

ORIGINAL ARTICLE

# The Role of Individualized Motivation in Fostering Student Engagement

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DOI: <https://doi.org/10.70372/jeltp.v2.i3.24>

## Abstract

Low levels of student engagement in online learning environments have been closely linked to poor academic outcomes and elevated dropout rates. This study introduces a personalized motivation framework designed to improve student engagement by delivering targeted feedback, timely advice, and tailored reminders. The framework operates by monitoring each learner's engagement patterns and responding with motivational interventions suited to their individual needs. The system was implemented and tested with a cohort of over one hundred students, allowing for a detailed evaluation of its effectiveness. Results indicate that when students received individualized motivational support, their engagement with the course content increased significantly. A comparative analysis with a previous group of students—who did not receive such personalized interventions—further underscores the framework's impact. The findings highlight the importance of individualized motivation as a powerful tool in promoting sustained student participation and involvement in digital learning contexts..

**Keywords**—Individualized motivation, Student engagement, Online learning, Personalized feedback, Learning analytics, Educational technology.

## Introduction

Student engagement is a crucial factor influencing academic achievement and retention in educational settings. Studies consistently indicate that students who actively participate in their learning tend to perform better than those who remain disengaged. Engagement is fueled by internal elements such as curiosity, intrinsic interest, and motivation, making it an important measure for educators to assess the effectiveness of teaching [1]. In online education environments, especially in massive open online courses (commonly known as MOOCs), maintaining student engagement is a persistent challenge, with completion rates often reported to be below 10%.

Although numerous techniques—ranging from interactive activities to personalized learning experiences—have been developed to promote engagement in digital courses, many learners still struggle to remain consistently involved [2]. The absence of direct, face-to-face interaction with instructors complicates efforts to identify and support students who begin to

disengage. This situation underscores the need for scalable solutions that can deliver individualized motivational support similar to that provided in traditional classrooms [3].

This paper introduces the Adaptive Motivation and Activity Support (AMAS) framework, which continuously monitors student behavior and engagement levels. The system offers personalized motivational messages, feedback, advice, and reminders to help sustain student involvement. By providing customized support based on learner activity, AMAS aims to improve motivation and foster ongoing engagement throughout the online learning experience [4].

## **Background and Review of Literature**

Learning Management Systems (LMS) have significantly influenced modern teaching and learning practices in higher education. In particular, Personalized Learning Environments (PLE) aim to improve the educational experience by delivering customized course content that adapts to individual student needs [5]. However, most widely used LMS platforms, such as Moodle, Blackboard, and Edmodo, operate on an asynchronous interaction model where students are expected to self-initiate engagement with course materials. This reliance on self-discipline can present challenges for learners who require more structured guidance [6].

These LMS tools do offer feedback mechanisms and notifications, but the scope and depth of feedback are often limited. For instance, Blackboard allows instructors to provide textual feedback on assessments, and many systems support instant feedback through quizzes with pre-configured answers. Edmodo facilitates various question types, including multiple-choice and true/false, enabling immediate feedback; yet, this feedback generally lacks personalization and does not support ongoing learner development [7].

Research by Vasilyeva and colleagues emphasizes the value of detailed feedback that not only confirms correct answers but also supplies supplementary explanations and learning resources [8]. Their adaptive feedback approach, which considers learners' answer certainty, was positively received by students. Similarly, Lubega et al. highlight the importance of personalized feedback based on continuous monitoring of student progress.

OFES (Online Feedback and Emotive System), a web-based tool, enables instructors to generate individualized feedback for specific assignments, incorporating emotive graphics designed to motivate learners. Evaluations of OFES indicate that students find such personalized feedback encouraging [9].

While feedback and notifications are critical for student engagement, current LMS and PLE solutions depend heavily on instructor input. Feedback either comes instantly through automated quizzes, which can be limited in scope, or as delayed, personalized comments post-assessment. Effective feedback should be timely, motivational, personalized, and easily understandable—four factors identified as essential for promoting engagement [10].

The Adaptive Motivation and Activity Support (AMAS) framework integrates these principles by continuously monitoring student behavior and dynamically delivering tailored motivational interventions. These interventions can be triggered immediately, at scheduled intervals, or by instructor command, and include interactive feedback, informative advice, and reminders.

Importantly, AMAS adapts its motivational messages to the individual learner's needs, preferences, and context, providing a more engaging and supportive online learning experience.

## Study Findings

The main goal of this study is to assess whether the personalized motivations provided by the AMAS framework have led to an increase in student engagement. Specifically, we analyze student interactions in an undergraduate SQL database course over two consecutive academic years: 2012-2013, when no motivational interventions were offered, and 2013-2014, when the AMAS framework delivered tailored motivations. Following this, we examine how engagement levels were distributed across both years to determine if there was a positive shift toward higher engagement. Lastly, we share insights from a student questionnaire that captures their perceptions of the motivational support provided [11].

### A. Course Comparison

This evaluation marks the third year AMAS has been applied in the SQL database course at Trinity College Dublin. During the 2013-2014 academic year, 112 students actively used the learning platform, compared to 88 in the 2012-2013 academic year. "Active students" refers to those who logged into the course portal at least once. Both iterations of the course lasted approximately eight weeks [12]. Table 1 offers a summary comparison between the two years. It displays average numbers of interactions and time spent by students on various course components. An initial review reveals that in 2013-2014, students showed higher engagement levels overall. Notably, there was an increase in both the number of interactions and the total time devoted to learning tasks [13]. For instance, while average interactions for learning tasks increased modestly from 109 to 146, the average duration students spent on these tasks nearly doubled from 27,648 seconds to 50,576 seconds. Similarly, engagement with supplementary course materials grew substantially. Interestingly, interaction with core learning content appeared lower in 2013-2014; however, this can be explained by the option given to students to download course materials in PDF format for offline study, which was not the case the previous year [14]. Additionally, students accessed their courses more frequently in 2013-2014, averaging 24 sessions over 20 different days compared to 19 sessions over 17 days in 2012-2013, further indicating enhanced engagement [15].

Table 1. Summary comparison between two academic years

<b>Learning Component</b>	<b>2012–13Avg. Interactions</b>	<b>2012–13Avg. Duration (sec)</b>	<b>2013–14Avg. Interactions</b>	<b>2013–14Avg. Duration (sec)</b>
Learning Content	198	18,346	113	12,114
Learning Tasks	109	27,648	146	50,576
Course Material	101	19,967	223	27,006

### B. Engagement Level

Next, we compare the overall engagement scores between the two years. As illustrated in Figure 1, the mean engagement rose from 68.09% in 2012-2013 to 76.22% in 2013-2014. The 95% confidence intervals for these means were [64.66% – 71.52%] and [73.58% – 78.84%], respectively. This represents an increase of 8.13% in engagement following the implementation of the AMAS motivational interventions. A two-sample t-test assuming unequal variances confirms that this increase is statistically significant:  $t(173) = 3.73$ ,  $p = 0.00025 < 0.05$ , with means (M) and standard deviations (SD) of  $M=0.6809$ ,  $SD=0.1617$  for 2012-2013, and  $M=0.7622$ ,  $SD=0.1403$  for 2013-2014.

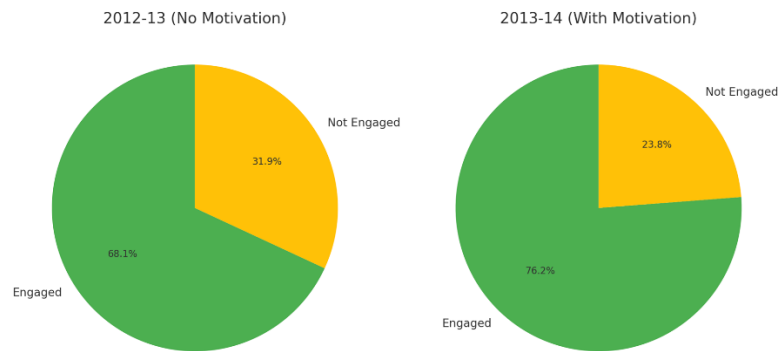


Figure 1. Comparison of overall engagement levels between two course periods

### C. Engagement Distribution

Further analysis explores how engagement scores are distributed across the two cohorts. Figure 2 demonstrates that a larger proportion of students achieved higher engagement levels in the year with motivations (2013-2014) compared to the previous year. The trendlines for the two distributions clearly indicate a shift towards higher engagement scores, suggesting that the motivational mechanisms embedded within AMAS positively influenced student behaviour.

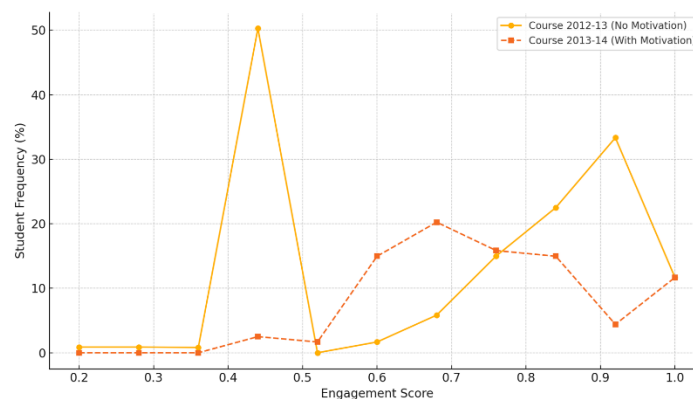


Figure 2. Distribution of engagement scores for both academic years

### D. Student Feedback and Insights

To understand students' subjective experiences with the motivational system, feedback from 96 respondents was analysed, summarized in Table 2. Four key questions were posed:

- a. *Distraction by Motivations*: 41.49% of students did not find the motivations or emails distracting or inappropriate, while 37.23% disagreed. Some students expressed feeling that motivations were occasionally intrusive or frustrating, leading to plans to refine the tone and wording of future communications to be less disruptive.
- b. *Motivations Throughout Course*: A majority (60%) felt that the system delivered motivations at various stages effectively, with only 1% strongly disagreeing.
- c. *Timing of Motivations*: Half of the students agreed that the timing of the motivational messages was appropriate, though 32% disagreed, partially due to schedule changes during the course that caused some confusion.
- d. *Helpfulness in Meeting Deadlines*: 42.55% believed the motivational prompts aided their focus and deadline management, whereas 39.16% felt otherwise, suggesting a desire for either more or fewer notifications.

Table 2. Student feedback results on motivation interventions

Question	Disagree (%)	Undecided (%)	Agree (%)
Q1	41.49	21.28	37.23
Q2	25.26	14.74	60.00
Q3	26.60	23.40	50.00
Q4	39.36	18.09	42.55

Overall, the feedback showed 48.51% positive and 32.11% negative responses. Correlating this with the system log data, it is clear that student engagement improved notably by 8% in the year when the AMAS framework provided dynamic and personalized motivational support.

Despite these positive outcomes, areas for enhancement have been identified. Future improvements will focus on adjusting the frequency, language, and tone of motivations and enabling students to customize the types and number of motivational communications they receive.

### Conclusion

This paper has explored the Activity-based Monitoring and Adaptive Support (AMAS) framework and its role in enhancing student engagement within online learning environments. Engagement is widely recognized as a key predictor of course success, particularly in digital learning formats such as Massive Open Online Courses (MOOCs), where students are expected to independently manage and regulate their learning to a much greater extent than in traditional settings. The evaluation of AMAS over two academic years demonstrated that the integration of personalized motivational strategies led to a measurable improvement in learner engagement—an overall increase of approximately

8%. This correlation was evident in the consistent rise in interaction levels and participation throughout the course duration when the motivational features were implemented. While the system effectively monitored student behavior and delivered dynamic, tailored motivations, student feedback also highlighted opportunities for further refinement. Some learners found certain prompts intrusive or poorly timed, emphasizing the need for more personalized control and a softer communication tone. These insights provide direction for enhancing AMAS in future implementations.

### Acknowledgments

I am gratefully acknowledge the support and participation of all students and instructors involved in this study. Appreciation is extended to colleagues and reviewers whose constructive feedback helped improve the quality of this work. This research would not have been possible without the collective contributions of everyone involved.

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