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Beyond Time on Task: A Novel Analytical Framework for Assessing Student Workload and Its Relationship with Learning

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Abstract
Student workload analysis has the potential to play a crucial role in providing both actionable insights to inform course design and curricular adjustments that promote student learning and well-being. While numerous studies have emphasized the need for analyzing workload beyond single-value metrics, such as credit hours, the interpretation and practical application of these metrics for educational interventions remains unclear. In this study, we explore the interplay between time-on-task measurements with student-perceived learning and difficulty. We move beyond average indicators of time-on-task by proposing and examining various metrics related to the dynamics of workload over time. Across 14 engineering courses taught at Pontificia Universidad Católica de Chile, we analyze three different sources of data: (1) self-reported time-on-task and perceived difficulty obtained through a weekly timesheet survey, (2) interactions with the learning management system (LMS), and (3) perceived learning attainment obtained from the course evaluation survey. Our results show that LMS-based and self-reported time-on-task were highly correlated. Also, workload dynamics metrics, such as the presence of workload peaks, were highly correlated with perceived learning and perceived difficulty. As such, this study provides evidence in support of considering workload dynamics, rather than average measures of time-on-task, to predict variables related to student learning. The metrics proposed by this framework could be used to implement practical tools for educators and administrators willing to optimize course design and improve learning attainment.

Notes for Practice

- Time-on-task has been predominantly studied using learning management system (LMS) data, aiming to provide more accurate estimations of student workload than traditional metrics, such as credit hours.
- Limited research has explored the relationship between students' self-reported workload and LMS time-on-task, particularly at a weekly level of granularity.
- Self-reported and LMS time-on-task measures showed strong positive correlations, both at week and course levels.
- Measures of workload dynamics over time, such as steep changes between consecutive weeks or the presence of high-intensity periods, strongly correlated with increased perceived course difficulty and negative learning outcomes.
- Analysis of workload dynamics facilitates the identification of potential work overload periods, enabling educators to implement targeted course design interventions that enhance student learning experiences.

Keywords
Student workload, workload peaks, workload distribution, time-on-task, learning management systems.

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1. Introduction

For many decades, workload as a subject of study has been gathering interest from multiple fields, such as psychology and education. Although workload has often been defined as a measure of physical work (Miller, 2001), there have been considerable changes in the conceptualization of workload, shifting from physical to cognitive or mental workload measures. By the late 1980s, more than 400 studies had already been devoted to the measurement of mental workload (Hicks & Wierwille, 1979). This was accompanied by research studying mentally and cognitively demanding processes, such as learning. An important milestone was the introduction of cognitive load theory with its prior distinctions between intrinsic and extrinsic load (Sweller, 1988; Sweller et al., 1990), and the later introduction of germane load (Sweller et al., 1998). Specifically, intrinsic load refers to the inherent complexity of the learning material, extrinsic load to how information is presented, and germane load to cognitive processes that contribute to the integration of new information into learners' existing knowledge structure (Sweller et al., 1998).

In higher education, student workload could also be understood from the perspective of cognitive load theory (Sweller et al., 1998), indicating that students' capacity to complete learning activities is subject to their prior knowledge of the related topic (intrinsic cognitive load), the way the activity is presented (extraneous cognitive load), and the information or aid elements that they were provided to complete it (germane cognitive load) (Liu & Evans, 2020). According to Kyndt and colleagues (2014), student workload has usually been categorized in the literature as either objective—measured through time spent on learning activities—or subjective—students' experiences of academic demands and their effects, such as feelings of pressure or stress. In this regard, an important aspect of the subjective experience of workload is work overload, which has been linked to experiences of difficulty, anxiety, and the desire to give up due to students' inadequate prior knowledge, faculty study habits, and insufficient learning skills (Karjalainen et al., 2006).

Burnout is both a manifestation and a symptom of student overload, resulting from prolonged exposure to excessive workload over time, characterized by emotional and cognitive exhaustion (Pastores et al., 2019). Numerous studies have been conducted on burnout as a consequence of periods with a highly concentrated workload (Maslach & Leiter, 2016; De Beer et al., 2016; Schaufeli et al., 2017; Edú-Valsania et al., 2022; Nassar et al., 2019). Many of these studies have addressed the effects of work overload in students, resulting in higher levels of stress, decreased academic performance, and increased indicators of depression and anxiety (Bachman & Bachman, 2006; Yang et al., 2021). This is of particular concern in the context of the growing prevalence and severity of mental health problems among higher education students (Bladek, 2021). Therefore, balancing workload and performance remains a primary objective today, with effective workload measurement being a key aspect for this endeavour.

The need for standardized quantification of student workload goes way back to 1896, with the introduction of Harvard's elective course system by its then president, Charles Eliot (Heffernan, 1973). A few years later, Andrew Carnegie created the Carnegie Foundation for the Advancement of Teaching, which in 1906 resulted in the establishment of the first standardized workload measure in education, known as the Carnegie Unit. By the mid-20th century, this unit was already widely known as the "credit hour" and was deeply embedded throughout the American higher education system (Silva et al., 2015). At the end of that century, the credit hours system was also part of the Bologna Declaration of the European Commission in 1999, giving rise to the European Credit Transfer System (ECTS). The goal of this system was to account for the amount of time required to achieve the learning objectives of a program, representing a declared shift from a teacher-centred to a student-centred learning paradigm (Gleeson et al., 2021).

Since having sufficient time has been recognized as one of the most stressful aspects of learning in higher education (Bennett & Burke, 2018), understanding how much time students spend on their academic activities has become crucial for many colleges and universities (Souto-Iglesias & Baeza_Romero, 2018). With the rise of information and communication technologies, many higher education institutions have adopted learning management systems (LMSs) in recent years (Abazi-Bexheti et al., 2018). A main advantage of these systems is that they allow the tracking of behavioural data on student interactions, which has been used to create models to predict student performance (Conijn et al., 2016; Riestra-González et al., 2021), define proxy variables of engagement and learning (Cerezo et al., 2016; Henrie et al., 2018; Jovanović et al., 2021), and estimate time-on-task (Kovanovic et al., 2015; Leinonen et al., 2022). According to Kovanovic and colleagues (2015), time-on-task in LMSs is often defined as the duration between consecutive clicks recorded in online learning environments. Along these lines, a study by Pardos and colleagues (2023) showed that LMS course-level features explained 36% of course workload variance, whereas the credit hours alone explained only 6% of what students experienced. Considering that credits could be an inadequate attribute for students to anticipate their course load for a specific academic period, more efforts have to be invested to use LMS data to estimate course time-load, among other possible metrics.

Also, despite the advancements in the field that address the need to move beyond credit hours, there remains a significant gap in understanding how the evolution of workload over time relates to learning outcomes and student perceptions of workload. By workload dynamics, we refer to the temporal patterns and fluctuations in workload over a specific period of time, such as the academic term. This concept encompasses quantitative measures that describe the variation, intensity, and distribution of workload through time, such as the rate of change in workload between consecutive time points (e.g., weeks) capturing steep increases or decreases, or the frequency and magnitude of periods of high concentration of academic tasks. These dynamics provide a more comprehensive understanding of student workload beyond static or average measures, offering insights into complex ways in which course design and academic demands evolve over time, potentially impacting student experience and learning outcomes.

Prior research has established important connections between the way workload is distributed and students' learning experiences. Studies by Smith (2019) and Kyndt and colleagues (2014) have demonstrated that workload fluctuations can significantly impact students' ability to process and retain information. Furthermore, Bachman and Bachman (2006) found that periods of concentrated workload correlate with decreased learning satisfaction and lower self-reported knowledge acquisition. Understanding these relationships is critical for designing educational experiences that support effective learning. In this study, we analyze the interplay between time-on-task measurements and students' perceived learning and difficulty in 14 engineering courses at Pontificia Universidad Católica de Chile. By examining this relationship, we aim to provide empirical evidence of how workload dynamics—not just total workload—might shape students' perceptions of their learning experiences. We conduct a comprehensive examination of workload metrics over time, transcending the conventional time-on-task framework and introducing the analysis of workload dynamics.

2. Related Work

Time-on-task has been conceptualized in various ways across the educational research literature. Carroll (1963) made a foundational distinction between elapsed time—that is, time allocated to a learning task—and actual engaged learning time. Since then, this construct and its estimation methods have evolved significantly over time. In the 1980s, estimation methods relied mainly on classroom observation, where researchers would monitor and code student activities to determine engagement levels (Karweit, 1984). These labour-intensive approaches, while providing rich contextual data, faced limitations in scale and consistency. The advent of digital learning environments transformed time-on-task measurement, enabling more automated and continuous tracking by means of simple metrics, such as login frequency and time spent online. Since the 2010s, different studies have demonstrated that patterns of online engagement, including the timing and regularity of interactions, are significant predictors of academic performance (Wang & Mousavi, 2023).

As LMSs became ubiquitous in higher education, more sophisticated techniques emerged to provide a deeper understanding of student behaviour and engagement. In learning analytics research, a number of studies have explored challenges associated with the estimation of time-on-task as the time that students spend on different learning activities according to trace data (Kovanovic et al., 2015), focusing mainly on Carroll (1963)'s conceptualization of elapsed time. Kovanovic and colleagues (2015) specifically operationalized time-on-task as the duration between consecutive clicks in an LMS environment, developing methods to address the methodological challenges of accurately measuring student engagement through log data. Then, Nguyen (2020) extended this work by focusing on the challenges of handling outliers in time-on-task estimation, arguing that outlier detection should account for individual time and task differences. Seeking to shift the emphasis from elapsed time to actual engaged learning time, Rotelli and Monreale (2022) further contributed by defining time-on-task as the amount of time dedicated to quality learning, stressing the need to improve the accuracy of measuring student engagement in online learning environments.

Although making sense of these is crucial for understanding students' time management, a high percentage of the variance of time-on-task estimations may also be explained by learning design and instructional conditions (Nguyen et al., 2017; Gašević et al., 2016). This is why there is a need to provide teaching staff members with useful ways to measure and assess student workload perceptions over time (Hilliger et al., 2021).

One of the main challenges for educators is to distribute a defined set of contents and learning activities into a limited time window, framed by class length and the duration of the academic period. Thus, keeping workload aligned with credit hours is one of many challenges educators face when planning their courses. In terms of the cognitive load theory (Sweller et al., 1998), course design should aim to reduce the extraneous load caused by the format of instruction to enhance the amount of load that can be dedicated to the intrinsic nature of the learning tasks (i.e., intrinsic load), so as to maximize the development of cognitive schemata or germane load (Van Merrienboer & Sweller, 2005).

The concern of achieving manageable levels of students' workload goes back decades (Armstrong, 1996). Almost 20 years ago, several studies had already showed that learning can be hindered not only by high extrinsic load but also by low intrinsic load when learning tasks do not challenge the learner—either because tasks are too easy or too much help is provided for them to be completed (Schnotz & Kürschner, 2007). A study conducted by Smith (2019) revealed that higher workload was associated not only with higher positive well-being and work efficiency but also with increased course stress and negative well-being. Thus, workload may initially be perceived as stressful but may also lead to increased motivation, study efficiency, and perceived learning attainment.

In the context of engineering education, the program has been characterized by often using quizzes, lab reports, and homework assignments as formative assessments to help students identify areas for improvement and reinforce learning by providing feedback to students during the learning process, while midterms, final exams, major projects, and presentations are often used as summative assessments, which are critical for determining final grades and overall course performance (Armstrong, 1996; Chadha et al., 2021). Consequently, students perceived an increase in time spent on academic tasks without necessarily achieving better learning outcomes, which influences their perception of workload. This is not only limited to engineering students, considering that prior work has already alluded to the influence of teaching and assessment methods in higher education broadly (Ruiz-Gallardo et al., 2011; Pardos et al., 2023).

As courses, through time, demand varying levels of workload, students manage their limited time via prioritization. Hilliger and colleagues (2023) found that student workload could vary notably during an academic semester, creating a saw-shaped graph, with as many peaks as the number of assignments. As the workloads of different courses overlap, this may result in higher student perceived workload, mental effort, and psychological stress (Pardos et al., 2023). Also, previous research has shown that objective workload explains only a small percentage of perceived workload variance (Kember & Leung, 1998; Pardos et al., 2023).

Nonetheless, there is still debate about which workload determinants most influence students' academic achievement. On one side, studies have linked academic success with internal student attributes (Marshall, 2018). For example, Jovanović and colleagues (2021) found that indicators such as activity level and regularity of study patterns explained a greater portion of course grading variance than those related to course design characteristics. Other studies have focused on how instructional design features impact students' perception of academic workload (Bowyer, 2012). Beer (2019) found that higher perceived workload correlated with both increased course stress and potentially higher positive well-being, suggesting a complex relationship between workload and learning experiences. Instructional design is understood as a systematic and knowledge-based approach to planning, managing, and evaluating instruction to improve learning and its retention (Baturay, 2008). A study led by Nguyen and colleagues (2017) found that course design explained 69% of the variance related to student activity, which was then also positively correlated with pass rates. Previously, Kember (2004) had found that the curriculum and learning environment of a course are strongly related to the students' perception of workload. Kyndt and colleagues (2014) showed how the temporal distribution of workload, especially the convergence of deadlines, significantly shapes students' perceptions of learning, suggesting that how work is distributed may be as important as total workload. However, there is still little evidence regarding how specific patterns of workload distribution over time shape both perceived difficulty and self-reported learning attainment.

In this context, the estimation of the number of hours that students actually dedicate to course activities—from face-to-face classes to autonomous study time—is a problem that has attracted the interest of multiple investigations for several decades up to this day (Karweit, 1984; Ruiz-Gallardo et al., 2011; Nguyen, 2020; Hilliger et al., 2021). A study by Souto-Iglesias and Baeza_Romero (2018) found that workload statistics of courses with the same nominal credits are generally not comparable, due to variability of workload being too large for ECTS to sensibly characterize. Furthermore, the translation of credits to working hours is also not standardized across universities (Ruiz-Gallardo et al., 2011; Pardos et al., 2023). Considering the above, researchers have attempted to measure the hours demanded by course learning activities, integrating variables associated with subjective student workload (Kyndt et al., 2014; Beer, 2019; Hilliger et al., 2023). These variables might be part of a complex interplay among student behavioural data, student perceptions, and course design indicators.

3. Methods

3.1 Research Design and Study Context

Based on a literature review conducted by Leitner and colleagues (2017) about learning analytics in higher education, we frame this work as a quantitative study to analyze and interpret quantitative data for decision-making from a statistical perspective, aiming to understand student behaviours. Specifically, this quantitative study analyzes the relationship between self-reported time-on-task and time-on-task obtained from trace data recorded in the LMS. Both measures primarily reflect elapsed time rather than actual engaged learning time, as both types of data may include periods of inactivity and distractions (Marshall, 2018; Ruiz-Gallardo et al., 2011). Despite this limitation, our approach aims to add significant value by triangulating behavioural data with student perceptions, providing a more comprehensive understanding of student workload. By combining these methods, we seek to expand the discussion on what is meant by time-on-task, ultimately contributing to better metrics for instructional design and student support.

To achieve this research goal, we analyzed 14 undergraduate engineering courses over a 16-week semester, from early March to late July in 2023, taught at Pontificia Universidad Católica de Chile. All courses had a one-week break on semester week 8 (calendar week 18). Our sample comprises 14 courses, with five from chemical engineering, four from computer science, and four from industrial engineering & systems, and one core-level engineering science course. The total number of students across all courses was 784, with most of them ranging between 18 and 22 years of age. Further demographic information could not be retrieved due to data anonymization. Complete details on the number of students per course with their corresponding departments can be seen in Table 5 (Appendix). Data was retrieved from three different sources: (1) course self-reported time-on-task and perceived difficulty obtained through a web-based weekly timesheet survey (WTS), (2) interactions with the LMS, and (3) perceived learning attainment obtained from the course evaluation survey. We selected engineering courses because the curriculum of this field has been particularly overloaded with different types of assessments (Armstrong, 1996; Chadha et al., 2021; Egea et al., 2022; Wentling & Variawa, 2020; Yangdon et al., 2021), which amplifies engineering students' levels of anxiety and academic stress, as noted by Hilliger and colleagues (2023).

All examined courses had 10 credit hours, which at Pontificia Universidad Católica de Chile represent 10 hours of weekly workload, including both inside and outside classroom activities (e.g., autonomous study time). Based on the analysis of these data, this study addresses the following research questions:

- **RQ1:** What is the relationship between self-reported time-on-task and LMS log data time-on-task among engineering courses?
- **RQ2:** How do time-on-task metrics help to understand the distribution of course workload over an academic period?
- **RQ3:** What is the relationship between time-on-task metrics and course perceived difficulty and learning outcomes?

To answer these questions, we employed Spearman's rank correlation analyses (Zar, 2005). This choice was motivated by Spearman's correlation's ability to detect monotonic associations without assuming linear relationships between variables. While being a nonparametric method, it's also appropriate to educational research, which mostly follows non-normal distributions (Bono et al., 2017). This method was also chosen for its robustness to outliers, a common feature in self-reported data (De Winter et al., 2016). This method's rank-based approach mitigates the impact of extreme values, making it particularly suitable for analyzing subjective measures of workload and learning experiences. Furthermore, Spearman's correlation can identify both linear and non-linear monotonic relationships, offering a more comprehensive analysis of our data.

3.2 Data Sources

3.2.1 WTS

Perceived workload was measured using a web-based WTS that tracked self-reported time-on-task and difficulty of each course activity. Each course survey was configured by the instructor one week prior to the academic period, based on the specific activities defined in the course design. These activities—which included classroom sessions, autonomous study time, and laboratory sessions, among others—recurred throughout the academic period but varied in frequency and presence across courses. For instance, while all courses included weekly classroom sessions in their design, laboratory sessions were only present in some courses and could have a monthly or bi-weekly frequency. Weekly reports can provide a balanced and detailed view of student workload distribution throughout a semester (Ruiz-Gallardo et al., 2011). Unlike workload-related items in mid-term and end-of-term questionnaires for student evaluations of teaching (Kember, 2004; Marshall, 2018), this approach helps identify periods of high workload concentration, capturing the dynamic nature of workload. This can subsequently serve as a guide for strategic planning, helping prevent student overload during peak periods, such as overlapping deadlines.

To conduct the WTSs, the web-based application was integrated into the university's LMS, allowing students to voluntarily submit their responses within each LMS course homepage. To self-report their weekly time-on-task, students responded to the survey from Sunday at 6 pm to the following Tuesday at 2 pm. Students received reminders on both Sundays and Tuesdays, stating that the response period was open or about to close. This timeframe was carefully defined to give students sufficient time to respond to the survey, while not overlapping with ongoing activities of the following week. It also aimed to minimize potential recall problems linked to self-reported time-on-task (Bentley & Kyvik, 2012).

Besides reporting the number of hours that students perceive to spend in these course activities, students who interacted with this application were required to report the perceived difficulty of course activities on a Likert scale from 1 (very easy) to 5 (very hard). The inclusion of difficulty in the survey reflects a broader conceptualization of workload that extends beyond a single time-based metric (e.g., credit hours). This approach integrates the learner's subjective experience of workload when interacting with different tasks (Bowling et al., 2015). The WTS questions are formulated as follows:

- Q1: How many hours did you dedicate to the following course activities in the past week from start day of week to end day of week?
- Q2: On a scale from 1 to 5, where 1 is very easy and 5 is very difficult, how would you rate the difficulty of this week's course activities?

The WTS was applied during the first semester of 2023 (from March until early July) in a subset of engineering courses taught at our research site. Before the semester started, the course activities of the survey were configured by the educators in charge of teaching each course. These activities ranged from classroom sessions to autonomous study time.

3.2.2 LMS Log Data

LMS log data was obtained by using the Canvas Data API, retrieving the page views click-stream, which returns a Page View Object. The full structure of this object can be reviewed at the Canvas Users API documentation. We kept columns that provided valuable information about the Page View, such as its timestamp, "context type," "controller," and "action," among others.

Data retrieval encompassed all student click-streams on the LMS, including those that occurred outside courses, such as platform navigational clicks. This provides a broader picture of course activity by examining which proportion of interactions occurred inside each course compared to all course activities and also to overall platform activity. Following an approach similar to the one proposed by Henrie and colleagues (2018) we analyzed both of these course-specific and general platform interactions, accounting for students' weekly sessions, views, and time spent on the LMS. We then categorized course-specific interactions based on their respective "controller" value, which allowed us to distinguish between different types of interactions. For example, while submissions in Canvas are linked to assignments and quizzes, they are handled by a separate controller. This information enables us to differentiate between students reviewing assignment instructions (controller: "assignments," action: "view") and students actually submitting their work (controller: "submissions," action: "create"). Similarly, "announcements" refer to instructor-generated communications to the class, while "discussions" involve interactive forums where both students and instructors can exchange ideas. Based on this logic, we analyzed interactions related to files, announcements, discussion topics, quizzes, assignments, and submissions.

Notably, we only analyzed interactions with resources identifiable by their unique LMS ID, extracted from the page view URL using regular expressions (RegEx). As a result, not all interactions within a controller (e.g., "Files") are accounted for. This allows us to also differentiate procedural clicks within a controller from substantive engagement with course learning resources—a distinction that aligns with the view that meaningful engagement is central to effective learning (Carroll, 1963). This approach also draws a parallel to the distinction stated by Maslennikova and colleagues (2023) who differentiate between the course activity taken on courses and the platform activity taken on platform areas, together forming the on-task activity. Figure 1 illustrates the composition of these interaction types across all 14 courses in our sample.

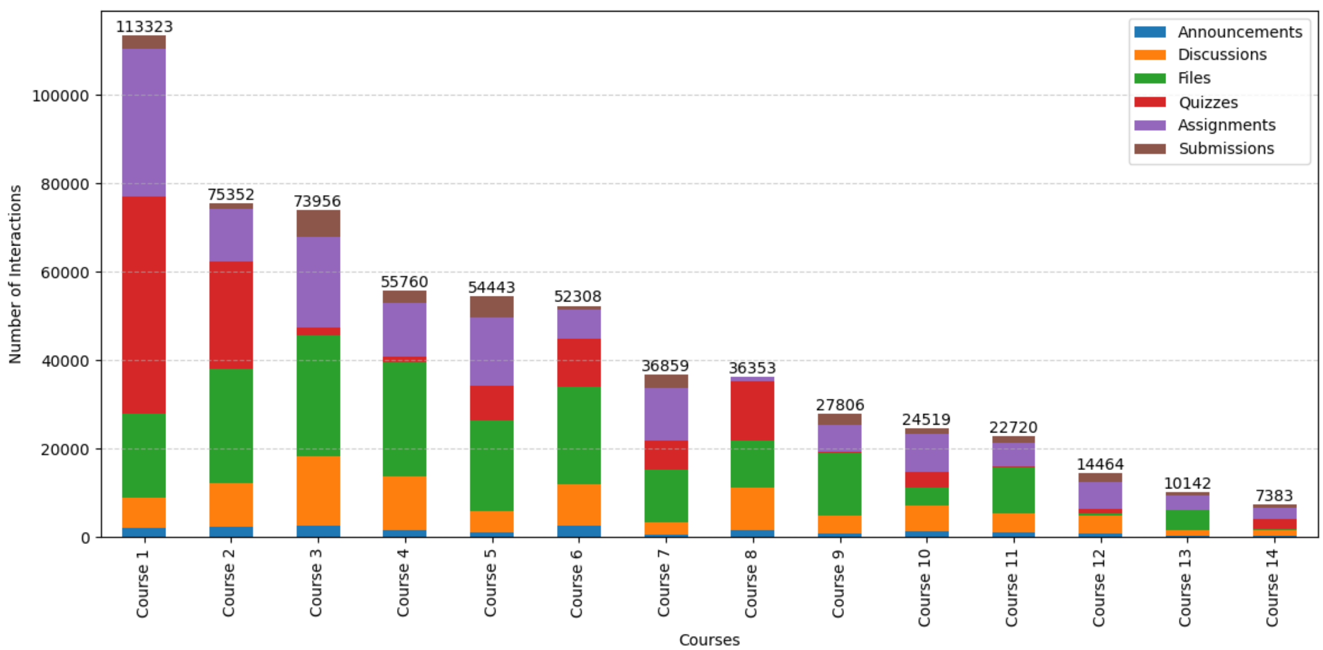

Figure 1. Courses' total LMS views by interaction type.

3.2.3 Course Evaluation Survey

Perceived learning attainment was obtained from a course evaluation survey. These voluntary surveys are applied at the end of each academic term to evaluate the effectiveness of teaching practices within a course, aiming to identify areas for improvement. We analyzed the responses of the 14 defined courses, focusing on a specific question regarding perceived learning: *Regardless of the grade you obtained, how much did you learn in this course?*. Students could answer this question by using a 4-point Likert scale: 1: "Much less than expected (MLTE)"; 2: "Less than expected"; 3: "As expected"; and 4: "Much more than expected (MMTE)". Data was obtained at course-level aggregation, so a student-level analysis of this dataset was not possible in our study.

3.3 Data Analysis

3.3.1 WTS Self-Reported Measures

To define our course sample, we first removed responses from the WTS reporting a weekly workload above 168 hours, which is the total number of hours in a week. We then applied Tukey's fences method (Tukey, 1977) to remove outliers from each course's weekly responses outside the range $[Q1 - 1.5 \cdot IQR; Q3 + 1.5 \cdot IQR]$. Since our study analyzed workload responses across multiple courses with varied instructional designs, Tukey's fences method provided a robust approach for detecting outliers without making assumptions about the underlying distribution. This is particularly important considering data from educational research mostly follows non-normal distributions (Bono et al., 2017). Tukey's fences is a nonparametric method that does not rely on distributional assumptions (Tukey, 1977), which is particularly valuable for identifying outliers on self-reported data (Zijlstra et al., 2011). Also, due to our objective of identifying multiple course patterns, this approach enhances the robustness of the analysis by mitigating the influence of extreme response values, without compromising the integrity of our dataset.

Following this process, we filtered out weeks with response rates below 10%, retaining only courses with responses for all 16 weeks of the academic period. Finally, we selected courses whose resulting average response rate was at least 20%. After these filters, we had an initial set of 16 courses. However, two of these courses had to be excluded from the analysis since they lacked substantial information in the LMS log due to their curricular designs not promoting interactions with LMS resources. The response rates across the 14 selected courses ranged between 21% and 51%, with an average of 35%. These thresholds, along with outlier removal, were established to ensure sufficient representativeness at the course level, as our primary focus was on analyzing instructional design patterns rather than individual student behaviours. By setting minimum response rate requirements, we aimed to capture a more reliable picture of course-level workload dynamics that could be meaningfully compared with weekly LMS interaction patterns on each course.

Based on this data, we estimated averages of self-reported time-on-task and perceived difficulty at both week and course levels. The *weekly time-on-task average* is the arithmetic mean of all student responses for a specific week, while the *course time-on-task average* is the arithmetic mean of all these weekly time-on-task averages. To examine how student workload evolves over time, beyond time-on-task averages, we calculated dispersion measures across weekly averages. We computed the *range*, *standard deviation* (SD), and *coefficient of variation* (CV) for course time-on-task and perceived difficulty. We reported only statistically significant correlations.

In addition to traditional dispersion metrics, we conducted what we refer to as "peak analysis." Based on prior work that illustrates how students may perceive being overloaded in specific weeks of their academic period (Hilliger et al., 2023), our peak analysis involves identifying high-intensity weeks whose average time-on-task is substantially above the course average time-on-task. For a week to be considered a peak, neither the preceding nor the following week can have a higher time-load than the week in question; the rationale being that if the previous week had a higher time-load, then that peak has already occurred, and, conversely, if the following week has a higher time-load, the peak has not been reached yet. This approach resembles what a local maximum represents in a function, but applied to workload as a time series. For the case of first and last academic weeks, we considered the next and previous week, respectively.

We classify peaks into three categories:

- *Type 1 peak* (low intensity): Weekly time-on-task is 25% above the course average weekly time-on-task.
- *Type 2 peak* (medium intensity): Weekly time-on-task is 50% above the course average weekly time-on-task.
- *Type 3 peak* (high intensity): Weekly time-on-task is 100% above the course average weekly time-on-task.

Another metric we consider is *time-on-task slopes*, which correspond to the the difference in time-on-task between consecutive weeks. Given that the difference between week numbers is always one (barring missing data points), these deltas are equivalent to time-on-task slopes between weeks. These measures provide additional information about how peaks are reached and left. A positive slope indicates increasing time-load from one week to the next, while negative slopes represent decreases. For ease of interpretation in correlation analyses, we converted negative slopes to absolute values. We also estimated dispersion measures (SD and CV) for time-on-task slopes in each course to further examine the variability of these time-load fluctuations. These features are also relevant as they inform how steeply time-load changes over time. For instance, courses might reach a peak gradually but descend to very low time-load levels compared to their initial state. Hence, an abruptly reached peak may not necessarily be followed by a proportional decline. Figure 2 illustrates this concept across two different courses. Weekly slope values are displayed above each bar, and weekly intensity is shown within each bar. Peaks are represented with different colours, and the y-axis represents the weekly average time-on-task.

3.3.2 LMS Time-on-Task and Interaction Features

Complementing self-reported time-on-task, we analyzed LMS log data from the courses selected via the WTS, aiming to compare weekly reported time-on-task with log-based time-related indicators. Upon examination, we excluded two courses from this analysis since they lacked substantial information in the LMS log due to their curricular designs not promoting

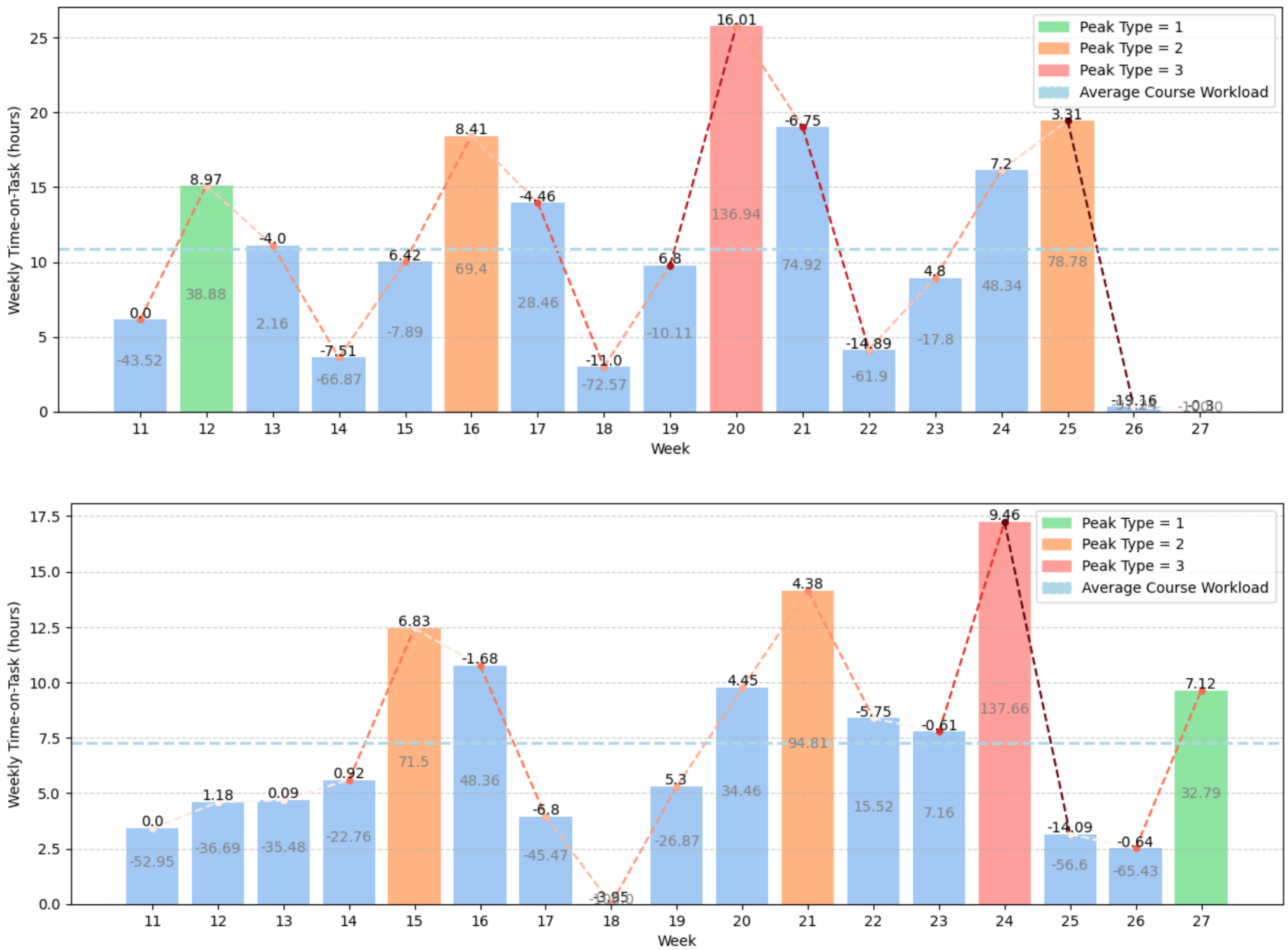

Figure 2. WTS course time-on-task slopes and peaks.

interactions with LMS resources. The resulting final sample comprises 14 courses (with 784 students): six from chemical engineering, five from computer science, and four from industrial engineering and systems, as well as one core-level engineering science course. A student-level comparison from both sources was not possible, as it would have required a 100% response rate from the selected courses in the WTS. Thus, we analyzed both WTS and log data at course and weekly levels of granularity. Data from the specified academic term comprised over 15 million page views. Sessions were delineated from LMS trace data as sequences of consecutive user interactions (clicks) occurring within the platform, separated by no more than 30 minutes of inactivity—a commonly adopted threshold in web analytics and educational data mining (Jovanović et al., 2017; Khan & Pardo, 2016; Kovanovic et al., 2015; Matcha et al., 2020). This was necessary as the LMS does not automatically close student sessions. To enhance data quality and mitigate artifacts arising from system-generated redirects or repetitive user actions (such as multiple rapid clicks on the same resource), we implemented a de-duplication process. Specifically, within each session, only the first instance of consecutive clicks on the same URL was retained. As a result of this preprocessing step, the total number of recorded entries decreased from 15,377,315 to 14,270,893.

We also analyzed each course's activity relative to students' overall platform activity during a given week. To achieve this, we calculated two key ratios: (1) weekly course activity relative to all course-related interactions (e.g., ratio of a course's weekly sessions relative to weekly sessions across all courses), and (2) course activity relative to all LMS interactions, including those outside courses (e.g., ratio of course weekly views to total weekly views on the platform). These ratios were calculated for sessions, views, and time indicators, averaged among students in each course. They serve as proxies for student prioritization across LMS activities, contextualizing course interactions within overall LMS behaviour. Additionally, we estimated ratios of interaction types within overall course activity on each week (e.g., percentage of weekly time-on-task regarding files relative to overall course weekly time-on-task). We calculated average views, sessions, and time-on-task for each interaction type to identify courses characterized by a higher prevalence of certain interactions. Then, we accounted for the total number of resources each interaction type had, based on their unique ID. Finally, we computed "participation rates," representing the percentage of students who interacted with specific interaction types among all students in the course. This participation rate was also estimated at a course, content-agnostic level. All these measures were compared with the corresponding WTS weekly time-on-task and perceived difficulty. Figure 3 illustrates the weekly evolution of these interaction type ratios throughout the academic period.

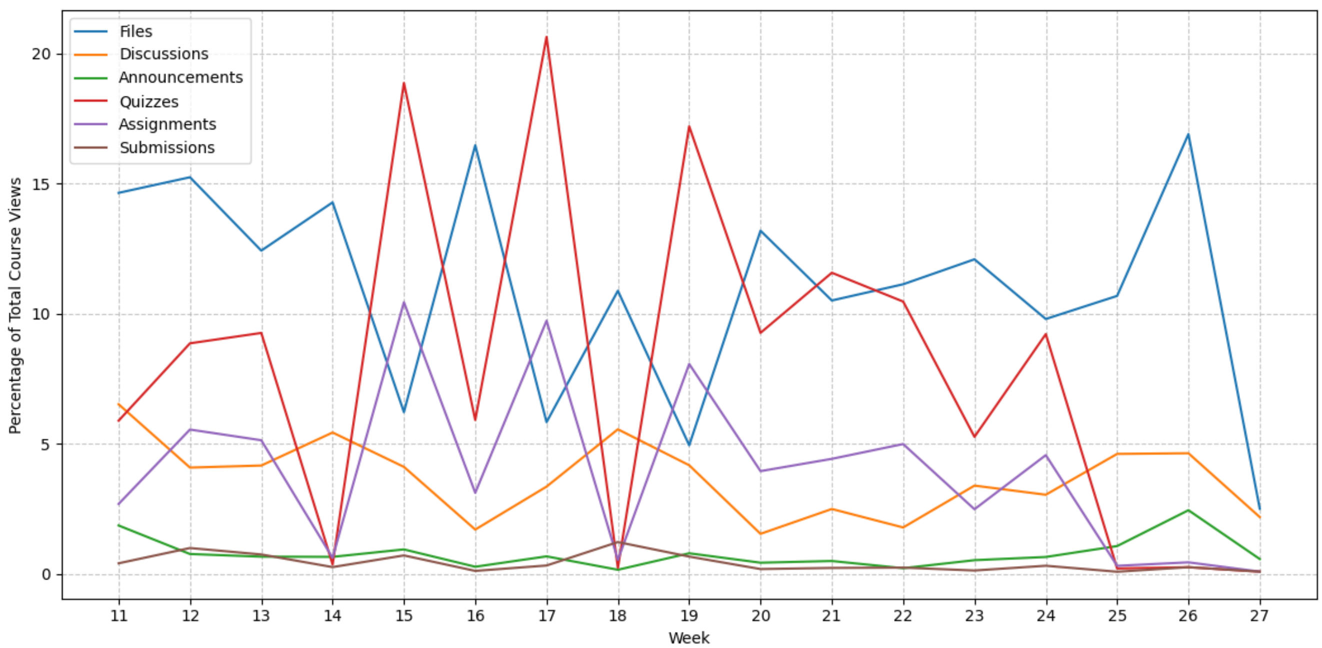

Figure 3. Ratio of interaction types to total course views (%).

3.3.3 Perceived Learning Attainment

Our analysis sought to elucidate the relationship between workload features, derived from both the LMS and WTS, and learning attainment indicators from the course evaluation survey (CES). It is important to note that this analysis was necessarily conducted at a course level, given that the CES is administered once per course rather than on a weekly basis. Consequently, the correlation analysis employed only course-level measures from the aforementioned data sources, providing an overall view of the relationships between workload characteristics and perceived learning outcomes across the entire academic term. We estimated the percentage of students who selected each alternative of the CES learning question—from (1) MLTE to (4) MMTE. This approach allows us to look beyond the arithmetic mean of student responses and analyze the composition of each course's response proportions.

4. Results

4.1 WTS and LMS Time-on-Task

Self-reported time-on-task demonstrated multiple significant correlations with LMS interaction measures, including LMS Time-on-Task. Table 1 presents the main correlations between LMS features and the WTS time-on-task, both at week and course levels.

At the week level, the WTS time-on-task exhibited a significant positive correlation ($r = 0.63$) with LMS overall course time-on-task (content-agnostic). Notably, the number of weekly LMS course sessions showed an even stronger correlation with WTS time-on-task ($r = 0.71$). When examining disaggregated LMS interactions by type, discussion topics time-on-task demonstrated the strongest correlation with WTS time-on-task ($r = 0.64$). This pattern was consistent across other weekly activity measures of discussion topics, including sessions, views, and participation rate ($r = 0.63$, $r = 0.62$, $r = 0.56$, respectively). Other content-specific activities related to higher levels of reported time-on-task included those regarding Files (across all sessions, views, and time metrics), followed by Assignments and Announcements. The percentage each content type represents relative to overall weekly course activities also showed significant positive correlations, albeit lower than their non-contextualized counterparts. Figure 4 illustrates the interplay between all interaction type ratios.

Table 1. WTS and LMS Time-on-Task correlations.

Week Level: LMS Features	Correlations with WTS time-on-task	Course Level: LMS Features	Correlations with WTS time-on-task
Course Sessions	0.71***	Discussions Time-on-Task	0.86***
Discussions Time-on-Task	0.64***	Number of Announcements	0.76**
Course Time-on-Task	0.63***	Number of Discussion Topics	0.73**
Discussion Sessions	0.62***	Discussions Views	0.73**
Discussions Views	0.62***	Course Sessions	0.72**
Files Sessions	0.59***	Discussions Sessions	0.69**
Course Views	0.59***	Max Positive Slope	0.68**
% of Total LMS Sessions	0.59***	Announcements Sessions	0.68**
% of Total Courses Sessions	0.57***	Announcements Views	0.66**
Discussions Participation Rate	0.56***	Announcements Participation Rate	0.65*
Assignments Sessions	0.56***	Sum of Positive Slopes	0.65*
Files Views	0.55***	Quizzes Time-on-Task	−0.65*
Files Time-on-Task	0.55***	Course Time-on-Task	0.63*
Announcements Views	0.52***	Course Views	0.63*

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Interestingly, while Discussions and Files were the most strongly related content-specific metrics to WTS time-on-task, their contextualized indicators yielded negative correlations between them. This dynamic was most pronounced between Files and Quizzes ($r = -0.425$; $p < 0.001$), as also observed in Figure 3. This suggests that their prevalence in Course Weekly time-on-task, although significant, is not usually concurrent and could even be mutually exclusive in some courses.

Course-level findings were largely consistent with week-level correlations, with discussion-related indicators again characterizing higher levels of reported time-load. Various announcements-related features were also strongly correlated with WTS time-on-task. Course-wide metrics also showed strong correlations with reported time-on-task, including Course Average Sessions, Time, and Views. Notably, none of these content-agnostic features had stronger correlations than those for specific interaction types. Consistent with results in Figure 4, the only negative correlation found between reported time-on-task and LMS features was regarding Quizzes, which was also evident in the Number of Quizzes per course ($r = -0.502$), though not statistically significant ($p = 0.07$). This negative correlation was more pronounced at the course level, with Quizzes Weekly time-on-task showing a negative, albeit non-significant, correlation ($r = -0.12$, $p = 0.064$). Finally, variability measures from LMS activity, such as LMS Max Positive Slope ($r = 0.68$) and LMS Sum of Positive Slopes ($r = 0.64$), were also positively correlated with WTS Course time-on-task, reinforcing that courses with higher reported time-on-task also exhibit more pronounced fluctuations in their LMS activity.

4.2 WTS Time-on-Task and Workload Distribution Measures

Having established the relationship between LMS and WTS time-on-task, which demonstrates a positive correspondence between reported time-on-task and LMS activity, we focused on examining how self-reported time-on-task relates to workload dynamic and variability over time. Table 2 presents the most significant correlations.

Notably, we found a strong positive correlation between Course time-on-task SD, which represents the variability between weekly average time-on-task, and Course Average time-on-task ($r = 0.86$). Similarly, Course Workload Range—as the difference between the highest and lowest Weekly Average Workload—exhibited an even stronger correlation with Course Average time-on-task ($r = 0.88$, $p < 0.001$).

Strong correlations were observed between slope features and Course Average time-on-task, with both the Sum of Negative Slopes and Sum of Positive Slopes among the strongest correlations. WTS Overall Slope SD—as the variability of weekly slopes regardless of their sign—and Max Positive Slope were also highly correlated with WTS Course time-on-task. The presence of medium-intensity peaks was also positively correlated with Course Average Workload ($r = 0.49$), but the correlation was not statistically significant ($p = 0.07$). However, the proportion of medium-intensity peaks in relation to total peaks was significantly correlated with course average time-on-task ($r = 0.64$). Curiously, both high-intensity ($r = -0.14$) and low-intensity ($r = -0.30$) peaks exhibited negative correlations with Course Time-on-Task, but neither of them was statistically significant.

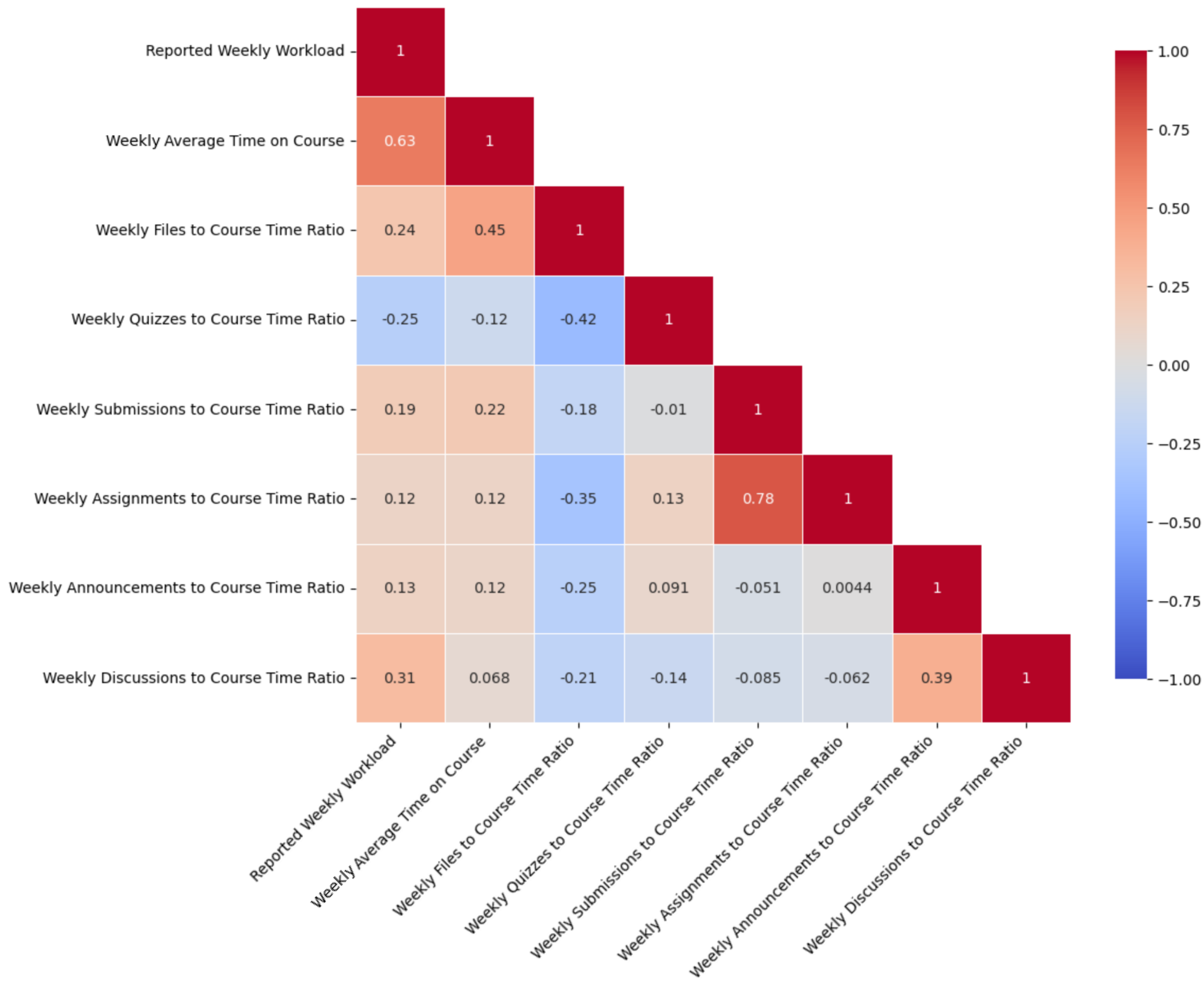

Figure 4. Correlation matrix of weekly time-on-task with LMS interaction type to course ratio.

Table 2. WTS average time-on-task and distribution measures correlations

WTS Time-on-Task Distribution Measures	WTS Course Average Time-on-Task	
	Coefficient	p-value
Course Time-on-Task Range	0.88***	< 0.001
Course Time-on-Task SD	0.86***	< 0.001
Sum Negative Slopes	0.82***	< 0.001
Course Slopes SD	0.82***	< 0.001
Sum Positive Slopes	0.75**	0.002
Max Positive Slope	0.73**	0.003
Negative Slopes SD	0.65*	0.011
Medium Intensity Peaks (%)	0.64*	0.015
Positive Slopes SD	0.58*	0.03
Number of Medium Intensity Peaks	0.49	0.073
Number of Low Intensity Peaks	−0.30	0.29
Number of High Intensity Peaks	−0.14	0.623

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

4.3 Perceived Difficulty and Workload Features

Our analysis revealed strong correlations between Perceived Difficulty and both WTS Time-on-Task and LMS activity indicators. Table 3 presents the main correlations at both week and course levels.

Table 3. Perceived difficulty and workload features correlations.

Week Level		Course Level	
Workload Features	Correlations with Perceived Difficulty	Workload Features	Correlations with Perceived Difficulty
WTS Time-on-Task	0.83***	WTS Time-on-Task	0.86***
LMS Course Sessions	0.71***	LMS Course Sessions	0.82***
LMS Course Time-on-Task	0.64***	WTS Time-on-Task Range	0.81***
LMS Discussions Sessions	0.60***	LMS Time-on-Task SD	0.75**
LMS Files Sessions	0.59***	LMS Course Part. Rate	0.75**
LMS Assignment Sessions	0.58***	WTS Max Positive Slope	0.75**
LMS Discussions Views	0.58***	LMS Assignments Sessions	0.74**
LMS Files Time-on-Task	0.58***	WTS Time-on-Task SD	0.73**
LMS Course Views	0.58***	LMS Course Time-on-Task	0.71**
LMS Discussions Time-on-Task	0.57***	LMS Max Positive Slope	0.70**
LMS Discussions Part. Rate	0.56***	WTS Slopes SD	0.70**
LMS Files Views	0.56***	LMS Discussions Time-on-Task	0.69**
LMS Assignments Part. Rate	0.54***	LMS Submissions Sessions	0.68**
WTS Positive Slope	0.45***	LMS Files Time-on-Task	0.67**
WTS Negative Slope	0.23***	LMS Quizzes Views	−0.63*

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

At the week level, the strongest correlation was observed between WTS Time-on-Task and Perceived Difficulty ($r = 0.83$), closely followed by course-wide LMS Course Sessions ($r = 0.71$) and LMS Course Time-on-Task ($r = 0.64$), showing a consistent pattern of relationship between time spent on coursework and perceived difficulty. Content-specific LMS interactions also showed positive correlations with perceived difficulty, with discussions ($r = 0.60$), files ($r = 0.59$), and assignments sessions ($r = 0.59$) at very similar levels. Slope measures were also related to higher levels of perceived difficulty, most notably in the case of the WTS Time-on-Task positive slope ($r = 0.45$). Interestingly, negative slopes were also related to higher perceived difficulty, albeit with milder correlation coefficients (WTS: $r = 0.23$, $p < 0.001$; LMS: $r = 0.17$, $p < 0.01$). Figure 5 shows the relations between Weekly Perceived Difficulty, WTS Weekly Time-on-Task, and LMS Weekly Sessions Count.

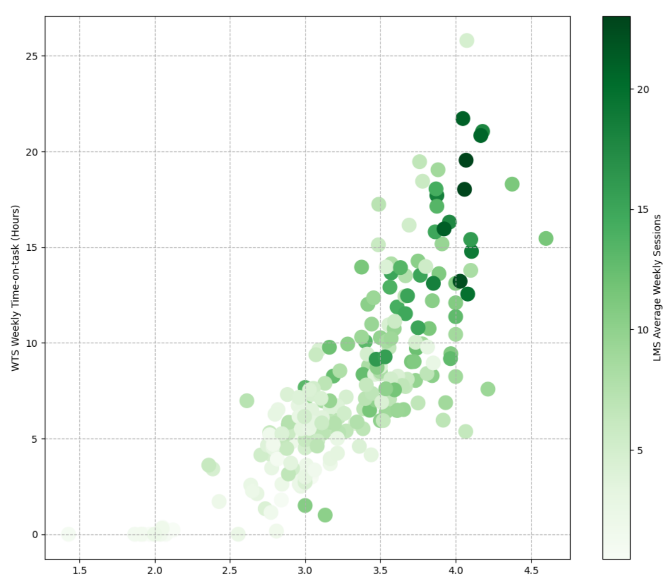

Figure 5. Relations between reported time-on-task, perceived difficulty, and LMS weekly sessions.

Course-level relationships with Perceived Difficulty were even more pronounced. The correlation between WTS course time-on-task and perceived course difficulty strengthened ($r = 0.86$), closely mirrored by LMS Course Average Sessions ($r = 0.82$). Notably, measures of variability showed strong correlations with Perceived Difficulty, primarily regarding WTS Time-on-Task Range ($r = 0.81$), LMS Time-on-Task SD ($r = 0.75$), and WTS Time-on-Task SD ($r = 0.73$). These relationships indicate that variability measures—from both LMS and WTS data—are key indicators of perceived course difficulty. Several other LMS activity metrics also showed significant correlations with Perceived Course Difficulty. The Course Average Participation Rate ($r = 0.75$), Average Assignments Sessions ($r = 0.74$), Average Discussions Time ($r = 0.69$), and Average Submissions Sessions ($r = 0.68$) were all associated with courses being perceived as more difficult. Interestingly, quizzes—specifically the average number of views—were again the only activity displaying a negative correlation with Perceived Course Difficulty ($r = -0.63$), replicating our previous findings with WTS Time-on-Task.

4.4 Learning Attainment and Workload Features

Building on our previous findings, we examined the relationships between various workload features and learning attainment and the course evaluation survey. Table 4 presents the main correlations between WTS workload features and Course Average Learning Attainment, percentage of course students reporting learning MLTE, and percentage of course students reporting learning MMTE.

Table 4. Main correlations with learning attainment.

	Correlations with		
Workload Features	Course Avg. Learning	% Learning MLTE	% Learning MMTE
WTS Max Positive Slope	−0.33	0.02	−0.70**
WTS Max Negative Slope	−0.40	0.11	−0.51
WTS Positive Slope SD	−0.36	0.05	−0.70**
WTS Negative Slope SD	−0.41	0.11	−0.48
WTS Positive Slope CV	−0.22	0.26	−0.05
WTS Negative Slope CV	−0.59*	0.33	−0.50
WTS Overall Slope SD	−0.22	−0.02	−0.50
WTS Overall Slope CV	0.18	−0.14	0.15
WTS Low Intensity Peaks	−0.61*	0.75**	−0.11
WTS Medium Intensity Peaks	−0.03	−0.06	−0.41
WTS High Intensity Peaks	0.20	−0.32	0.14
WTS Total Peaks	−0.57*	0.58*	−0.31
WTS Course Time-on-Task	−0.26	0.01	−0.52
WTS Course Perceived Difficulty	0.03	−0.31	−0.31
WTS Course Time-on-Task SD	−0.46	0.17	−0.69**
WTS Course Difficulty SD	−0.41	0.42	−0.39

Note: $*p < 0.05$, $**p < 0.01$

First, we found that Course Average Learning was negatively correlated with the number of Total Peaks ($r = -0.57$)—regardless of their type—particularly with the presence of Low-Intensity Peaks ($r = -0.61$). The Negative Slope CV also showed a negative correlation with Course Average Learning ($r = -0.59$), indicating that greater variability in time-load decreases might also affect learning attainment. When examining the percentage of students who answered extreme values of the survey—both MLTE and MMTE—we found correlations in the same direction, and even stronger in magnitude. The percentage of students that reported learning MLTE was also positively correlated with the Total Number of Peaks ($r = 0.58$) and with the number of Low-Intensity Peaks ($r = 0.75$). Conversely, the percentage of students that reported learning MMTE showed negative correlations with Max Positive Slope ($r = -0.70$), Positive Slope SD ($r = -0.70$), and Course Time-on-Task SD ($r = -0.69$).

However, it's worth noting that none of the workload distribution metrics derived from the LMS showed significant correlations with learning outcomes, with all significant correlations being obtained from WTS features. For instance, neither LMS Time-on-Task SD ($r = -0.16$, $p = 0.59$), LMS Overall Slope SD ($r = 0.02$, $p = 0.95$), nor LMS Max Positive Slope ($r = -0.05$, $p = 0.87$) showed significant correlations with Course Average Learning, despite these being some of the strongest correlated features from the WTS with learning attainment. Finally, both WTS Course Perceived Difficulty and Time-on-Task were negatively correlated with the percentage of students learning MMTE, but these correlations were not statistically significant. Notably, workload distribution measures were more strongly correlated with learning attainment than those referring to WTS Course Time-on-Task or Course Perceived Difficulty. This underscores the importance of considering workload dynamics when assessing the impact of course design on learning attainment.

5. Discussion

One of the primary objectives of this work was to examine the alignment between student self-reported time-on-task and LMS log data activities. To the best of our knowledge, no previous studies have explored the relationships between self-reported and LMS workload measures on a weekly basis. Our findings provide compelling evidence that self-reported measures of time-on-task are positively correlated with student LMS time-on-task. Furthermore, LMS activity—particularly the number of sessions—also had a positive correlation with greater levels of perceived difficulty. These correlations are especially noteworthy considering that, on average, a course's LMS weekly time-on-task represented less than 9% of the total self-reported weekly time-on-task. This underscores the potential of LMS indicators as proxy variables of student-perceived workload beyond their platform behaviour, so both types of metrics can be crucial for identifying courses with potential overload issues.

These results are in contrast to previous research that has questioned the reliability or predictive power of self-reported time-on-task measures. For instance, a work by Bentley and Kyvik (2012) identifies the struggle to accurately recall and report time dedicated to academic activities as a potential limitation of these tools. Additionally, Cho and Yoo (2017) found that LMS log data was more powerful in predicting students' achievements than self-reported survey data on self-regulated learning. Moreover, other studies also highlight limitations of LMS data. A work by Conijn and colleagues (2016) asserts that LMS data does not provide concrete measurements of previously defined theoretical concepts, underscoring the need for better insights into what LMS data represents, its effects, and how it can be converted into concrete measurements of concepts. Our approach allows for a more granular analysis of workload dynamics from both data sources, providing unprecedented findings of their relationship at this level of detail.

While self-reported weekly time-on-task correlated with LMS time-on-task, views, and number of sessions, content-specific measures of platform activity were crucial for understanding more complex patterns of LMS behaviour. By disaggregating LMS interactions by type, we were able to elucidate how students prioritize different interaction types based on specific weekly workload demands. Although discussion topics and files were the most strongly correlated activities with higher levels of self-reported time-on-task (refer to Table 1), the ratio these activities constitute to total LMS course activity provided deeper insights into their interplay. Notably, when weekly course interactions in the LMS were predominantly file-oriented, all other activity types tended to decrease, particularly those related to quizzes and assignments. This dynamic generates a pattern of interleaved behaviour, where some content-specific activities can even be mutually exclusive, as illustrated in Figure 3. A plausible explanation for this phenomenon is that students engage more with the platform to access files in preparation for upcoming assignments and quizzes. Moreover, all LMS activity types were positively correlated with higher levels of self-reported workload, with the exception of quizzes. Considering that courses with a higher number of quizzes were also correlated with lower levels of perceived workload, concentrating more content into fewer assessments may result in more densely packed weeks in terms of workload, underscoring the importance of workload distribution in course design. These results align with recent findings indicating that work overload typically occurs proximate to assignment and quiz deadlines (Hilliger et al., 2023; Pardos et al., 2023).

Our analysis of workload dynamics yielded multiple significant results related to higher workload levels. We observed that courses with higher overall workload were characterized by greater variability in their time-load evolution. Steep workload changes between consecutive weeks, along with higher time-on-task standard deviations and ranges, strongly correlated with courses being perceived as both more challenging and more time-demanding by students (refer to Table 2 and Table 3). Credit hours—which aim to provide students with an estimate of the approximate time investment required for weekly academic activities—have recognized limitations as a measure of student workload (Pardos et al., 2023). However, our findings underscore the limitations of analyzing time-on-task based solely on average indicators, including, but not limited to, credit hours.

In that same vein, our most remarkable finding was that workload dynamics affect not only overall levels of course workload but also students' learning attainment. Previous research has indicated that time pressure can impede learning processes (Chuderski, 2016). Our study deepens this understanding by revealing that the temporal evolution of workload, rather than absolute workload values or average time-on-task, has a more significant impact on students' learning. Specifically, abrupt changes in time-load demands were negatively correlated with students' learning attainment. This was evident through slope measures, both positive and negative, which showed that irregular and substantial fluctuations in workload are negatively correlated with learning outcomes. Additionally, our peak analysis revealed that courses with a higher number of workload peaks were negatively correlated with perceived learning outcomes. Although LMS features were not among the strongest correlations regarding learning attainment, previous research has found that students who reported higher satisfaction on learning activities also tended to review assignments with more anticipation (Henrie et al., 2018). The interleaved behaviour observed in some courses regarding their LMS interaction types (refer to Figure 3) could potentially serve to identify courses in which students anticipate assignments or quizzes by reviewing resources—such as files—on previous days or weeks, which might be an indicator of higher learning attainment.

However, distinguishing between factors that hinder exceptional learning experiences and those that contribute to poor learning experiences is crucial for targeted course design improvements. An example of this idea, which may seem counterintuitive at first glance, can be illustrated with the Maximum Positive Slope of workload in a course. While courses with these abrupt workload increases showed a strong negative correlation (-0.70) with the percentage of students learning MMTE, its correlation with students learning MLTE was negligible (0.02). This suggests that steep workload increases primarily act as barriers to outstanding learning outcomes rather than as determining features of poor learning experiences. In other words, mitigating abrupt workload increases may be more effective in fostering exceptional learning rather than preventing subpar outcomes. Conversely, Low-Intensity Workload Peaks exhibit the opposite pattern. These peaks show the strongest negative correlation with course average learning (-0.61) and are strongly positively correlated (0.75) with the percentage of students learning MLTE, but showed a very weak negative correlation (-0.11) with the proportion of students learning MMTE. This indicates that the presence of Low-Intensity Peaks acts as a strong indicator of courses where students are more likely to underperform, but their absence doesn't necessarily guarantee exceptional learning outcomes. These findings suggest that different workload features may have asymmetric effects on learning, with some primarily affecting high achievers and others mainly impacting struggling students in terms of perceived learning. By examining the relationships with both extremes of the learning spectrum (MMTE and MLTE), we gain a more comprehensive understanding of how workload dynamics influence the full range of student experiences and outcomes. Consequently, educators should focus not only on eliminating features associated with poor outcomes but also on cultivating conditions that foster meaningful learning experiences.

6. Conclusions, Limitations, and Future Work

We have introduced a novel analytical framework for assessing student workload which highlights the importance of conceptualizing and measuring workload dynamics. This framework addresses the need to move beyond static measures of time-on-task, such as credit hours or workload averages. By conducting a comparative analysis of self-reported time-on-task with LMS activity on a weekly basis, we provided a granular view of workload evolution over time, a perspective that has been scarce in previous research. The strong correlations between self-reported time-on-task and LMS activity metrics support the use of LMS data as a proxy for overall student workload. Still, these findings are particularly interesting given that LMS activity represents only a small fraction of total self-reported time-on-task. Moreover, our study's approach to contextualizing LMS interactions provides a more comprehensive view of time-on-task indicators. We found complex dynamics in how students prioritize and engage with different types of course content over time, which underscores the complexity of LMS data interpretation as a non-trivial issue. Findings such as the negative correlation between quiz interactions and perceived workload suggest that more frequent, less intensive assessments might be beneficial in reducing overall workload pressure.

Our analysis of peaks, slope fluctuations, and variability measures revealed that not only the amount of time spent on coursework, but most importantly how the evolution of that workload occurs throughout the course, has a more profound impact on students' perceptions of learning and difficulty. This work unveiled complex patterns that were only evident when considering workload dynamics, transcending indicators that represent a single point in time over the academic term. Notably, drastic workload slopes and high workload intensity periods are not just a byproduct of uneven workload distribution, but a characteristic of courses that might be hindering learners' potential, which should be addressed through strategic workload and content redistribution.

The main challenge of workload assessment is understanding the distribution of course load over time, and how that distribution affects student learning experiences. We provide a concrete set of measures to analyze this issue, which can serve as guidelines for educators designing curricular adjustments in courses potentially affected by work overload. These nuanced measurements can assist educators in making data-driven course design choices while providing students with more reliable information about potential workload interplay across different courses, helping them avoid periods of excessive workload overlap. Our findings also support previous theory remarking that merely decreasing workload is not always beneficial for learning outcomes. Instead, reducing extraneous load, particularly course design features revealed by workload dynamics analysis, emerges as a more effective solution.

Our work also posits various limitations and opportunities for future work. First, it's important to note that while many of the course-level correlations were stronger than those observed at the week level, the reduced sample size at the course level, compared to the week level, necessitates cautious interpretation. Additionally, the self-reported data collected through the WTS may be subject to inaccuracies due to memory distortion and biases in students' recall of their weekly activities (Marshall, 2018; Ruiz-Gallardo et al., 2011). A significant limitation is that both self-reported and trace data primarily reflects elapsed time rather than actual engaged learning time, which can affect the precision of workload measurements. However, triangulating these data sources adds value by enhancing the reliability of our findings and supporting more informed decision-making. Future implementations might consider complementary approaches, such as encouraging students to maintain activity logs during the week before submitting their final responses to further enhance measurement precision.

Concerning the peak analysis, its introduction revealed promising results associated with increased perceived difficulty and negative relationships with learning. However, while low- and medium-intensity peaks showed similar trends, high-intensity peaks yielded contrasting results. This inconsistency may be attributed to the relative scarcity of high-intensity peaks in our dataset, constituting only 11% of total observed peaks. Future research should focus on refining the thresholds used for peak categorization to adequately capture the full spectrum of workload variations, especially at the higher end. This could significantly enhance the validity and reliability of our findings, potentially uncovering a more complex, non-monotonic relationship between workload distribution and learning outcomes.

Also, the interpretation of LMS prioritization is complex due to the varying amount of resources each course inherently possesses, as illustrated in Figure 1. Consequently, higher levels of activity in specific courses may be more reflective of instructional design choices rather than students' internal prioritization of courses. In conclusion, further research is necessary to elucidate how LMS course design influences these contextualized measures of prioritization, thereby providing a more comprehensive understanding of course LMS interactions within a broader context. Additionally, we observed unexpected negative correlations between certain activity types (e.g., files with announcements or discussions) that contrast with the positive correlations found among other activities. These counterintuitive relationships are not readily explicable and present intriguing avenues for future investigation.

Despite its limitations, this study contributes to the existing body of knowledge in various ways. Rather than viewing workload as a static dot in time or as an isolated value, our framework conceptualizes it as a dynamic pathway that students navigate throughout their academic term. This perspective highlights the importance of understanding workload as a systemic issue, one that emerges from the complex interplay of demands across various concurrent courses. These findings represent a significant advancement in the field of learning analytics, providing both theoretical insights and practical implications for enhancing course design and student learning experiences. The analytical framework presented here offers a foundation for future research and can inform evidence-based practices in educational policy and course development. As we continue to refine our understanding of workload dynamics, this work paves the way for more effective, student-centred approaches to curriculum design and workload management in higher education. By recognizing these dynamics, we can better assess how each course's characteristics combine to create the holistic workload experience of students. A main challenge for educators is to consider not just the workload within their own courses, but how it fits into the broader academic landscape of their students. As we refine our analytical tools and deepen our understanding of workload dynamics, we aim to create educational environments that not only challenge learners without overwhelming them but ultimately foster meaningful learning. After all, let's not forget that learning analytics should be about learning.

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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References

Abazi-Bexheti, L., Kadriu, A., Jajaga, E., Apostolova-Trpkovska, M., & Abazi-Alili, H. (2018). LMS solution: Evidence of Google Classroom usage in higher education. *Business Systems Research: International Journal of the Society for Advancing Innovation and Research in Economy*, *9*(1), 31–43. https://doi.org/10.2478/bsrj-2018-0003

Armstrong, J. (1996). Workload in engineering courses and how to reduce it. *Proceedings of the Eighth Annual Conference of the Australasian Association for Engineering Education* (AAEE 1996), 15–18 December 1996, Sydney, Australia.

Bachman, L., & Bachman, C. (2006). Student perceptions of academic workload in architectural education. *Journal of Architectural and Planning Research*, *23*(4), 271–304. https://www.jstor.org/stable/43030781

Baturay, M. H. (2008). Characteristics of basic instructional design models. *Ekev Academic Review*, *12*(34), 471–482. https://www.academia.edu/42158434/

Beer, N. (2019). Estimating student workload during the learning design of online courses: Creating a student workload calculator. In R. Ørngreen, M. Buhl, & B. Mayer (Eds.), *Proceedings of the European Conference on E-Learning* (ECEL 2019), 7–8 November 2019, Aalborg, Denmark (pp. 629–638). ACPI. https://research.lancaster-university.uk/en/publications/estimating-student-workload-during-the-learning-design-of-online-/

Bennett, A., & Burke, P. J. (2018). Re/conceptualising time and temporality: An exploration of time in higher education. *Discourse: Studies in the Cultural Politics of Education*, *39*(6), 913–925. https://doi.org/10.1080/01596306.2017.1312285

Bentley, P. J., & Kyvik, S. (2012). Academic work from a comparative perspective: A survey of faculty working time across 13 countries. *Higher Education*, *63*, 529–547. https://doi.org/10.1007/s10734-011-9457-4

Bladek, M. (2021). Student well-being matters: Academic library support for the whole student. *The Journal of Academic Librarianship*, *47*(3), 102349. https://doi.org/10.1016/j.acalib.2021.102349

Bono, R., Blanca, M. J., Arnau, J., & Gómez-Benito, J. (2017). Non-normal distributions commonly used in health, education, and social sciences: A systematic review. *Frontiers in Psychology*, *8*, 1602. https://doi.org/10.3389/fpsyg.2017.01602

Bowling, N. A., Alarcon, G. M., Bragg, C. B., & Hartman, M. J. (2015). A meta-analytic examination of the potential correlates and consequences of workload. *Work & Stress*, *29*(2), 95–113. https://doi.org/10.1080/02678373.2015.1033037

Bowyer, K. (2012). A model of student workload. *Journal of Higher Education Policy and Management*, *34*(3), 239–258. https://doi.org/10.1080/1360080x.2012.678729

Carroll, J. B. (1963). A model of school learning. *Teachers College Record*, *64*(8), 1–9. https://doi.org/10.1177/016146816306400801

Cerezo, R., Sánchez-Santillán, M., Paule-Ruiz, M. P., & Núñez, J. C. (2016). Students' LMS interaction patterns and their relationship with achievement: A case study in higher education. *Computers & Education*, *96*, 42–54. https://doi.org/10.1016/j.compedu.2016.02.006

Chadha, D., Kogelbauer, A., Campbell, J., Hellgardt, K., Maraj, M., Shah, U., Brechtelsbauer, C., & Hale, C. (2021). Are the kids alright? Exploring students' experiences of support mechanisms to enhance wellbeing on an engineering programme in the UK. *European Journal of Engineering Education*, *46*(5), 662–677. https://doi.org/10.1080/03043797.2020.1835828

Cho, M.-H., & Yoo, J. S. (2017). Exploring online students' self-regulated learning with self-reported surveys and log files: A data mining approach. *Interactive Learning Environments*, *25*(8), 970–982. https://doi.org/10.1080/10494820.2016.1232278

Chuderski, A. (2016). Time pressure prevents relational learning. *Learning and Individual Differences*, *49*, 361–365. https://doi.org/10.1016/j.lindif.2016.07.006

Conijn, R., Snijders, C., Kleingeld, A., & Matzat, U. (2016). Predicting student performance from LMS data: A comparison of 17 blended courses using Moodle LMS. *IEEE Transactions on Learning Technologies*, *10*(1), 17–29. https://doi.org/10.1109/tlt.2016.2616312

De Beer, L. T., Pienaar, J., & Rothmann Jr, S. (2016). Work overload, burnout, and psychological ill-health symptoms: A three-wave mediation model of the employee health impairment process. *Anxiety, Stress, & Coping*, *29*(4), 387–399. https://doi.org/10.1080/10615806.2015.1061123

De Winter, J. C., Gosling, S. D., & Potter, J. (2016). Comparing the Pearson and Spearman correlation coefficients across distributions and sample sizes: A tutorial using simulations and empirical data. *Psychological Methods*, *21*(3), 273. https://doi.org/10.1037/met0000079

Edú-Valsania, S., Laguía, A., & Moriano, J. A. (2022). Burnout: A review of theory and measurement. *International Journal of Environmental Research and Public Health*, *19*(3), 1780. https://doi.org/10.3390/ijerph19031780

Egea, G., Rodríguez-Lizana, A., Pérez-Urrestarazu, L., Pérez-Ruiz, M., Rallo, P., & Suárez, M. P. (2022). Assessment of actual workload and student performance in the agricultural engineering final degree project in a Spanish higher education context. *Education Sciences*, *12*(6), 418. https://doi.org/10.3390/educsci12060418

Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education*, *28*, 68–84. https://doi.org/10.1016/j.iheduc.2015.10.002

Gleeson, J., Lynch, R., & McCormack, O. (2021). The European Credit Transfer System (ECTS) from the perspective of Irish teacher educators. *European Educational Research Journal*, *20*(3), 365–389. https://doi.org/10.1177/1474904120987101

Heffernan, J. M. (1973). The credibility of the credit hour: The history, use, and shortcomings of the credit system. *The Journal of Higher Education*, *44*(1), 61–72. https://doi.org/10.1080/00221546.1973.11776844

Henrie, C. R., Bodily, R., Larsen, R., & Graham, C. R. (2018). Exploring the potential of LMS log data as a proxy measure of student engagement. *Journal of Computing in Higher Education*, *30*, 344–362. https://doi.org/10.1007/s12528-017-9161-1

Hicks, T. G., & Wierwille, W. W. (1979). Comparison of five mental workload assessment procedures in a moving-base driving simulator. *Human Factors*, *21*(2), 129–143. https://doi.org/10.1177/001872087902100201

Hilliger, I., Astudillo, G., & Baier, J. (2023). Lacking time: A case study of student and faculty perceptions of academic workload in the COVID-19 pandemic. *Journal of Engineering Education*, *112*(3), 796–815. https://doi.org/10.1002/jee.20525

Hilliger, I., Miranda, C., Schuit, G., Duarte, F., Anselmo, M., & Parra, D. (2021). Evaluating a learning analytics dashboard to visualize student self-reports of time-on-task: A case study in a Latin American university. In *Proceedings of the 11th International Conference on Learning Analytics and Knowledge* (LAK 2021), 12–16 April 2021, Irvine, California, USA (pp. 592–598). ACM. https://doi.org/10.1145/3448139.3448203

Jovanović, J., Gašević, D., Dawson, S., Pardo, A., & Mirriahi, N. (2017). Learning analytics to unveil learning strategies in a flipped classroom. *The Internet and Higher Education*, *33*, 74–85. https://doi.org/10.1016/j.iheduc.2017.02.001

Jovanović, J., Saqr, M., Joksimović, S., & Gašević, D. (2021). Students matter the most in learning analytics: The effects of internal and instructional conditions in predicting academic success. *Computers & Education*, *172*, 104251. https://doi.org/10.1016/j.compedu.2021.104251

Karjalainen, A., Alha, K., & Jutila, S. (2006). *Give me time to think: Determining student workload in higher education, five years, two degrees* (tech. rep.). Ministry of Education, 2004–2006, Finland. Oulu University Press. https://oula.finna.fi/Record/oy.9910448063906252

Karweit, N. (1984). Time-on-task reconsidered: Synthesis of research on time and learning. *Educational leadership*, *41*(8), 32–35. https://files.ascd.org/staticfiles/ascd/pdf/journals/ed_lead/el_198405_karweit.pdf

Kember, D. (2004). Interpreting student workload and the factors which shape students' perceptions of their workload. *Studies in Higher Education*, *29*(2), 165–184. https://doi.org/10.1080/0307507042000190778

Kember, D., & Leung, D. Y. (1998). The dimensionality of approaches to learning: An investigation with confirmatory factor analysis on the structure of the SPQ and LPQ. *British Journal of Educational Psychology*, *68*(3), 395–407. https://doi.org/10.1111/j.2044-8279.1998.tb01300.x

Khan, I., & Pardo, A. (2016). Data2U: Scalable real time student feedback in active learning environments. In *Proceedings of the Sixth International Conference on Learning Analytics and Knowledge* (LAK 2016), 25–29 April 2016, Edinburgh, Scotland, UK (pp. 249–253). ACM. https://doi.org/10.1145/2883851.2883911

Kovanovic, V., Gašević, D., Dawson, S., Joksimovic, S., & Baker, R. (2015). Does time-on-task estimation matter? Implications on validity of learning analytics findings. *Journal of Learning Analytics*, *2*(3), 81–110. https://doi.org/10.18608/jla.2015.23.6

Kyndt, E., Berghmans, I., Dochy, F., & Bulckens, L. (2014). "Time is not enough." Workload in higher education: a student perspective. *Higher Education Research & Development*, *33*(4), 684–698. https://doi.org/10.1080/07294360.2013.863839

Leinonen, J., Castro, F. E. V., & Hellas, A. (2022). Time-on-task metrics for predicting performance. *ACM Inroads*, *13*(2), 42–49. https://doi.org/10.1145/3534564

Leitner, P., Khalil, M., & Ebner, M. (2017). Learning analytics in higher education—A literature review. In A. Peña-Ayala (Ed.), *Learning analytics: Fundaments, applications, and trends: A view of the current state of the art to enhance e-learning* (pp. 1–23). Springer. https://doi.org/10.1007/978-3-319-52977-6_1

Liu, Q., & Evans, G. (2020). *Supporting information for student workload quick guides for instructors and students* (tech. rep.). Institute for Studies in Transdisciplinary Engineering Education and Practice, University of Toronto. https://istep.utoronto.ca/wp-content/uploads/sites/35/2020/08/Supporting-Information-for-Student-Workload-Quick-Guides-for-Instructors-and-Students-Aug10-2020.pdf

Marshall, S. J. (2018). Student time choices and success. *Higher Education Research & Development*, *37*(6), 1216–1230. https://doi.org/10.1080/07294360.2018.1462304

Maslach, C., & Leiter, M. P. (2016). Understanding the burnout experience: Recent research and its implications for psychiatry. *World Psychiatry*, *15*(2), 103–111. https://doi.org/10.1002/wps.20311

Maslennikova, A., Rotelli, D., & Monreale, A. (2023). Session-based time-window identification in virtual learning environments. *Journal of Learning Analytics*, *10*(3), 7–27. https://doi.org/10.18608/jla.2023.7911

Matcha, W., Gašević, D., Jovanović, J., Uzir, N. A., Oliver, C. W., Murray, A., & Gasevic, D. (2020). Analytics of learning strategies: The association with the personality traits. In *Proceedings of the 10th International Conference on Learning Analytics and Knowledge* (LAK 2020), 23–27 March 2020, Frankfurt, Germany (pp. 151–160). ACM. https://doi.org/10.1145/3375462.3375534

Miller, S. (2001). *Workload measures* (tech. rep.). National Advanced Driving Simulator, University of Iowa. https://www.nads-sc.uiowa.edu/publicationstorage/200501251347060.n01-006.pdf

Nassar, A. K., Waheed, A., & Tuma, F. (2019). Academic clinicians' workload challenges and burnout analysis. *Cureus*, *11*(11). https://doi.org/10.7759/cureus.6108

Nguyen, Q. (2020). Rethinking time-on-task estimation with outlier detection accounting for individual, time, and task differences. In *Proceedings of the 10th International Conference on Learning Analytics and Knowledge* (LAK 2020), 23–27 March 2020, Frankfurt, Germany (pp. 376–381). ACM. https://doi.org/10.1145/3375462.3375538

Nguyen, Q., Rienties, B., Toetenel, L., Ferguson, R., & Whitelock, D. (2017). Examining the designs of computer-based assessment and its impact on student engagement, satisfaction, and pass rates. *Computers in Human Behavior*, *76*, 703–714. https://doi.org/10.1016/j.chb.2017.03.028

Pardos, Z. A., Borchers, C., & Yu, R. (2023). Credit hours is not enough: Explaining undergraduate perceptions of course workload using LMS records. *The Internet and Higher Education*, *56*, 100882. https://doi.org/10.1016/j.iheduc.2022.100882

Pastores, S. M., Kvetan, V., Coopersmith, C. M., Farmer, J. C., Sessler, C., Christman, J. W., D'Agostino, R., Diaz-Gomez, J., Gregg, R. A., Sara R.and Khan, Kapu, A. N., Masur, H., Mehta, G., Moore, J., Oropello, J. M., & Price, K. (2019). Workforce, workload, and burnout among intensivists and advanced practice providers: A narrative review. *Critical Care Medicine*, *47*(4), 550–557. https://doi.org/10.1097/ccm.0000000000003637

Riestra-González, M., del Puerto Paule-Ruíz, M., & Ortin, F. (2021). Massive LMS log data analysis for the early prediction of course-agnostic student performance. *Computers & Education*, *163*, 104108. https://doi.org/10.1016/j.compedu.2020.104108

Rotelli, D., & Monreale, A. (2022). Time-on-task estimation by data-driven outlier detection based on learning activities. In *Proceedings of the 12th International Conference on Learning Analytics and Knowledge* (LAK 2022), 21–25 March 2022, online (pp. 336–346). ACM. https://doi.org/10.1145/3506860.3506913

Ruiz-Gallardo, J.-R., Castaño, S., Gómez-Alday, J. J., & Valdés, A. (2011). Assessing student workload in problem based learning: Relationships among teaching method, student workload and achievement. A case study in natural sciences. *Teaching and Teacher Education*, *27*(3), 619–627. https://doi.org/10.1016/j.tate.2010.11.001

Schaufeli, W. B., Enzmann, D., & Girault, N. (2017). Measurement of burnout: A review. In W. B. Schaufeli, C. Maslach, & T. Marek (Eds.), *Professional burnout* (pp. 199–215). Routledge. https://doi.org/10.4324/9781315227979-16

Schnotz, W., & Kürschner, C. (2007). A reconsideration of cognitive load theory. *Educational Psychology Review*, *19*, 469–508. https://doi.org/10.1007/s10648-007-9053-4

Silva, E., White, T., & Toch, T. (2015). *The Carnegie unit: A century-old standard in a changing education landscape*. Carnegie Foundation for the Advancement of Teaching. https://www.luminafoundation.org/files/resources/carnegie-unit-report.pdf

Smith, A. P. (2019). Student workload, wellbeing and academic attainment. In L. Longo & M. Leva (Eds.), *Human mental workload: Models and applications. H-WORKLOAD 2019. Communications in computer and information science* (pp. 35–47, Vol. 1107). Springer. https://doi.org/10.1007/978-3-030-32423-0_3

Souto-Iglesias, A., & Baeza_Romero, M. T. (2018). A probabilistic approach to student workload: Empirical distributions and ECTS. *Higher Education*, *76*(6), 1007–1025. https://doi.org/10.1007/s10734-018-0270-1

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, *12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Sweller, J., Chandler, P., Tierney, P., & Cooper, M. (1990). Cognitive load as a factor in the structuring of technical material. *Journal of Experimental Psychology: General*, *119*(2), 176. https://doi.org/10.1037//0096-3445.119.2.176

Sweller, J., Van Merrienboer, J. J., & Paas, F. G. (1998). Cognitive architecture and instructional design. *Educational Psychology Review*, *10*, 251–296. https://doi.org/10.1023/a:1022193728205

Tukey, J. W. (1977). *Exploratory data analysis*. Addison-Wesley.

Van Merrienboer, J. J., & Sweller, J. (2005). Cognitive load theory and complex learning: Recent developments and future directions. *Educational Psychology Review*, *17*, 147–177. https://doi.org/10.1007/s10648-005-3951-0

Wang, Q., & Mousavi, A. (2023). Which log variables significantly predict academic achievement? A systematic review and meta-analysis. *British Journal of Educational Technology*, *54*(1), 142–191. https://doi.org/10.1111/bjet.13282

Wentling, S., & Variawa, C. (2020). Investigating differences between instructor expectation and student workload in undergraduate engineering [Conference scheduled 18–21 June 2020, Montréal, Québec, Canada (cancelled due to COVID-19)]. In *Proceedings of the Canadian Engineering Education Association (CEEA)*. CEEA. https://doi.org/10.24908/pceea.vi0.14189

Yang, C., Chen, A., & Chen, Y. (2021). College students' stress and health in the COVID-19 pandemic: The role of academic workload, separation from school, and fears of contagion. *PloS One*, *16*(2), e0246676. https://doi.org/10.1371/journal.pone.0246676

Yangdon, K., Sherab, K., Choezom, P., Passang, S., & Deki, S. (2021). Well-being and academic workload: Perceptions of science and technology students. *Educational Research and Reviews*, *16*(11), 418–427. https://doi.org/10.5897/ERR2021.4197

Zar, J. H. (2005). Spearman rank correlation. In P. Armitage & T. Colton (Eds.), *Encyclopedia of biostatistics* (Vol. 7). Wiley Online Library. https://doi.org/10.1002/0470011815.b2a15150

Zijlstra, W. P., van der Ark, L. A., & Sijtsma, K. (2011). Outliers in questionnaire data: Can they be detected and should they be removed? *Journal of Educational and Behavioral Statistics*, *36*(2), 186–212. https://doi.org/10.3102/1076998610366263

Appendix

Code	Section	Course Students	WTS Course Response Rate	Department
ING2030	6	61	22.54%	Core Engineering
IIQ2673	1	55	29.41%	Chemical
IIQ2043	1	65	29.95%	Chemical
IIQ2023	2	61	47.06%	Chemical
IIQ2013	1	62	40.51%	Chemical
IIQ2003	1	32	39.34%	Chemical
IIC2613	1	138	41.35%	Computer Science
IIC2233	2	444	40.83%	Computer Science
IIC2026	1	84	28.92%	Computer Science
IIC1253	1	338	20.82%	Computer Science
ICS2813	3	101	38.24%	Industrial and Systems
ICS2813	2	135	29.31%	Industrial and Systems
ICS2813	1	140	38.19%	Industrial and Systems
ICS1513	1	54	50.81%	Industrial and Systems

Table 5. Course Sample Enrollments and Response Rates