitation: they require additional interfaces to be user-friendly, as query languages and the Protégé interface are too complex for non-technical users.

Another common solution involves using *human-defined rules* to discover knowledge from ontologies (e.g., Bensassi et al., 2019; Ghazal et al., 2020; L. Romero et al., 2019) or proposing *custom solutions and algorithms* tailored to specific applications and purposes (e.g., Demaidi et al., 2018). These approaches can be resource-intensive, requiring significant input from experts to define rules and program algorithms, and may not fully leverage the inherent benefits of ontology support.

3.3 Research Gap Identification

From a brief summary and analysis of related works, we have identified several research gaps that highlight the motivation behind our research and provide a clear direction for how our work can address the current limitations in the existing literature. These limitations are outlined as follows.

There is Insufficient Focus on Aligning Multiple Ontologies to Enhance Teaching and Learning. Improving LD/LA requires teachers to have a strong knowledge not only in their specific teaching domain but also in pedagogical strategies to create effective learning scenarios. *Aligning these ontologies should be clearly defined and integrated into a unified framework* that can holistically facilitate their implementation and application in LD/LA.

There is a lack of user-friendly tools for utilizing knowledge from the end-user perspective. Numerous types of ontologies have been proposed, but we still lack an efficient means to deliver the knowledge contained within these ontologies to users. Current methods do not pay enough attention to bridging the gap between the complex, structured data within ontologies and the practical, accessible insights needed by end users. This highlights a *critical need for developing user-friendly interfaces and tools* that can facilitate the efficient extraction and application of knowledge from ontologies.

There is a Lack of a Unified Framework That Incorporates a Knowledge-Based Approach to Promoting LD/LA. Such a framework would facilitate a more cohesive and systematic application of ontological principles and could serve as a blueprint for the future conception and development of these services. The framework needs to *encompass all phases, from collecting data and integrating it into knowledge bases to delivering the knowledge effectively to end users through efficient means*.

4 KNOWLEDGE COMPONENTS

This section introduces EduP constructs in detail to clarify the key knowledge components involved in knowledge-based learning design and analytics.

These constructs are organized into a multi-level structure to facilitate reusability and future extension. The abstract level adopts the 5W1H model (**w**ho, **w**hat, **w**hy, **w**hen, **w**here, and **h**ow) as proposed by (Jang & Woo, 2012). This model enables general reasoning to anwser the question such as "who achieves what in which context (when, where)?".

Inherited from the abstract level, concepts at lower levels are tailored specifically to the education sector. This level encompasses three core knowledge types in a KB-based LD/LA framework: **p**edagogical knowledge (learning goal, learning outcome, learning level, activity); learning **d**omain knowledge (topic); **u**sers (individual learner, group). Additionally, contextual knowledge is defined to facilitate connections among these three knowledge types (see Figure 1 for the proposed constructs and their relationships).

5 KNOWLEDGE MODEL

This section defines a generic knowledge structure that we use to organized the proposed constructs.

Pedagogy-Pedagogy Linking involves connecting various aspects of teaching and learning to ensure that educational strategies are aligned with learning goals (the relations *"includes", "achieves", "targets", "involves"*). It encompasses two main components: first, defining the learning goals, which are the specific objectives students are expected to achieve; and second, developing learning activities that help students meet these goals through measurable learning outcomes. The connection between learning outcomes and activities is mediated by the context in which learning occurs,

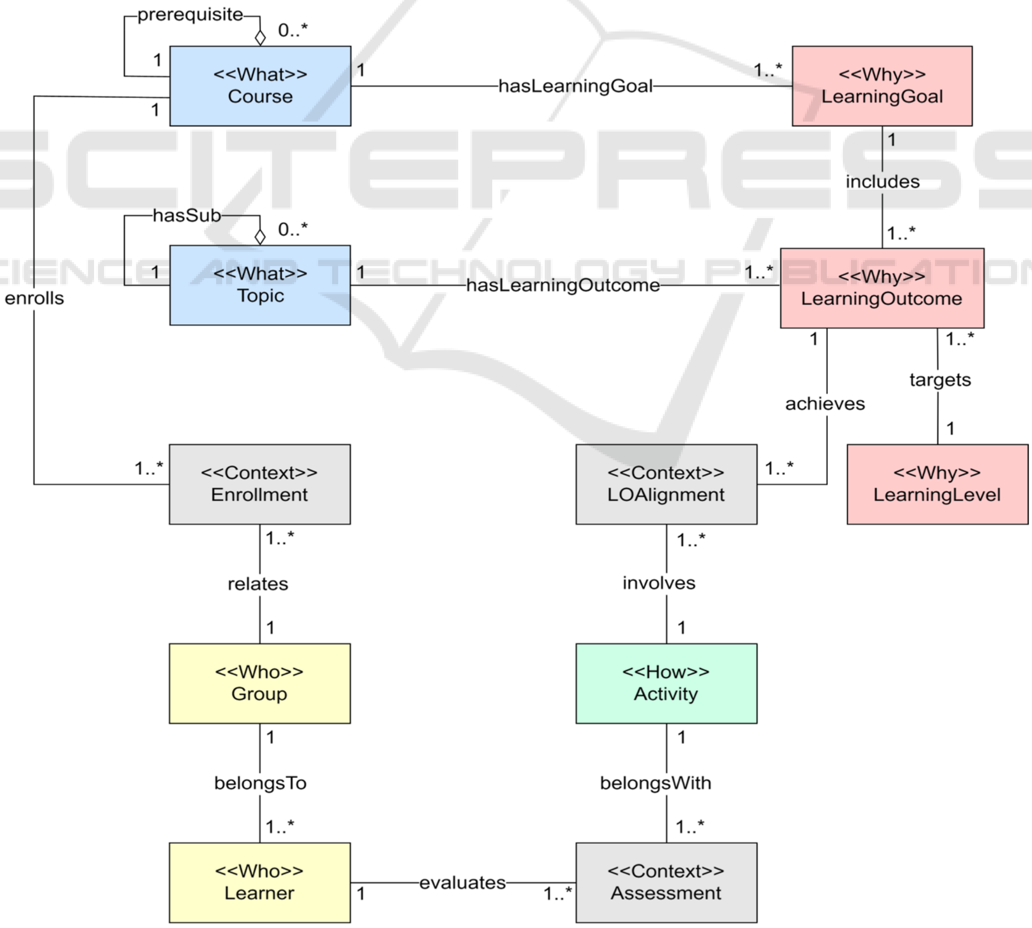

Figure 1: Knowledge Model.

emphasizing that the design of activities should be adapted to the specific "when" and "where" of the learning environment. For instance, the activities chosen to achieve a particular learning outcome may vary between in-class sessions and homework assignments, reflecting the need for context-sensitive pedagogical approaches.

Domain-Pedagogy Linking involves integrating pedagogical knowledge with learning domain content to enhance learning analytics (the relations *"hasLearningGoal", "hasLearningOutcome"*). This process connects various elements of pedagogy—such as learning outcomes, learning goals, and instructional activities—with the content-specific knowledge relevant to a course. By linking these pedagogical components with the learning domain knowledge, educators can better track and analyze what topics learners have mastered. This alignment supports the effective measurement of student progress and achievement, facilitating more accurate and actionable insights into learning outcomes. It helps in identifying which specific topics students have successfully learned and which areas may require additional focus, thereby enabling targeted interventions and improved educational strategies.

Domain-Pedagogy-Learner Linking involves integrating pedagogical and learning domain knowledge with individual learner profiles to enhance educational experiences. This approach aligns learning outcomes, goals, and activities with learner assessments and enrollment contexts. This integration also enables sophisticated analytics to track which topics learners have mastered and at what level of proficiency. Furthermore, it allows for the creation of personalized tools that enable learners to monitor their own performance and progres.

6 INSIGHT ENGINE

This section details the EduP insight engine, proposed as a method/process within the EduP framework to address RQ#2: how can knowledge be elaborated and used effectively? The method defines multiple modules for representing, elaborating, and reasoning about knowledge, aiming to generate insights in Learning Design (LD) and Learning Analytics (LA).

To propose a unified approach that covers the entire process from handling raw data to delivering insights and to highlight the transitions of data to knowledge and knowledge to insights, the process proposed here relies on the DIKW (**D**ata, **I**nformation, **K**nowledge, **W**isdom) model, which is hierarchical framework that allows structuring processes in a systematic way (Rowley, 2007).

Accordingly, EduP Insight Engine composes of the three main components, as presented in Figure 2.

- **Data Module:** Organize and preprocess data to be imported into the ontology.
- **Information Module:** Create an ontologie from the data processed in the Data Module.
- **Knowledge Module:** Reason with the ontology to generate knowledge for predefined specific use cases (**Wisdom**).

This is a semi-automatic process that involves some actions performed automatically by programs (denoted by rectangles in light red) and others requiring user intervention (denoted by rectangles in light blue). The details are presented below.

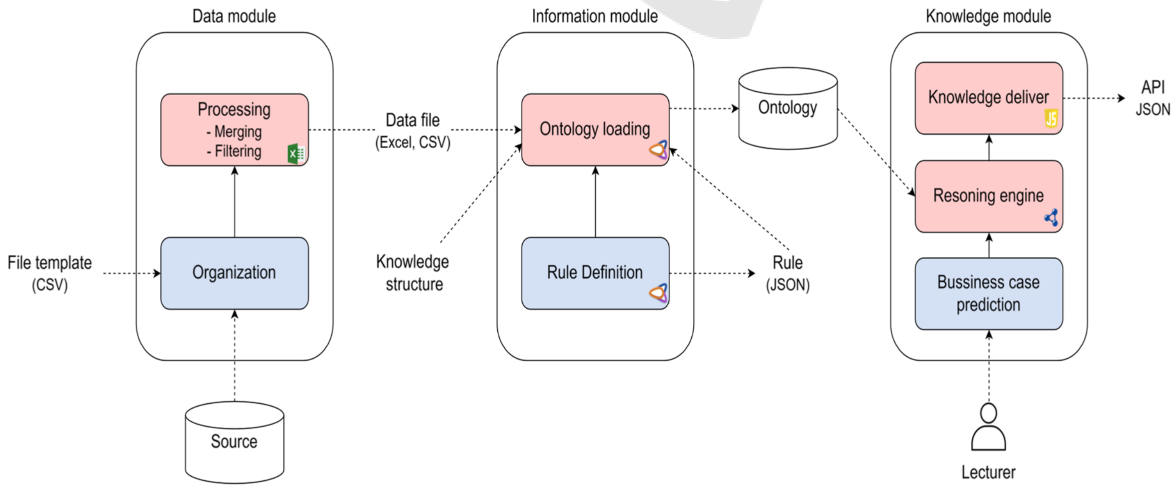

Figure 2: Insight Engine.

6.1 Data Module

The objective of this module is to collect, process, and transfer data from different sources into data files in CSV format, based on predefined structures (file templates). These data files will then be imported into the proposed ontology structure in the information module.

Data Source. Three primary data sources are considered here: *syllabus documents* used to identify pedagogical knowledge (learning outcomes, learning goals, learning activities) and a portion of the learning domain knowledge (topics to be acquired by learners); *data from LMS* used to acquire user history and interaction; *databases* from institutions providing learner assessment information.

Organization. This submodule aims to transfer data from various sources into CSV files. Some parts of this submodule require intervention from educators or teachers, particularly in identifying essential pedagogical knowledge from textual syllabus.

Processing. This submodule involves preprocessing the data to prepare it for import through Python programs. Tasks include handling missing values, removing duplicates, and merging or splitting files if necessary. The output is a properly formatted spreadsheet that can be automatically imported into the ontologies.

6.2 Information Module

This module is responsible for creating ontologies (also known as knowledge bases) from the data processed in the data module. This ensures that the data is structured in a way that facilitates reasoning in the knowledge module. Protégé is used as the editor for constructing these ontologies.

Ontology Loading. This submodule begins by creating the ontology's abstract structure based on the EduP knowledge model in Protégé. This structure includes the main concepts and their relationships and remains nearly unchanged throughout the ontology's lifecycle. In subsequent steps, ontology data from CSV or Excel files will be imported into this abstract structure.

Rule Definition. These are JSON-based rules that define the mapping between the content of CSV/Excel files and the ontology structure. They specify how each part of the data files can be identified and mapped into a component of the ontology structure. Since the data is complex and large, automatic loading using these predefined rules is essential.

6.3 Knowledge Module

This module focuses on exploring ontologies to generate insights and subsequently delivering these insights to other systems through APIs.

Reasoning Engine. This submodule consists of a set of SPARQL queries that can be used to reason the ontology created from the information module. The query system is defined based on predefined use cases analyzed and proposed from the perspectives of educators and teachers.

Business Case Prediction. These predefined use cases are declared as elements in the wisdom module. For each specified use case, the required knowledge is identified, and appropriate queries are invoked. This module is responsible for mapping the predefined use cases to suitable knowledge. This task is currently conducted through collaboration between educators/teachers and programmers.

Knowledge Deliver. This submodule manages the interaction between the EduP Insight Engine and other applications, such as web-based interfaces, through APIs. It handles receiving requests and responding to them, enabling the delivery of insights to educators and teachers. This allows for visualizing results in an accessible format, facilitating informed decision-making and enhancing the educational process.

6.4 Wisdom Module

This module is not a software component. Instead, it results from requirement analysis from the perspectives of educators and teachers. The predefined use cases capture essential knowledge for common requirements in learning design and analytics (see Figure 3 for more details).

Use case	Sub use case	Description
Data Management	Import	Lecture imports data from local
	Modify	Lecture modifies data
	Export	Lecture exports data
Knowledge Reasoning	Course Reasoning	Analyze and reason about Course
	Topic Reasoning	Analyze and reason about Topic
	Group Reasoning	Analyze and reason about Group
	Learner Reasoning	Analyze and reason about Learner
	Activity Reasoning	Analyze and reason about Activity
	LO Reasoning	Analyze and reason about Learning Outcome
Learning Analytics	Course Analytics	Analyze data related to Course
	Topic Analytics	Analyze data related to Topic
	Group Analytics	Analyze data related to Group
	Learner Analytics	Analyze data related to Learner
	Activity Analytics	Analyze data related to Activity
	LO Analytics	Analyze data related to Learning Outcome

Figure 3: Wisdow Management Module.

Data Management. This group enables end-users import, export, and modify ontology data through user-friendly interfaces.

Knowledge Reasoning. This group supports teachers and educators in reflecting on various types of knowledge. Each case study outlines potential outputs based on the input knowledge type. For instance, given a specific learning outcome for a course, the related data might include the associated learning goal, relevant topics, the required learning level according to Bloom's Taxonomy, and the learning activities designed to achieve this outcome. Understanding these types of knowledge is crucial for assisting teachers and educators in learning design. However, the conception and development of learning design tools is beyond the scope of this research.

Learning Analytics. This group focuses on data analytics based on knowledge types defined in ontologies. For example, analyzing the connection between learning outcomes and learner assessment results can generate statistics on which learners achieve or do not achieve the outcomes.

7 INSTANTIATIONS

This section presents two instantiations developed to validate the EdUP framework. First, the EduP knowledge structure and process are applied to create an ontology for a database course, demonstrating the framework's applicability. Second, the EduP web-based reasoner is constructed to illustrate how the ontology can support learning design and learning analytics through real-world scenarios. The reasoner processes the constructed ontologies to generate insights for teachers through interactive user interfaces.

As illustrated in Figure 4, the reasoning process provides results related to specific learning outcomes. By default, all relationships associated with a specified learning outcome are presented in a simple table format, which facilitates easy consultation for teachers. This user-friendly presentation allows educators to quickly access and interpret relevant information, aiding in the evaluation and refinement of teaching strategies. The interactive nature of the interface enhances the usability of the insights, making it easier for teachers to leverage data in their decision-making processes.

Figure 5 displays the interface for descriptive analytics, which highlights the number of students who have completed specific activities within a course. This straightforward statistical overview demonstrates how the knowledge extracted from ontologies can be effectively applied in learning analytics. By providing clear metrics on student participation and achievement, the interface showcases the practical value of integrating ontological knowledge into educational analysis. This integration not only aids in tracking student progress but also illustrates how such knowledge can be used to derive actionable insights for improving course design and instructional strategies.

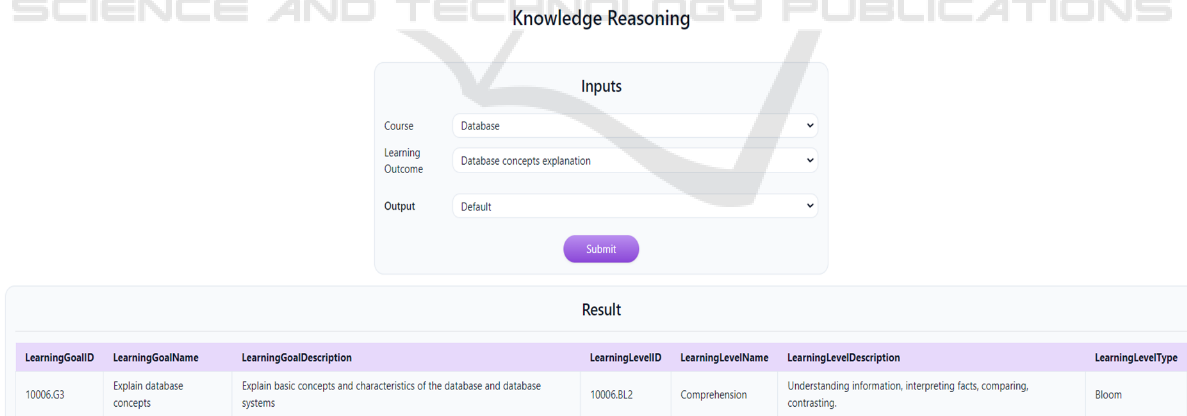

Figure 4: Knowledge Reasoning Interface.

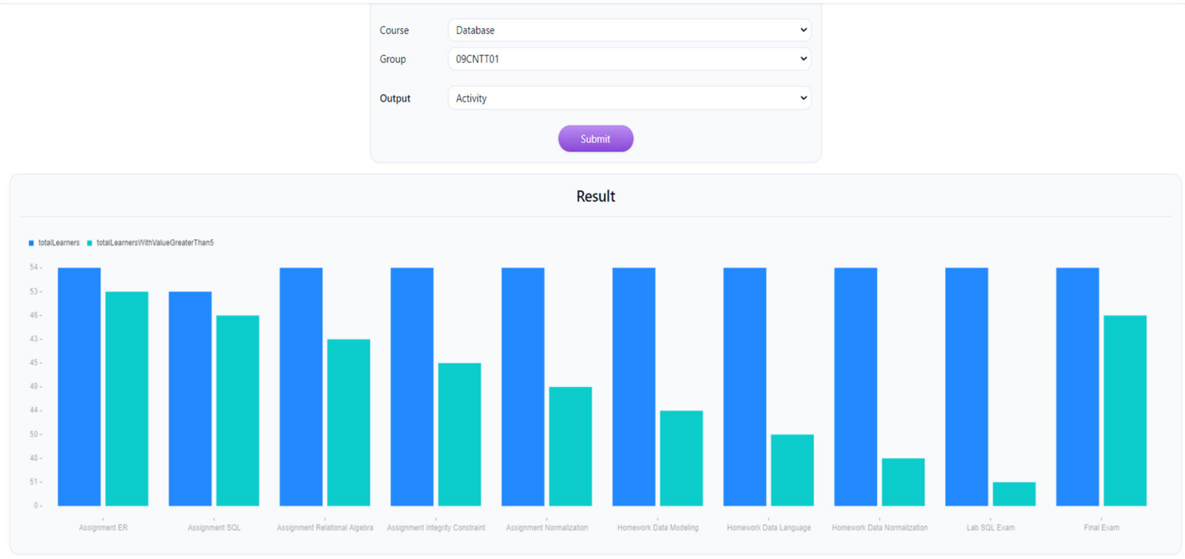

Figure 5: Learning Analytics Interface.

8 CONCLUSIONS

This section summarizes the contributions of the paper and offers suggestions for future research directions.

In terms of **contribution**, the paper first presents a comprehensive knowledge model that integrates various types of knowledge within the context of LD/LA. This model provides teachers with a holistic overview of how domain-specific knowledge can be acquired through various pedagogical strategies. The second contribution is a method that defines the main phases and associated components to facilitate reasoning on knowledge bases. By linking multiple knowledge types and providing a structured method for reasoning on knowledge bases, this paper offers valuable tools for educators and researchers. The case studies used for validation highlight the potential for implementing the proposed framework in the future.

In terms of **future research**, since the framework is a proof of concept, the knowledge model is currently simple and needs further development to meet the requirements of LD/LA. Additionally, some components of the proposed method can be automated to reduce costs, leveraging advancements in AI, for example, automatically identifying learning topics from syllabus. Finally, more research is needed to explore how knowledge can be translated into measurable indicators within learning analytics.

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