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Log-based learning analytics of gamified Moodle activities: Quantifying student engagement

Abstract

This study presents a log-based learning analytics pipeline for quantifying user engagement in Moodle, demonstrating how event log data can be transformed into analyzable interaction patterns through extraction, anonymization, categorization, and statistical modeling. The approach applies distributional testing using chi-square statistics and Cramér's V to identify structural differences in user activity. As a case study, the method was implemented in an English for Specific Purposes (ESP) course, comparing a control group following a traditional LMS configuration (N = 40) and an experimental group using a gamified Moodle environment (N = 40). Results indicated that the gamified configuration generated significantly higher frequencies of system-level and assessment-related interactions, as well as more sustained activity across the instructional period, while the control group relied primarily on static content access and exhibited declining participation over time. Engagement was operationalized through event frequencies, capturing observable behavioral differences rather than cognitive or learning outcomes. Beyond the educational setting, the study illustrates how reproducible event-log analytics can be used to detect behavioral shifts in technology-supported environments, offering a methodological template that is potentially transferable to similar contexts in applied computer science.

1. INTRODUCTION

Learning management systems (LMSs) such as Moodle generate large volumes of fine-grained digital traces that provide a rich basis for computational modeling of user behavior. These systems are not only repositories of instructional materials but also complex information environments where every action is recorded as a system event. Viewed as event-driven information systems, LMS platforms continuously generate time-stamped interaction logs that can be processed as structured data streams. Such logs are comparable to interaction traces in enterprise information systems or other digital platforms, where behavioral modeling relies on the statistical analysis of event frequencies and temporal patterns.

Despite their ubiquity in higher education, numerous studies have shown that the mere adoption of digital platforms does not automatically translate into meaningful engagement or improved learning outcomes (Cuban, 2001; Kirschner & Selinger, 2003; Selwyn, 2011). This observation has motivated both educational and computational researchers to explore how system design features and interaction patterns can be optimized through data-driven analysis. In particular, behavioral engagement, defined through frequency and persistence of activity, is often considered the most measurable dimension of student participation (Fredricks et al., 2004). In LMS environments, such engagement can be objectively captured through event logs, which have proven to be reliable indicators of online activity and predictors of academic outcomes (Dawson et al., 2010; Macfadyen & Dawson, 2010).

The growing field of learning analytics (LA) and educational data mining (EDM) exemplifies how computer science methods can be applied to technology-supported environments. Event logs collected in LMS platforms enable reproducible, data-driven workflows that move beyond self-reported measures toward quantifiable evidence of user engagement.

Within this framework, a gamified version of the LMS provides a suitable case for examining how different system configurations shape engagement patterns. Rather than focusing on the pedagogical aspects of gamification itself, this study approaches the context as an opportunity to analyze how variations in platform design correspond to measurable behavioral differences in user activity. By applying statistical modeling to event log data, it becomes possible to detect structural shifts in interaction patterns and to evaluate whether system design interventions are reflected in observable engagement metrics.

Accordingly, the study analyzes Moodle log data from an ESP course to identify systematic differences in engagement between two LMS configurations. Specifically, it tests whether a gamified LMS environment produces statistically significant distributional shifts in engagement patterns compared to a traditional configuration. Its contribution lies in demonstrating a transparent and reproducible log-processing pipeline that transforms raw LMS event data into analyzable behavioral structures using standard statistical techniques, while using the educational setting as an applied case for event-log analytics rather than as an end in itself.

1.1. Research overview

One proposed strategy for addressing low engagement in digital learning environments is gamification. In its most widely cited definition, gamification refers to the use of game design elements in non-game contexts (Deterding et al., 2011). In education, this typically involves integrating features such as points, levels, badges, progress bars, and leaderboards into LMS activities. The rationale is that these elements can make learning environments more interactive, provide clear feedback on progress, and create a sense of achievement or competition, thereby stimulating learners to participate more actively.

Empirical studies confirm that gamification can, under certain conditions, lead to measurable increases in motivation and engagement. For example, Hamari et al. (2014) synthesized findings across multiple domains and reported generally positive effects on activity levels and persistence. Seaborn and Fels (2015) likewise concluded that gamification can enhance both motivation and user experience in learning environments. However, both reviews emphasize the contextual dependency of these effects. Some implementations produce only short-term spikes in participation, while others sustain engagement across entire courses. In contrast, several studies have found that gamification yields no significant improvements, or even has negative effects, such as fostering superficial participation driven by extrinsic rewards rather than meaningful learning.

This variability highlights an important point that gamification is not a simple “add-on” or motivational shortcut. Its effectiveness depends on the alignment of elements with learner profiles, pedagogical goals, and the instructional context. For instance, points and leaderboards may increase engagement for competitive learners but can demotivate others if perceived as unfair or irrelevant. Similarly, badges and progress indicators may encourage persistence when linked to meaningful achievements but risk trivializing learning if awarded too easily. These mixed outcomes underscore the danger of what critics describe as “pointsification”, i.e., the superficial application of game mechanics without grounding in learning theory (Bogost, 2015).

In addition, research shows that the impact of gamification can be more precisely understood when analyzed through objective digital traces such as LMS log data (Macfadyen & Dawson, 2010; Domínguez et al., 2013). These data provide system-level evidence of participation and allow researchers to move beyond self-reported motivation toward measurable indicators of engagement. Moreover, gamified environments generate a wider variety of loggable events (e.g., interactions with badges, progress indicators, or points-based activities), which makes them particularly suitable for computational analysis within learning analytics and educational data mining. Without careful design, however, gamified strategies may provide only temporary novelty or even undermine intrinsic motivation by shifting focus from learning itself to external rewards.

1.2. Literature review

Two theoretical perspectives provide a deeper rationale for understanding when gamification may enhance engagement. The first is Self-Determination Theory (SDT), which emphasizes that learners’ motivation varies in quality depending on how well their basic psychological needs are supported. According to SDT, the needs for autonomy, competence, and relatedness are universal and essential for optimal functioning (Deci & Ryan, 1985; Ryan & Deci, 2000, 2017). Autonomy refers to experiencing choice and volition in one’s actions, competence to feeling effective and capable of mastering challenges, and relatedness to establishing meaningful social connections. Research in educational contexts consistently shows that environments that support these needs foster more self-determined forms of motivation, including intrinsic motivation and identified regulation, which predict persistence and deeper learning (Vansteenkiste et al., 2004; Niemiec & Ryan, 2009).

Gamification can be interpreted as a design approach that introduces elements to meet these needs. Points, levels, and feedback systems provide immediate signals of competence, scaffolding learners' perception of progress. Choice in tasks or learning paths supports autonomy by enabling students to regulate their learning experience. Social features such as leaderboards, visible badges, and collaborative quests can foster a sense of relatedness. However, SDT also warns against the indiscriminate use of extrinsic rewards. When rewards are perceived as controlling, they can undermine autonomy and intrinsic interest, reducing the quality of motivation (Deci et al., 1999). This perspective helps explain why some gamification interventions succeed in fostering durable engagement, while others lead only to short-lived increases in activity or even disengagement.

A complementary perspective is provided by the Cognitive Theory of Multimedia Learning (CTML) (Mayer, 2009; 2014). While SDT addresses why students are motivated to engage, CTML explains how they process information once they do. CTML is based on three assumptions: (1) humans possess dual channels for processing verbal and visual information, (2) each channel has limited capacity, and (3) meaningful learning requires active processing that integrates information into coherent mental models. On this basis, CTML distinguishes between intrinsic load, determined by the inherent complexity of the material; extraneous load, caused by poor design or irrelevant information; and germane load, devoted to schema construction. Effective learning design reduces extraneous load while fostering germane processing through principles such as signaling, coherence, and redundancy reduction (Mayer, 2009).

Gamified activities in LMSs often involve interactive multimedia tasks, such as H5P modules, branching scenarios, or quizzes with immediate feedback. When structured according to CTML principles, such activities can be both motivationally attractive and cognitively effective, i.e., feedback, progress indicators, and interactivity can support attention management and elaboration while preventing overload. Conversely, poorly designed gamified elements may add unnecessary visual or auditory features that increase extraneous load and distract from learning goals.

A third theoretical lens, Flow theory, enriches this discussion by focusing on the experiential quality of engagement. Flow describes the psychological state in which individuals experience deep absorption, concentration, and enjoyment in an activity when there is an optimal balance between challenge and skill (Csikszentmihalyi, 1990). Gamification can provide conditions for flow by offering clear goals, immediate feedback, and progressively calibrated challenges. However, sustained flow requires precise alignment. Tasks that are too difficult induce anxiety, while those that are too easy cause boredom. In language learning, this balance is especially critical, as students' prior knowledge and domain-specific demands vary widely.

Taken together, SDT, CTML, and Flow provide a multidimensional framework for gamified learning design. SDT clarifies the motivational mechanisms that attract and sustain participation, CTML explains how engagement can be directed toward effective cognitive processing, and Flow highlights the conditions under which engagement becomes a rewarding experience in itself. This synthesis suggests that the effectiveness of gamification lies not simply in increasing the number of learner actions, but in designing environments that invite sustained participation, channel engagement toward cognitive learning processes, and make learning experiences meaningful and enjoyable.

Building on this theoretical grounding, the present study adopts a learning analytics perspective in which engagement is conceptualized using log data generated in Moodle. This shift from theoretical explanation to computational operationalization reflects a broader trend in learning analytics research, in which behavioral engagement is increasingly modeled using event-log data. Recent learning analytics research further supports the use of LMS log data as a robust basis for modeling behavioral engagement in technology-supported learning environments. Empirical studies and systematic reviews emphasize that engagement patterns derived from log data reflect not only activity volume but also persistence, consistency, and temporal structure of participation, which are critical for interpreting user behavior in LMS-based settings (Ifenthaler & Yau, 2020; Balalle, 2024; Goh, 2025; Ngulube & Ncube, 2025).

1.3. Problem statement and contribution

The domain of English for Specific Purposes is a particularly suitable context for testing these theoretical connections. ESP courses require learners to acquire specialized vocabulary, genre conventions, and communicative practices tied to professional or disciplinary settings (Hutchinson & Waters, 1987; Dudley-Evans & St. John, 1998). Students frequently perceive ESP as peripheral to their main studies, which can reduce motivation and result in low levels of voluntary engagement. At the same time, ESP learning demands sustained practice and repeated exposure to domain-specific language, which LMS platforms are well-positioned to provide.

Gamification offers a potential means of bridging this motivational gap, but empirical studies of gamification in ESP remain scarce. Most existing work on gamification in language learning focuses on general English, vocabulary games, or mobile applications, and relies heavily on self-report measures of motivation and satisfaction rather than objective indicators of engagement. Learning analytics provides a methodological advance. By analyzing LMS log data, researchers can capture patterns of actual behavior across activity types and time periods, offering more reliable operationalizations of engagement.

The present study addresses these gaps by comparing a traditional non-gamified ESP course with a gamified ESP course implemented in Moodle. Its contribution lies in demonstrating how a theory-informed gamification design can reshape engagement patterns in an ESP context and in showing how log-based learning analytics can provide robust statistical evidence of these effects. By combining pedagogical theory with quantitative analysis of system data, the study advances understanding of how gamification influences learner behavior in LMS environments.

2. METHODOLOGY

The study employed a quasi-experimental design to investigate the effects of gamification on student engagement in an English for Specific Purposes course delivered via Moodle. Two parallel groups were compared. One group participated in a traditionally structured non-gamified course (control group), while the other experienced a gamified version of the same course (experimental group). Both courses were taught by the same instructor, covered identical content, and followed the same semester schedule. The only difference lay in the integration of gamification elements into the experimental group's Moodle environment.

2.1. Participants and context

The study was conducted during the summer semester of the 2024 academic year at University North in Croatia, among second-year undergraduate students enrolled in the Department of Multimedia, Design, and Application. The ESP course is a compulsory part of the undergraduate curriculum.

A total of 80 students participated in the study. They were divided into two groups of equal size: a control group (n = 40), which completed a traditionally structured non-gamified version of the course, and an experimental group (n = 40), which completed the gamified version. The division into groups was managed through Moodle, using the Choice activity. Before the semester began, students independently selected the class schedule that best suited their availability. Once a choice was submitted, the system automatically registered the student into the corresponding group. This selection process took place before the first class session, and students were unaware that the course would later be included in a study. Their group membership was therefore determined entirely by institutional procedures, with no intervention by the researcher. This quasi-experimental arrangement ensured balanced group sizes while maintaining ecological validity within the natural structure of the study program.

All students belonged to the same age cohort, ranging from 20 to 22 years. They had all previously passed the national high school leaving exam (state graduation exam) in English, which is a standardized requirement for university admission in Croatia. Performance on this exam corresponds to intermediate-to-upper-intermediate proficiency, i.e., approximately B1–B2 on the CEFR scale. This provided a relatively homogeneous baseline while still leaving space for growth in discipline-specific vocabulary and professional discourse practices. Learners at this stage are an appropriate target group for gamification interventions, as motivation often fluctuates during the transition from general to specialized language learning.

Both groups received identical ESP materials and pursued identical learning objectives, but the mode of delivery differed. In the control group, students worked through weekly materials primarily in the classroom with the instructor, while Moodle was used as a repository for resources and a submission platform. In the experimental group, the same materials were presented in a gamified format on Moodle, where students completed most of the practice activities online. Classroom sessions took place for both groups according to the timetable, but the distinction lay in how materials were engaged with. Namely, in the control group, they were addressed face-to-face, whereas in the experimental group, they were embedded into the LMS environment. Crucially, the researcher did not intervene in the delivery of activities in the gamified group. The gamification elements were part of the standard course setup, ensuring that the comparison reflected authentic institutional practice.

By holding the content constant and varying only the LMS configuration, the study generated two directly comparable sets of Moodle log data, which served as the empirical basis for the learning-analytics analysis.

2.2. Gamification design

The experimental version of the ESP course was implemented on Moodle and designed to incorporate gamification elements to stimulate student engagement while maintaining alignment with pedagogical objectives. The design drew on the principles of Self-Determination Theory (Deci & Ryan, 1985; Ryan & Deci, 2000, 2017) and the Cognitive Theory of Multimedia Learning (Mayer, 2009; 2014), ensuring that gamification would not merely add superficial features but actively support motivation and cognitive processing.

Several Moodle plugins and tools were combined to create a cohesive gamified environment. The central element was the Level Up XP plugin, which awarded students experience points (XP) for completing online activities. Points accumulated over time allowed students to progress through levels, with a visual progress bar displayed on their Moodle dashboard. This feature provided immediate feedback on competence, encouraging persistence and giving students a sense of accomplishment.

In addition to the Level Up XP plugin, the gamified environment relied on H5P interactive activities, which offered a range of task types, including drag-and-drop vocabulary exercises, branching scenarios, timed quizzes, flashcards, and crosswords. A key feature of these activities was the provision of immediate automated feedback, enabling students to monitor their performance after each attempt and identify areas for improvement. This feedback mechanism reinforced perceptions of competence and sustained engagement, consistent with the principles of Self-Determination Theory. By embedding these interactive tasks directly into Moodle, students were encouraged to participate regularly and engage more deeply with discipline-specific language practice. The combination of varied task formats, visible progress through the XP and Level Up system, and automated feedback created a structured but motivating learning environment in which gamification elements supported both persistence and active cognitive processing.

To support relatedness, badges were awarded for milestones such as completing a set number of activities or reaching specific XP levels. Although competition was not emphasized, leaderboards were made visible within the group to acknowledge achievement and foster a sense of community. Students were informed that participation in these activities contributed to their progress in Moodle but did not directly affect their final course grade, ensuring that the system complemented, rather than replaced, formal assessment.

The control group completed the same content and assignments, but their Moodle environment contained only the standard non-gamified features. Both groups covered identical syllabus content, had the same instructor, and followed the same weekly schedule, ensuring that any differences in engagement could be attributed to the presence or absence of gamification rather than to other variables.

The gamification design was intended to create an environment where students were motivated to engage with ESP content more frequently and more actively, while also ensuring that their participation contributed to deeper cognitive processing. By embedding gamification within Moodle rather than through an external platform, the intervention reflected authentic educational practice and demonstrated how learning management systems can be adapted to support theory-informed innovation in higher education.

2.3. Procedure

The course lasted seven weeks. Week 1 was dedicated to orientation, during which students were introduced to the course structure and use of Moodle. The experimental group additionally received guidance on the gamification features, with explicit clarification that these would support participation but not influence final grades. All participants were informed in advance that their activity data would be collected in anonymized form, that participation would not affect academic standing, and that withdrawal was possible at any time without penalty. The study design adhered to institutional guidelines for research involving human participants and followed the ethical standards of educational research.

Weeks 2 through 6 constituted the instructional period, with students attending three 45-minute sessions per week, totaling 135 minutes. Both groups worked through identical ESP content, covering specialized vocabulary, reading comprehension, and written communication. The control group engaged primarily in face-to-face classroom tasks, while the experimental group completed the same tasks in a gamified Moodle environment. Classroom sessions were held for both groups according to the timetable, with the LMS configuration representing the only systematic difference between conditions.

In Week 7, the intervention concluded, and Moodle log data were retrieved from the institutional server. These data, comprising event records of student interactions, were prepared for statistical processing and served as the empirical basis for the analyses reported in this study. By embedding the intervention within regular course delivery, the design preserved ecological validity while ensuring that comparable log-based data sets were generated for both groups.

2.4. Data collection and analysis

The primary data source for this study consisted of Moodle system logs, which record fine-grained, time-stamped traces of student actions in the LMS. Logs were collected continuously across the seven weeks of the course and exported in raw format at the end of the semester. To ensure confidentiality and compliance with institutional ethical guidelines and GDPR requirements, all personal identifiers were removed prior to analysis and replaced with pseudonymous codes linked only to group membership. The raw log files were exported from Moodle's standard logging subsystem in CSV format and contained multiple system-level fields (e.g., time, user identifier, activity context, component, and event name).

Table 1 presents an illustrative example of raw Moodle system-level log events. The examples are synthetic and are provided solely to demonstrate the structure and variety of events captured by the Moodle logging subsystem. This approach was adopted to protect student privacy and ensure compliance with GDPR and institutional ethical requirements. The examples do not represent the analyzed dataset.

Tab. 1. Illustrative example of Moodle log entries including gamified H5P activities

Time	User	Related to	Activity Context	Component	Event Name	Description (Synthetic)	Source
15/04/24, 15:09	Student A	Student A	Course Page	System	Course viewed	Synthetic example of a core Moodle system event related to course access	web
15/04/24, 15:09	Student B	Student B	File resource	System	Resource Viewed	Synthetic example of a core Moodle system event for accessing course materials	web
15/04/24, 15:09	Student C	Student C	Forum activity	System	Discussion Viewed	Synthetic example of a system-level interaction with a forum component	web
15/04/24, 15:09	Student E	Student E	Course Overview	System	Course Content Viewed	Synthetic example of general course interaction	web
15/04/24, 15:09	Student D	Student D	Assignment overview	System	Assignment Viewed	Synthetic example of a system-level interaction with an assignment resource	web

Following export, the raw log data were processed through a structured, reproducible pipeline, summarized in Figure 1, which outlines the transformation of raw system events into analyzable engagement data through extraction, anonymization, categorization, and aggregation.

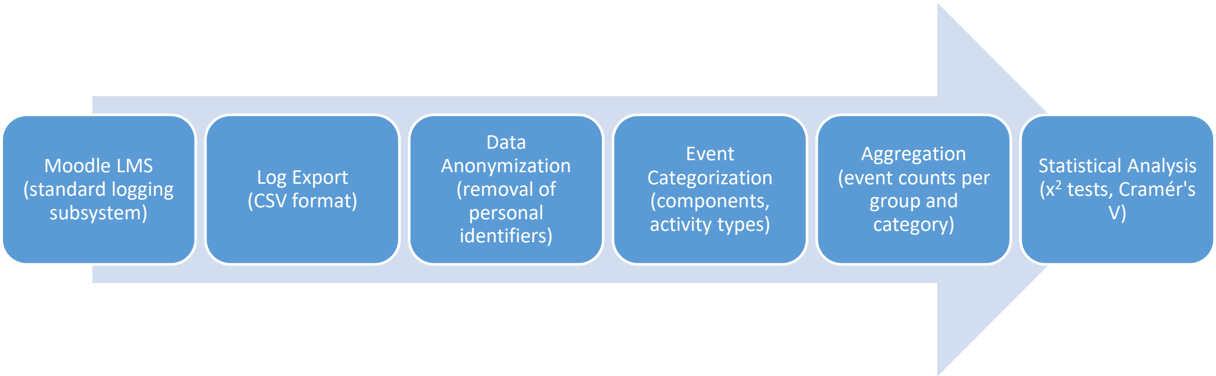

Fig. 1. Moodle log processing and analysis pipeline

For the purposes of this study, the cleaned data were analyzed at three complementary levels: (i) differences in the distribution of Moodle components common to both groups; (ii) differences in the distribution of activity types common to both groups; and (iii) differences in the distribution of student activity across instructional weeks, providing a descriptive overview of engagement patterns over time.

Descriptive analysis was based on absolute frequencies of log events in each category. Group-by-category contingency tables were constructed and compared between the control and experimental groups using chi-square tests of independence (χ^2), which are appropriate for categorical frequency data, do not assume normality, and were evaluated at the event level with significance set at $p < .05$. Although the participant sample was moderate (N = 80), the large volume of logged events (N > 40,000) ensured sufficient statistical power for distributional inference. To address potential non-independence of events generated by individual students, effect sizes were calculated using Cramér's V and interpreted as distributional differences rather than person-level outcomes, applying conventional thresholds for 2×k tables (≈ 0.10 small, ≈ 0.30 medium, ≈ 0.50 large).

Plugin-specific events (e.g., those generated solely by gamification add-ons) were excluded from all component-level and activity-type comparisons, i.e., only core Moodle log fields common to both the control and experimental groups were retained for analysis. Low-frequency event types were preserved as distinct categories. Given the large number of observations, the chi-square results remained robust. As a sensitivity check, collapsing very low-frequency event types into a single residual category did not materially affect significance levels or effect sizes, indicating that results were not driven by sparse cells.

This procedure transformed LMS interactions into formal contingency models, enabling the quantification of distributional differences in engagement patterns directly from event log data and situating the analysis within learning analytics and educational data mining practices. Although event frequency represents a limited operationalization of engagement, it provides an objective and reproducible behavioral proxy that enables transparent comparisons of engagement patterns across system configurations without relying on self-report measures.

3. RESULTS

For this study, cleaned log data from N = 80 students (40 in the control group and 40 in the experimental group) were analyzed for the duration of the intervention. Instructor accounts and system logs unrelated to student activity were excluded. The results are presented in three sections: (i) distribution of Moodle components common to both groups, (ii) distribution of activity types common to both groups, and (iii) weekly patterns of student activity.

Tab. 2. Distribution of Moodle components common to both groups

Moodle component	Control group	Experimental group	Total
File	860	357	1,217
Forum	82	102	184
Student report	3	12	15
System	1,853	10,616	12,469
Test	2	722	724
Total	2,800	11,809	14,609

Table 2 presents the distribution of Moodle components that were equally available to both groups (File, Forum, Student Report, System, Test). The chi-square test indicated significant differences in usage patterns, $\chi^2(4, N = 14{,}609) = 2475.92$, $p < .001$, with an effect size of Cramér's V = 0.41 (medium-to-large).

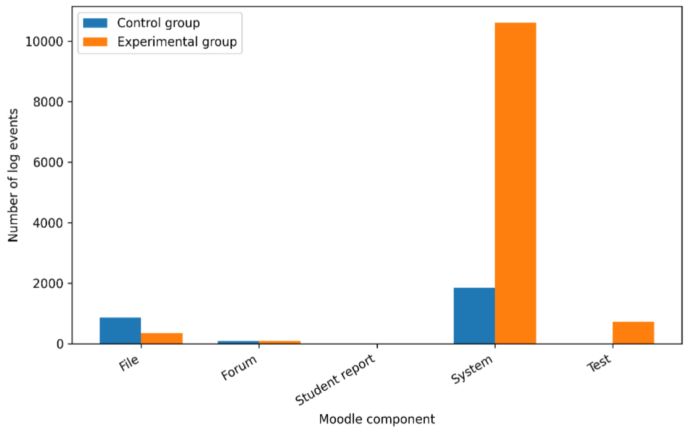

Fig. 2. Distribution of Moodle components by group

As shown in Figure 2, students in the experimental group generated markedly more events in the System and Test components, whereas those in the control group relied far more on the File component. Low-frequency categories such as Forum and Student Report contributed minimally to overall distributions. Taken together, these results indicate that students in the experimental condition engaged predominantly with system-level and assessment-related components, whereas the control group focused on accessing course files.

Tab. 3. Distribution of activity types common to both groups

Activity	Control group	Experimental group	Total
Student report viewed	3	12	15
Course module viewed	927	9,463	10,390
Test attempt refreshed	0	2,084	2,084
Test attempt submitted	0	204	204
Test attempt reviewed	0	1,147	1,147
User list viewed	162	1	163
Course content viewed	637	2,543	3,180
Test attempt summary viewed	0	180	180
Discussion viewed	210	47	257
Test attempt started	0	3	3
Total	1,939	16,584	17,623

Table 3 presents the distribution of activity types that were equally accessible to both groups (Student Report viewed, Course module viewed, Test attempt refreshed, Test attempt submitted, Test attempt reviewed, User list viewed, Course content viewed, Test attempt summary viewed, Discussion viewed, Test attempt started). A chi-square test confirmed significant differences between the groups, $\chi^2(9, N = 17{,}623) = 3371.78$, $p < .001$, with an effect size of Cramér's V = 0.44 (medium-to-large).

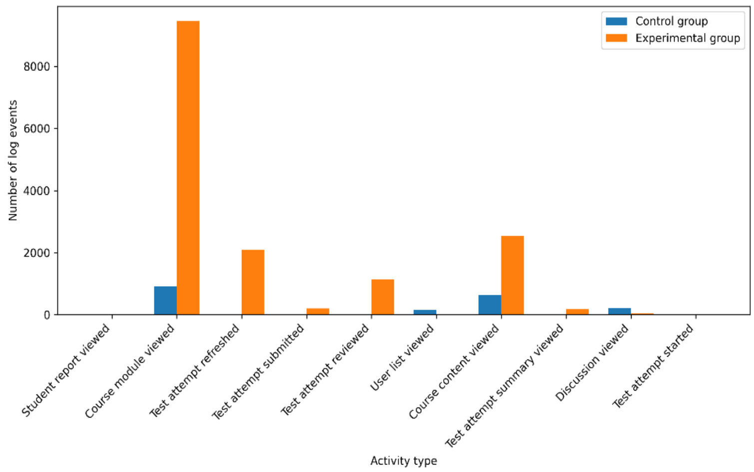

Fig. 3. Distribution of activity types by group

As it can be seen from Figure 3, the experimental group generated a markedly larger number of events linked to assessment-related activity (such as starting, refreshing, submitting, and reviewing attempts), alongside a high frequency of course module views. By contrast, the control group's activity was concentrated primarily on viewing course content and user lists. Low-frequency categories such as student-reported views, discussions, and test-attempt starts contributed negligibly to overall differences. Taken together, these results show that engagement in the experimental group was driven by repeated interaction with assessment workflows, whereas the control group relied mainly on access to static content.

Tab. 4. Distribution of student activity across weeks

Week	Control group	Experimental group	Total
1	999	9,065	10,064
2	512	10,807	11,319
3	293	10,321	10,614
4	166	6,320	6,486
5	0	3,610	3,610
Total	1,970	40,123	42,093

As shown in Table 4, for weekly analyses, we report the five instructional weeks (course Weeks 2–6, labeled as Weeks 1–5 in the tables for clarity). Orientation (Week 1) and the concluding week (Week 7) were not included in the weekly distribution. A chi-square test indicated significant differences between groups, $\chi^2(4, N = 42{,}093) = 951.87$, $p < .001$, with an effect size of Cramér's $V = 0.15$ (small).

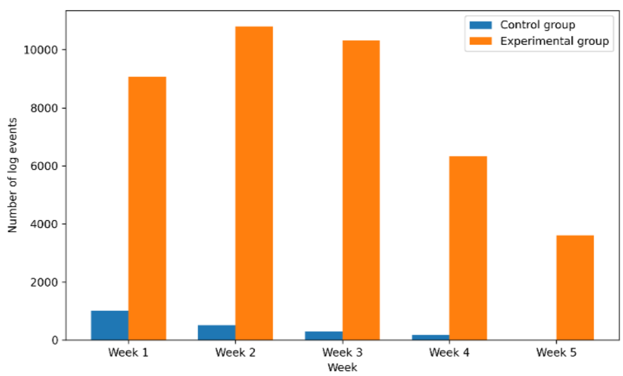

Fig. 4. Distribution of student activity across weeks

As shown in Figure 4, the experimental group maintained consistently high activity throughout the period, with peaks in Weeks 2 and 3. In contrast, the control group displayed considerably lower engagement overall, with a gradual decline from Week 1 to Week 4 and no recorded events in Week 5. Low-frequency control activity in the later weeks contributed minimally to the chi-square differences, underscoring the robustness of the finding. These results indicate that the experimental group maintained engagement consistently throughout the instructional period, whereas the control group's activity declined sharply as the course progressed.

Taken together, the analyses across all three levels revealed systematic differences between the groups. The experimental group consistently displayed higher levels of engagement, with greater interaction in system-level and assessment-related components, a broader range of activity types, and more sustained participation across weeks. In contrast, the control group's engagement was concentrated in file access and content viewing and declined notably over time. These distributional patterns provide the basis for interpreting how the intervention influenced engagement dynamics, which is addressed in the following discussion.

4. DISCUSSION

The present study examined the impact of gamified Moodle activities on student engagement in an ESP course, using learning analytics to analyze log data from N = 80 participants. The results demonstrated clear differences between the control and experimental group. Students in the gamified group generated more events in system-level and assessment-related components, engaged in a broader range of activity types, and sustained higher levels of participation across weeks. These findings confirm that gamification can significantly shape interaction patterns in online learning environments (Hamari et al., 2014; Seaborn & Fels, 2015).

Interpreted through Self-Determination Theory, the experimental group's greater activity in assessment-related tasks suggests that gamified elements contributed to the satisfaction of autonomy and competence needs, which in turn fostered persistence and engagement (Deci & Ryan, 1985; 2000; Ryan & Deci, 2000). The consistent engagement observed over time aligns with SDT predictions that the fulfillment of basic psychological needs supports self-regulated learning and long-term motivation.

The results also resonate with the Cognitive Theory of Multimedia Learning. While the control group focused primarily on accessing files and static content, the experimental group participated more actively in tasks requiring processing, responding, and reflecting. Such interactive behaviors correspond to Mayer's principles of active processing, in which learning is enhanced when learners engage in meaningful interaction with instructional material (Mayer, 2009; Clark & Mayer, 2016). By incorporating gamified structures, the experimental group's environment fostered deeper cognitive engagement than the largely passive engagement observed in the control group.

From the perspective of Flow theory, the sustained engagement of the experimental group across weeks indicates that gamification helped establish a balance between challenge and skill, enabling students to remain immersed in the learning process (Csikszentmihalyi, 1990; Shernoff et al., 2003). In contrast, the control group's marked decline, culminating in no recorded events in the final instructional week, suggests a lack of conditions necessary to achieve Flow, leading to disengagement as the course progressed.

At the same time, engagement in this study was operationalized through event frequencies derived from LMS logs, which capture observable behavioral activity but represent only one dimension of student engagement. Other behavioral indicators, such as diversity of activity types, persistence across sessions, session duration, or temporal regularity of participation, may provide complementary insights into how learners interact with digital learning environments. These dimensions were beyond the scope of the present analysis but represent important avenues for future research, particularly in studies that aim to link behavioral engagement to cognitive processes or learning outcomes.

Hence, beyond these theoretical perspectives, the study contributes to the field of applied computer science by demonstrating the value of learning analytics as a computational approach for understanding educational phenomena. By applying statistical analysis to Moodle log data, this research demonstrates how large-scale event traces can reveal behavioral patterns and quantify the effects of pedagogical interventions (Siemens, 2005; Siemens & Long, 2011). Such methods are transferable beyond ESP courses and can be implemented across diverse disciplines and learning management systems, highlighting the scalability of learning analytics approaches (Siemens, 2005).

From an instructional design perspective, the findings suggest that gamified designs can increase student activity in system-level and assessment-oriented components, which are critical for learning outcomes in ESP contexts (Deterding et al., 2011). For practitioners, this underlines the importance of designing online courses that go beyond static content delivery and incorporate interactive, motivating tasks that sustain engagement over time.

At the same time, the present study can be read through a broader lens of applied computing. The analytical workflow employed, i.e., log extraction, cleaning, categorization, aggregation, and distributional testing, reflects standard event-log analysis practices used across technology-supported systems beyond education. Comparable approaches are routinely applied in production engineering, management information systems, and digital service environments to model system behavior and support optimization. By focusing on transparent distributional comparisons rather than predictive modeling, the study emphasizes interpretability and reproducibility, positioning log-based learning analytics as an instance of applied event-log analysis rather than a method confined to educational research.

Several limitations should be acknowledged. The study was conducted with a relatively small sample ($N = 80$) in a single course and over a limited seven-week period, which constrains the generalizability of the findings. Additionally, the control and experimental groups differed not only in LMS configuration but also in the modality used to complete learning activities: the control group engaged primarily in face-to-face sessions, whereas the experimental group completed most tasks online via Moodle. Consequently, observed differences cannot be attributed exclusively to gamification effects. Finally, the analysis focused solely on behavioral engagement captured through system logs; no direct measures of learning outcomes, language proficiency gains, or qualitative learner perceptions were included.

Taken together, the results suggest that gamified Moodle activities significantly influenced both the structure and the sustainability of student engagement. The integration of theoretical perspectives from Self-Determination Theory, the Cognitive Theory of Multimedia Learning, and Flow provides a robust framework for interpreting the observed behavioral patterns and highlights the mechanisms through which gamification may support motivation, cognitive processing, and immersive learning experiences. At the same time, this study advances methodological practice in learning analytics by showing how engagement can be captured through a reproducible log-processing pipeline. The contribution is threefold: (i) transparent mapping of events into analyzable categories, which makes behavioral constructs auditable; (ii) distributional testing with χ^2 and Cramér's V, which quantifies structural shifts in interaction patterns; and (iii) a lightweight, LMS-native workflow that other institutions can replicate without additional infrastructure. This positions the study within the educational data mining tradition and extends its application to ESP contexts.

5. CONCLUSIONS

This study provides evidence that gamified activities on Moodle can significantly reshape student engagement patterns in ESP courses. By focusing on log data equally accessible to both control and experimental groups, the analysis showed that gamification encouraged interaction with system-level and assessment-related components, diversified the types of student activity, and sustained participation over weeks.

The contribution of this research is threefold. Theoretically, it demonstrates how established frameworks of SDT, CTML, and Flow can be jointly applied to interpret engagement in online learning. Methodologically, it highlights the role of learning analytics as a robust tool within applied computer science for detecting and quantifying behavioral change in LMS environments. In practice, it suggests that course designers can foster more persistent and meaningful engagement by embedding gamified structures in ESP courses.

Beyond these immediate findings, the log-processing pipeline and statistical workflow introduced in this study illustrate how standard LMS data can be transformed into analyzable features. These features, i.e., component distributions, activity-type profiles, and temporal engagement signatures, can be directly reused to design dashboards that visualize engagement patterns, develop early-warning heuristics for at-risk students, and serve as input for predictive modeling or adaptive learning systems. While we do not build predictive models here, the study demonstrates how event log data can be prepared to make such models feasible, scalable, and generalizable across LMS platforms.

Limitations of the study include its relatively small sample, single-course context, and short duration. These findings should therefore be generalized with caution. Future research should replicate the design across different courses and contexts, integrate qualitative data with log-based analytics, and further disentangle which gamification features most strongly support engagement.

Collectively, these findings highlight that gamification, when thoughtfully designed and analytically monitored, demonstrates strong potential to enhance both the structure and sustainability of student engagement in technology-supported language learning.

Ethics Statement and Data Availability

All participants were informed that their LMS activity data would be collected and analyzed in anonymized form for research purposes. The study followed institutional ethical guidelines and complied with GDPR requirements. Due to institutional regulations governing student data, the datasets generated and analyzed during the current study are not publicly available.

Conflicts of Interest

The authors declare no conflict of interest.

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