Διεθνές Συνέδριο για την Ανοικτή & εξ Αποστάσεως Εκπαίδευση

Τόμ. 13, Αρ. 1 (2026)

ICODL2025

When Clicks Reveal Student Frustration: A Sensor-Free Analytics Approach with Adaptive Thresholds

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doi: 10.12681/icodl.8654

When Clicks Reveal Student Frustration: A Sensor-Free Analytics Approach with Adaptive Thresholds

Τα κλικς ως δείκτης απογοήτευσης φοιτητών: Μία προσέγγιση με προσαρμοστικά κατώφλια χωρίς χρήση αισθητήρων

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Abstract

The process of learning is deeply intertwined with students' emotional states, with frustration recognized as a particularly disruptive affective condition that undermines motivation, engagement, and achievement. This study investigates frustration detection in an online postgraduate course delivered through a Moodle-based learning environment. Building on prior work in affect-aware tutoring, we propose a sensor-free approach that relies on anonymized logfiles that capture student interactions. An adaptive thresholding method was applied to identify anomalous bursts of activity, such as repeated clicking, that signal frustration. Results revealed 4,763 frustration incidents, with navigation and forum activities generating the majority of signals, while submissions and quizzes were secondary contributors. Peaks in frustration closely aligned with assignment deadlines, quizzes, and examinations, though sustained navigation and forum engagement also proved highly indicative of stress. The findings highlight the importance of contextual and category-specific analysis in capturing frustration dynamics, and they underscore the need for inclusive support strategies that extend beyond high-stakes assessment moments.

Keywords

Learning Analytics, Distance Learning, Frustration Signs, Sentiment

Περίληψη

Η διαδικασία της μάθησης είναι άρρηκτα συνδεδεμένη με τη συναισθηματική κατάσταση των φοιτητών, με το αίσθημα απογοήτευσης να αναγνωρίζεται ως μια ιδιαίτερα επιβαρυντική συναισθηματική κατάσταση που υπονομεύει το κίνητρο, τη στοχοπροσήλωση και την επίδοση. Η παρούσα μελέτη διερευνά την ανίχνευση της απογοήτευσης σε μία θεματική ενότητα μεταπτυχιακού επιπέδου του Ελληνικού Ανοικτού Πανεπιστημίου. Βασιζόμενοι σε προηγούμενες έρευνες σχετικές με αναγνώριση συναισθημάτων σε ευφυή συστήματα διδασκαλίας, προτείνουμε μια μέθοδο χωρίς χρήση αισθητήρων, η οποία αξιοποιεί ανωνυμοποιημένα αρχεία καταγραφής (logfiles) αλληλεπιδράσεων φοιτητών στην διαδικτυακή πλατφόρμα μάθησης. Εφαρμόστηκε μια μέθοδος προσαρμοστικού κατωφλίου για την ανίχνευση ασυνήθιστων «εκρήξεων» δραστηριότητας, όπως τα αλλεπάλληλα γρήγορα κλικς, τα οποία αποτελούν ένδειξη απογοήτευσης. Τα αποτελέσματα αποκάλυψαν 4.763 σχετικά περιστατικά, με τις δραστηριότητες *“πλοήγηση”* και *“φόρουμ”* να παράγουν την πλειοψηφία των σημάτων, ενώ οι ενέργειες που αφορούν τις υποβολές και τα κουίζ αποτέλεσαν δευτερεύουσες πηγές γεγονότων που υποδεικνύουν απογοήτευσης. Οι κορυφώσεις των περιστατικών απογοήτευσης συνέπεσαν σε μεγάλο βαθμό με τις καταληκτικές προθεσμίες εργασιών, κουίζ και τις ημερομηνίες των εξετάσεων, ωστόσο η συνεχής πλοήγηση και η συμμετοχή στα φόρουμ αποδείχθηκαν επίσης ιδιαίτερα ενδεικτικές του στρες. Τα ευρήματα αναδεικνύουν τη σημασία της σχετικής με το πλαίσιο, κατηγοριοποιημένης ανάλυσης για την κατανόηση της δυναμικής της ματαίωσης και υπογραμμίζουν την ανάγκη για συμπεριληπτικές στρατηγικές υποστήριξης των φοιτητών καθ’ όλη τη διάρκεια του ακαδημαϊκού έτους και ιδιαίτερα κατά τις περιόδους υψηλής πίεσης.

Λέξεις-κλειδιά

Αναλυτική εκπαιδευτικών δεδομένων, εξ αποστάσεως εκπαίδευση, ριπές απογοήτευσης, ανίχνευση συναισθήματος

Introduction

The learning process is a complex cognitive process including multiple interactions highly affected by the emotional state of the learner. Students’ emotions also play a

crucial role in the design and development of intelligent tutoring systems (Yadegaridehkordi et al., 2019; Hasan et al., 2020). One especially useful feature of these systems is the capacity to provide automated of affect-aware feedback. Beyond the obvious benefit of timely responses, such feedback can motivate students (Jiménez et al., 2018) and has been linked to higher academic achievement (Cunha-Pérez et al., 2018; Rajendran et al., 2019).

Specifically, the emotion of frustration is a problematic cognitive affective state, often described as a "state of being stuck", that fosters negativity and disrupts progress (Meldrum, 2002; Rajendran et al., 2013). In online learning frustration can have highly negative impact (Rajendran et al., 2013; Richey et al., 2019). Classic work characterizes frustration as the blocking of behavior directed toward a valued goal (Morgan et al., 1986), a dynamic that is especially critical in educational settings (Rajendran et al., 2013; Lawson, 1965). When frustration is left unacknowledged and get prolonged, students are more likely to disengage with the risk of dropping out (Rajendran et al., 2013; Lawson, 1965; DeFalco et al., 2018).

Students are especially prone to frustration when they perceive low control over outcomes they value (Pekrun, 2024). Confusion can also act as a precursor, often evolving into frustration and a sense of disappointment if it is not resolved (Baker, 2025). Many factors can trigger frustration emotions during learning (D'Mello & Graesser, 2012) these are often amplified in distance-learning contexts, where physical separation from instructors and peers can reduce timely support (Tsoni et al., 2014). Key findings indicate that frustration that arises from sources such as overly challenging tasks, academic pressure, and social stressors, undermines both intrinsic and extrinsic motivation. It undermines self-efficacy, impairs goal setting, and reduces the ability to persist on a certain learning task. Similarly, frustration reduces students' engagement, gradually disconnecting them from the learning process and undermining overall achievement. Detecting students' frustration is essential in order to address the issue cultivating a positive learning experience. Supportive and inclusive learning environments can help students cope more effectively, promoting emotional well-being and sustaining motivation.

As Picard (2000) notes, there is an important distinction between universal and person-specific patterns in the behavioral signs that indicate particular emotions. In

this work, we make use of a commonly observed frustration cue (Klein, 1998; Edwards, 2016; Safaei & Ghafourian, 2022; Hertzum & Hornbæk, 2023) that is repeated, rapid clicking on the same interface element.

Related work

One of the early studies on affect-aware tutoring, including the detection of frustration in tutoring systems, is presented in Woolf et al. (2009). In this work, the authors identified emotional indicators which, when combined with on and off task variables, represented desirable and undesirable states linked to student learning.

Building on this line of research, Olguin Muñoz et al. (2021) tracked both system and task states in real time, while also recording biometric data from wearable sensors. Their findings showed that stressful events slowed down task performance and triggered frustration-related actions. Similarly, Woolf et al. (2010) employed automated multi-sensor emotion recognition systems in intelligent tutoring environments. Their results, compared against student self-reports, achieved an overall accuracy of 80%.

Although sensor-based approaches, such as those relying on physiological sensors (e.g., webcam, microphone) and neurological sensors (e.g., EEG), often yield higher accuracy and can be generalized across diverse learning contexts, they present several challenges. These include the need for adequate technical expertise for deployment, calibration issues, potential hardware failures, and risks of mis-tracking (Leong, 2015; Henderson, 2023; Henderson et al., 2020). Moreover, obtaining high-quality physiological data for affective analysis requires carefully designed experimental setups (Shu et al., 2018). Such requirements substantially increase both the cost and the complexity of implementation, while also raising significant privacy concerns (Yang et al., 2019; Richey et al., 2019).

In this study, to address the abovementioned limitations, a sensor-free frustration detection process was adapted. Instead of relying on external devices, the approach presented in this paper leverages logfiles generated through students' interactions with the online platform. By analyzing anonymized log data, our method allows us to infer the affective state of frustration in a cost-effective and privacy-preserving manner, while avoiding the technical risks inherent in sensor-based systems.

Methodology

In this section, the methodology is described, based on the theoretical framework outlined above and shaped by the study's research goals. It sets out the methodological rationale and documents each step to facilitate transparency, replicability, and practical implementation.

Dataset

The dataset is derived from anonymised logfiles of postgraduate students' activity. In total, 175 students engaged with a Moodle-based online learning environment for a postgraduate course at the School of Science and Technology of the Hellenic Open University during the 2022–2023 academic year. The course comprised five optional synchronous support online meetings, six mandatory written assignments, and six online quizzes. To be eligible to sit the final examinations, students were required to achieve a minimum grade of 5 out of 10.

ETL Process

The ETL (Extract–Transform–Load) process consists of seven steps, ranging from data extraction to the generation of the final results report. The first step involved loading the logfile and transforming specific columns into the appropriate format, such as converting the "*time"* column. The second step was to extract a unique id number for each student and to exclude members of the teaching staff from the dataset. In the next step students' action were categorized in broader groups, namely: *login, quiz, submission, forum, navigation, or other*. The fourth step involved the creation of a per-minute summary. Events were aggregated by "*Student ID", "Minute"* and *"Category"*. For each grouping, the total number of events was calculated, and representative event names were retained to provide contextual information.

The subsequent step that is the creation of adaptive threshold per student, per category, was particularly critical, as it introduced an adaptive dimension to the process, enabling the methodology to respond more effectively to the characteristics of the data. The aim is to detect episodes of unusually high activity intensity possibly indication students' frustration, not by applying a universal cut-off, but by calibrating thresholds relative to the typical students' behavior. This personalized approach

addresses the well-documented heterogeneity of engagement in online learning environments (Hernández-García et al., 2024; Goh & Sigala, 2025). The activity counts were then summarized for every student and category at the per-minute level. Descriptive statistics (mean and standard deviation) were used to create a baseline. An adaptive threshold was then derived by combining this baseline with a dispersion factor, while category-specific minimum values ensured that thresholds did not become unrealistically low. That is, in cases of very limited activity history or zero variance, the predefined minimum thresholds prevailed to avoid false positive signals. Other alternative approaches include median-based thresholds, were also considered to mitigate the impact of outliers (Han et al., 2022; Zamanzadeh Darban et al., 2023; Peña, 2023). This adaptive framing treats activity bursts as potential anomalies in event streams, aligning with recent advances in anomaly detection for time series (Han et al., 2022; Zamanzadeh Darban et al., 2023; Pang et al., 2024). Within the LMS setting, tailoring thresholds at the student- and category-level helps to reduce bias caused by differing baseline activity levels and resonates with findings linking persistence and consistency of engagement to academic performance (Goh & Sigala, 2025).

The operational term “frustration signal” was defined follows: an incident that is considered to be a frustration signal is any minute in which the number of actions for a given student and activity category exceeds the final adaptive threshold established in the previous step (Step 5). Minute-level resolution was selected given the timestamp accuracy of the dataset and the observation that bursts of activity often occur as short-lived spikes. Each record was evaluated against the corresponding threshold, and flagged instances were logged in a detailed register including student identifier, timestamp, category, observed count, threshold applied, and a small sample of representative events. If thresholds were exceeded simultaneously across multiple categories within the same minute, separate entries were generated to preserve category specificity. Additionally, quality-control measures were incorporated in order to enhance reliability. A persistence filter required at least two flagged minutes within a five-minute window to define an episode, reducing false positives due to isolated fluctuations. Adjacent flagged minutes separated by short

gaps (≤2 minutes) were merged into single episodes to better capture continuous bursts.

In the final step, the results were generated and presented in both tabular and visual formats. The outputs included the Detailed Signals, a Summary by Student ID, the Per-ID Thresholds, and the corresponding Parameters.

Results and discussion

A total of 4763 instances of frustration were recorded among students during the academic year. Each episode was classified by the online activity in which it was detected into five categories: *"navigation," "forum," "submission," "quiz,"* and *"other."* In the navigation category, 1902 signs were observed, in forum 1609, in submission 1070, in quiz 154, and 28 incidents did not fit any of the above and were labeled "other."

Figure 1 shows the cumulative count of flagged minutes (i.e., minutes during which frustration signs were detected). As expected, the curve increases over time; however, the most informative feature is the slope of the line. Periods of steeper slope correspond to sharper rises in incidents, indicating intervals of increased stress. The figure also includes vertical lines marking key course dates: green lines denote tutorial meetings, red lines indicate assignment and quiz due dates, and purple lines mark the examination dates.

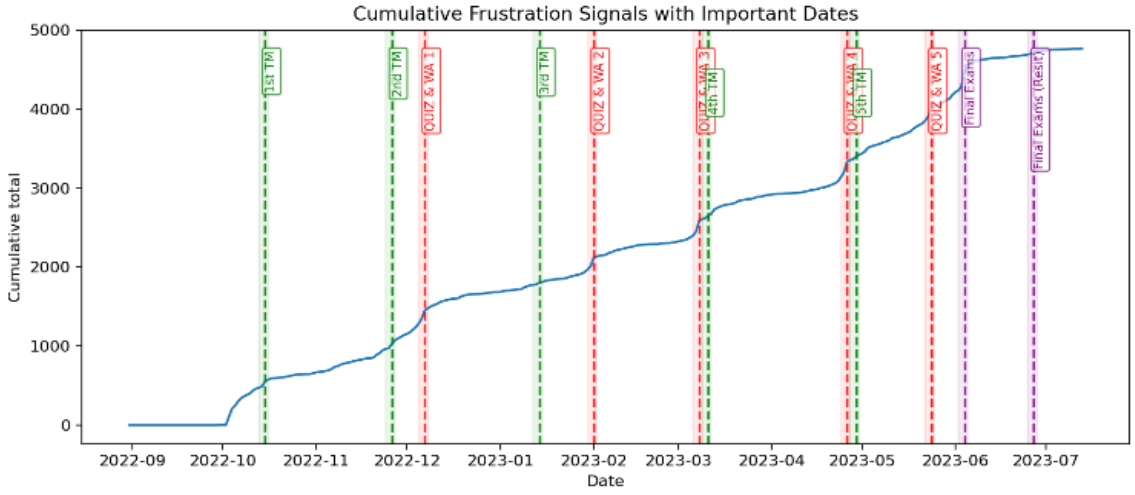

Figure 1: *Cumulative count of flagged minutes*

The following bar charts display the total number of frustration signals by month (Figure 2, left) and by weekday (Figure 2, right). October, the first active month, shows elevated levels of frustration signals consistent with early-term anxiety at the start of the course. Overall, the most stressful month is May, which is unsurprising given the final written assignment deadline and the approaching examinations.

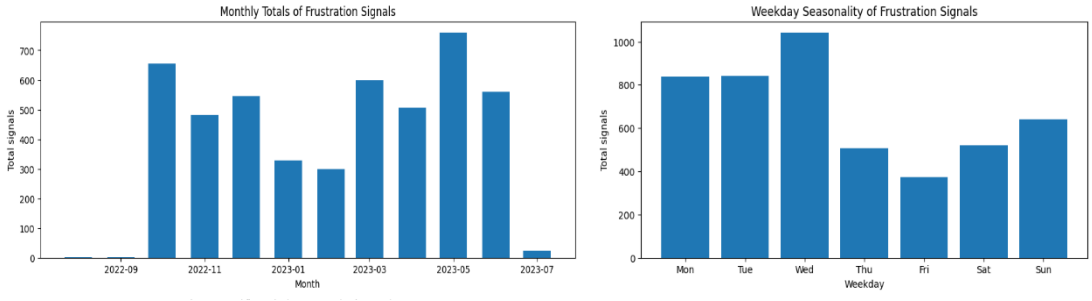

Figure 2: *Left: Total number of incidents per month Right: Total number of incidents per weekday*

By weekday, frustration is highest at the start of the week, peaking on Wednesday, whereas Friday is the least frustrating day, with the fewest incidents. The next graph (Figure 3) also indicates Wednesday as the day of the week with the most frustration signals. Additionally, it provides information about the time-of-day density of the incidents. Monday, Wednesday, and Sunday evenings have the highest density, and this even continues late into the night. This finding is consistent with previous research (Tsoni et al., 2019; 2021; Karapiperis et al., 2023; Verykios et al., 2023; Paxinou et al., 2024a; 2024b) and with the profile of most HOU students: working adults with substantial professional and family responsibilities who study in the evening or late at night, often after a full day's work.

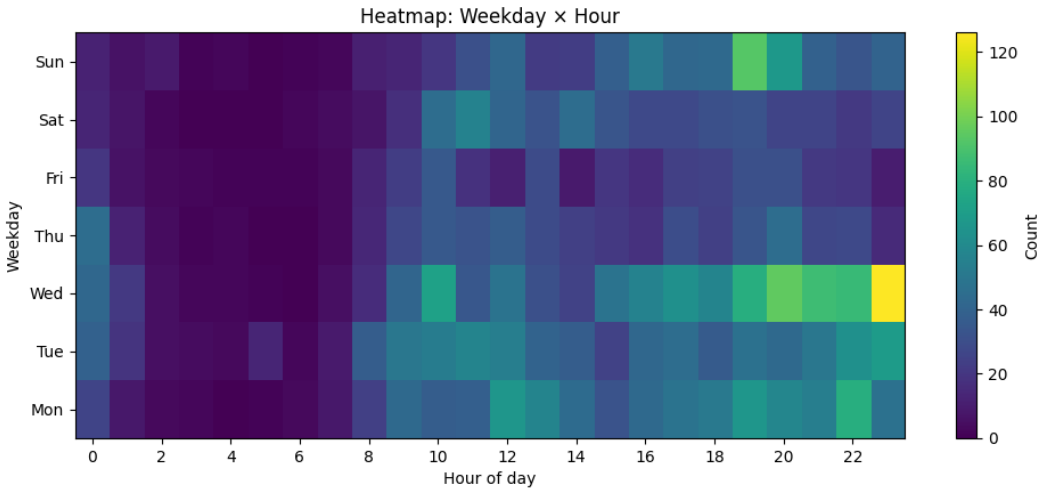

Figure 3: *Distribution of incidents across the weekly cycle*

Flagged minutes indicating stress and frustration occur daily. However, there are sharp spikes corresponding to key course events. Figure 4 presents the daily counts of frustration signals. The peaks align closely with the deadlines for quizzes and written assignments. There is also a smaller yet pronounced spike on the dates of the first and second tutorial meetings, reflecting early-term anxiety. The only instance where a spike follows, rather than coincides, with the important date is the final examination. There, the peak occurs a few days later, indicating anxiety while awaiting their grade to be announced.

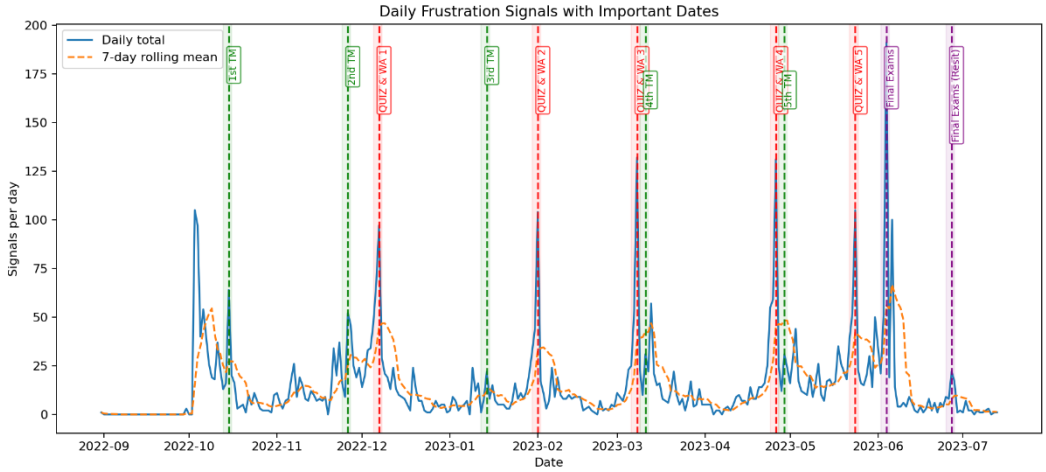

Figure 4*: Daily signal counts*

A similar graph in Figure 5 shows the daily counts of frustration signals by category. Navigation related signs dominate at the beginning of the course, as students explore the course site and orient themselves. On the other hand, submission related signals

spike on each due date which is expected given last-minute uploads and time pressure. Forum signals rise around almost each tutorial meeting and again in the final period before the exams, when students interact more to seek help, exchange information, and share their stress. Overall, these category-wise patterns align closely with the course schedule and typical student behavior.

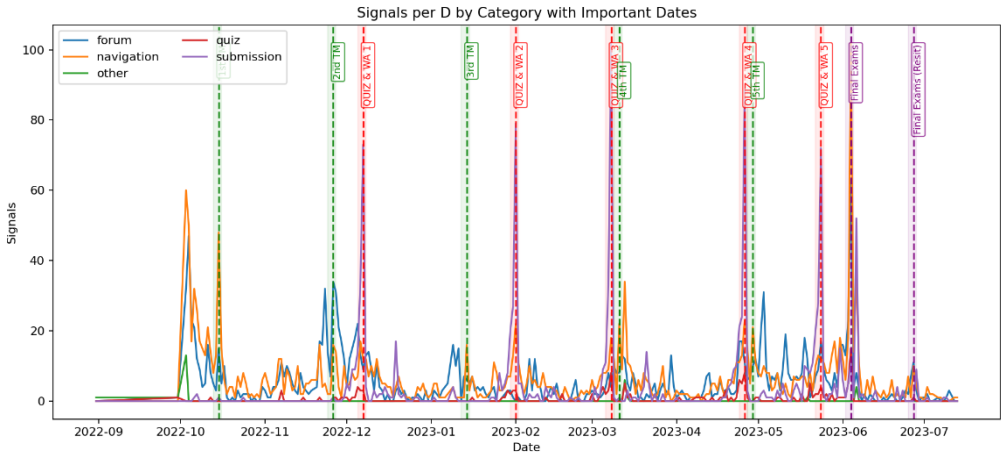

Figure 5: *Category-wise signals*

It is clear that some days have markedly higher counts of frustration signals than the typical daily totals. To identify these “spike days,” we standardized the daily counts using the z-score. For each day with total x, we computed $z = (x - \mu) / \sigma$, where μ is the mean daily count over the period and σ is the corresponding standard deviation. A z-score indicates how many standard deviations a value lies above or below the average. We used a one-sided threshold of $z > 2$ to flag spike days that is, days more than two standard deviations above the mean. This corresponds to roughly the top 2.5% of days (Montgomery & Runger, 2011, p. 135), which is a sensible cutoff for highlighting unusually high, stress-intensive days while ignoring routine variations. Eleven spike days were identified, most of which coincide with the deadlines for the written assignments.

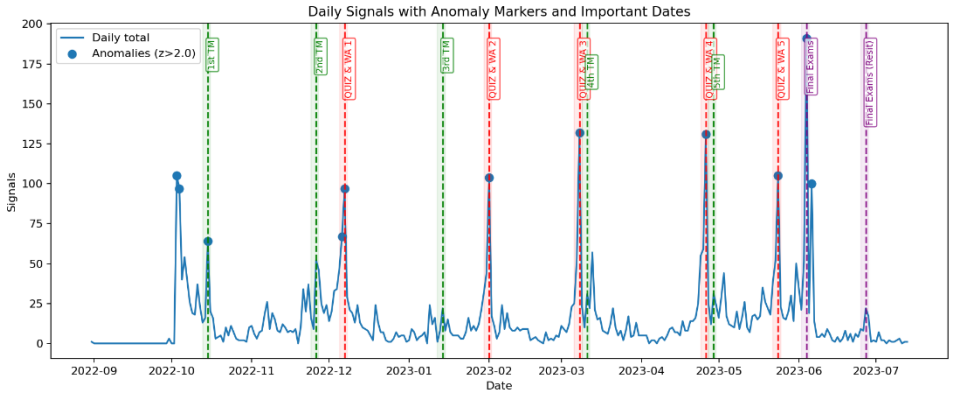

Figure 6: *Spike Days*

As expected, the most stressful event of the academic year is the final exam, which shows the highest concentration of frustration signals. This result can be shown in the bar chart (Figure 7) presenting the number of frustration signals within a time window [-48h, +24h] around each important date. Marked minutes are tallied in the 48 hours before the event (tutorial meeting, quiz and assignment deadline, and exam) and the 24 hours after. The second most stressful event was the deadline for Quiz and Assignment 4, followed by the other assignments. Tutorial meetings rank lower. The low ranking of the resit exam is due to the small number of students who participate (typically fewer than 10%).

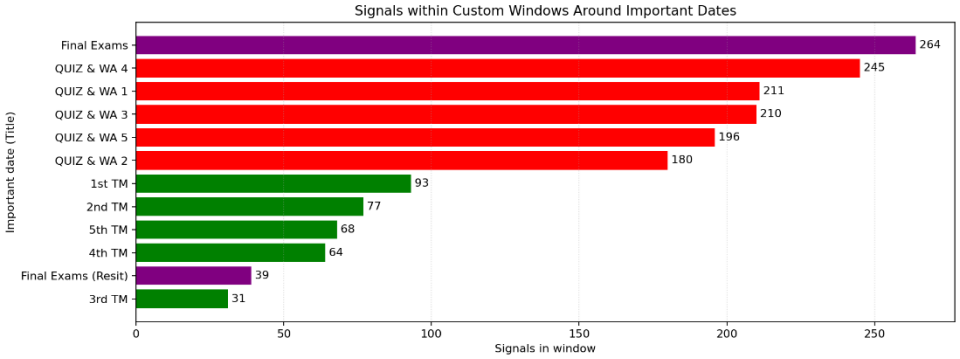

Figure 7: *Incidents count around important dates*

Conclusion and future work

This study aims to advance understanding of how frustration manifests in online learning environments and by proposing a sensor-free method for detecting it. By analyzing logfiles using adaptive thresholds, we were able to identify frustration-related activity patterns with fine temporal resolution. It was found that frustration

incidents clustered around predictable high-stakes events such as written assignments, quizzes, and examinations. However, a key insight is that the majority of frustration was expressed during navigation and forum activities. These findings suggest that frustration is a pervasive condition that surfaces throughout the complete learning process, often outside the direct boundaries of assessment activities.

From a pedagogical perspective, these results reinforce the need to design learning environments that are not only academically supportive but also emotionally responsive. In particular, forums and navigation pathways, typically regarded as neutral components of the learning platform, can become critical spaces where students express their emotional state and frustration accumulates. Detecting such signals offers opportunities for timely interventions, such as adaptive prompts, peer support facilitation, or simplified navigation structures, which can prevent disengagement and dropout.

The methodological contribution of this work lies in demonstrating the feasibility of logfile-based frustration detection without relying on intrusive and costly sensors. This approach offers scalability, reduces implementation barriers, and addresses privacy concerns, making it particularly relevant for distance-learning institutions. Nevertheless, certain limitations remain, such as relatively low accuracy when capturing the nuanced, multimodal nature of emotions.

One of the most noteworthy findings is that, although quizzes, written assignments, and examinations are typically stressful, the largest share of frustration signs did not occur during submission or quiz events. Instead, general navigation activity and forum participation were more indicative of students' emotional state, accounting for the majority of frustration signals.

In future work, we intend to analyze frustration signals at the individual-student level and integrate these insights with our prior findings. Our aim is to build learner profiles that power a study-recommendation system sensitive to students' emotional states with sensor free techniques. The system will adapt content sequencing, pacing, and support prompts when elevated frustration is detected, while safeguarding privacy through anonymization and opt-in consent.

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