Data-Driven Decision Support System for Analyzing Student Engagement in Learning Analytics

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Abstract. In the landscape of higher education, a significant portion of student learning occurs within digital environments, facilitated by interconnected networks such as Learning Management Systems (LMS), Massive Open Online Courses (MOOCs), and various online platforms. This digital landscape generates a vast repository of educational data, offering valuable insights for educational stakeholders. However, evaluating student engagement in online learning presents a critical challenge. This study addresses this challenge by focusing on the evaluation of student engagement using Learning Analytics (LA). We introduce DDS-Eng, a Data-Driven Decision Support System designed to analyze students' engagement. Our approach involves thorough requirement analysis to define decision-makers' needs and selected data sources, followed by the development of a multidimensional model capturing engagement aspects and associated metrics. We then implement a dedicated interface utilizing Online Analytical Processing (OLAP) queries and a Learning Analytics Dashboard (LAD) to analyze individual student behavior and overall student engagement comprehensively. Finally, we present an empirical evaluation of our LAD conducted in a controlled environment. This research underscores the importance of student engagement in online learning and emphasizes the need for innovative approaches to evaluate learner engagement in multimodal and informal learning environments.

Keywords: Learning Analytics, Data-Driven Decision Support System, Informal learning, Online Analytical Processing, Learning Record Store.

1 Introduction

In the perpetual quest for knowledge and enhancement of their skills, university students extend their learning beyond formally organized courses, engaging also in informal learning contexts [1]. These contexts encompass various forms, including social interactions, practical experiences, and alternative means of knowledge acquisition outside the conventional framework of formal education [2].

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1.1 Context and work positioning

With the advent of digital technologies, student learning unfolds across a myriad of platforms, ranging from formal Learning Management Systems (LMS) to Massive Open Online Courses (MOOCs), alongside social networks and online platforms like GitHub and Coursera [9, 25, 22]. This diversification of learning environments results in a wealth of generated data [20, 26], necessitating the development of tools and methodologies for analysis, such as Learning Analytics [11]. These tools play a pivotal role in optimizing teaching and learning processes by furnishing invaluable insights into learner behavior and performance [5]. Crucially, it is acknowledged that learning occurs ubiquitously, transcending singular systems or tools. Learning occurs ubiquitously, spanning beyond conventional educational settings. Within this framework, the Experience API (xAPI), endorsed by the IEEE (IEEE 9274.1.1-2023), emerges as a revolutionary instrument for monitoring and comprehending learning dynamics. In contrast to SCORM, xAPI enables the comprehensive capture of all learning experiences, including informal ones like web browsing or reading [8, 15]. This groundbreaking standard not only facilitates the collection of learning data but also enables in-depth analysis, thereby providing valuable insights into individuals' learning processes [13, 10].

1.2 Problem statement

Rendering an assignment in Moodle, crafting a blog post in HubSpot, watching a YouTube video, or collaborating on shared projects via GitHub—all such actions represent learning opportunities captured by xAPI and logged in a Learning Record Store (LRS). Indeed, xAPI permits both data writing and reading from an LRS, fostering seamless information exchange across diverse educational platforms and analytical tools. This capability holds profound implications for educational research and instructional improvement, offering an innovative avenue for studying and comprehending learning processes across varied contexts. Student engagement in online learning is widely acknowledged by researchers as a critical factor influencing their academic success. It serves as a pivotal determinant in both student progress and potential academic setbacks. The ability of online educators to accurately, efficiently, and timely detect and improve their students' level of engagement holds paramount significance.

1.3 Our Contribution

While extensive literature exists on analyzing student engagement based on their learning traces in formal learning environments, exploration of this approach in multimodal and informal settings remains relatively underexplored [6]. This gap presents a significant challenge for researchers and practitioners in the field of online education. Indeed, a substantial portion of learning occurs in informal contexts characterized by diverse interactions and often less structured experiences. Hence, it becomes imperative to develop suitable methodologies and analytical tools to assess student engagement in these complex environments. Such efforts will not only enhance understanding of the underlying mechanisms of student engagement in online learning but also improve the design and implementation of online learning programs.

Recognizing this, our study addresses the Problem Statement: How can we effectively evaluate and improve student engagement in higher education by leveraging Learning Analytics (LA) techniques, including data warehousing and mining? To tackle this challenge, we introduce a comprehensive solution called DDS-Eng (Data-Driven Decision Support System for Engagement Analysis). This system is designed to not only capture the nuances of student engagement but also to provide actionable insights for instructional stakeholders. Our approach involves rigorous requirement analysis, the development of a multi-dimensional model, and the implementation of a dedicated interface featuring OLAP queries and a Learning Analytics Dashboard (LAD). Through this introduction, we set the stage for exploring the intricacies of student engagement in the digital era of higher education, emphasizing the urgency and significance of our proposed solution in addressing this pertinent issue.

1.4 Roadmap

The rest of this paper is structured as follows. Section 2 presents the preliminaries, with Motivating Examples. Section 3 explains the proposed approach. Section 4 present our proof of concept. Section 5 discusses related works. Section 6 concludes the paper.

2 Background and Related Work

In this section, we present background and our motivating example.

2.1 Learning analytics

The different components involved in Learning Analytics are: Requirements, Activity, Data, and Indicators. The requirements represent the LA usage from the three main application domains: learning (e.g., learner behavior, learning outcomes, process, strategies, self-regulated learning, motivation, engagement), teaching (e.g., learning/curriculum design, feedback, recommendations), and institutional (e.g., dropouts, admissions, quality). The activity represents digital tracking related to students' learning from both formal and informal worlds. The indicators express metrics related to learning behavior and content.

For instance, analyzing student behavior requires modeling this behavior through a process or data model, which must be expressed in a common format used in Learning Analytics (LA) called xAPI [19]. Learning Analytics is the collection, analysis, evaluation, and communication of data related to the learner in terms of their context, with the aim of understanding and optimizing learning and its environment. It consists of: the exploitation of digital data produced by learners, modeling to discover information and social connections, in order to anticipate, predict, and advise learning.

As defined by Georges Siemens on his blog, its purpose is "the use of intelligent data produced by the learner and analysis models to discover information and social connections, and to predict and advise learning. The objective is to track and analyze all data produced by learners, regardless of their production context, with the aim of personalizing and adapting learning on a predictive basis. LA encompasses the measurement, collection, analysis, and processing of data from learners and their learning contexts, in order to understand and optimize learning and its environments. It consists of: exploiting digital data produced by learners, modeling to discover information and social connections, in order to anticipate, predict, and advise learning [19].

2.2 Motivating Example

Consider a motivating example when a student in higher education who has a personal learning environment consisting of (Student Information Systems (SISs), Learning Management Systems (LMSs) like Moodle Open-source learning platform, Teaching & learning survey data, and other Teaching & Learning data, etc (see Figure 1). Student engagement in learning activities appears in various data sources that may be heterogeneous and collected through different digital tools (e.g. the keyboard/mouse/screen actions or camera). Massive data generated during student interaction with these learning environments.The analysis of student behaviors from these aggregated data is a difficult task because of the characteristics of these data which are distributed with scattered and heterogeneous systems: different systems and data structures (e.g. Relational DBMS, XML file, LRS (xAPI data)), these data are detailed: organization of the data according to the functional processes, overabundant data for the analysis, i.e. little/not adapted to the analysis. Consequently, extraction process requires a query languages such as, SQL (Structured Query Language) query for tabular data model, OQL Language (Object Query Language) for object data model , APIs (Application Programming Interface) dedicated for a specific applications, and specialized scripts etc..

To meet the needs of decision makers, we must answer some decision-oriented queries such as.

RQ.1: Who are my students only engaged in my learning activities?
RQ.2: Why and how does the Students' academic performance decrease?.
RQ.3: How to assess qualitatively and quantitatively the determinants of student engagement?.

So, the educators can switch between the data source, and cross all this visualization to link students' behavior aspects aspects with their digital learning activities to get a state about each student and a big picture about the overall students. However, analyzing students' behavior is a process composed by a set of steps that must be applied to the data sources in order to understand his/her behavior from the performance of learning activity. With the aim of guiding educators to analyze students' behavior and their digital learning activities using measurements and metrics of the learning process such as the learning behavior indicators LBI (e.g. timing of starting activities, timing of completing activities, user statistics) and content progress indicators CPI (e.g. completed learning activities).

The need for these decision makers (i.e. teacher, support staff, educational stakeholders) is to have a synthetic view with aggregated metrics on the engagement of students in their learning activities. However, to have a mental image of the student's behavior, it is necessary to set up an information system dedicated to decision-making applications: The latter must be a central system for decision-making organized to support a decision-making process. The question that arises in this situation, how to respond to the demands of decision makers and giving quick and easy access to information related to learner behavior.

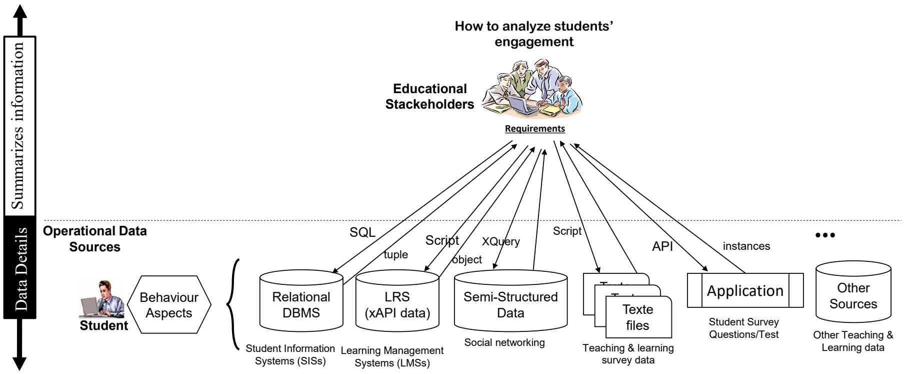


Fig. 1: Illustration of decisional needs from multiple data sources in the case of student behavior analysis

3 Our Framework

Our framework extracts data from various sources, both informal and formal learning environments and loads it into our warehouse using a hybrid storage approach that combines SQL and NoSQL. This storage can be explored by educational stakeholders for various purposes, such as predicting success or failure, analyzing behavior—including student engagement—and exploring descriptive statistics as illustrated by the figure 2.

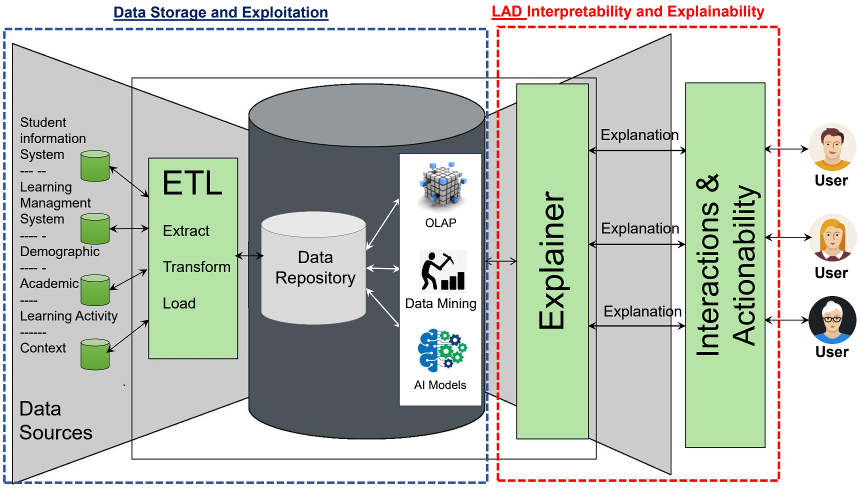


Fig. 2: Our Proposal: DSS – Eng, Side right represent the data storage and exploitation , Side left represent the Explainable Engagement Dashboard

3.1 Our Methodology

Our study at *the university of Tiaret* is based on an analysis of the needs of instructional stakeholders and data sources (see Figure 3). Initially, we focused on understanding stakeholder needs to determine the processes to be analyzed. We then examined the data sources to assess whether they could meet these needs and to identify additional sources if necessary. This approach can be summarized in three steps: we collected information using interviews, questionnaires, and documentation techniques.

3.2 Data Source

Our data source comes from two learning worlds: formal and informal. In the formal world, data is collected from the LMS Moodle, representing interactions of students with courses, forums, wikis, etc. On the other side, data is derived from informal learning, representing all services and platforms used in learning, such as GitHub, YouTube, and social media. We believe that student engagement appears by crossing these data sources, in which the student has experienced a learning opportunity. Additionally, analyzing educational stakeholders allows for identifying certain data sources. Here's an example of stakeholders' needs:

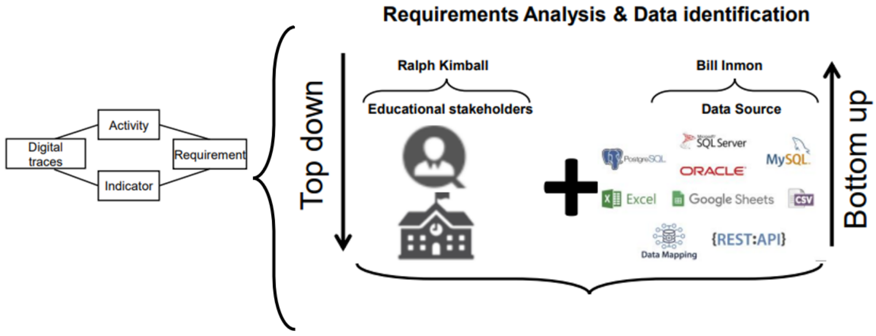


Fig. 3: Our methodology for requirement analysis and data collection is based on Bill Inmon and Ralph Kimbal: To study the data sources, we drafted and validated the summary collection of needs.

Researcher

- Analyzes student engagement and completion rates.
- Conducts statistical analysis on student activity data.

Instructor

- Reviews student activity to assess comprehension.
- Identifies areas where students may need additional support.

3.3 Data pre-processing and Data integration

The data integration is handled using a standardized specification conforming to xAPI to be stored in LRS (Learning Record Store). We believe in using a common structure to store data, allowing enhanced stakeholder interpretation and analysis. Note that several services provide their API publicly to extract student interactions. Listing 1.1 shows an example of an xAPI statement for a student watching a YouTube video.

Listing 1.1: Example of an xAPI statement for a student watching a YouTube video.

```
"actor": {
    "name": "John Doe",
    "mbox": "mailto:john.doe@example.com"
  },
  "verb": {
    "id": "http://adlnet.gov/expapi/verbs/watched",
    "display": { "en-US": "watched" }
  },
  "object": {
    "id": "https://www.youtube.com/watch?v=VIDEOID",
    "definition": { "name": { "en-US": "Title of the Video" } }
  }
}
```

3.4 Data Repository warehouse of Student Engagement

In order to make available a student learning environment and its corresponding learning data expressed in our conceptual model (see Figure 4), we propose a relational data warehouse solution that perfectly fits our requirement. The elements of the test environment can be translated to dimension tables. Two fact tables characterized this warehouse; one for learning behavior indicator and another for the learning behavior indicator (see Figure 4). This warehouse can be utilized by researchers and practitioners for several purposes: (i) checking students' effort, (ii) extending for fine exploitation using, for instance, machine learning techniques, (iii) comparison with other databases of learning-related data within the same context, (iv) predictive analytics, etc. This data warehouse is dedicated to developing future learning behavior indicators and content behavior indicators.

Also, Figure 4 shows the data warehouse schema which plays the cornerstone of the proposed metrics. The data warehouse schema represents a descriptive model of the tested system and not the system itself (i.e., not a prescriptive model). For instance, in the query dimension we store the description of the query and not the SQL expression. The objective behind this idea is to retrieve easily performed tests similar to a given manifest (which does not necessarily have the same conceptual database model).

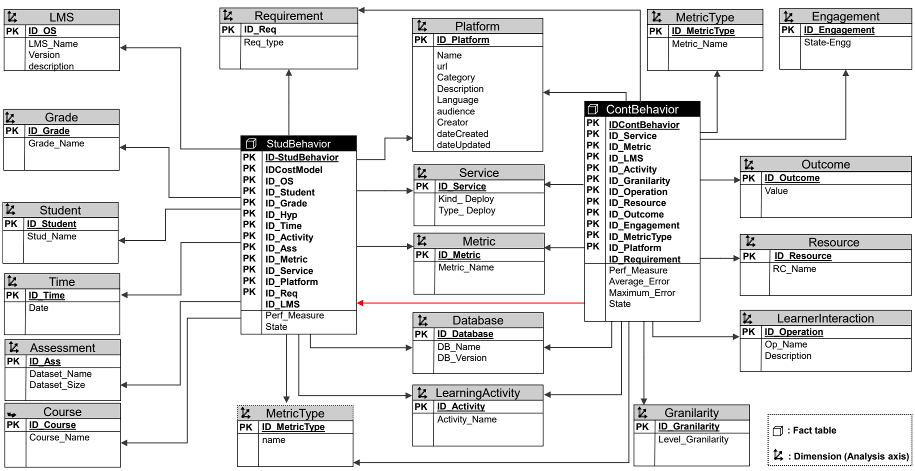


Fig. 4: The Schema of our Data Repository Warehouse (simplified excerpt)

3.5 DDS-Eng Framework capabilities

In this section, we present *DDS-Eng* capabilities — an interface custom-crafted for seamless navigation, provision, exploration, and analyzing students' engagement.

Interface for OLAP navigation The OLAP Engine supplies a query interface for OLAP navigation that uses our warhouse as entry and a navigation GUI. Users can express their requirements as OLAP queries to aggregate test results (e.g., SUM, AVG, MEDIAN), specify error types (e.g., Average-Error, Maximum-Error, Error-Rate-MRE), and plot sets of metrics using the LAD tool's GUI. Additionally, they can store these queries for later studies and plotting.

Forecast interface for predicting student behavior In essence, the aim of inference operators is to use stored information about the learning environment and student learning data to forecast the success or failure of students. This involves transitioning from basic descriptive data to more sophisticated analytics, such as predicting the outcomes for students. The insights gained from this process can then be leveraged by educational stakeholders like teachers and support staff to craft strategies that enhance student motivation and engagement, thereby maintaining and nurturing their educational journey.

Recommending and Feedback Another essential use of these operators is to aid teachers by providing recommendations and feedback to enhance their students' learning experience. This guidance aims to improve both the learning outcomes for students and the overall learning environment.

4 Proof of concept

To emphasize our approach and demonstrate its utility and effectiveness, we've created a support tool that enables the perception and visualization of students' engagement states.

Technical Implementaion The service-based pipeline in our approach is organized and orchestrated by three services. Service 1: Data Source, Service 2: Data Curation Process, and Service 3: is frontend service responsible for displaying the right content on the different actors, i.e. teachers/support staff and students. To show how our system works, we have implemented a demonstrator application into two sides **(ii)** a single-page applications stack is developed as dashboard to more understand visual perception and perceive visual changes states to each student, and **(i)** oriented motivation learning by a mobile application system.

4.1 Learning analytics dashboard

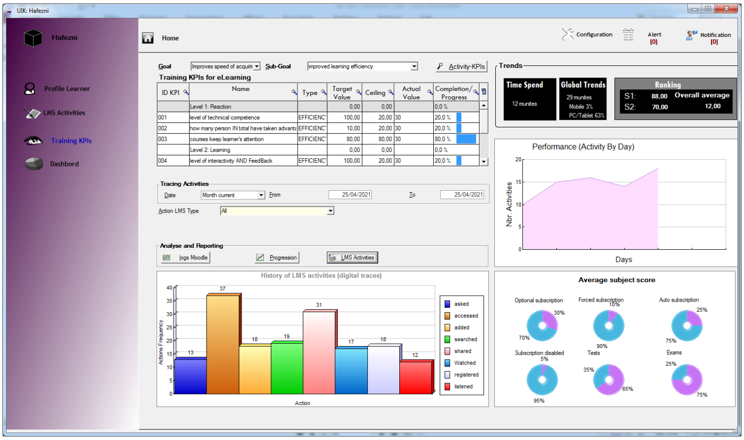
In this section, we introduce our learning analytics dashboard designed specifically for educational stakeholders, including teachers and support staff.

Student behavioral engagement analysis dashboard We remind ourselves that our primary objective, as per RQ1, is to understand how to perceive student engagement aspects at a high level of abstraction. To address the first research question, we have developed a Learning Analytics Dashboard (LAD) tailored for educational stakeholders. Our LAD offers visual representations of student behavioral interactions synchronized with engagement aspects. In this section, we outline its capabilities.

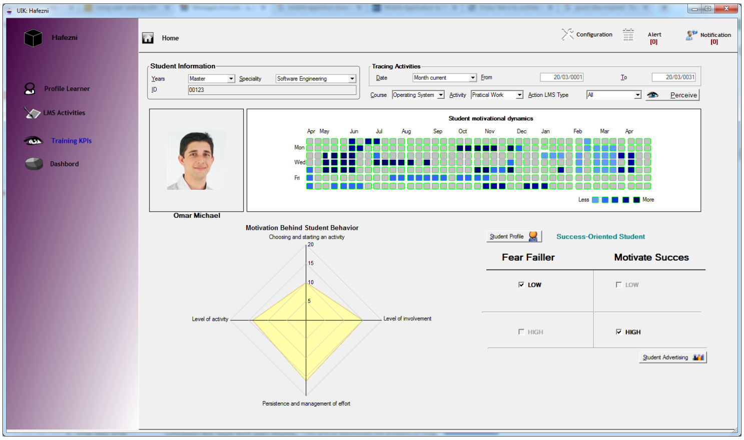
Interface for reporting activities students Our tool provides an overview of a student's activity on their profile. Enabling the activity overview section offers viewers more context about the actions the student takes. This section allows viewers to see detailed information about the student's actions and enables filtering of actions and activity timelines for a specific student (see Figure 5a). In Figure 5a, the Learning Behavioral Indicators (LBI) are loaded and ready for querying. Our tool offers users a wide range of analysis possibilities and collects all necessary information for decision-making, providing timely activity reports. LBIs are used to monitor student performance relative to their behavior, with actual LBI values and threshold values serving as indicators of student motivation. These indicators offer a comprehensive view of the student's behavior. To track these indicators, our dashboard presents one or more LBIs along with contextual information and activities related to a particular course, aiding decision-makers in identifying deviations and their underlying causes.

Interface for engagement state perceive On a student's profile, we display an actions graph inspired by the Github contribution graph. The graph consists of blue squares representing different levels of activity, ranging from less to more advanced. Some squares appear darker, indicating that the actual value of the indicator tends towards its limited value, while others are lighter. When observing an active, established student's profile, there is usually a balanced mix of light and dark blue squares, reflecting their learning activity performance.

In the bottom right corner of the dashboard (see Figure 5b), our system provides an overview of various aspects of the student's behavior, including their motivation for success and fear of failure (whether low or high). This allows users, such as teachers, to track the student's motivation levels and adjust learning activities accordingly. The Figure 5b facilitates the effective use of data to assist decision-makers in tailoring learning activities to fit the student's motivational profile, whether they are success-oriented or focused on avoiding failure. Moreover, we anticipate that users will gain insights into the student's motivation state by assessing the impact of motivation for success versus fear of failure. This enables them to view and monitor progress and comprehension indicators effectively. Our aim is to encourage e-Learning communities to address the challenges associated with conceptualizing and explaining student motivation states in a machine-readable format. [23].



(a) screenshot of reporting activities students.



(b) screenshot of engagement state perceive.

Fig. 5: Proof-of-concept prototype (Screenshots).

5 Related work

There is a long line of studies on design a LAD of students behavior analysis and self-reporting LAD. From the industry and academia, there has been much research on student behavior analysis problems such as Designing Student Engagement, Analyzing Failure and Success, Evaluating Academic Outcomes, etc. (e.g. [17, 18]. Within the LA community, there is a prominent research trend exploring how Artificial Intelligence (AI) can enhance the analysis of student behavior (e.g. [24, 16, 4, 14]). The LAD, in turn, invokes the existing data source through its provider solution, which must be implemented in a way that allows developers to access it — a task that is not always easy. This is achieved by leveraging the capabilities of the *application programming interface (API)*. After evaluating he different forms of graphs and objects are presented in the dashboard, They cross-reference this information without omitting information about learners and their learning environment. However, each assistant tool in traditional LAD systems suffers from several limitations. Firstly, they often rely on specific systems like formal Learning Management Systems (LMS) such as Moodle. Secondly, the data sources are often tailored to particular systems and lack generalizability to consider informal learning. Lastly, these tools often overlook the learning experiences derived from platforms and tools provided as RESTful API solutions (e.g., Github, Trello). Similar work has been considered in decision support systems for learning analytics (e.g. [7, 3]). However, these works don't extend their extraction to formal learning environments that encompass the student learning experience. In another line of research, authors try to provide a transparency strategy to support the analysis of student behavior. The pioneering works of explainable student behavior are introduced in [12, 21, 21].

6 Conclusion

This study addresses the critical challenge of evaluating student engagement by leveraging Learning Analytics (LA). Through the development of DDS-Eng, a Data-Driven Decision Support System tailored for this purpose, we provide educational stakeholders with a comprehensive tool for analyzing and understanding student engagement patterns. Our approach begins with meticulous requirement analysis to ascertain the needs of decision-makers and identify relevant data sources. Subsequently, we construct a multidimensional model encompassing various engagement aspects and associated metrics. This model serves as the foundation for the development of a dedicated interface, incorporating OLAP queries and a Learning Analytics Dashboard (LAD), enabling in-depth analysis of individual student behavior and overall engagement levels.

Our empirical evaluation of the LAD, conducted in a controlled environment, underscores the efficacy and potential of our approach. By shedding light on the intricacies of student engagement in online learning, this research emphasizes the importance of innovative methodologies for evaluating learner engagement in diverse and evolving learning environments. The findings highlight the significant impact that detailed engagement analysis can have on improving learning outcomes and reducing dropout rates.

Moving forward, it is imperative for educational institutions and stakeholders to continue exploring novel approaches to harness the power of data analytics in enhancing student engagement and facilitating meaningful learning experiences. Future research should focus on refining DDS-Eng by incorporating more diverse data sources, enhancing predictive capabilities, and validating its application across various educational settings. By addressing these areas, we aim to contribute to the development of more robust and versatile tools for assessing and enhancing student engagement in both formal and informal learning environments.

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