Project Advanced Web Technologies Adaptive Learning Analytics Dashboard Group 2

Emilia Teresa Stepien
Technische Universität Berlin
Berlin, Germany
stepien@campus.tu-berlin.de

Cecilie Viktoria Kudlek
Technische Universität Berlin
Berlin, Germany
c.kudlek@tu-berlin.de

Merlin Schumann
Technische Universität Berlin
Berlin, Germany
m.schumann@campus.tu-berlin.de

***Abstract*—This report presents the comprehensive documentation for the design and implementation of the adaptive learning analytics dashboard developed in the Advanced Web Technologies project. The dashboard addresses the challenge of presenting personalized learning analytics to different stakeholder groups in a digital self-regulated educational setting. We generated a synthetic user interaction dataset based on learning personas and outliers and incorporated it into a responsive React web application. Building upon this application, the dashboard provides distinct views for learners, educators, and content creators, with tailored metrics, data visualizations, and recommendation services for each stakeholder. By offering actionable insights into the learning process, it supports informed decision-making to improve the learning experience and outcomes.**

I. Introduction

In today's digital education, stakeholders such as educators, learners, and content creators, often lack real-time insights into learning progress, individual knowledge levels, and specific learning needs. Unlike in a traditional classroom setting, where learners interact directly with teachers and each other, without adequate tracking and data visualization methods, it becomes challenging to understand how learners progress and to identify possible issues in student engagement, teaching methods, or course content [1]. This lack of insight can limit the ability of stakeholders to make informed decisions that optimize learning outcomes.

To address this challenge, this project aims to develop an adaptive learning analytics dashboard that consolidates key metrics and indicators relevant for the three stakeholder groups mentioned above, as well as built-in services that provide actionable recommendations, supporting them in making data-driven decisions to improve the learning process.

The dashboard integrates synthetic user interaction data, adhering to the Experience API (xAPI) and Learning Objects Metadata (LOM) standards. The utilization of these interoperable standards ensures that the system can effectively capture, store, and analyze learning experiences across various educational contexts. As different stakeholders approach learning analytics with unique perspectives and requirements, the dashboard adopts an adaptive design philosophy. Each stakeholder receives a customized view that highlights the specific metrics, visualizations, and actionable insights that are most relevant to their roles and responsibilities. This role-based customization ensures that stakeholders can efficiently access and interpret the data that drives their decision-making processes.

Throughout this project, we explore the research question: "How can a synthetic learner dataset be generated and incorporated into an adaptive learning analytics dashboard for different stakeholders to offer valuable insights and actionable recommendations that optimize the learning process?"

This work is organized as follows: the next two sections cover related work and our approach to the design and implementation of the dashboard. Subsequently, the results of the implementation are explained together with the added value for each stakeholder. The last sections discuss implications, limitations, possible future work, and draw conclusions.

II. Related Work

Several studies have investigated the design methodologies and impact of dashboards for learning analytics. This section outlines the key works that have informed the development of our dashboard.

Klerkx et al. [2] give an introduction to learning analytics dashboards in the field of learning analytics and illustrate noteworthy implementation examples. Their proposed guidelines for the development of these include the following actions: understanding the goals (problem domain, intended end-users, and typical tasks they perform), data acquisition and processing, mapping design (choosing a visualization technique that best answers the questions of the end-users), documentation, adding interaction techniques, and continuous evaluation. They conclude that learning analytics dashboards have the potential to shape the learning process by concisely visualizing relevant metrics and thereby supporting stakeholders to explore and gain insights into learning patterns.

The Student Activity Meter (SAM) [1] was one of the early dashboards that visualizes the time spent by students over the course period and their use of resources. By providing insights on the progress in the course for teachers and learners, SAM raises awareness and self-reflection. It includes a line chart illustrating the cumulative amount of time spent by each student, where the inclination of the line shows how intensively the respective student has studied. The total time spent and resources used are visualized through a histogram. This dashboard was developed in four design iterations and evaluated both quantitatively and qualitatively. The results show that SAM supports teachers in identifying outlier students, high-performing students, and students at risk, as well as providing a better overview over the course.

Podgorelec and Kuhar [4] recognized the importance of developing different dashboard views for different target groups and created two Moodle dashboards, designed for lecturers and teaching assistants, respectively. Previously, they conducted a survey with those two target groups, inquiring their major objectives for using Moodle and what kind of data they would prefer to see in the form of diagrams. Based on these results, they designed the dashboards including metrics and diagrams relevant for the respective target group. One notable visualization is a box and whisker chart that provides a detailed overview of assignment grades, allowing educators to easily identify assignments with a high variance in grades or with a low maximal score.

A more recent paper by Verbert et al. [7] presents past and current trends in the research of learning analytic dashboards and proposes a research agenda for the future. Recent trends include the use of participatory design methods to better meet the needs of end-users, a focus on improving the pedagogical foundations that guide the design, and creating dashboards for additional stakeholders, such as study advisers. For future development of dashboards, the authors propose that successful and proven patterns from existing learning analytics dashboards should be reused to ensure a solid theoretical foundation. Furthermore, they suggest that dashboards should go beyond presenting data by incorporating actionable suggestions to help users make informed decisions on improving the current situation.

III. Approach

To develop an adaptive learning analytics dashboard that offers valuable insights and actionable recommendations to optimize the learning process, we focused on two key tasks:

1. Generating a realistic synthetic learner interaction dataset that adheres to the xAPI schema and aligns with the given course data specified by LOM.
2. Developing stakeholder-specific views in the dashboard that utilize this synthetic dataset, incorporating relevant metrics, intuitive data visualizations, and recommendation services that provide actionable instructions.

The following subsections outline the steps taken to achieve these objectives.

A. Personas and Outliers

An important aspect of generating a realistic synthetic dataset is considering different types of learners that are likely to be encountered in the real world. Mojarad et al. [3] analyzed data from 700 students who used ALEKS, a web-based learning system, and clustered them based on characteristics related to their academic performance and behavior. They applied mean-shift clustering to determine the number of clusters and k-means clustering to identify five distinct learner profiles. We adapted the identified attributes from these profiles and created five learner personas for our dataset, as shown in Table I.

To enrich the data with outliers that should later be easily recognizable in the dashboard diagrams, we draw on the work of Treuillier and Boyer [6]. Next to categorizing homogeneous groups of students, they also identified outliers in a dataset consisting of 1303 students from the Open University, a distance learning university. For our synthetic dataset, we decided to include the following outliers:

- Outlier A: initially high consistency, high effort, and high scores, but the behavior changes and the student does not complete the last assignments
- Outlier B: low effort, loses consistency over time, but achieves average scores
- Outlier C: frenetic activity with extremely high effort and very high consistency, average to high scores
- Outlier D: very high consistency, high effort, excellent scores

B. Synthetic User Interaction Data Generation

Our approach for generating realistic synthetic user interaction data started by analyzing the available data structures, which were provided as part of the project scope. The given xAPI profiles provide a structured approach to capture learning interactions with ten statement templates covering performance tracking and activity monitoring. These include three activity types and ten specific verbs essential for realistic learning scenarios.

The project's course content is given in the form of an IMS Common Cartridge as an XML file. It is organized hierarchically into three main modules, each containing multiple activities. For each of the 15 activities, there is an XML file with LOM, detailing educational aspects such as learning time, difficulty, interactivity level, resource type, and semantic density. We will use these metadata to create our user data.

Using this data, we developed a multistage data generation pipeline implemented in React with a Node.js/Express backend, interfacing with MongoDB for data persistence. The pipeline begins with the course data generator class, by extracting and parsing the content from the XML-, LOM- and xAPI-profiles JSON files that are fetched from an URL. The parsed data that include the activities, verbs, and LOM educational values are then mapped into activity objects and the course structure interface, which are now in normalized, machine-readable formats. The parsed LOM and verbs are saved in the database. We also adjusted the values such as typical learning time and difficulty for each LOM to have a more diverse set of activities.

The activity generator then creates learning interactions based on these course activities, following our designed verb flow process. Individual progress is tracked and achieved

TABLE I
LEARNER PERSONAS

Learner Profile	Description	Proportion	Consistency	Effort	Scores	Duration
Strugglers	Very low prior knowledge, puts in low effort and has an average pace of learning	30%	Average	Low	Very Low	Average
Average Students	Average in all characteristics	39%	Average	Average	Average	Average
Sprinters	Average prior knowledge, low consistency in learning and low effort, but have a high pace	8%	Very Low	Very Low	Low	Short
Gritty	Average prior knowledge, high consistency and high effort, but work at a slow and steady pace	10%	High	Very High	Very High	Long
Coasters	Very high prior knowledge, however, they have average pace and consistency, and put in low effort	13%	Average	Low	Average	Average

scores are calculated for each activity. We specified different probabilities for the selection process of the activities, so some activities are used more often than others.

In the session generator, the created learning interactions are used to create learning sessions for each learner for a specified number of weeks. This includes calculating individual sessions per week, session start times, and session durations for learners based on their persona type.

A fixed number of learner profiles is generated in the learner generator, which implements the learning preferences of the different persona and outlier types. All learner profiles are stored in the database.

All generated data are then combined in the xAPI statements generator, where the user interactions for each learning session are transformed into xAPI statements. Based on the given example xAPI statements we created an interface containing the learner, verb, and activity id's to which the user interactions are mapped. The statements are saved in the database and can be used to fill the analytics dashboard with data.

For data generation, we created profiles for 55 learners (50 standard personas and 5 outliers) over a 12-week period. Learning sessions are generated based on persona-specific parameters, including session frequency, duration, and timing patterns. The resulting interactions are transformed into xAPI statements, providing a comprehensive dataset that represents ongoing learning processes rather than completed courses. This approach enables both realistic analytics visualization and meaningful recommendation generation for our dashboard.

To get a better overview of the generated xAPI statements we also created a section in the website that displays statistics about information like learner distribution, average learning times and average scores. This web app will act as a starting point for our dashboard implementation.

C. Stakeholders and Metrics

In their systematic literature review of learning dashboard research, Schwendimann et al. [5] identified four types of target users: learners, teachers, administrators, and researchers, with a strong focus on learners and teachers. While we also incorporated learners and teachers, we decided to include an additional stakeholder, the content creator, because we believe that learning progress and outcomes depend on the quality of the course content, and can be optimized through its appropriate adaptation. To decide on the metrics and visualizations, we partly adapted successful elements from existing learning analytics dashboards and used our own experiences as students participating in various online learning activities.

D. Dashboard Implementation

Building upon our existing React application that already handles synthetic user data, we implemented a comprehensive dashboard architecture.

The foundation starts with our database services, that feed the main app component with all necessary data, particularly the xAPI statements, from the database. For the actual dashboard implementation, we took a systematic approach. Each dashboard for educator, learner, and content creator is built as a separate TypeScript class. These classes handle both the layout management and the integration of various components.

For each of the selected metrics and indicators, we designed and implemented components as individual classes and integrated them into their respective dashboards view. The data for these components is dynamically calculated using our generated xAPI statements. Additionally, we designed and implemented recommendation services for each dashboard, which analyze the processed data to provide stakeholder-specific suggestions. This architecture ensures that each stakeholder not only gets the data they need but also receives actionable insights to enhance the learning experience.

IV. RESULTS

The following section presents the results of our dashboard implementation. Each component and its value for the respective stakeholder are described in detail. For each dashboard view, we grouped similar metrics and charts into sections that are visually clearly distinguishable by different background colors. Additionally, most of the charts are equipped with tooltips that provide a textual description of the information visualized in the chart.

A. Learner Dashboard

The learner dashboard, as shown in Fig. 1, provides an individualized overview of a single student's progress, performance, and recommendations based on their learning behavior. A learner can be selected via the drop-down menu at the top.

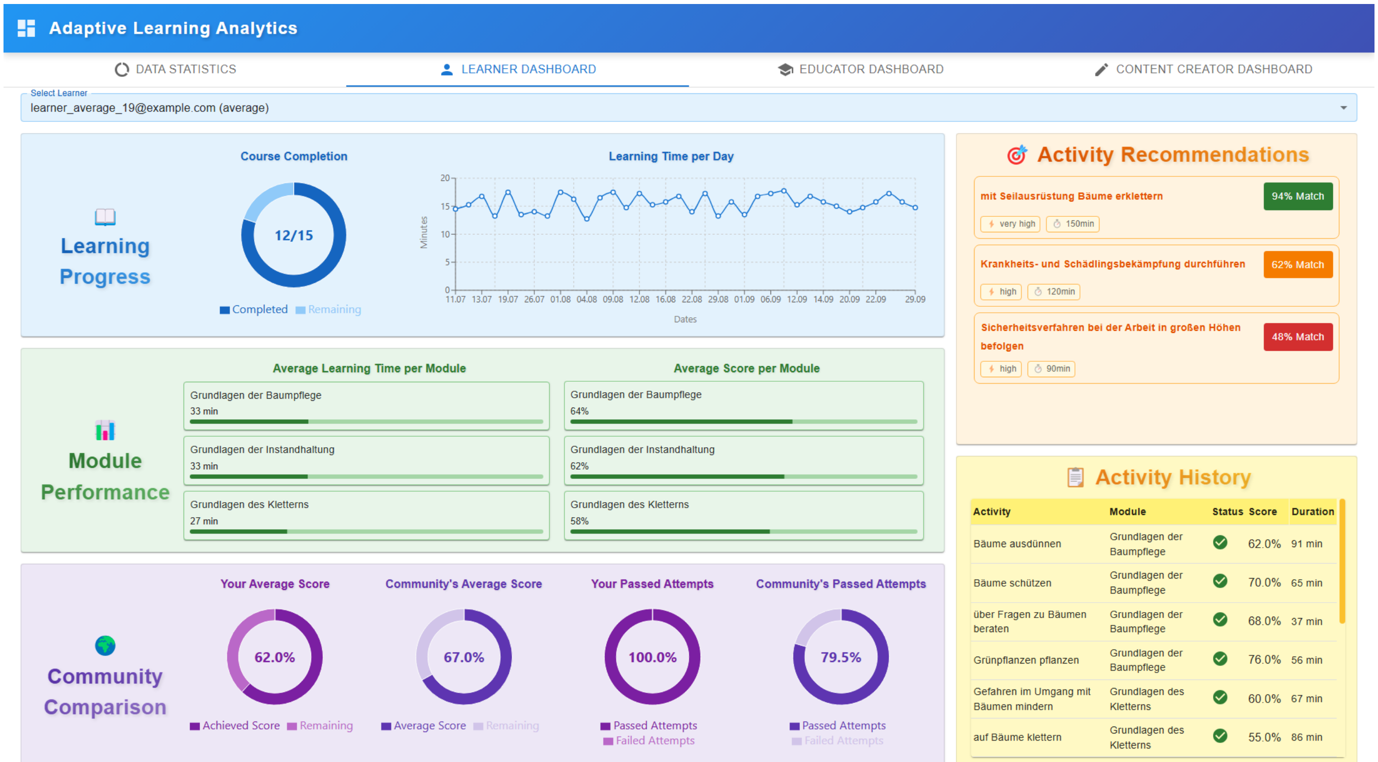

Fig. 1. Learner Dashboard

The "Learning Progress" section displays the number out of the total 15 activities completed in a ring chart, which offers a quick visual representation of the learner's overall progress. Additionally, the time they spend learning on a certain day is tracked in a line chart. By analyzing this graph, learners can identify patterns in their study habits, such as periods of high engagement or days when they may have neglected learning. They can therefore adjust their learning strategies accordingly.

In our dataset, the 15 activities are grouped into three modules based on their content. In the "Module Performance" section, the learner gets an overview of their average learning time and their average score per module. This allows the student to see whether their study time and grades are balanced across different modules and which modules may need more attention.

The "Community Comparison" section allows the learner to compare their performance with the whole learner community. It displays the average score, as well as the ratio of attempts passed and failed, over all courses for both the learner and the community in two ring diagrams each. This can serve as motivation for the learner to improve, or give reassurance if the learner performs above average.

In the "Activity History" section, the learner gets a concise overview of the activities they completed so far, their achieved score, and the duration they needed to complete it, allowing them to quickly reflect on their past performance and progress.

Finally, the recommendation service for the learner is represented in the "Activity Recommendations" section. It calculates a matching score for all the remaining activities the learner has not started yet by considering their learning type, average scores, and average learning time so far and matches this information with the difficulty and typical learning time of open activities. The recommended activities are sorted by their matching score and each is listed with the difficulty and typical learning time. Learners can use these recommendations to make informed decisions about which activities to take next to optimize their learning journey.

B. *Educator Dashboard*

The educator dashboard, illustrated in Fig. 2, provides an overall view of students' learning behavior and performance, allowing educators to monitor progress, identify struggling students, and adjust their teaching strategies accordingly.

In the"Learning Progress" section, a line chart on the left side shows the cumulative learning time for every student, where each student is represented by one line. This chart was adapted from the SAM dashboard introduced by Govaerts et al. [1]. Steep inclines signify periods of intensive learning, while flat sections indicate that the student was inactive during this time. This chart helps the educator to identify outlier students. Those who are highly engaged and study quickly will appear in the upper range, while those who invest less time in learning will cluster towards the bottom. Additionally, there are two ring charts in this section, displaying the average score and the ratio of passed and failed attempts of the entire student community. These charts help educators assess overall class

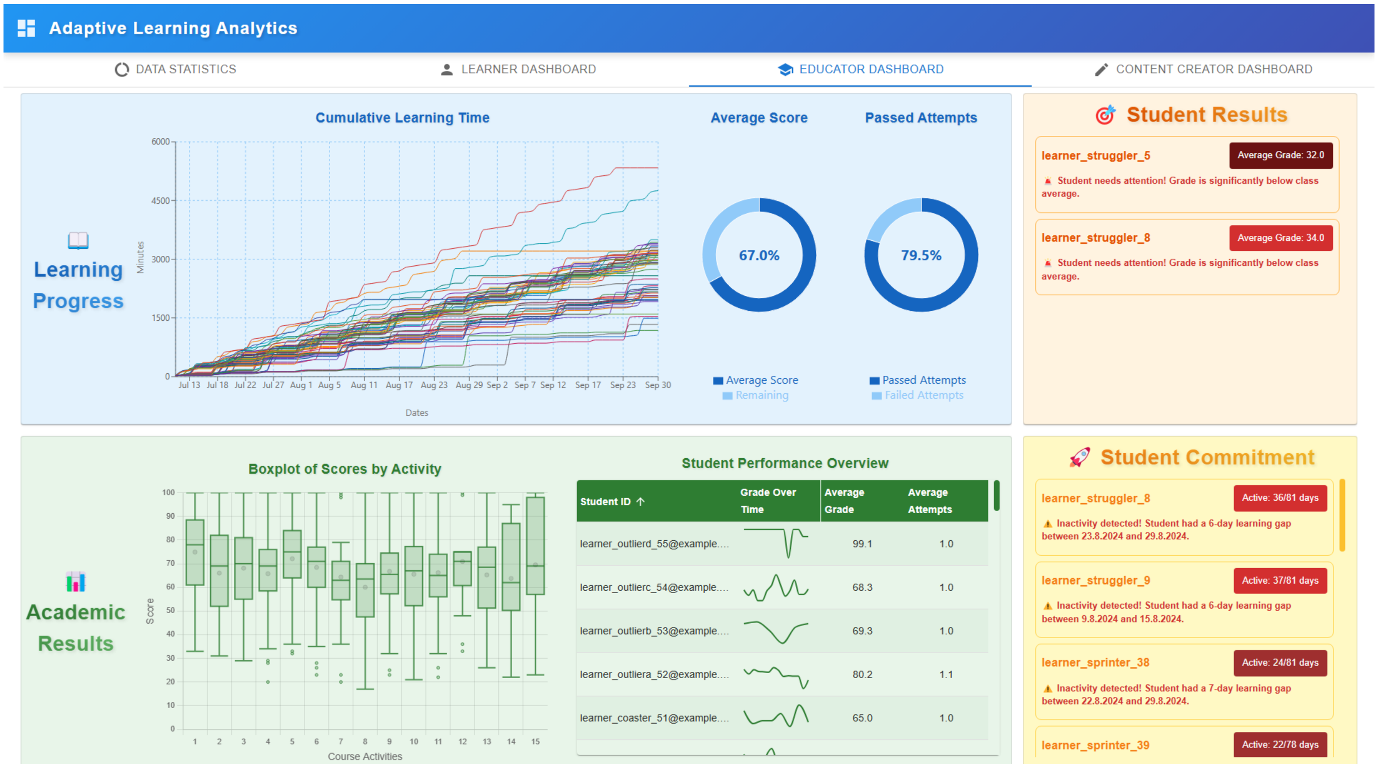

Fig. 2. Educator Dashboard

performance at a glance and identify trends. A high failure rate, for instance, might indicate difficult course material or ineffective instruction.

The “Academic Results” section contains a box plot diagram of the scores by activity and a table containing an overview of the students’ performance. Those metrics were partly inspired by the dashboards created for educators that were introduced in [4]. The boxplot of scores by activity allows the educator to identify those activities where the majority of students perform low and therefore need an adjustment in content or teaching methods. The student performance overview table lists all students, together with a line graph displaying their grades over time, their average grade, and the average attempts they needed to pass a course. It is possible to sort the table by student ID, average grade, and average attempts. By examining this table, an educator can easily filter out students who need help because their grades declined over time. Moreover, a high number of attempts may indicate that this student is relying on trial-and-error rather than adequately working through the course material before assessment. Recognizing this enables the educator to provide targeted guidance and help the student prepare adequately for exams.

The “Student Results” service filters out all students who may be at risk because they have a significantly lower average grade than the community average. Additionally, the “Student Commitment” service identifies all students who were inactive during a long period of consecutive days at some time. By detecting these learning patterns, educators are enabled to intervene timely and offer support to students who may be struggling with their time management, motivation, or learning effectiveness.

C. *Content Creator Dashboard*

The content creator dashboard, as shown in Fig. 3, provides insights across all 15 activities, enabling content creators to assess and adjust course content based on students’ performance and feedback provided through ratings. An activity can be selected via the drop-down menu at the top.

In the “Activity Review” section, a chart shows the distribution of ratings for the selected activity, given by students on a scale from 1 to 10. This visualization helps the content creators quickly understand overall student satisfaction. If an activity is rated very poorly by the students, the content creator can review the content and adjust it if it does not appeal to the students to increase satisfaction. The distribution of the actual learning time of the students is displayed in a histogram. This allows the content creator to assess how many students are spending an appropriate amount of time engaging with the activity relative to its contents. If students spend unusually little time, the activity may be too easy or students keep skipping through contents. Conversely, very long learning times may indicate that the activity is too complex or not clearly structured.

The “Course Overview” table gives a concise overview of all 15 activities along with relevant metadata from the LOM (resource type, interactivity type, interaction level, semantic

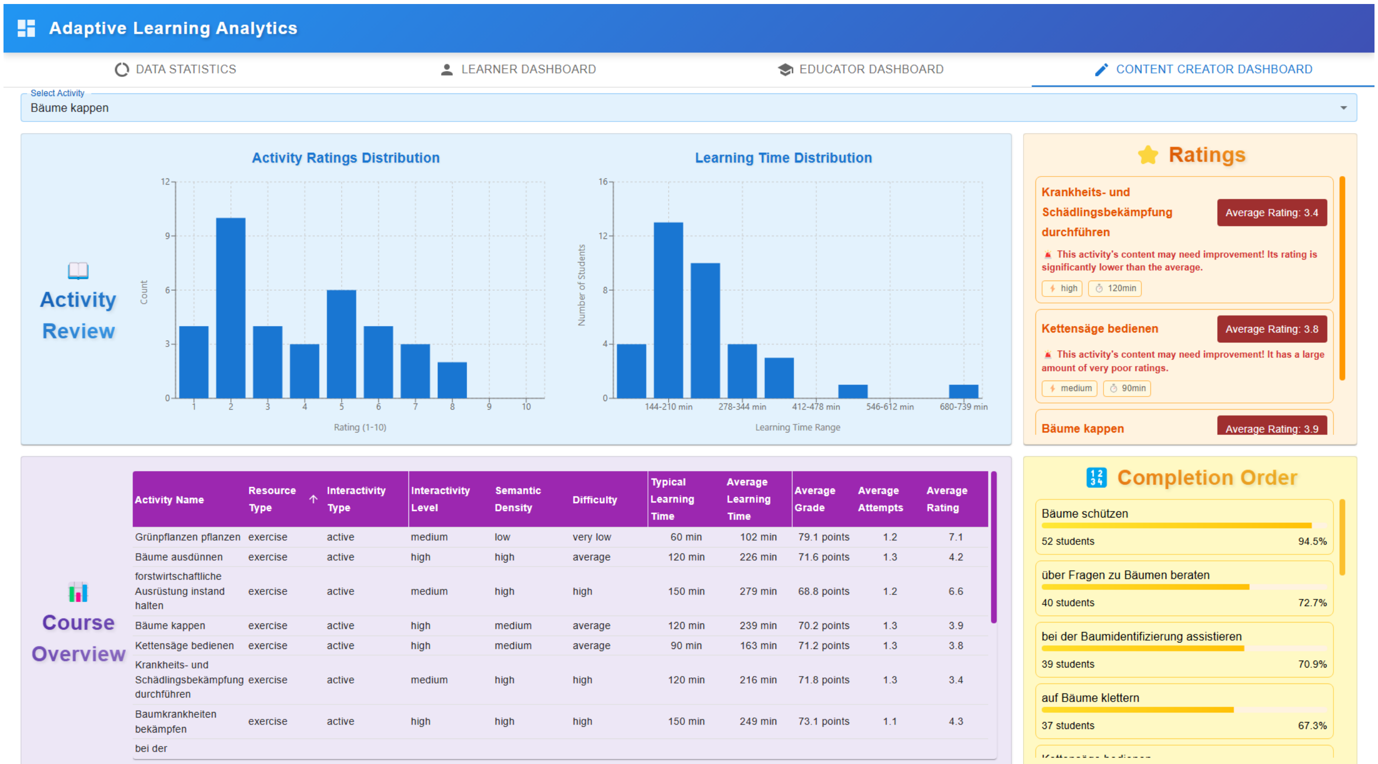

Fig. 3. Content Creator Dashboard

density, difficulty, typical learning time) and metrics regarding the actual performance of the students (average learning time, average grade, average attempts to pass, average rating). This enables the content creator to see how the different properties specified in the LOM of the activity may be reflected in the real student performance. By examining the actual metrics, activities that might require adjustments, for example due to low ratings or grades, or an untypical average learning time, become easily identifiable.

The "Completion Order" component shows which other activities were completed by which proportion of students before the selected activity. This helps content creators to make informed decisions regarding the prerequisites of the activity. If a large proportion of students have completed a specific activity beforehand, it is reasonable to assume that knowledge from that activity is already present, allowing the content creator to design the current activity to build upon that prior knowledge. Conversely, if a certain activity has not been completed by the majority of students, the knowledge taught in this activity should not be assumed to be present and necessary foundations should be included in the current activity.

Lastly, the "Ratings" recommendation service identifies activities with significantly lower ratings than the average or those with a high number of very negative ratings, regardless of the average. Through this, content creators can quickly identify problematic activities that may require modification to improve the learning experience for students.

V. Discussion

The adaptive learning analytics dashboard developed in this project has important implications for digital education and student engagement. By providing data visualizations and actionable recommendations that are customized to the needs of different stakeholder groups, it supports informed decision-making, which is essential to improve learning outcomes.

The dashboard supports learners in their self-regulated learning by providing clear visualizations of their learning progress, performance, and personalized advice for activity selection. Students can easily identify areas that require improvement, which facilitates optimizing their learning strategies. By enhancing awareness of their own progress and allowing comparison of key metrics with their community, it can help promote greater motivation and thereby learning success.

For educators, the dashboard serves as a valuable tool for monitoring student progress, identifying high-performing and struggling learners, and adjusting their teaching methods accordingly. Identifying students with low motivation and poor results early enables timely intervention. By providing targeted guidance, each student can get the support they need, presumably reducing dropout rates and enhancing the success of the learners. Furthermore, the dashboard offers insights into trends across the entire student community and therefore facilitates the identification of broader issues, such as activities with unfitting difficulty or ineffective teaching methods, which can then be improved to enhance overall success and learning experience.

For content creators, the dashboard offers insights into the effectiveness of activities and supports them in refining course content based on the feedback and performance of the students. By analyzing students' ratings, average learning time, attempts to pass, and grades, they can identify activities that need improvement to be more efficient and engaging, ultimately supporting the learning process. Since this stakeholder group is underrepresented in existing research, especially the dashboard for the content creator may serve as a starting point for other researchers and developers.

A limitation of our work is the lack of testing the usability and usefulness of our dashboard implementation with real users belonging to the stakeholder groups, as this was not in the scope of this project. Klerkx et al. [2] recommend a user-centric design approach, in which evaluation is carried out during each iteration of the development. Another aspect is the generation of a realistic synthetic dataset, which is helpful to evaluate the impact of the different dashboard diagrams to provide meaningful insights. Even though we created the data using multiple persona and outliner learner types, a real dataset would allow a better assessment of the dashboard's effectiveness in identifying learning patterns, challenges, and opportunities for intervention. Future work should include testing our current dashboard implementation with real data and users and improving its functionality and user interface based on the results. Furthermore, the services that offer actionable instructions could be enhanced by incorporating machine learning methods. For example, predicting future learner engagement or performance based on past behaviors might help identify learning problems before they arise, enabling proactive interventions to address them.

VI. Conclusion

In this project, we developed an adaptive learning analytics dashboard, with separate views for learner, educator, and content creator stakeholders. It is based on a synthetic user interaction dataset, that we generated based on learner personas and outliers, and that conforms to the interoperable xAPI and LOM standards. Each dashboard view incorporates metrics and data visualizations relevant to the specific stakeholder, as well as recommendation services that calculate actionable instructions. It raises awareness for learners and allows them to adapt their learning strategies, offers support for educators to identify struggling students and adapt their teaching methods accordingly, and helps content creators design course content that is appropriate and engaging for students, ultimately the enhancing learning experience and learning outcomes.

References

[1] S. Govaerts, K. Verbert, E. Duval, and A. Pardo, "The student activity meter for awareness and self-reflection," in *CHI '12 Extended Abstracts on Human Factors in Computing Systems*, Austin, TX, USA, 2012, pp. 869–884. doi: 10.1145/2212776.2212860.

[2] J. Klerkx, K. Verbert, and E. Duval, "Learning analytics dashboards," in *The Handbook of Learning Analytics*, C. Lang, G. Siemens, A. F. Wise, and D. Gašević, Eds. Alberta, Canada: Society for Learning Analytics Research (SoLAR), 1st ed., 2017, pp. 143–150. doi: 10.18608/hla17.012.

[3] S. Mojarad, A. Essa, S. Mojarad, and R. S. Baker, "Data-driven learner profiling based on clustering student behaviors: learning consistency, pace and effort," in *Proc. Int. Conf. Intell. Tutoring Syst.*, vol. 10858, Springer, 2018, pp. 130–139. doi: 10.1007/978-3-319-91464-0_13.

[4] V. Podgorelec and S. Kuhar, "Taking advantage of education data: Advanced data analysis and reporting in virtual learning environments," *Elektronika ir Elektrotechnika*, vol. 114, pp. 111–116, Oct. 2011. doi: 10.5755/j01.eee.114.8.708.

[5] B. Schwendimann, M. Rodríguez-Triana, A. Vozniuk, L. Prieto, M. Shirvani Boroujeni, A. Holzer, D. Gillet, and P. Dillenbourg, "Perceiving learning at a glance: A systematic literature review of learning dashboard research," *IEEE Trans. Learn. Technol.*, vol. 10, pp. 1–1, Oct. 2016, doi: 10.1109/TLT.2016.2599522.

[6] C. Treuillier and A. Boyer, "A new way to characterize learning datasets," in *Proceedings of the 14th International Conference on Computer Supported Education - Volume 2: CSEDU*, INSTICC, SciTePress, 2022, pp. 35–44. doi: 10.5220/0010982500003182.

[7] K. Verbert, X. Ochoa, R. De Croon, R. A. Dourado, and T. De Laet, "Learning analytics dashboards: The past, the present and the future," in *Proc. 10th Int. Conf. Learn. Analytics Knowl. (LAK '20)*, Frankfurt, Germany, 2020, pp. 35–40. doi: 10.1145/3375462.3375504.