Empowering Students: A Reflective Learning Analytics Approach to Enhance Academic Performance

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Abstract: The surge in online education has accentuated the importance of practical Learning Analytics (LA) tools, traditionally designed to support educators. In the meantime, a notable gap exists in empowering students directly through user progress insights and reflective components. This paper presents our research effort in designing a novel approach: a Self-reflective Tool (SRT) with data indicators on student performance designed to actively engage students in their learning journey. Our research explores the landscape of existing LA tools, pinpointing the lack of technological supports for students, and the limitations in empowering students. The methodology involves data extraction, and a comparative analysis of classifiers to predict student performance (SP). Our reflective tool is therefore built, not only to support students in their learning activities, but also to provide them with a more relevant assistance according to their SP. Surveys are made to assess our proposal of SRT. The findings illustrate how students perceive it and how SRT oriented data indicators increase awareness, regulation, and motivation of individual learning patterns. Our qualitative analysis also demonstrates a positive correlation between student engagement with the reflective tool and improvements in academic outcomes. This research contributes to the discourse on LA by emphasizing the importance of reflective tools for students in Metacognition Online Learning Environments (MOLE), providing valuable insights for future developments in student-centric approaches to education.

1 INTRODUCTION

Learning Analytics (LA) is a powerful tool that substantially supports educators and content creators in enhancing the teaching and learning experiences (Banihashem et al., 2022; Hernández-de Menéndez et al., 2022). However, while existing tools and services in LA are mostly dedicated to instructors, there is a lack of similar supports that directly empower students (Arthars et al., 2019). Yet, it has been demonstrated that students strongly need self-assessment throughout their learning process to gain motivation and higher achievement (McMillan and Hearn, 2008; Andrade, 2019). Thus, providing reflective tools that allow students to do so is not only crucial from a pedagogical standpoint but also a significant research challenge. Our paper delves into the necessity of addressing this gap by proposing a novel approach leveraging specific and selective tools to enable students through reflective LA, focusing on self-regulation and user progress insights.

LA has traditionally emphasized data analysis, visualization, and the creation of indicators to aid educators in understanding and improving their teaching methodologies (Ndukwe and Daniel, 2020; Silvola et al., 2021). While these approaches have proven valuable, a need for more emphasis exists on tools that create and foster students motivation in their learning journey (Joksimović et al., 2019; Arthars et al., 2019). The absence of these tools becomes more pronounced than the traditional LA when considering the implications for student performance (SP). Our research is motivated by the conviction that students, provided with a better understanding of their learning behaviors, can significantly enhance their academic performance and cultivate self-regulation skills.

The research effort presented in this paper pinpoints shortcomings in existing practices and

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proposes a transformative solution with our self-reflective tool (SRT) that allows and incites students to monitor their progress, analyze behavior, and actively participate in improving their learning performance. We explore the landscape of existing LA tools, highlighting their current focus and limitations, particularly in the context of student empowerment. We then introduce our design approach, which places students at the center of the analytics process, providing them with indicators on a Learning Management System (LMS).

The primary research questions guiding our studies include:

1. How can LA better support students in Metacognition Online Learning Environments (MOLE)?
2. What role does SRT play in addressing SP, the risk of failure, and motivational loss?

To contextualize our work, we examine the current state of SP analysis and outline our approach to data mining, drawing on existing methodologies. In the context of our research, SP refers to the academic achievements, learning outcomes, and overall success of students within an educational setting. It encompasses a multifaceted evaluation beyond traditional metrics such as grades and exam scores. As per our context, SP involves a holistic assessment that considers various factors, including attendance, interaction with learning materials, engagement in quizzes, assignments, and tasks on the LMS, and the ultimate academic production and outcome.

For the experimental setup, the cohort of 160 students, primarily associated with the CADT (Cambodia Academy of Digital Technology), actively engages in various educational activities on the Moodle LMS. Throughout the year, these students participate in courses, attend classes, submit assignments, and interact with the learning materials available on the platform. In the context of our research, the SP aspect is the key focus. We aim to delve into the intricacies of learning patterns exhibited by these students on the Moodle LMS.

To identify key attributes that can predict SP, we have conducted a literature review to understand the factors influencing student outcomes. First, we collected data from CADT's Moodle platform and Google Sheets, which provided insights into student engagement and performance outcomes. Second, we carefully selected a subset of crucial attributes from the collected data to develop a predictive algorithm using a Random Forest classifier. Third, we further refined the algorithm by employing oversampling techniques to handle imbalanced data. Last but not least, we evaluated the algorithm's performance and adjusted it to enhance accuracy. By adopting such an approach, we are able to not only effectively identify attributes contributing to student performance, but also to develop a reliable predictive model.

As for the reflective tools, they refer to tools and mechanisms designed to help students reflect on their learning processes, identify weaknesses and strengths, and make informed decisions to improve their academic performance. Specifically, the self-reflective tool (SRT) is a user progress instrument tailored to individual students, which includes personal insight and a group-level overview feature that enables students to gain insights into their performance compared to their peers. SRT integrates our predicting model and key attributes to provide a dynamic and supportive learning environment, fostering students' self-awareness, self-regulation, self-evaluation, and self-motivation. We aim to create a sophisticated SRT, offering a novel approach to improve students' educational practices at CADT.

With this experimental setup, we can work on designing and implementing our SRT, including a dashboard with program-level and user progress indicators. The ”program-level” refers to an assessment or analysis conducted at an entire academic program of study level. Rather than focusing on individual courses or specific components, a program-level perspective takes a holistic view, considering an academic program's overall objectives, outcomes, and performance.

The rest of the paper is structured as follows. Related works are presented in section 2. Sections 3 and 4 are dedicated to our SP analysis approach. The design of our SRT presented in section 5. The outcomes of our study are discussed in section 6, providing valuable insights into the perceptions of students and the impact of our reflective learning analytics approach on their academic performance.

2 RELATED WORKS

In recent years, many studies have paid significant attention to exploring the LA applications and their impact on educational practice (Dawson et al., 2019; Wong et al., 2018; Papamitsiou and Economides, 2014; Viberg et al., 2018; Wong and Li, 2020). In this section, we review the existing literature to contextualize our research within the broader landscape of LA, focusing on e-learning practices, support for students, technological solutions, and the research issues related to students and SRT.

2.1 Learning Analytics

Numerous studies covered the integration of LA into MOLE. A systematic review by (Banihashem et al., 2018; Tepgeç and Ifenthaler, 2022; Banihashem et al., 2022) addressed LA's crucial role in optimizing the online learning experience. The review highlighted LA's potential to improve student and overall satisfaction in digital learning environments. Additionally, (Mangaroska et al., 2021) focused on the specifics of employing LA in online learning platforms, providing insights into its effectiveness in identifying patterns (Khosravi and Cooper, 2017) and refining instructional design for virtual classrooms (Jovanovic et al., 2017; Volungeviciene et al., 2019). A systematic mapping review by (Sghir et al., 2023) examined the published articles between 2012 and 2022 that utilized LA for predicting students' performance and risk of failure or dropout. They found that LA provides insights into the classroom by analyzing data about learners, allowing for a deeper understanding of the learning process and optimizing the learning environment.

2.2 Supports for Online Learning

In the past decade, we have witnessed a growing of both theoretical and technological solutions to support online teaching practices. (Bakharia et al., 2016; Alowayr and Badii, 2014) formulated a conceptual framework to assist teachers in evaluating learning activities, learning performance, and making informed decisions. Additionally, (Arthars et al., 2019; Dyckhoff et al., 2012; Sergis and Sampson, 2016) have developed dashboards with data indicators to support teachers in their instructional roles. Moreover, (Volungeviciene et al., 2019) have designed a professional monitoring tool for teachers to understand students' different learning habits, recognize their behavior, assess their thinking capacities and engagement, and design their curriculum.

Thus far, while witnessing prior studies that predominantly focused on designing monitoring and evaluation tools for teachers, we also support the claim of (Wong, 2023) and acknowledge the necessity for customized technological solutions to answer the unique needs of students. Therefore, our research is motivated by the imperative to address the absence of direct support that enhances students learning experiences. Our goal is not to imitate the existing supports for teachers and recreate new ones for students, but to take a closer look at how we can provide them with reflective tools, enabling them to gain insights on their own behaviors, then adapt their learning pace and strategy throughout their learning activities. The reflective tools become the primary and direct support for students as they do not solely rely on feedback from their teachers, and mostly at the end of a learning session. Our proposal places a strong focus on an innovative approach to design and implement reflective tools with data indicators on student performance in order to foster student self-regulation and empowerment in MOLE.

2.3 Students and Reflective Tools

Research within MOLE has identified core issues related to students and the integration of reflective tools in online learning. (Ndukwe and Daniel, 2020) conducted a study exploring the expectations of students regarding LA tools in online courses. Their findings indicated that students desired more user progress feedback and a greater emphasis on real-time progress tracking. These insights shed light on specific areas for improvement in LA tools, suggesting a need for enhancements in features related to user progress learning experiences (Fatma Gizem Karaoglan Yilmaz, 2020; Hegde et al., 2022; Fatma Gizem Karaoglan Yilmaz, 2022; Karaoglan Yilmaz, 2022) and continuous monitoring of academic progress (QAZDAR et al., 2022). (Silvola et al., 2021) examined the expectations of educators and online learners concerning LA dashboards, emphasizing the need for user progress insights in virtual classrooms.

In the context of online learning, the existing body of literature unveils the potential of LA to provide valuable understanding of student engagement and performance. It emphasizes the need for tailored support and technological solutions in online education. Furthermore, the research mentioned core issues related to students and integrating reflective tools in virtual classrooms. Despite all that, a significant gap persists in developing reflective tools that empower students within online learning. Not to mention that most existing supports are often designed to assess the final outcomes of learning activities. Accordingly, the data indicators provided are not exactly exploited by the students as reflective tools during their learning process, but are mainly used at the end as feedback or report on their final academic outcomes. Our work seeks to contribute to filling this gap by introducing a unique reflective tool designed to address research challenges that cover two aspects: (i) the prediction of student performance and (ii) the elaboration of SRT oriented data indicators to enhance student performance.

3 STUDENT PERFORMANCE

This section provides an overview of our current work on understanding and enhancing SP from LA perspectives. The illustration in Figure 1 unfolds the comprehensive research methodology adopted at the CADT. The key attributes influencing learning patterns are identified. These attributes seamlessly feed into the SP Prediction Model, employing data mining approaches. The predictions from the SP model drive the development of SRT, which include Performance Evaluation, Progress Tracking, Recommendation Engine, and Personal Indicators. The ultimate goal is to translate SRT utilization into tangible academic outcomes, fostering self-awareness, self-regulation, self-evaluation, and self-motivation for students at CADT. The illustration encapsulates the interconnected stages of data-driven predictions and the development of tools, emphasizing the student-centric approach adopted for enhancing academic success.

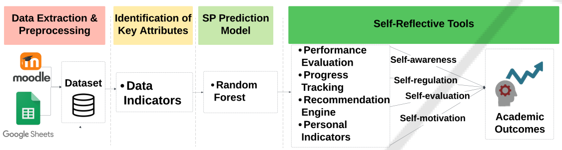


Figure 1: Unveiling the Iterative Journey: From Data Mining to Self-Reflective Empowerment.

3.1 Current Work and Approach

Our study on SP involves a comprehensive analysis of data gathered from students engaged in online courses. Leveraging data mining techniques, we explore existing approaches to SP analysis, seeking to identify patterns, trends, and factors influencing students' learning outcomes (la Red Martínez and Gómez, 2014; Brahim, 2022). By understanding the intricacies of SP, we can tailor our SRT to fulfill the unique needs and challenges of online learning (Jaggars and Xu, 2016). Our approach strongly emphasizes empowering students to take an active role in monitoring their progress and regulating their learning pace. Comparing to traditional LA tools, which primarily focus on providing retrospective insights for educators, our framework shifts the paradigm by directly involving students in analyzing their performance data. This student-centric approach is pivotal in fostering a sense of ownership and autonomy, contributing to improved engagement and academic success.

3.2 Necessity of a Reflective Tool

As our analysis progresses, it becomes evident that SP analysis lacks a reflective component dedicated to students. Reflective tools are essential for students to learn and to improve learning (McKenna et al., 2019). Yet these tools are not systematically included in the basic set of tools for educational settings. Also pointed out by (Volungeviciene et al., 2019) reflective tools often offer students the means to gain deep insights into their learning patterns, preferences, and areas that may require additional attention. The absence of those tools is particularly pronounced in online learning, where students may face challenges related to self-motivation (Ainley and Patrick, 2006). By integrating a reflective tool into the learning environment, we aim to incite students to actively shape their educational experiences (Perrotta and Bohan, 2020), identify areas of improvement (Talay-Ongan, 2003), and optimize their learning strategies (Majeed et al., 2021).

In conclusion, our research work on SP in the context of LA addresses the current limitations in SP analysis, especially in MOLE. By leveraging data mining techniques and emphasizing a student-centric approach, we aim to develop a SRT that enhances SP analysis and encourages students to become active participants in their learning journey. The following sections detail the experimental setup, data analysis, and the implementation of our SRT.

4 STUDENT PERFORMANCE ANALYSIS

4.1 Attributes and Learning Patterns

We comprehensively analyzed existing literature to identify the attributes for predicting student performance. To be accurate and objective, we considered the frequency of attribute appearance in the literature, their relevance, practicality, and importance in our study, and the data available in the LMS. A meta-study by (Felix et al., 2018) reviewed 42 papers, and (Namoun and Alshanqiti, 2020) examined 62 papers that used data mining techniques to predict student outcomes, which mainly used attributes such as assessment data/grade, interaction logs, quizzes data, assignment data, access logs, resources logs, and tasks data. Another study by (Felix et al., 2019) utilized a dataset of 1,307 students' activity logs in a course, including variables related to quizzes submitted, activities, time spent on the platform, and grades, to build a predictive model of student outcomes.

In the same context as the previous study, (Hirokawa, 2018) collected information from a Japanese institution and used machine learning methods to forecast academic achievement. The result found that previous academic grade were essential for predicting academic performance. Furthermore, (Gaftandzhieva et al., 2022) used a machine learning algorithm to predict students' final grades in an Object-Oriented Programming course using data from Moodle LMS activities such as exam results, and online activities. Other studies have focused on predicting various aspects of student outcomes, such as the likelihood of dropout (Quinn and Gray, 2020), the likelihood of success in a course (Arizmendi et al., 2023) or predicting student grades using both academic and non-academic factors (Yağcı, 2022). In the meantime, some studies have also explored specific contexts, such as analyzing interaction logs (Brahim, 2022), assessing grades and online activity data (Alhassan et al., 2020).

As a result of all these studies, we have selected specific attributes and learning patterns that correlate with positive or negative SP outcomes at CADT. By identifying these correlations, we have collected dataset from CADT's Moodle LMS and from Google Sheets, as shown in Table 1, covering over 160 students from three classes and eight separate courses including Linear Algebra, Discrete Mathematics, Probability and Statistics, C Programming Language, Visual Art, Soft Skills and Information Technology Essentials. This dataset includes two semesters and represents two program levels. Plus, it also incorporates Hypothesis Video Player (HVP) scores, which measure student engagement in interactive video activities. Right below, we describe the attributes in our dataset that provide information on student engagement and performance.

1. **attendance** - This attribute represents the number of modules in all courses that a student has completed.
2. **number_of_interaction_log** - This attribute represents the number of interactions a student has had with all courses.
3. **total_quiz_submitted** - This attribute represents the number of quizzes a student has submitted in all courses.
4. **total_assignment_submitted** - This attribute represents the number of assignments a student has submitted in all courses.
5. **total_tasks_submitted** - This attribute represents the number of tasks a student has submitted in all courses.
6. **outcome score** - The outcome score is a numeric measure of a student's academic performance after completing a first-year program. It is typically calculated by taking the weighted average of the final scores of each course in the program, with the weight assigned to each course based on various factors such as credit hours, difficulty level, or course importance. The outcome score is an important metric used in academic and employment contexts to evaluate a student's academic performance and potential.

4.2 Data Mining Approaches

Our research uses data mining techniques and predictive algorithms to forecast SP in the Moodle environment. To predict student outcomes and select the best classifier, we used few classification methods with our dataset for comparison. (Felix et al., 2018) reviewed 42 studies that used data mining techniques to predict student outcomes, as the result, the nine of ten highest accuracies (95%-100%) found in the review are reached through classification methods. Similarly, another systematic review by (Namoun and Alshanqiti, 2020) examined 62 papers that used data mining and machine learning to predict student outcomes, General findings from the review show that the machine learning algorithms, including Decision Trees, Neural Networks, Support Vector Machines, Naïve Bayes, and Random Forests, accurately predict student outcomes, with some studies reporting prediction accuracies of over 90%. In a specific study, (Felix et al., 2019) utilized a dataset of 1,307 students' activity logs in a course, including variables related to student interactions in forums, chats, quizzes, activities, time spent on the platform, and grades. Simultaneously, the study built a predictive model of student outcomes using Naïve Bayes, Decision Trees, Multilayer Perceptron, and Regression algorithms, with the Naïve Bayes model performing the best with an accuracy of 87%. In the same context of the previous study, (Gaftandzhieva et al., 2022) used a machine learning algorithms to predict students' final grades in an Object-Oriented Programming course using data from Moodle LMS activities and online lectures. They found that the Random Forest algorithm had the highest prediction accuracy of 78%.

Thus, in our research, we have made comparisons of the five classifiers (Decision Tree, Random Forest, Bayesian Classification (Naïve Bayes), Support Vector Machines, and Neural Network) with our dataset. Our comparison aimed to evaluate the performance and accuracy of these classifiers in predicting student outcomes based on our specific dataset. In the same way, we have identified the most effective classifier for our research context by applying these classification algorithms to the collected data. Moreover, to adopt our classifier approach, a grading system was used to translate the outcomes score, ranging from 0 to 100, into grades A to F.

This section has presented the foundation of our SP analysis at CADT. The experimental setup, encompassing a diverse dataset from CADT, as shown in Table 1, and an array of data mining techniques, positions us to uncover valuable insights into the dynamics of student learning in online environments. The subsequent section will introduce our SRT design with the SP prediction technique to create data indicators for bridging the gap between analysis and actionable student insights.

5 SRT AND DATA INDICATORS

In this section, we introduce the design and functionality of our SRT, emphasizing incorporating data indicators to provide students with a comprehensive view of their academic progress. Our tool empowers students at CADT by offering group-level overviews and user progress insights, fostering a student-centric approach to LA.

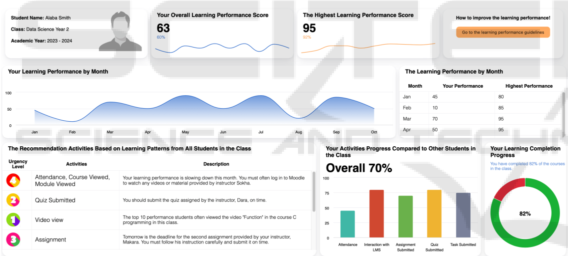


Figure 2: Dashboard of SRT and SP Data indicators.

5.1 Self-Reflective Tool Design

The dashboard in Figure 2 provides an intuitive interface, offering students a visual representation of their learning process in real time. Our design goal is offering friendly user experience, ensuring accessibility for students with varying levels of technological proficiency. Indeed, we would like to make sure that students spend less time understanding the dashboard, but start exploiting right away the SRT-oriented data indicators to enhance their SP.

5.1.1 Group-Level Overview

At the group level, our tool aggregates data to present a comprehensive overview of class performance trends. Visualizations such as distribution of highest learning performance, as shown in Figure 3 and Figure 4, engagement metrics allow students to gauge their standing relative to their peers (Figure 6), and learning guideline for improving their learning performance. This group-level insight promotes a sense of healthy competition, encouraging students to set ambitious but achievable goals in metacognition.

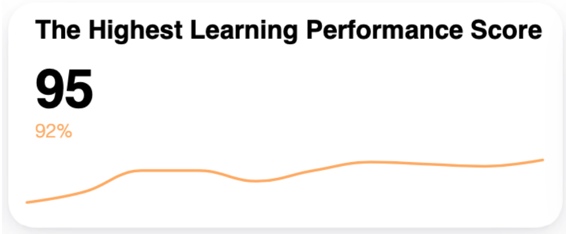
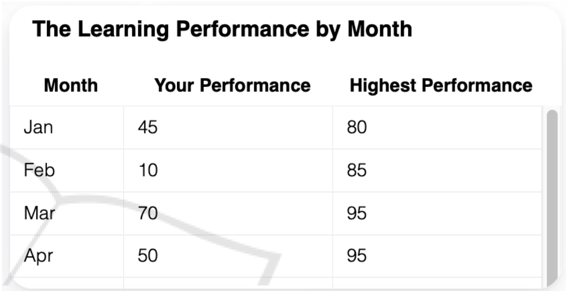


Figure 3: The highest learning performance in the class.


The Learning Performance by Month

Month	Your Performance	Highest Performance
Jan	45	80
Feb	10	85
Mar	70	95
Apr	50	95

Figure 4: The comparison of learning performance in the class.

5.1.2 User Progress Indicators

The heart of our SRT lies in its ability to provide user progress indicators for individual students, as shown in Figure 5. These indicators are derived from a nuanced analysis of each student's learning patterns, considering attendance, number of interaction to the LMS, assignments, quiz, tasks scores, and participation in collaborative activities. By customizing feedback for each student's progress according to their SP score, our tool facilitates targeted interventions and encourages proactive self-evaluation.

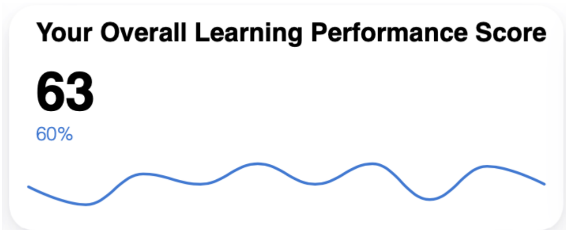


Figure 5: The overall learning performance.

Our learning performance dashboards provide individual learning performance scores (Figure 5) and highlights the highest learning performance scores within the class (Figure 3). Additionally, it presents a

Table 1: The CADT's dataset.

Attendance	Interaction log	Quiz submitted	Assignment submitted	Tasks submitted	Grade
0.279412	0.265866	0.000000	0.166667	0.304348	F
0.382353	0.798456	0.333333	0.333333	0.521739	A
0.397059	0.421098	0.333333	0.309524	0.478261	B+
0.397059	0.482847	0.333333	0.309524	0.478261	A
0.161765	0.325043	0.000000	0.214286	0.391304	B

percentage comparison to the maximum score attainable. For instance, if the maximum score is 110, a student with a learning performance score of 63 might be at approximately 60%, while the highest performance score in the class, say 95, could be around 92%. Our dashboard's individual learning performance scores, class averages, and percentage comparisons are comprehensive metrics to gauge academic achievements. These figures provide a clear overview of where a student stands compared to peers and the maximum achievable score. This comparative aspect fosters a sense of self-awareness by allowing students to evaluate their performance relative to the class's highest achiever and the overall class average. The visual representation of these scores not only offers transparency but also acts as a motivational tool. Knowing one is standing in the class can catalyze self-regulation, prompting students to set personal goals and enhance their learning strategies.

5.2 Dashboard Features

Our tool incorporates various features to enhance the student experience:

5.2.1 Learning Patterns and Progress Tracking

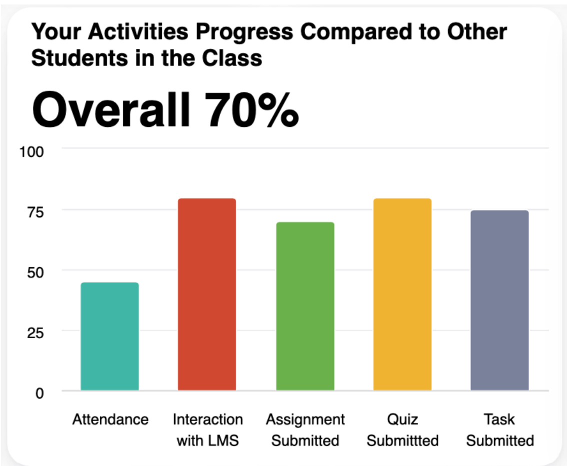


Figure 6: The learning activities progress.

The tool visualizes individual learning patterns, allowing students to identify their strengths and areas for improvement in Figure 6. Insights into preferred study times, resource utilization, and engagement peaks empower students to optimize their study habits. As for the progress tracking, it is dynamic, as shown in Figure 7 providing students with real-time updates on their academic performance. This feature aids in goal setting and time management, fostering a sense of accountability and self-motivation.

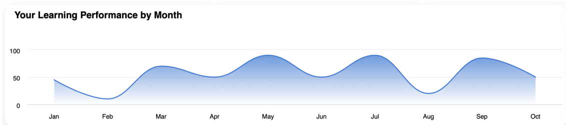


Figure 7: The learning performance progress by month.

5.2.2 Recommendation Engine

Our SRT includes a recommendation engine, as shown in Figure 8 to assist students in maintaining and achieving positive performance. Based on historical data and learning patterns, this engine provides user progress suggestions for resources, study materials, and time management strategies to enhance the learning experience, as well as to gain self-awareness and self-regulation. Additionally, our recommendation engine assigns urgency levels ranging from 1 to 5 with the highlight color, alerting students to take immediate action based on predictions generated by our performance algorithm. The tool suggests individualized actions by predicting SP, learning from their patterns, fostering proactive engagement, and addressing potential challenges before they escalate.

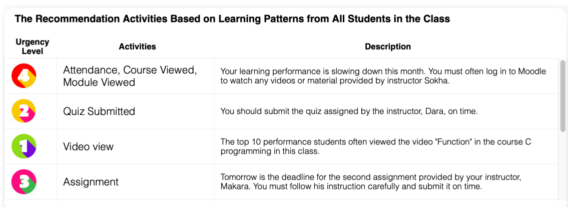


Figure 8: The recommendation activities for each course in the class.

5.3 Implementation and Integration

The SRT is seamlessly integrated into CADT's online learning platform, ensuring a cohesive user experience for students. It operates in real-time, allowing for continuous monitoring and adaptation to evolving learning patterns. Up to this point, we have implemented this tool with and for students, enabling them not only to take part of the design process, but also to naturally adopt the tool and use it for reflective analysis of their learning activities.

With the integration of group-level overviews and user progress insights, we are pursuing our effort in making our tool as a valuable resource for students. We also seek to improve our approach (both SP and SRT), and the way that students utilize it to shape their academic experiences. For that, we have conducted a study, focusing on how the SRT is perceived by students and its impact on their overall SP. The following section will present the results of our study.

6 STUDY RESULTS & FINDINGS

6.1 Data Analysis Protocol

The study employed a comprehensive data analysis protocol to extract valuable insights responses from the survey conducted in December 2023 and for six days, which reached 123 participants from CADT, as shown in Figure 9. Descriptive statistics were employed to summarize survey responses, and qualitative data was analyzed thematically to identify recurring patterns and trends.

Figure 9 shows the overall positive feedback and student perception of the SRT, and data indicators reflect a significant enhancement in the learning experience. Students have consistently expressed satisfaction with the user progress insights and tools designed to support their academic performance. The tools dedicated to self-reflection, particularly those assessing performance and tracking progress, received acclaim for their effectiveness in enhancing students' metacognition. The recommendation engine, offering user progress insights aligned with individual learning patterns, garnered appreciation for its motivational impact on students' commitment to academic tasks. Regarding progress indicators, students recognized the high efficacy of monitoring attendance data, viewing it as a significant factor contributing to improved understanding and academic performance. The value of the number of interaction logs with the LMS was acknowledged, with increased interactions indicating active engagement and enriching the learning experience. Similarly, tracking quizzes, assignments, and submitted tasks received praise for its effectiveness in self-assessment, aiding students in staying on course with their coursework and ensuring timely submissions.

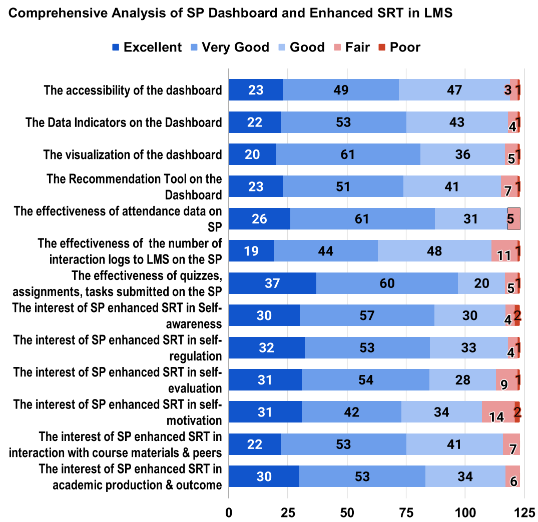


Figure 9: The survey results from SP dashboard enhanced with SRT in LMS.

6.2 Unveiling Novel Findings

As we take a closer look at the data from our study, three significant findings have emerged and will be selected for discussion. These findings unveil not only the relevance of SRT in SP enhancement, but also the correlation among learning components, including students' interactions, SRT oriented data indicators, and the impacts of SRT on not only individuals but also the community.

6.2.1 Integrated Dashboard Experience: A Symphony of Connectivity

As interactions are part of the learning process, a well-integrated SRT will incite more interactions, thus leading to a more active learning and better performance. The dashboard experiences of the SRT were analyzed, with participants providing ratings on a scale from Excellent to Poor. Figure 10 illustrates how these experiences encourage students to interact more with LMS.

Figure 10 demonstrates notable and positive SRT's Dashboard Experience, where the accessibility, data indicators, visualization, and recommendation tool collectively orchestrate a symphony of connectivity. Our findings confirm that when these elements harmonize positively, the number of interaction logs in the LMS increases proportionally. It un-

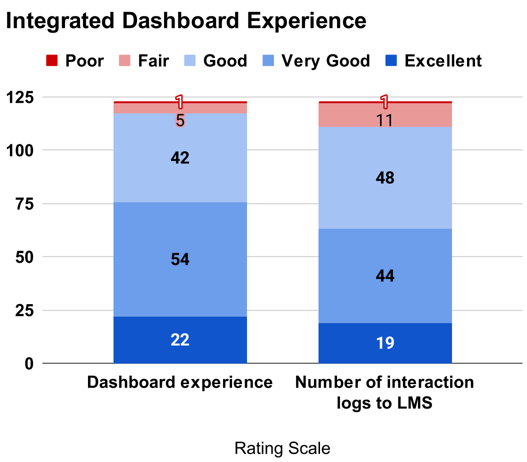


Figure 10: The advantages of dashboard design encourage students to interact with LMS.

veils a compelling correlation, suggesting that a well-designed and informative dashboard enhances individual components and creates a ripple effect, fostering increased engagement and interaction within the learning environment. This correlation in this finding reinforces the essential role of a cohesive dashboard with self-reflective data indicators in shaping and amplifying student interaction.

6.2.2 Performance Analytics and Engagement Mastery: A Virtuous Cycle

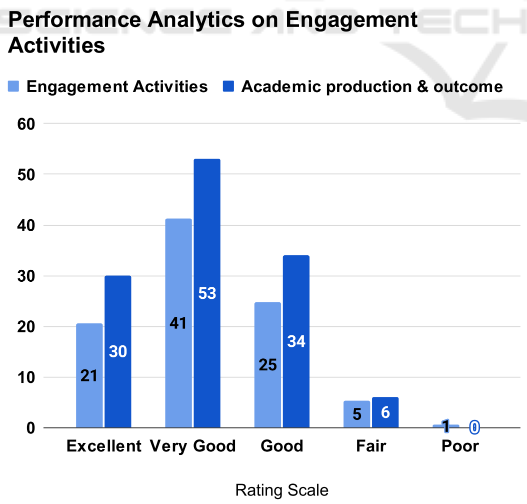


Figure 11: The effectiveness of engagement activities on academic production and outcome.

Our research also uncovered a virtuous cycle in performance analytics and engagement mastery. When students actively participate by attending classes, engaging more interactions with the LMS, and diligently completing quizzes, assignments, and tasks, a cascade of positive outcomes follows, as shown in Figure 11. The academic production and overall outcome align with these engaged behaviors. This intrinsic connection illustrates that student engagement is a catalyst for immediate academic tasks and a predictor of broader academic success. It challenges conventional wisdom, emphasizing the dynamic relationship between consistent engagement and sustained high-level academic performance. As for SRT in that matter, it plays a crucial role in helping students become aware of their engagement, thus inciting them to participate even more.

6.2.3 Cognitive Self-Regulation Hub: Empowering Holistic Growth

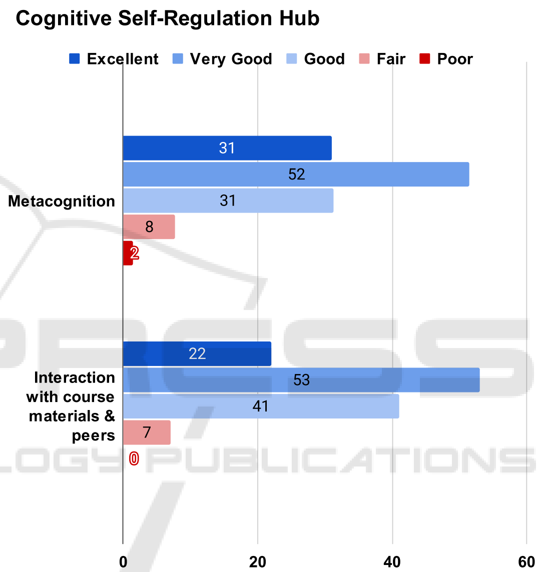


Figure 12: The empowering of metacognition on interaction with course materials and peers.

If we take a look at SRT from a broader perspective and particularly from the Cognitive Self-Regulation Hub domain, our findings show the relevance of SRT in cultivating metacognition such as self-awareness, self-regulation, self-evaluation, and self-motivation, as shown in Figure 12. The tools that empower individual cognitive processes extend their influence, fostering increased interaction with course materials and peers. The data from Figure 13 reveal the profound impact of cognitive self-regulation on individual introspection and as a catalyst for collaborative learning. They also demonstrate the positive impact of SRT in self-assessment for students while interact with others and learning resources. This finding presents SRTs as tools for personal development and contributing factors in creating a vibrant, interactive learning community. It marks a paradigm shift, positioning cognitive self-regulation as the foundation for a thriving and collaborative educational ecosystem.

In summary, these three key insights address part of complex challenges in educational research, with a special focus on reflective analytics to help students enhance their academic performance. Our research efforts aim to provide a fresh perspective on the intricate dynamics that shape student experiences and outcomes. Thus, we hope they invites further exploration and a redefinition of established paradigms in the ever-evolving education landscape.

7 DATA PRIVACY

As we navigate the data privacy landscape within SRT, assessing the impact of stringent data privacy constraints becomes imperative. SRT uses granular data from detailed logs to construct meaningful data indicators. While this granularity enhances the relevance and pertinence of data indicators, it inevitably raises questions regarding user privacy. The compromise lies in striking a delicate balance between data utility and privacy preservation. For that matter, we utilize data anonymization and aggregation methods. We ensure that SRT continues evolving and provides valuable insights without exposing individual user details. It involves implementing techniques that allow the extraction of meaningful patterns and trends without revealing sensitive information, thus respecting users' privacy.

Compliance with the General Data Protection Regulation (GDPR) is a cornerstone of our research methodology. Ethical considerations are at the forefront, with participants fully informed about the nature of their involvement, their rights, and the procedures in place for data management. Transparency is maintained through clear communication, and participants can request the deletion of their data. An ethics committee, including research team members, oversees and approves all aspects of our research design and execution.

8 CONCLUSION

The research efforts presented in this paper focus on a reflective learning analytics approach to empower students and improve their learning experiences. We have pointed out the lack of supports in terms of reflective tools for students, yet reflective analytics is crucial to the learning process and has positive impacts in student self-regulation and self-evaluation. Our research was motivated by the identified gap in empowering students through LA tools, particularly in MOLE. Instead of imitating the existing supports for teachers to recreate new ones for students, we addressed research challenges on how we can provide them with reflective tools, enabling them to gain insights on their own behaviors, then adapt their learning pace and strategy throughout their learning activities. On top of that, the originality of our work lies in our proposal that places a focus on student performance. An experimental setup involved over 160 students from CADT participating in our study. The setup lasted over a year, during which students are invited to participate in the design process of SRT as well as the evaluation of our proposal.

Our design approach covers two aspects: the prediction of SP and the implementation of SRT with data indicators on SP. Our goal is to provide students with personalized insights, real time progress tracking, and reflective components, thus enabling them not only to conduct reflective analytics with specific data indicators on their academic performance, but also to interact and participate more in their learning environment. To achieve this, our research methodology involved a multifaceted approach, combining data extraction, classifier comparison, and performance evaluation. Indeed, our SP approach relies on selecting key attributes to efficient predicting student performance. As for the design of our SRT, we propose a set of data indicators based on SP computed data, featuring student attendance, participation, interaction, quiz, assignment and grading, etc. These SRT-oriented data indicators provide more than just feedback, they are pertinent information about SP on both individual and community scales. Plus, they are accessible in real time, and not only at the end of a learning session, making reflective analytics more prompt, and suitable for different learning paces and strategies.

Our research effort also includes both quantitative and qualitative analyses of our SRT and its impact on SP. A total of 123 students participated in our study through a survey, allowing us to evaluate the correlation between student engagement with the SRT and improvements in SP. Students who actively used the tool reported statistically significant enhancements in their academic outcomes. Data from the survey highlighted the value of personalized data indicators regarding self-awareness, self-regulation, self-evaluation, and self-motivation of individual learning patterns. Moreover, qualitative insights demonstrated that the SRT contributed to students' sense of empowerment, control over their learning journey, and proactive engagement with academic challenges.

To sum up, through this research work, we hope to make a contribution to the discourse on LA by emphasizing the importance of SRT designed explicitly for students in MOLE. Integrating personalized indicators in our SRT at CADT showcases its potential to empower students and actively shape their educational experiences. As we move forward, the implications of this research extend to the broader realm of online education, promoting student-centric approaches to enhance engagement, motivation, and academic success. This work serves as a foundation for future research endeavors, encouraging the continued exploration and development of tools that prioritize student empowerment and self-regulation in the evolving landscape of metacognition online education.

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