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Designing the Course Load Analytics Platform

Conrad Borchers[1] [0000−0003−3437−8979], Shreya Sheel[2] [0000−0001−6149−118X], Anirudh Pai[2] [0009−0000−3083−5058], Sher Shah[2] [0009−0002−6057−7904], and Zachary A. Pardos[2] [0000−0002−6016−7051]

[1] Carnegie Mellon University
cborcher@cs.cmu.edu
[2] University of California, Berkeley
{shreya_sheel,apai25,pardos}@berkeley.edu, sher.shah010@gmail.com

Abstract. Increasing empirical evidence suggests that credit units are an insufficient proxy for student workload in higher education. Course load analytics (CLA) could support course selection and academic advising by offering a more accurate prediction of course load based on data from a learning management system and historical enrollments. We describe the development of a CLA platform for academic advising. The CLA platform surpasses time-bound credit hour metrics by predicting cognitive demand and psychological stress associated with courses while identifying workload spikes throughout the semester on a weekly basis. We describe how the platform enables students and advisors to plan semesters using a course catalog tool, allowing them to explore alternative semester workload scenarios. We contribute generalizable knowledge and procedures for instrumenting similar platforms that support students in managing and preparing for their academic course workload. We also contribute open-source code for researchers and practitioners to adopt and deploy our CLA platform.

Keywords: higher education, academic advising, course selection, learning analytics, course load analytics, pathways, workload, enrollment data

1 Introduction and Related Work

The EC-TEL community has long recognized the potential of data-driven tools to support learning in higher education [18]. Beyond learning skills and facts during course completion, the choice of *what courses* students take is a key part of the higher education learning experience. Crucial learning outcomes such as degree completion are related to course choice [1]. Accordingly, the field has produced technology that supports learning and path-finding in higher education, for example, through course recommendation systems [8].

Every semester, students in higher education institutions must decide which courses to enroll in. Higher education institutions in the United States typically give students high flexibility in course choice [15]. However, even in countries with commonly set course plans per major, such as in the EU, students often decide to switch courses between semesters to regulate their workload by planning their schedules [11]. In the context of these course and degree choices, analytics platforms offer the potential to enhance processes traditionally reliant on human expertise. Platforms have already empowered a wide range of stakeholders—including students, faculty, advisors, and administrators—to navigate complex tasks such as course selection, academic advising, and degree planning [14, 19, 6, 7]. However, in these lines of work, one important aspect of student course choice that is typically overlooked in platform design is course workload.

Higher education has historically quantified workload in terms of credit hours. This time-oriented system, which gauges students' time commitment toward coursework and course attendance, dates back to the early 20th century and the elective course system in the United States [15]. Recent findings question the reliability of credit hours as a representation of course workload. For instance, research by Pardos et al. [12] indicated that credit hours accounted for only a small portion of the variability in student-reported workload (6%). In contrast, features drawn from learning management systems (LMS) captured a substantially higher variance (36%). As another example, a study using large-scale data from two European universities concluded that ECTS credit units may systematically underestimate student semester workload and are unfit to meaningfully capture workload, which varied substantially across courses with the same ECTS designation [17]. Such findings highlight the need for refined workload measurements, like Course Load Analytics (CLA) [1]. CLA utilizes data from LMS interactions, co-enrollment, and course features to model the effective workload students experience, offering a more granular perspective on semester-by-semester workload [1]. It does so by acknowledging that workload encompasses multiple facets, including time commitment, cognitive demand, and psychological stress [13]. Prior work has documented the feasibility of producing CLA at scale [1].

1.1 The Present Study

Recent empirical evidence shows that access to these analytics led students to pay more attention to workload, including dimensions beyond time, and make more resource-conscious decisions [2]. This study, however, was situated in a low-stakes context. Research gaps remain in understanding how to translate these insights into long-term implementations that balance institutional priorities with students' evolving needs. To arrive at these scientific observations, we must develop and design a platform that supports students and advisors in planning semester course choices with CLA in mind. We designed and engineered a novel learning analytics platform. We make the following contributions:

1. We developed CLA Platform, a data-driven tool that leverages learning management system (LMS) data and historical enrollment patterns to provide granular workload predictions for academic advising.
2. We discuss future theories of change for how the CLA platform could improve student learning in higher education, specifically how the CLA platform enables students and advisors to anticipate workload spikes at a weekly resolution across time load, mental effort, and psychological stress.

2 CLA Platform Design

The CLA platform is a web application with a React.js frontend and an AWS lambda backend. It leverages machine learning predictions (stored in the application via JSON files) and interactive data visualizations to display weekly workload patterns based on historical enrollment data and learning management system (LMS) metrics learned from student workload perceptions [1]. The platform's code is open-source.[3]

The CLA platform's interactive course load dashboard (Fig. 1) offers a dynamic interface for exploring predicted workload patterns across semesters. The dashboard visualizes projected workloads across three key dimensions: *Time Load* (TL), *Mental Effort* (ME), and *Psychological Stress* (PS) [13]. These predicted dimensions range from 1 to 5, based on a five-point Likert scale serving as the ground truth. Prediction procedures followed Borchers and Pardos [1].

The platform's main page provides interactive visualizations of the projected workload distributions for each course plan. Visualizations are segmented into workload dimensions, which students can analyze both as cumulative semester totals or by individual course contributions to anticipate weeks with challenging workloads. Toggle options facilitate focus on specific workload dimensions and courses, allowing students to experiment with various course load configurations and gain a nuanced understanding of potential semester demands.

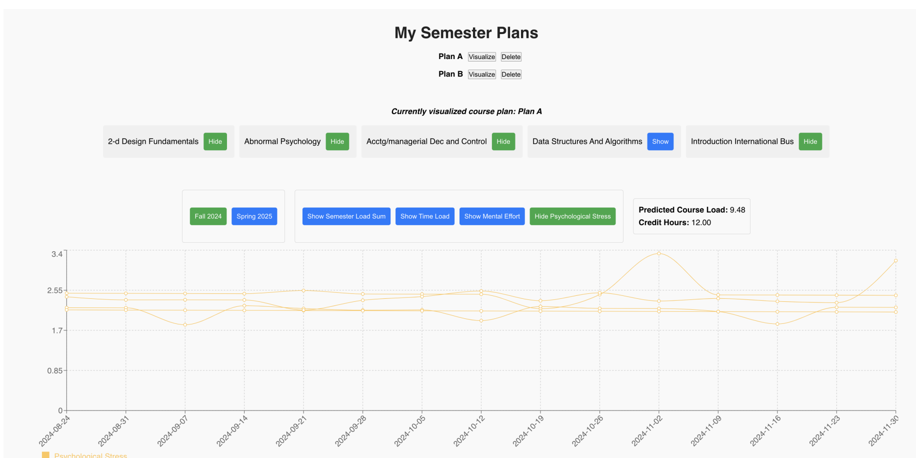

Fig. 1: Interactive dashboard visualizing predicted semester workloads—Time Load, Mental Effort, and Psychological Stress.

Course Catalog Search and Entries The CLA platform allows students to compare course plans (i.e., course sets) by workload. The Course Catalog Search al-

[3] https://github.com/CAHLR/cla-platform/

lows users to search for courses to add to their plans. Users can search for course titles using a search bar. The course search algorithm ranks courses based on the similarity between search query words and course titles using word-level Levenshtein distance. For each course, it computes a vector of minimum distances for each query word, then ranks courses by the average and minimum distances using stable sorting to prioritize close or exact matches. Additionally, the interface highlights exact word matches from the search query in course titles. Every entry in the course catalog includes the title, course load analytics, credit hour units, and a button to add the course to the student's plan.

Course Plan Management Students initiate the planning process by creating and naming new course plans. The course catalog search allows students to locate and add courses to their selected plan. Each course plan accommodates a maximum of 15 unique courses. **Plan Editing and Updating.** The platform enables students to add, remove, or modify courses within each plan dynamically. **Course Workload Previews.** Each time a modification is made to a selected course plan, the platform provides an updated workload preview, giving students immediate feedback on the impact of their adjustments. This preview includes the sum of a given course plan's TL, ME, PS, and overall predicted workload, calculated as the average of the three sub-dimensions, based on past research [1, 13].

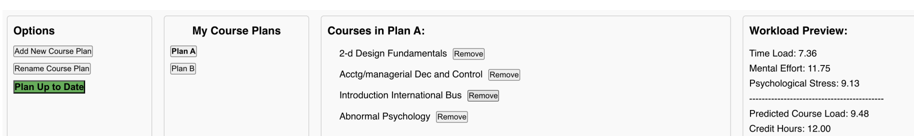

Fig. 2: Workload preview during course planning.

Log Database Structure The CLA platform produces timestamped *logs* representing user interactions with all interactive elements. We follow a selection-action-input log format. The *action* attribute of each document in the *logs* table specifies the type of action the user performed. The input (i.e., *value* attribute) gives more granular metadata regarding the state of the action. For a search query, for example, the action would be *search*, and the corresponding *value* would be the entered query string. The *selection* corresponds to the interface element being interacted with. The platform logs minimal user attributes (i.e., an anonymous ID and whether consent has been completed upon first login). A **course_buckets** attribute stores a complex object that includes details about each course plan a user has created, along with metadata like the last modified timestamp. Other user information includes their **email** (e.g., `jamesdoe@university.com`) and **name** (e.g., `James Doe`), which are used solely for encrypted account management and are not stored in log data.

3 Discussion and Future Directions

3.1 Theoretical Rationale

Two key research areas serve as the conceptual underpinnings of our CLA platform design: (1) critiques of using credit-hour-based metrics to represent course workload [12, 17] and (2) theoretical models on student persistence that emphasize the importance of student success expectations [9] as well as the avoidance of excessive workload to preserve well-being [16]. Hence, the platform's goal is to give students insights into the discrepancy between peer workload perceptions and institutional credit hours as well as weekly fluctuations of their chosen workload to improve preparedness and persistence. To adequately gauge workload, we consider mental effort and psychological stress, which students describe to be less manageable than time load [12].

3.2 Intended Stakeholders

At the institutional level, academic advisors and program administrators can detect mismatches between official credit hours and predicted workload, especially in early prerequisite-intensive STEM courses [1]. Intervening by providing targeted advising or early support resources to students may help preempt the cumulative stress that could lower academic performance and course attrition [4]. By highlighting workload differences on a fine-grain level, CLA encourages early engagement with academic support services and time-management strategies.

To measure theories of change that evaluate CLA's impact on student course selection, the socio-technical infrastructures in which the platform is embedded must be accounted for. To ensure sustainable success, the platform ought to be designed with careful consideration of pedagogical implications, stakeholder needs, institutional contexts, and technical constraints [5]. Establishing formal governance protocols that involve faculty, administrators, and students in decision-making—particularly regarding transparency, data usage, and ethical safeguards—could strengthen trust in the platform. As future work, value-sensitive design research [10] could help surface and formalize the competing values presented in this study for future co-design with stakeholders.

Empirically, longitudinal studies are necessary to assess the CLA platform's long-term impact on student decision-making, enrollments, and academic performance. Also, scalability and generalizability of workload predictions raise questions regarding cross-institutional generalizability. Preliminary evidence suggests that fine-tuning on survey data collected at new institutions is needed [3].

A final methodological consideration involves the temporal scope of data: learning management system (LMS) features could be limited to a few years of course iterations, depending on the institution. Data scope may introduce minor fluctuations in predictive variation, as reusing prior-year LMS data may not fully capture annual variations in instructional practices that broader averages can smooth out. Future work could address this by averaging LMS features across multiple years—a strategy successfully employed in similar contexts [1]—to mitigate noise and enhance robustness.

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