# Improving Student Engagement through Learning Analytics and Early Interventions with Learning Locker

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**Abstract.** This paper presents the results of a pilot study conducted at Belgrade Metropolitan University within the framework of the Erasmus+ ISILA project which investigates how data-driven early interventions can enhance student engagement and academic performance in higher education courses. Three pilot implementations are carried out in three courses, where each course has integrated the University's Learning Management System, Learning Locker as a Learning Record Store, while Self-Regulated Learning (SRL) surveys are conducted to collect and analyze student activity data. Learning analytics dashboards are used to identify students at risk of disengagement or low achievement, prompting personalized and general interventions during key points in the semester. Results indicate that targeted communication, flexible deadlines, and additional learning sessions positively influenced engagement and submission rates. The study demonstrates how combining SRL data and learning analytics supports early identification of learning barriers and offers practical insights for improving academic outcomes through evidence-based decision-making .

**Keywords:** Learning Analytics · Early Intervention · Student Engagement · Self-Regulated Learning.

## 1 Introduction

In recent years, universities have increasingly relied on learning analytics (LA) to understand and improve how students engage with learning materials and digital environments. The collection and analysis of learner data, when aligned with pedagogical frameworks such as Self-Regulated Learning (SRL), enables educators to design timely and data-informed interventions that prevent dropout, increase motivation, and foster continuous engagement. Within the European Erasmus+ project ISILA, which aims to enhance the quality and sustainability of learning by developing and testing methodologies for early interventions based on

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learning, the authors implemented several pilot studies. For the study, data was used from various sources which comprise Belgrade Metropolitan University's learning ecosystem. Namely, we have use BMU Educational Information System (iMet), Learning Activity Management System (LAMS), and Learning Locker, an open-source Learning Record Store (LRS) that stores learner interactions in xAPI format. These pilots were conducted in three core Information Technology courses: Object-Oriented Programming 1, Fundamentals of Web Development, and Distributed Systems, which represent different levels of study and student experience. Together, the pilots provide a comprehensive overview of how learning analytics can be applied in both foundational and advanced programming contexts.

Student engagement is a persistent challenge in computer science education, especially in blended and online settings. Engagement is often multidimensional, encompassing behavioral participation, emotional involvement, and cognitive investment. When these dimensions decline, students risk academic underperformance or course withdrawal. The ISILA project's core hypothesis is that data-driven early intervention, based on real-time analytics and SRL feedback, can indeed mitigate these risks by identifying disengagement early and supporting students through personalized communication on one side, and utilizing adaptive instructional design as well.

Each of the three pilot courses follows a similar structure: data collection through the LMS and SRL surveys, creation of course dashboards in Learning Locker, and the design of both general interventions and personalized interventions. General interventions include announcements, extended deadlines, additional sessions, while personalized interventions include targeted emails or consultations. The timing and content of these interventions varied slightly across courses to reflect contextual needs and observed trends in engagement.

In the course CS101 Object-Oriented Programming 1, interventions are planned in weeks 6 and 13, focusing on students with missing activity or elevated anxiety levels. For the course CS105 Fundamentals of Web Development, three interventions are planned at weeks 9, 14, and 15, offering repeated opportunities for inactive students to rejoin the learning process. These two courses are for first-year students. Finally, the only course for students in the second year of studies, CS230 Distributed Systems, interventions are planned as for CS101. This multi-course implementation allows us to assess the effectiveness of early intervention strategies under diverse conditions. It also provides comparative insight into how different instructional approaches, such as in-person consultation versus email-based communication, impact re-engagement patterns. The goal of this paper is to synthesize findings across all three pilots to answer the following research questions:

1. How can learning analytics be used to identify early signs of student disengagement?
2. What forms of personalized and general intervention are most effective for improving student participation and performance?

3. How can SRL data complement quantitative learning analytics to guide more empathetic and context-aware academic support?

The paper is structured as follows. Section 2 outlines the research methodology, including the data sources, instruments, and analysis techniques. Section 3 describes the implementation process of the three pilots and summarizes the intervention designs. Section 4 presents the results and discussion, focusing on measurable engagement changes and qualitative feedback. Section 5 concludes the paper with implications for future applications of learning analytics in higher education.

## 2 Related Work and Methodology

### 2.1 Related Work

Learning analytics (LA) has emerged as a central component of educational innovation, enabling universities to transform raw digital traces of learning activity into actionable insights [1–3]. Defined by the Society for Learning Analytics Research (SoLAR) as "the measurement, collection, analysis and reporting of data about learners and their contexts", LA aims to improve both teaching practices and learning outcomes [4].

A growing body of research has explored the application of LA for early detection of at-risk students and targeted interventions [5, 6]. The authors of [7] demonstrated that the Course Signals system could predict students' academic risk and deliver proactive feedback that improved course completion rates. Similarly, in [8] showed that LMS interaction data could serve as a reliable indicator of engagement and academic success. More recent studies extend this approach by combining behavioral indicators with self-reported psychological data, linking analytics with motivational and affective constructs [9, 10].

Self-Regulated Learning (SRL) theory [11–16] provides a valuable framework for interpreting these analytics. SRL emphasizes learners' capacity to plan, monitor, and evaluate their own progress, a process that aligns well with data-driven feedback loops. In [17] and [18], the authors highlighted that dashboards supporting reflection on SRL processes increase students' metacognitive awareness and motivation. However, they also caution that analytics alone are insufficient without pedagogical scaffolding.

Recent European initiatives advocate for institution-wide frameworks that connect analytics to ethical governance, teacher training, and continuous improvement [19, 20]. Within this landscape, the ISILA project contributes by focusing not only on institutional adoption but also on practical intervention design, ultimately linking dashboard insights to individualized and empathetic student communication.

This paper builds on these foundations by presenting an integrated model that combines Learning Locker dashboards, SRL survey data, and context-sensitive interventions within three university-level IT courses from multiple sources at multiple universities, as shown in Fig. 1. Unlike prior studies that concentrate on a single course or technology, the ISILA pilots test the scalability of such interventions across multiple curricular contexts affected by external socio-political disruptions.

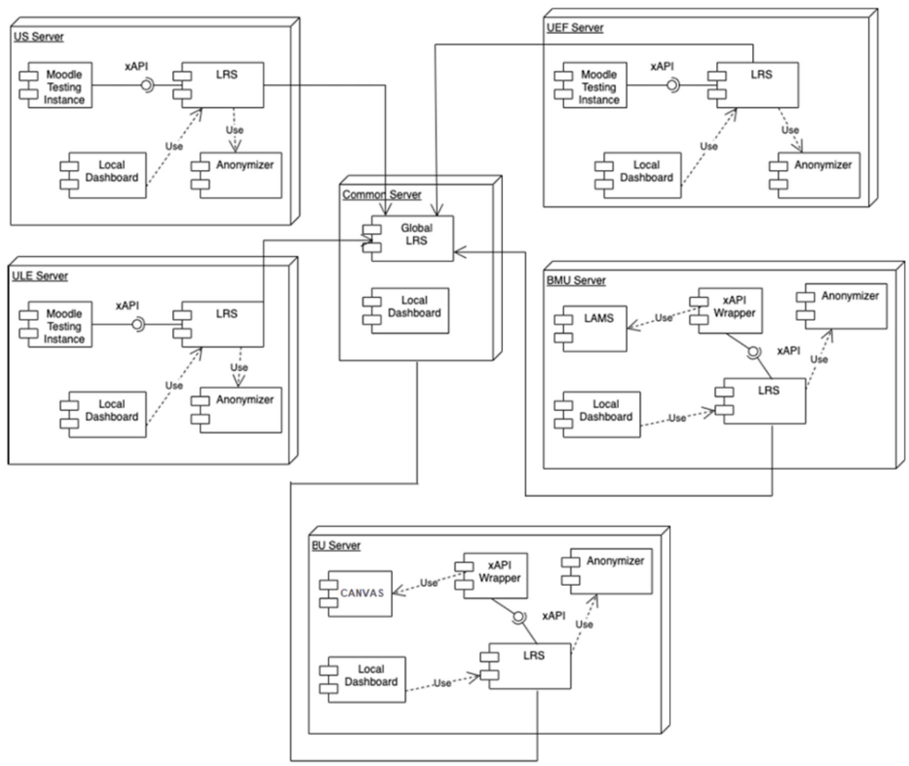


**Fig. 1.** The ISILA LRS model, comprising of multiple local LRSs connected to a global LRS running on a common server.

### 2.2 Research Design

The research followed a mixed-methods approach, combining quantitative analysis of learning analytics data with qualitative interpretation of student responses and instructor reflections. The pilot activities were implemented during the spring semester of 2025 at BMU as part of the Erasmus+ ISILA project. Each course served as a separate case study, but shared an aligned methodological framework. This design allowed both longitudinal tracking throughout the 15-week semester and cross-course comparison. We can summarize the phases as follows.

1. Data collection phase, in which extraction of student activity data from institutional platforms is performed.
2. Dashboard analysis phase, where Learning Locker gives the needed visualizations of learning patterns.
3. Intervention phase, performing the targeted actions which are emails, consultations, or extra sessions for students.
4. Evaluation phase, in which the analysis of behavioral changes and qualitative feedback after each intervention is performed.

## 3 Implementation and Interventions

### 3.1 Data Sources and Tools

Learning data were aggregated from several institutional systems, which include BMU's iMet Educational Management System (EMS), which is needed to provide enrollment records, assignment submissions, and grades. Next, we used the LAMS Learning Management System, where we captured weekly activity logs, exercise completion, and access time. For student communication, we used Discord. Finally, each week we gave students SRL surveys, focused on goal-setting, time management, anxiety, and perceived overload.

### 3.2 Participants and Context

The three courses involved 204 students in total, divided as follows.

- CS101 Object-Oriented Programming 1 with 90 students, first-year undergraduate, at two campuses.
- CS105 Fundamentals of Web Development with 61 students, first-year undergraduate at one campus.
- CS230 Distributed Systems with 53 students, second-year undergraduate students at one campus.

All participants were Computer Science or Information Technology majors. Participation in data collection and interventions was voluntary and conducted under explicit consent in accordance with institutional ethics guidelines. The Learning Locker is shown in Fig. 2.

### 3.3 Analysis Procedures

Data analysis combined descriptive statistics, dashboard interpretation, and thematic coding:

1. Quantitative metrics (number of active users, submission counts, average grades, SRL index values) were extracted from Learning Locker and analyzed in order to identify engagement trends before and after interventions.

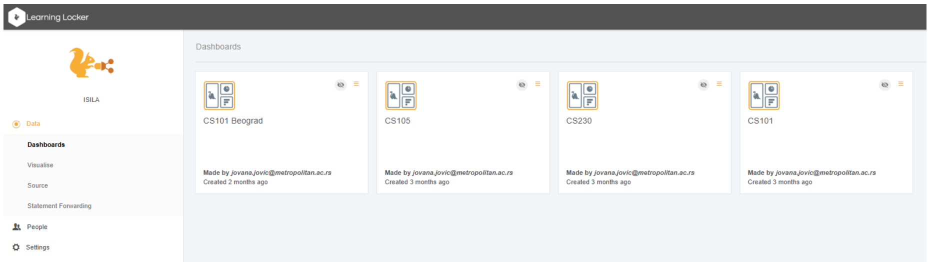


**Fig. 2.** Learning Locker dashboard.

2. Qualitative data, including open-ended survey responses and email correspondence, were coded using inductive thematic analysis [21] to identify recurring patterns related to motivation, stress, and perceptions of support.
3. Cross-case synthesis compared patterns among the three pilots to evaluate the consistency and scalability of early-intervention outcomes.

Reliability was ensured through double-checking dashboard exports and triangulating analytics data with SRL responses. Internal validity was strengthened by aligning interventions with clearly defined student categories (dropout risk, average activity, high achievers with anxiety, etc.).

Each course used a common set of institutional tools (iMet, LAMS, Discord, Learning Locker), but differed slightly in the frequency and type of interventions, as presented in Table 1.

Instructors were trained to interpret analytics dashboards and to act upon indicators of low engagement, such as missing assignment submissions, inactivity on the LMS, or negative SRL survey responses.

**Table 1.** Overview of pilot courses, number of students, and timing of interventions.

| **Course** | **Students** | **Intervention Weeks** | **Tools Used** | **Key Focus** |
|---|---|---|---|---|
| Fundamentals of Web Development | 61 | Weeks 9, 14, 15 | iMet, LAMS, Learning Locker | Flexibility and repeated support opportunities |
| Object-Oriented Programming 1 | 90 | Weeks 6 and 13 | iMet, LAMS, Learning Locker | Early detection and SRL-based communication |
| Distributed Systems | 53 | Weeks 6 and 13 | iMet, LAMS, Learning Locker | Personalized feedback and stress management |

Note that the implementation was heavily influenced by contextual factors: Serbia's ongoing student protests during the semester disrupted regular classes and reduced student motivation and attendance. Consequently, the pilots offered a unique opportunity to evaluate interventions under crisis conditions, testing whether timely communication and flexible scheduling could help mitigate external disruptions.

### 3.4 Data Collection and Dashboard Setup

Data were collected continuously from the institutional systems, first converted into the xAPI format, and then automatically exported to Learning Locker using system integrations and the `csv2xapi` converter developed under the ISILA project. Each student's activity, including login frequency, time spent on exercises, assignment submissions, and survey participation, was transformed into xAPI statements, allowing for cross-platform analysis. The Learning Locker dashboards were customized to visualize engagement trends at both course and individual levels. Key dashboard components included:

- Total time spent on the course per student
- Number of exercises and assignments completed
- SRL survey scores (motivation, anxiety, time management)
- Cumulative grade progress


**Fig. 3.** Learning Locker dashboards for CS230 after Week 6.

These dashboards were updated weekly, providing instructors with actionable insights into participation trends.

This early diagnostic phase was crucial for designing the first round of interventions, which aimed to re-engage inactive students before mid-semester deadlines.

### 3.5 General Intervention Strategy

Each pilot followed a similar three-step approach:

1. Identification, using dashboard data to detect low-engagement or high-anxiety students;
2. Classification, grouping students into categories according to performance and SRL data;
3. Intervention, sending personalized or general messages and providing additional support sessions.

The classification model distinguished five main student profiles:

1. No learning activity detected (dropout risk)
2. Average activity, missing SRL data
3. Below-average performance, high SRL
4. Average performance, high anxiety
5. High performance, high anxiety

This taxonomy allowed instructors to adapt both the tone and content of interventions. For example, students with no activity received empathetic outreach emphasizing re-engagement opportunities, while those with high anxiety but good performance received reassurance and stress management guidance.

In addition to individual emails, general interventions included announcements, deadline extensions, and group consultations designed to create opportunities for re-entry into the learning process.

**Table 2.** Example student classification and corresponding intervention types.

| **Student** | **Intervention 1: Week 6** | **Intervention 1 actions** |
|---|---|---|
| S1 | Average SRL. Submitted all exercises and high grades | NONE |
| S2 | Average level of activity. No SRL data available. | CONTACT PERSONALLY |
| S3 | No learning activity detected on the system – dropout. | CONTACT PERSONALLY |
| S4 | No learning activity detected on the system – dropout. | CONTACT PERSONALLY |
| S5 | No learning activity detected on the system – dropout. | CONTACT PERSONALLY |

### 3.6 Course-Specific Implementation

**CS101 Object-Oriented Programming 1**
The CS101 course focused on core Java programming concepts such as classes, inheritance, and exception handling. Data analysis during the first six weeks revealed an alarming number of inactive students, with over 50% had no recorded activity in LAMS or iMet.

**First Intervention (Week 6):**
Personalized emails were sent to all students showing inactivity, missing SRL data, or high anxiety levels. The emails, written in a supportive tone, encouraged students to restart their coursework and offered additional help. Five different email templates were used, addressing dropout risk, low engagement, or anxiety

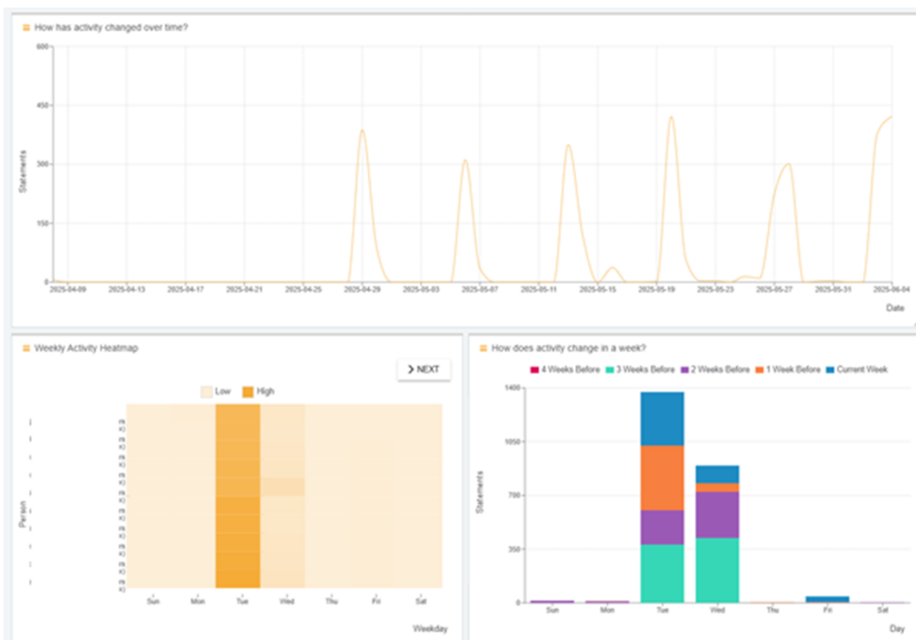


**Fig. 4.** Learning Locker dashboards for CS101 after Week 6.

**Second Intervention (Week 13):**
A follow-up round included reminders about final assessments and invitations to group consultations, organized on middle of July, 2025. Activity peaks were observed shortly afterward, showing a measurable increase in platform usage and assignment submissions. Several students explicitly stated in their replies that time management tips and clarity about remaining obligations motivated them to resume their studies.

Despite external disruptions, around 35% of previously inactive students re-engaged by Week 13, while high-performing students maintained consistent progress. However, approximately 20% of the cohort remained inactive throughout, often citing personal or work-related issues.

**CS105 Fundamentals of Web Development**
The CS105 course introduced students to front-end programming with HTML, CSS, and JavaScript. This pilot included four successive interventions, making it the most extensive implementation among the three.

**First Intervention (Week 9):**
Due to widespread inactivity, all students received an online questionnaire designed to identify barriers to engagement. Survey results revealed recurring challenges:

- Inability to attend classes due to student protests and transport blockades;
- Preference for online instruction and asynchronous completion of tasks;
- Personal or health-related obstacles;
- Lack of motivation due to non-mandatory attendance.

**Second and Third Interventions (Weeks 14 and 15):**
Based on feedback, instructors organized additional pre-exam sessions for students to catch up on missed work. Personalized emails invited low-performing students to these sessions.

Dashboard analytics in Fig. 5 indicated clear activity spikes in Weeks 14 and 15 with the number of submitted statements rising from 904 to 1200 and the average grade increasing from 2.3 to 3.0.

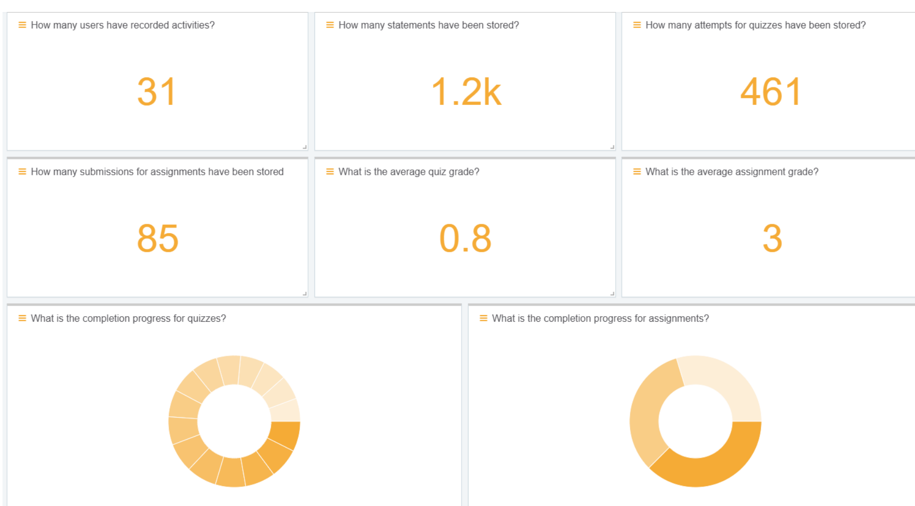


**Fig. 5.** Learning Locker dashboards for CS105 after Week 15.

Although some students remained inactive, most respondents expressed appreciation for the extra opportunities and flexibility. The iterative approach in CS105 showed that repeated, flexible interventions were most effective under crisis conditions.

### CS230 Distributed Systems

The distributed systems course, which included topics on process synchronization, communication models, and blockchain security, served as an advanced-level pilot. Engagement analysis in Week 6 revealed that two-thirds of students had yet to begin any course activities.

**First Intervention (Week 6):**
Students were contacted individually according to the same five-profile model as in CS101. Particular attention was given to those who reported high anxiety or stress through the SRL survey. Some students expressed gratitude for the personalized support, noting that it reduced their sense of isolation.

**Second Intervention (Week 13):**
A similar follow-up was conducted with personalized feedback and suggestions for workload organization. Dashboard visualizations shown in Fig. 6 indicated modest improvements in engagement, especially among students who had previously responded positively to the first intervention. However, nearly half of the cohort remained unresponsive, highlighting the limitation of email-based outreach alone.


**Fig. 6.** Learning Locker dashboards for CS230 after Week 13.

Overall, the CS230 course underscored the importance of multimodal intervention strategies, including direct conversations and group consultations, rather than relying solely on asynchronous communication.

### 3.7 Cross-Course Summary

Across all three pilots, several common trends emerged:

- Early inactivity was widespread (40–60% in Weeks 1–6) but decreased after the first intervention.
- Response rates to personalized emails varied (10–30%), but those who replied often demonstrated consistent improvement.
- Flexible opportunities (extra sessions, extended deadlines) yielded the most significant engagement increases.
- SRL indicators (particularly self-reported anxiety) correlated strongly with performance fluctuations.

These findings collectively demonstrate that data-driven and empathetic intervention models can effectively re-engage students even in challenging academic environments. The pilots also validated the functionality of the Learning Locker dashboard as a tool for monitoring engagement and guiding instructors' decision-making

## 4 Results and Discussion

### 4.1 Overview of Results

The three pilot implementations at Belgrade Metropolitan University provided a broad dataset for examining how early interventions informed by learning analytics can affect student engagement and academic performance.

Across all courses, the data reveal consistent trends:

1. Student engagement was initially very low in the first half of the semester (Weeks 1–6 or 1–9).
2. Targeted interventions, whether through personalized emails, surveys, or additional sessions, corresponded to visible increases in LMS activity and higher assignment submission rates.
3. Students' self-reported SRL indicators (motivation, anxiety, and organization) were closely aligned with observed behavioral changes in Learning Locker dashboards.

The interventions were implemented at different points of the semester (Weeks 6, 9, 13, 14, and 15), but in all cases, dashboard visualizations displayed clear peaks in activity immediately following outreach.

In the CS101 course, approximately 35% of previously inactive students became active after the first intervention. In the CS105 course, the number of submitted learning statements increased from 904 to 1200, and the average assignment grade rose from 2.3 to 3.0 after two rounds of interventions.

In the CS230 course, engagement improved modestly, primarily among students who had responded to initial communication, while others remained inactive.

**Table 3.** Quantitative summary of key engagement metrics before and after interventions.

| Course | Week of Initial Intervention | Average Submissions Before | Average Submissions After | Active Students Before | Active Students After | Average Grade Change |
|---|---|---|---|---|---|---|
| CS101 | Week 6 | 45 | 82 | 43% | 65% | +0.5 |
| CS105 | Week 9 | 904 (statements) | 1200 (statements) | 50% | 70% | +0.7 |
| CS230 | Week 6 | 25 | 47 | 37% | 53% | +0.4 |

The results summarized in Table 3 confirm the hypothesis that timely, data-informed interventions can reactivate disengaged students, even in semesters marked by significant external disruptions.

### 4.2 Impact on Student Engagement

Engagement was assessed through multiple dimensions, namely behavioral (activity logs), cognitive (task completion), and emotional (SRL self-reports).

Following the first intervention in each course, dashboards recorded increased frequency of logins, message exchanges, and assignment submissions. This trend aligns with prior findings that early communication and personal acknowledgment can trigger renewed motivation [7, 17].

However, engagement patterns differed by the type and timing of intervention.

In CS101 and CS230, where the first outreach occurred in Week 6, engagement improved temporarily but plateaued after several weeks, suggesting that a single intervention round is insufficient to maintain momentum.

By contrast, in the CS105 course, where three consecutive rounds were organized between Weeks 9 and 15, the engagement curve displayed sustained improvement, peaking during final pre-exam sessions.

The CS105 data therefore suggest that iterative interventions, even if similar in content, serve as recurring reminders that sustain engagement over time.

This finding supports [10], who observed that repeated prompts based on analytics encourage self-regulatory behaviors such as planning and time management.

### 4.3 Patterns in SRL Indicators and Student Feedback

The integration of SRL surveys provided deeper insight into the psychological and motivational factors underlying student behavior.

Across all pilots, high levels of reported anxiety were observed among both high- and low-performing students.

This aligns with findings from and [9, 12], who note that even high achievers may experience reduced self-efficacy when external disruptions or increased workload occur. In the BMU courses, SRL data informed the tone and focus of interventions:

- Students reporting high anxiety received messages emphasizing stress management and reassurance.
- Students with low self-regulation received suggestions for time planning and breaking tasks into smaller goals.
- Students lacking SRL data were reminded to complete the survey to enable tailored support.

Analysis of email correspondence and survey responses revealed several recurring themes, summarized in Table 4, and given as follows:

1. Appreciation of personalized contact: Many students expressed gratitude that instructors noticed their inactivity or stress, indicating that acknowledgment alone contributed to motivation.
2. Preference for flexibility: Students valued additional sessions and deadline extensions, especially when facing external challenges (e.g., protests, transport blockades).
3. Persistent barriers among some students: Despite support, roughly one-quarter of students remained inactive, suggesting deeper issues such as lack of intrinsic motivation or competing life obligations.

**Table 4.** Summary of thematic codes from student feedback.

| **Theme** | **Description** | **Example Student Comment** |
|---|---|---|
| Recognition | Students valued being noticed and supported | "I didn't expect anyone to follow up on my work and it really helped me refocus." |
| Flexibility | Requests for online or additional sessions | "I could finally complete assignments thanks to the extra class." |
| Emotional support | Acknowledgment of anxiety and stress | "I feel less pressure knowing the teacher understands our situation." |
| Structural barriers | Transportation, protests, work obligations | "I simply couldn't attend because of the road blockades." |

The inclusion of SRL-based personalization thus enhanced the human dimension of data-driven interventions, combining analytics precision with empathetic communication as an aspect emphasized in recent LA studies [17, 19].

### 4.4 Comparative Discussion Across Courses

While all three pilots shared common objectives and tools, they produced distinct insights depending on course structure and student maturity level. Regarding CS101 course, results shown that this was the most structured and technically demanding course. Early interventions had moderate impact, improving participation but not entirely eliminating inactivity. Advanced students responded best to individualized guidance. The most flexible and iterative implementation was conducted in CS105. The use of surveys and repeated sessions demonstrated the highest overall engagement increase. This supports the idea that multiple micro-interventions outperform single, large-scale actions. Finally, for CS230, despite clear data visualization and tailored communication, improvements remained modest. The findings for this course highlight the limitations of asynchronous email communication and the need for real-time support channels such as live consultations or mentoring.

These differences suggest that while the Learning Locker infrastructure effectively centralizes analytics, the pedagogical responsiveness of instructors ultimately determines impact. The best results occurred when interventions combined data insights with context-sensitive teaching actions, such as extending deadlines, organizing catch-up labs, and maintaining regular communication loops.

### 4.5 Interpretation in Light of Literature

The results from the BMU pilots support existing research emphasizing the value of continuously monitoring students' engagement through learning analytics dashboards, complemented by SRL survey data, in order to design timely and personalized interventions. Consistent with [7], early detection of disengagement led to measurable improvements in participation and grades. The integration of SRL surveys parallels findings in [11, 17], who argue that feedback rooted in metacognitive awareness enhances learners' capacity for self-regulation.

However, the pilots also reveal key practical limitations that echo concerns from [2, 18]:

- Data analytics alone cannot ensure engagement; they must be paired with pedagogical empathy.
- Sustained impact requires iterative, multi-channel communication.
- External contextual factors (sociopolitical disruptions, mental health issues) significantly shape students' responsiveness to interventions.

Moreover, these findings contribute to the emerging body of European research advocating for institution-wide frameworks that connect learning analytics with ethical use, teacher training, and early-warning systems. The BMU implementation shows that such systems can be scalable and adaptable across courses, provided that instructors receive proper support and interpret analytics as a diagnostic tool.

## 5 Conclusion

This study examined how learning analytics and early interventions can be applied to improve student engagement and learning outcomes in higher education. Within the framework of the ISILA project, three pilot courses at BMU served as testing grounds for the integration of Learning Locker dashboards, SRL surveys, and targeted communication strategies.

Across all pilots, the results confirmed the central premise that data-driven insights combined with timely pedagogical action can positively affect engagement, motivation, and academic performance. The use of learning analytics enabled early identification of disengaged or anxious students, while SRL data provided the necessary context to tailor interventions to individual needs. This dual approach demonstrated that learning analytics are most effective when interpreted through a human-centered, empathetic lens rather than as a purely technical monitoring tool. Several key findings emerged from the analysis. Firstly, early intervention matters significantly increased engagement after the first outreach in each course, confirming that students respond to acknowledgement and structured support. In addition, frequency and flexibility of interventions proved decisive. The course that implemented multiple interventions recorded the largest and most sustained improvement, showing that repeated prompts and opportunities for participation maintain engagement more effectively than single interventions. Third, the pilots revealed the importance of addressing affective factors, such as anxiety and stress, which directly influence academic persistence. Personalized messages and flexible deadlines mitigated these issues and encouraged students to take proactive control of their learning.

At the same time, several limitations must be acknowledged. A consistent group of students (roughly one quarter) remained inactive despite multiple interventions, suggesting that external or personal factors, such as employment, mental fatigue, or systemic disengagement, require alternative strategies beyond email communication. Furthermore, the socio-political context of the semester, characterized by nationwide protests and disrupted class schedules, limited the generalizability of the findings. These external stressors underscore how contextual factors can amplify disengagement, and why institutional resilience and adaptability are essential components of successful learning analytics initiatives.

Building on these findings, future work at BMU and within the ISILA consortium will focus on automation and predictive analytics by expanding the Learning Locker system with predictive models that can automatically flag at-risk students and trigger early notifications for instructors. Secondly, we will incorporate multimodal communication channels such as in-app notifications, learning platform chatbots, or short video messages to complement traditional email communication. Regarding expanding SRL, we plan to introduce longitudinal SRL instruments to measure how students' self-regulation evolves over the semester and how interventions affect metacognitive growth.

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