# Co-Design of an Adaptive Personalized Learner Dashboard

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***Abstract*—Learning Analytics Dashboards (LAD) equip learners with visual insights into their study activities, enabling informed decision-making. This paper introduces a LAD plugin tailored to individual needs to improve distance learners' skills in metacognition and self-regulation. Through a co-design approach involving focus groups and interviews, students identified desired features like comprehensive resource overviews, deadline tracking, progress highlights, and enhanced interactions with peers and instructors. The final dashboard design allows learners to assess and track their knowledge, progress, and upcoming tasks, with metrics that facilitate comparisons against their goals and provide adaptive feedback. A user study (N=177) confirmed that users are engaged with the dashboard, but the planning and reflection tools were used less than the monitoring tools.**

***Index Terms*—Learning Analytics Dashboard, Co-Design, Adaptive Learning**

## I. Introduction

The field of Learning Analytics (LA) utilizes online learning data to enhance teaching and learning processes, aiming to improve learning outcomes through personalized learning pathways, adaptive assessments, and timely feedback [3]. Learning Analytics Dashboards (LAD) consolidate various learner and learning process indicators into unified visualizations [6]. While LADs increase student awareness and encourage reflection, their effectiveness often falls short without alignment to clear educational objectives [4], and non-adaptive designs may negatively impact learning [4, 7, 8].

This paper addresses the shortcomings of predominantly instructor-facing LADs [6, 1] that fail to directly enhance key learning skills like metacognition and self-regulation [2]. Given the diversity at distance universities, LADs must be specifically designed to adapt to varied learner needs and backgrounds [3, 8]. An adaptive LAD personalizes content based on individual user data and preferences, supporting learners with tailored feedback to improve their skills and knowledge acquisition. Therefore, the LAD presented in this paper was developed through a co-design process involving students and was tested in a field study, emphasizing self-regulated learning and grounded in established learning theories.

## II. Co-Design

A 7-step participatory design approach (Fig. 1) including the field study reported in section IV was followed to better understand the learners' needs.

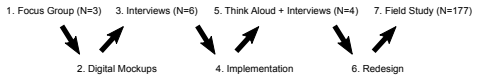


Fig. 1. The co-design process with the participation of students as the target audience of the LAD.

### A. Methods

*1) Research Design and Participants:* A qualitative research approach, guided by Design Thinking principles, was utilized to understand individual preferences for the LAD design. This included empathizing with users, defining problems, ideating, prototyping with paper, and testing with digital mockups. The initial focus group used open-ended discussions, persona creation, and paper prototyping to gather insights, allowing participants to visually express ideas. These prototypes informed digital mockups for user interviews to refine design concepts based on participant feedback.

The study involved seven participants (5 females and 2 males, aged 26-30) from diverse educational backgrounds and experience with online learning environments. Three participated in the initial focus group, with two continuing to the interview phase, totalling six interviews.

*2) Material and Procedure:* The LAD development began with an in-person focus group comprising three participants, dedicated to persona creation, ideation, and paper prototyping for three hours, resulting in digital mockups. These mockups served as the basis for six user interviews—four following the mockup phase and two during implementation—conducted both in-person and online using tools like Figma and web conferencing. During these interviews, participants interacted with the mockups, customized layouts, and discussed how the LAD could adapt to their needs throughout the semester.

*3) Data Collection and Analysis:* During the focus groups and interviews, detailed notes were taken instead of audio or video recordings to address participant discomfort. The data collected included personas, paper prototypes from the focus groups, and dashboard layouts from the interviews. These notes underwent qualitative coding and thorough analysis to identify key themes and patterns, which informed the final design of the LAD.

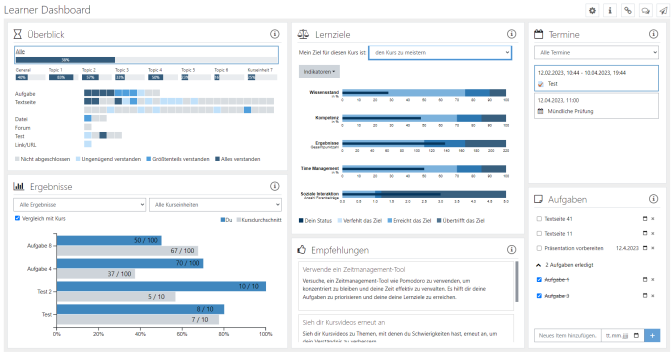


Fig. 2. User interface of the LAD integrated into Moodle.

### B. Results

The co-design process for the LAD identified several essential requirements: First, the LAD should be customizable to meet individual user needs, allowing users to tailor displayed items, reference frames, and learning indicators. Second, it should promote interaction among students and instructors, featuring tools to showcase course progress and achievements. Third, the LAD should support effective study planning, organization, and monitoring to optimize time management. Finally, it requires adaptive features like personalized recommendations and alerts, with a focus on maintaining transparency and trust.

Overall, these needs correspond to Zimmerman's SRL model, particularly enhancing support in the forethought and performance phases more than in the self-reflection phase.

## III. Concept and Implementation

The LAD was developed as a Moodle course format plugin, utilizing Vue.js, Vue Router for single-page application functionality, and Vuex Store to manage state and the *learner model*. The LAD is open-source and available at https://github.com/CATALPAresearch/format_serial3.

The *learner model* integrates data from university administrative systems and the learning environment to create a detailed student profile. This includes sociodemographic data, enrollment details, course load per semester, and academic performance, which are regularly updated. The model captures detailed metrics for individual course activities like quizzes, assignments, videos, and *longpage* text sections, and aggregates these for a holistic view of all course activities. Metrics tracked include first and last access, session count and duration, active days, and total time spent. Specific activity metrics, such as the percentage of text read and the number of annotations in course texts, are also recorded. For courses divided into units, metrics for each activity are recursively integrated into the *learner model* for each unit.

The LAD features a customizable tiled layout with various interactive widgets: The *progress chart* widget displays course activities such as quizzes and assignments as coloured squares, indicating the level of self-reported understanding. Users can click on these squares to rate their understanding and access relevant course activities directly. The *learner goal* widget uses bullet charts to track progress towards learning goals (e.g., overview, passing, mastery) across five indicators: knowledge gain, competency, assessment results, time management, and social interaction, categorized by performance levels in different colours. The *task list* allows learners to set personal goals and tasks with optional due dates, which can be marked as completed and archived. The *deadlines* widget consolidates all due dates from the Moodle course calendar and the *task list* to help manage deadlines effectively. The *feedback* widget delivers adaptive feedback based on specific conditions and actions defined in the Adaptation Rule Interface (ARI) plugin[1]. Feedback, formulated to support self-regulated learning strategies, integrates data-driven insights from the *learner model* with actionable steps, displayed along with user ratings for each piece of feedback.

User interactions with feedback items are tracked for ongoing refinement by a *reinforcement learning agent*, enhancing the feedback's relevance and effectiveness.

## IV. Evaluation in the Field

### A. Methods

*1) Research Design and Participants:* The field study was conducted in the compulsory course "Operating Systems and Computer Networks" of a distance learning B.Sc. Computer Science (CS) course at a German university. For the enrolled students a supplementary course was set up in a Moodle learning environment. The use of the learning environment was voluntary but conditional on a two-step consent to use the platform and to participate in the study.

*2) Material and Procedure:* The LAD, detailed in section III and shown in Fig. 2, was featured on the entry page of the learning environment. The course comprised four units with texts, 42 self-assessment tasks [5], 23 multiple-choice questions, and 30 tutor-corrected exercises. Additional resources included a Usenet forum, recordings of live sessions, and exam preparation questions.

The adaptation rules for providing feedback on self-regulated learning within the LAD resulted from a nine-step co-design approach with two teachers considering LA methods. In step 1 we've chosen the level of learning opportunities to which the feedback should relate (e.g. task, task type, course unit, course, study programme). For step 2 we characterized 27 Personas for low, medium, and high learning progress and outcomes for temporal patterns like continuous learning, latecomers, and early drop-outs. Then, in step 3 we identified characteristic situations where students would need SRL support along deviating behavior along the dimensions amplitude (e.g. low quiz scores), frequency (e.g. frequent failures), sequence (e.g. reverse task order), variance (e.g. avoidance of assessments), continuity (e.g. longer inactivity), and duration (e.g. time spent on a task). Based on these learning analytics insights, in step 4, teachers described their

[1]See https://github.com/CATALPAresearch/local_ari (accessed 2024/02/02).

general assumptions and beliefs for each of the six dimensions. In addition, rule mining algorithms were used (step 5) and teachers iteratively created High Information Feedback texts (step 6). In steps 7–8 the adaptation rules were validated to adjust thresholds and simulate rule executions using data from past cohorts. In the last step, teachers were enabled to monitor the rule execution.

*3) Data Collection and Analysis:* Although the course started in October 2023, students were free to choose when to start learning. User interactions and user inputs have been captured in the Moodle database, including clickstream data from the LAD usage and visible LAD widgets on the user's screen. Thus, the time spent watching and using the LAD can be approximated. The presented adaptive feedback including the users' responses was tracked as well.

### *B. Results and Discussion*

177 of the 514 CS course participants agreed to take part in the study and to use the Moodle instance. The participating students were between 21 and 62 years old (M = 37), 117 male and 60 female.

The duration of engagement with the LAD was determined based on log events from the Intersection Observer of individual LAD widgets. Initially, events were grouped into sessions, considering a break of more than 20 seconds with no user activity (scroll, click/tap, hovering) on the course overview page as a session boundary. Subsequently, data from widgets not fully visible (less than 90 %) on users' displays were excluded. Sessions shorter than 5 seconds were also omitted from the duration calculation. The total engagement time was then derived from the cumulative duration of all sessions. Average engagement time (M=8.7 min.) correlated with the average number of sessions (M=19.88).

Despite relatively intense receptive use of the LAD, participants made relatively little use of advanced planning and reflection tools. 66 students actively modified their learning goals in the LAD. Among them, 22 shifted their focus to achieving mastery, 38 aimed for passing, and 2 each expressed a desire to gain an overview or develop practical skills. Only 14 participants took advantage of self-rating their competencies, doing so with an average of 6.5 items each. In total, 16 tasks have been defined in the *task list*.

In the study, 144 participants engaged with the provided feedback, viewing it on average 5.24 times, with each viewing lasting approximately 20.19 seconds. This data indicates a noteworthy level of engagement with the feedback mechanisms in the learning environment.

## V. Conclusions

The goal of this project was to develop a LAD for the Moodle LMS, tailored to individual user needs to improve distance learners' metacognition and self-regulation. A co-design approach involving focus groups and interviews was used to align the LAD with student needs, who desired features for managing resources and deadlines, tracking progress, and enhancing interaction with peers and instructors. However, students were sceptical about relying solely on Moodle's interaction data for adaptive features, as many learning activities occur outside the platform. To address this, the LAD was designed to allow learners to self-assess their knowledge, providing a quick view of their progress and upcoming tasks, with defined metrics to compare their learning against their goals and generate rule-based personalized feedback. While the dashboard implementation increased interaction with the LAD, the support for self-regulated learning (SRL) strategies like planning and monitoring was underused. The field usage significantly diverged from the co-designed specifications, suggesting a potential need to integrate co-design more deeply into ongoing agile adjustments to better meet real-world usage and dynamics. This experience underscores the challenges of balancing user-centred design with practical application.

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