Meta-LAD: Developing a Learning Analytics Dashboard with a Theoretically Grounded and Context-specific Approach

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Abstract*—The use of Learning Analytics Dashboards (LADs) has gained popularity as a means of supporting the self-regulated learning (SRL) skills of learners in large-scale online courses. Despite many studies proposing LAD designs, LADs are often criticized for their weak theoretical foundations, lack of actionable feedback, and tendency to encourage excessive social comparison. Furthermore, many LAD designs have missed context-specific details. Hence, it is not uncommon for some dashboard designs to have negative effects on learners, such as discouragement or anxiety. In this study, we designed the Meta-LAD, a LAD that supports SRL processes using theoretical and contextual foundations. We used data from a credit-bearing Massive Open Online Course (MOOC) on supply chain management to contextually ground the dashboard. We performed usability testing interviews to evaluate the design and confirmed that the Meta-LAD could fulfill learners' needs for references and actionable feedback. This study contributes to the field of online learning by presenting a theoretically grounded and contextually specific LAD design process. This paper expands the understanding of how to support SRL in MOOCs.

***Keywords*—MOOC, Learning Analytics Dashboard, Self-regulated Learning**

I. Introduction and Related Work

One common challenge faced by learners in Massive Open Online Courses (MOOCs) is the difficulty of receiving individual feedback for self-regulated learning, which plays a crucial role in comprehending course materials and completing a course [6]. Self-regulated learning (SRL) involves learners actively participating in a cycle of planning, monitoring, and evaluation, and then using feedback from the evaluation step to enhance the subsequent cycle [19]. Despite the widely recognized benefits of SRL in enhancing academic accomplishments [25], many learners struggle in engaging in the SRL process due to a lack of motivation or insufficient skills [3, 16].

Learner-faced Learning Analytics Dashboards (LADs) have the potential to support SRL in MOOCs. LADs are commonly defined as a set of visualizations presenting indicators of learners' performance, progress, and context on a single display [15, 18]. LADs can support developing SRL skills by building awareness of learners' current progress, fostering self-evaluation, and enabling better planning [1, 12, 18].

Despite their potential benefits, LAD designs often lack a rigorous theoretical foundation [13, 18]. Matcha et al. [18] showed that 68% of the papers reviewed did not provide a clear theoretical rationale for selecting specific indicators presented on LADs. Furthermore, no paper explicitly considered SRL theory in LAD designs, even though they claimed to support SRL. Although several studies [2, 20] have proposed or developed LADs with a stronger theoretical foundation after Matcha et al.'s review [18], further research is still necessary for a better understanding of how to support different MOOC contexts and how to incorporate data and theories to LAD designs.

The COPES model [22, 23] can provide a stronger theoretical foundation for LAD designs. COPES stands for Conditions, Operations, Products, Evaluations, and Standards. During the SRL process's planning phase, learners identify internal and external *conditions* relevant to tasks and build plans on what cognitive and metacognitive *operations* to perform. During the monitoring phase, they generate *products* as a result of *operations*. Finally, learners *evaluate* these products with *standards*. The *evaluation* results are fed back into the planning stage which completes the cycle of the SRL process.

Another concern with LADs is that they often cause intense social comparison among learners. LADs typically provide reference points that allow learners to compare their progress with peers' progress. However, these references often discourage learners due to intensified social comparison [1, 9, 21]. Valle et al. [21] found that a LAD presenting peer information decreased learners' motivation. Aguilar et al. [1] revealed that when an advisor compared an advisee's performance to that of their peers using a LAD, such comparison had a detrimental impact on the advisee's SRL process.

One potential solution for this issue is using information from learners who have already passed the course as a reference rather than information from peers from the same cohort. Davis et al. [7] demonstrated that this approach increased course completion rates while reducing the stress associated with real-time social comparisons of peer achievement. Another comparable solution is providing multiple references to cater to different goals. Previous studies have revealed that different learners have different goals, such as passing the course, achieving high grades, or mastering skills [11, 24]. With multiple references available, learners can evaluate their progress based on a reference that aligns with their personal goals instead of relying on a one-size-fits-all reference. This approach can remind learners of their goals and reduce the likelihood of feeling overwhelmed by constant competition with peers.

Many LADs have also faced criticism for imposing a high inference cost on learners. This inference cost is related to the potential difficulty of interpreting the feedback provided by the dashboard [12]. Learners are less motivated to use a LAD when the inference cost is high. Complex visualizations, for example, can increase inference costs. Previous research [10] showed that certain visualizations, such as spider charts, are more difficult to understand compared to bar charts and line graphs. Complex visualizations can hinder a learner's ability to develop actionable plans due to an incomplete or incorrect understanding of the visualized information [10]. Davis et al. [7] found that learners with lower levels of education did not experience an increase in course completion rates after interactions with a LAD. There was a statistically significant increase at 0.05 level for learners with higher education degrees. The authors suggested that the complexity of spider charts might have been challenging for individuals with lower educational backgrounds.

One strategy for mitigating inference costs is to use clear and easily comprehensible visualizations, such as bar charts or line graphs [10]. In addition, LADs can provide actionable feedback alongside visualizations to help learners 'read beyond data.' This can be particularly beneficial in MOOCs where learners come from diverse demographic, educational, and professional backgrounds.

II. Design Goals

A. Course Contents

Understanding the implementation context of a LAD is crucial since SRL practices are shaped by contextual factors [19, 22, 23]. Our Meta-LAD was designed for the gateway course for a credential-bearing online edX program on supply chain management. Most learners taking this MOOC reported having a full-time day job. Learners could audit the course for free or purchase a course verification. Learners who verified and achieved a course grade of 60% or above, earned a course certificate. This course was self-paced, and the enrollment and verification period closed a month before the scheduled final exam. Only verified learners had access to graded problems and received final grades. Verified learners' goals ranged from just passing the course to achieving an A or A+ grade (since this course is a pathway for credit for a master's degree at several universities).

The course taught basic analytic techniques relevant to supply chain management. It consisted of five content modules. Each module focused on one topic: data management, probability, statistics, optimization, and algorithms, simulations & approximations. Every module was composed of: lecture videos, quick questions, practice problems, supplemental materials, and a module test. Quick questions checked the understanding of each video, while practice problems assessed learners' knowledge taught in the entire unit. Learners had up to three attempts to submit answers to each quick question and practice problem. Only after using up all their attempts, learners could view solutions. A module test consisting of two or three graded problems was located at the end of each module. Module tests accounted for 10% of the overall course grade, while the final exam accounted for the remaining 90%.

B. Identifying LAD Indicators

The authors of the present paper had multiple rounds of discussion with the course instructor and other teaching staff to understand the course and the learners and identify potential indicators to be included in the Meta-LAD. Then, data analysis was conducted using historical learner data to identify which indicators were relevant. Specifically, multiple linear regression and elastic net regression models were applied to clickstream data collected between January 2021 and September 2022 through edX. Only data from verified learners were used in the analysis. Through this process, five indicators with a statistically significant positive influence on learners' performance were selected: (1) the number of unique lecture videos completed, (2) the number of unique practice problems submitted, (3) the number of solutions for unique practice problems checked, (4) time period (in hours) between finishing a module and starting the following module, and (5) time period (in hours) between starting and finishing a module. These indicators showed statistical significance (at a 0.05 significance level) in the multiple linear regression model or displayed non-zero coefficients in the elastic net regression model.

The first two indicators showed the importance of learners' engagement with course materials on the final grade, which could be connected to *operations* and *products* in the COPES model. Learners were expected to learn concepts by watching lecture videos and applying those concepts to practice problems. The third indicator was associated with *evaluations* and *standards*. By comparing their answers with the given solutions (i.e., *standards*), learners were able to understand what they did well and what they missed (i.e., *evaluations*). The fourth and fifth indicators were related to *conditions* in the COPES model. Learners needed to understand their conditions, such as time constraints or final exam schedules, to strategically plan their study sessions and avoid procrastination. This aligned with the spacing effect, which states that individuals learn better when information is presented in spaced intervals rather than in concentrated blocks [8].

C. Design Goals

This section presents the Design Goals (DGs) for LADs, developed by integrating relevant theories with context-specific needs.

1) DG 1: Standards based on the previous cohort

The exploratory analysis showed that learners sought *standards* to *evaluate* their progress (Indicator 3). To provide standards without fostering stressful social comparison, the first

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DG was determined to provide references using data from previous cohorts who successfully passed the course instead of learners' peers taking the same course run. Specifically, the references were focused on course activities, such as watching lecture videos, working on practice problems, and checking problem solutions. These were identified as significant predictors of the final grade (Indicators 1 and 2).

2) DG 2: Standards supporting different goals

Learners have various goals [11, 24]. Providing a uniform *standard* can discourage their progress. For instance, learners who aim to simply pass the course may feel overwhelmed and stressed if a *standard* for higher grades is offered. Consequently, the second DG was to establish multiple *standards* to accommodate diverse goals.

3) DG 3: Actionable feedback

A lack of actionable feedback increases the inference cost, demotivating learners from engaging with their LADs [12]. Thus, the third DG was included to provide straightforward and actionable feedback in a textual message format in addition to the visualizations showing learners' progress. The individualistic and promoting framework [7] was adopted to craft effective and appealing feedback messages. Visualization with a low level of complexity was also used, such as bar and line graphs to decrease inference costs [7, 10].

4) DG 4: Spacing effect

Analysis showed that the spacing effect [8] had a positive impact on learners' performance. Indicators 4 and 5 revealed that learners who spaced their study sessions, both between modules and within a module, generally achieved better outcomes compared to those who concentrated their study sessions in a shorter timeframe. Thus, the fourth DG was to encourage learners to space out study sessions

III. Dashboard Design

Using the established DGs, Meta-LAD was designed to support learners' SRL and to help them to successfully complete the course. Meta-LAD had five components (Fig. 1). Component (a) 'Course Activity Progress' displayed the reference (the region with three lines marked as (a1) above the red line) and learners' progress (the red line marked as (a2) near the x-axis). The component displayed reference and individual learners' progress on three course activities: watching lecture videos, submitting answers to practice problems, and checking provided solutions for practice problems. These activities were identified as statistically significant predictors of the final grade through the exploratory analysis. The top and bottom lines in reference region (a1) respectively showed the 75th and 25th percentiles for learners who achieved passing grades in the previous course run. The yellow line between these two lines represented a median. When a user hovered a cursor over (a1) or (a2), an info tip would display the precise values of the references as well as the user's progress in the course. Component (a) addressed DGs 1 and 2 by providing multiple *standards* for self-evaluation without inducing unnecessary social comparison.

Component (b) 'Time Estimate' also provided a *standard* to help learners plan and evaluate progress. The stacked bar graph (b1) showed the estimated time in hours required to complete each module. Another stacked bar graph (b2) enabled learners to monitor their time spent in each module. Both stacked bar graphs (b1) and (b2) were color-coded based on the corresponding module, with a legend at the top of the component. When a learner hovered a cursor over either graph, an info tip would appear to display the time estimate in hours for each module (Fig. 1). Component (b) addressed DGs 1 and 2.

Components (c) and (d) aimed to encourage learners to plan and maintain spaced study sessions. Component (c) 'Streak' tracked the number of consecutive weeks a learner visited the target course. In particular, Component (c) was designed to motivate learners to continue their weekly engagement with the course, rather than taking longer breaks that could potentially lead to procrastination or cramming. Some learners might game the system, increasing their week streak by visiting the course for a short time without making any progress. To counter this, Component (d) was added. Component (d) 'Time Spent Last Week' displayed the number of hours spent in the course during the previous week. Components (c) and (d) allowed learners to

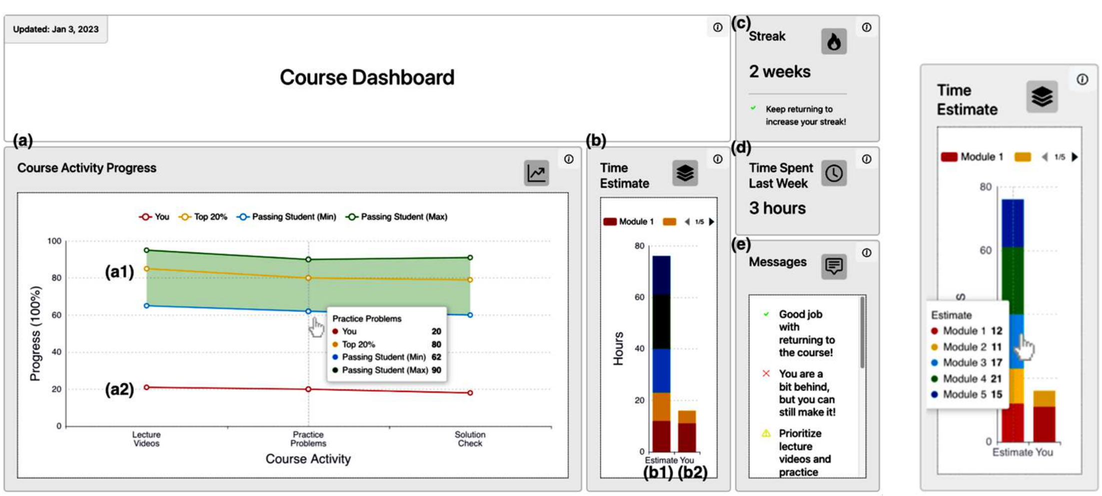

Fig. 1. (Left) Screenshot of the prototype of Meta-LAD, (Right) A screenshot of component (b) 'Time Estimate' with a pop-up

gain a more accurate and less biased understanding of their course visit patterns and encouraged them to regularly come back to the course, which addressed DG 4.

Component (e) 'Messages' addressed DG 3 by offering actionable feedback (DG 3). Each feedback message was tailored to each learner's progress, motivating them to maintain their current pace or catch up if they were falling behind. Meta-LAD categorized learners into three groups: ahead, on-target, and behind using the logic below.

$$\frac{n}{w} < \frac{k_i}{a_i} \tag{1}$$

$$\frac{n}{w} = \frac{k_i}{a_i} \pm error \tag{2}$$

$$\frac{n}{w} > \frac{k_i}{a_i} \tag{3}$$

where:

n = Number of weeks between learner's enrollment and the course's final exam.

w = Number of weeks since a learner's enrollment.

k_i = Number of activities of type i completed by the learner.

a_i = Total number of activities of type i available in the course.

$i \in$ {lecture videos, practice problems, solution checks}

Equation (1) represents the 'ahead' group, it contains learners whose progress is greater than expected, considering the time left until the final exam. Equation (2) represents the 'on-target' group, it will contain learners whose progress is aligned with expectations. Equation (3) represents the 'behind' group, it will contain learners who need to catch up to complete the course in time. Messages offered to learners in the three groups through the Meta-LAD were written in individualistic and promotional motivational language to maximize their effects [4, 7].

IV. EVALUATION: USABILITY TESTING STUDY

A. Study Overview

Usability testing was conducted to examine the potential impact of learners' interaction with the Meta-LAD on their SRL processes. Data were gathered through semi-structured interviews and the System Usability Scale (SUS) [15]. The interview questions were specifically crafted to collect users' hypothetical behavior in scenarios representing varying levels of progress in a course. The SUS is a widely used questionnaire composed of ten 5-point Likert-scale questions to quantitively measure the usability of the dashboard.

Participants were recruited through emails sent to learners who had taken the target course. They did not receive any reward for study participation. Once participants agreed to take part in the study, a 40-minute-long session started. A researcher explained the components of Meta-LAD to participants. When the participant no longer had any clarification questions regarding the components, the researcher started a semi-structured interview. During the interview, three distinct versions of the Meta-LAD were presented: two versions exhibiting data of a learner who is behind schedule (i.e., group 'behind') and one version displaying data for a learner whose progress is ahead of schedule (i.e., group 'ahead'). Among the two versions for learners behind schedule, one provided only messages of encouragement, while the other included action items as well as encouragement. Participants were prompted to imagine each dashboard version as their own and respond to the interviewer's questions (e.g., 'What kind of information displayed on this dashboard would motivate you to invest more effort in completing the course rather than giving up?'). Once the interview ended, participants were requested to fill out two surveys: the SUS [15] and the demographic survey. The demographic survey collected their self-identified gender, age, and ethnicity.

B. Data Analysis

We analyzed qualitative and quantitative data using a parallel mixed grounded theory approach. It involves analyzing (1) qualitative data by applying grounded theory [5] with the exploratory stance and (2) quantitative data with the confirmatory stance [14]. The approach helped the researchers triangulate findings across different data sources.

1) System Usability Scale (SUS)

Based on the guidelines offered by Lewis and Sauro [15], the usability score of Meta-LAD was calculated. According to the guidelines, the highest possible score was 100. Then, the mean of the score was compared to the benchmark score range [15], which is between 78.9 and 80.7.

2) Interview

A grounded theory approach was employed to analyze the interview data. Iterative open coding was conducted until data saturation was achieved [5, 14]. To ensure the consistency of the coding process, the first author alone performed open coding. Then, focused coding was conducted to establish categories and sub-categories for the codes. The final step was theoretical sampling, which refined categories, constructing a theoretical framework that encapsulates the observed data patterns [5].

C. Findings: System Usability Scale (SUS)

Participants positively evaluated the usability of Meta-LAD. The mean of the SUS scores was 87.81 (SD = 8.70) which exceeded the benchmark score range [15]. Table I shows the means and standard deviations of responses to each SUS statement. Means of positively worded statements were all above 4 out of 5. Means of reverse-worded statements were below 2 out of 5.

D. Findings: Interview

Ten participants were recruited, with eight completing the interview and survey (female = 3, male = 5, age M = 31.37, age SD = 7.11, Asian/Pacific Islander = 4, White/Caucasian = 2, Black/African American = 1, Hispanic = 1).

1) Effect on self-regulated learning

Participants generally agreed on the benefits of Meta-LAD for SRL processes. P0, P2, P3, P6, and P7 said all the components would be helpful to monitor and improve their

TABLE I. SYSTEM USABILITY SCALE RESPONSE SUMMARY

	System Usability Scale Statement	*M*	*SD*
1	I think that I would like to use this dashboard frequently.	4.75	0.46
2	I found the dashboard unnecessarily complex.*	1.5	0.75
3	I thought the dashboard was easy to use.	4.25	0.88
4	I think that I would need the support of a technical person to be able to use this dashboard.*	1.25	0.46
5	I found the various functions in this dashboard were well integrated.	4.37	0.51
6	I thought there was too much inconsistency in this dashboard.*	1.25	0.46
7	I would imagine that most people would learn to use the dashboard very quickly.	4.12	0.64
8	I found the dashboard very awkward to use.*	1.25	0.7
9	I felt very confident using the dashboard.	4.25	0.46
10	I needed to learn a lot of things before I could get going with this dashboard.*	1.37	0.74

Note 1. M = mean, SD = standard deviation.

Note 2. Statements with an asterisk (*) are reverse-worded. The lower the score, the more positive the participants' evaluations are toward the Meta-LAD.

progress toward goals (*condition*, *operation*, *products*). P1 liked Component (c) 'Streak' and Component (d) 'Hours Spent Last Week' as these features would be useful to *evaluate* their course engagement (*condition*, *evaluation*, *standards*). Three out of eight participants explicitly mentioned that visualized progress would "motivate" if they were behind.

Two participants shared detailed strategies on how to use the information displayed on Meta-LAD. P6 said they would evaluate a gap between suggested and actual time spent on lecture videos using Component (b) 'Time Estimate' and adjust their study plan by "adding like an extra 10% time for the course because I need a little extra to re-watch certain videos" (*condition, evaluation, standard*). P3 pointed out that Component (a) 'Course Activity Progress' would give "a nice insight into your standing. [Although] You shouldn't always compare yourself to others, in [an] asynchronous class like this it's [a] nice guide point" (*evaluation*, *standard*). P3 also mentioned that they could also infer if they joined the course too late considering their time constraints and goals (*condition*).

2) Standards supporting different goals

Two participants agreed with the importance of standards supporting different goals. Component (a) 'Course Activity Progress' provided multiple references on course activities. One participant shared that they adjusted a goal from earning a high final grade to passing the course when they took the course (P6). They stated that it was "good to be able to see where I am using the Meta-LAD" along with their own goal, indicating that Meta-LAD would be useful to support their personal goal (*evaluation*, *standard*). Another participant mentioned that "different people have different targets" and providing multiple goals is better to avoid discouraging or overwhelming learners (P2).

3) Combining encouragement and action items

Learners preferred to see both encouragement and action items in Component (e) 'Messages'. When participants were asked to compare a version with only words of encouragement to a version with both action items and words of encouragement, six out of eight participants preferred the one with both types of feedback. For example, the "actionable bullets" were "helpful to know what to prioritize" to catch up on course materials (P3, P6), and they would "definitely utilize" such feedback (P0).

The participants also agreed that words of encouragement are important to motivate learners who are behind to continue studying. They "like[d] the motivating messages a lot" since the encouragements were "reaffirming" which would be important to the "discouraged" students (P1, P3, P6).

4) Learners' feedback

Four participants said that they wanted to see a countdown feature until the final term to gain more control over their time left and plan better (*condition*, *evaluation*, *standards*). One of them mentioned that, even for learners who are ahead of the course schedule, a countdown would be helpful as "a caution point that one shouldn't become complacent since it is just midway and there are still things to cover" (P0).

Participants were also looking for details on how each indicator was calculated. They stated that these details would help to build learners' trust in Meta-LAD. Although the information buttons provided the necessary details, the participants did not recognize their presence.

Three participants wanted to see tips or quotes from previous learners on Component (e) 'Messages.' They believed learning from others who were in a similar situation could provide 'study hacks.' They would like to see tips such as "watching videos while I'm cooking food" (P2) and messages such as "inspiring quotes" (P5).

E. Study Limitations

The usability testing study provided promising results and multiple insights, but we would like to acknowledge its limitations. The usability data were not collected from authentic learning environments. The study had a small sample.

V. DISCUSSION AND CONCLUSION

In this study, we have developed the Meta-LAD, a learner-facing Learning Analytics Dashboard (LAD) to enhance the SRL skills of MOOC learners and ultimately improve their performance and facilitate successful course completion. To achieve this, we identified fundamental theoretical foundations for LAD design. Furthermore, an exploratory analysis was conducted on historical data of a specific MOOC to include context-specific LAD indicators in the design. Drawing from these insights, we established specific design goals to guide the development of the Meta-LAD. The Meta-LAD was then evaluated by usability testing.

The usability testing revealed that the Meta-LAD has the potential of motivating learners to actively engage with course materials and to utilize SRL skills. Participants positively assessed the provision of references based on previous cohorts' behavior and performance (DG 1) and the inclusion of multiple references for different goals (DG 2). Participants in the usability test appreciated such references since they allowed them to set their own goals without inducing social comparisons with their peers. Participants also mentioned that Component (c) 'Streak' and Component (d) 'Time Spent Last Week' would motivate them to space study sessions (DG 4).

Participants in the usability test showed a strong preference for displaying both encouragement and actionable feedback messages in the dashboard (DG 3). This finding underscored the significance of combining moral and practical support when providing feedback. Participants also expressed interest in tips and inspiring quotes from previous learners, which could help MOOC learners build a sense of community and connection with their peers.

This study underlines the importance of integrating theoretical foundations and contextual-specific considerations for effective LAD design. It also prompts more research on the LAD design process, specifically with a specific focus on MOOC learners. The paper suggests potential SRL behavioral indicators that could apply to various MOOC contexts. We will extend this research by implementing the Meta-LAD in a MOOC setting and evaluating its effect on learning outcomes such as learning strategy, completion rate, and performance.

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