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Course Load Analytics Interventions on Higher Education Course Selection: Experimental Evidence

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Abstract

Inadequate consideration of course workload in undergraduate students' course selections has contributed to adverse academic outcomes. At the same time, credit hours, the default institutional metric to convey time-based course workload to students, has been shown to capture students' experienced workload insufficiently. Recent research documents the accuracy of analytics learned from enrolment and learning management system data that promise to convey course facets other than time to students. To investigate the feasibility of scalable interventions of such analytics on course selection, we conducted a preregistered and randomized forced-choice experiment of two courses satisfying equal requirements across 61 undergraduate students at a large public university. The control condition mimicked a university's standard course catalogue, while the intervention condition augmented this catalogue with analytics on time load, mental effort, and psychological stress alongside institutional credit hours. We find that course load analytics (CLA) significantly influenced students' course selection decisions, leading them to more deliberately optimize their expected workload relative to credit hours. Specifically, we document a strategy regarding students being more likely to take a higher credit hour course that minimizes the expected workload associated with each credit hour. Among all three dimensions of workload, students' course selection decisions were most guided by predicted mental effort, followed by psychological stress, highlighting the limitations of a time-based credit hour metric. The intervention effect of CLA was constant across first-year students and comparatively senior students. We further discuss the implications of our findings for CLA interventions at scale and the institutional stakeholders that could be involved.

Notes for Practice

- Students traded off credit hours and predicted load in the intervention condition, indicating that analytics-based interventions can heighten student attention to workload in course selection decisions.
- Mental effort and psychological stress were more impactful workload measures than time load and time-based credit hours.
- Course catalogues should emphasize mental effort and psychological stress alongside time load and highlight discrepancies between credit hours and workload predictions.
- Low-stakes evaluation of course load analytics interventions to augment higher education course catalogues indicates readiness for real-world deployment.

Keywords

Higher education, course selection, learning analytics, course load analytics, experiments, interventions, pathways, workload.

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1. Introduction

Inadequate consideration of course workload in undergraduate student course selection has been a potential source of adverse academic outcomes (Karimi-Haghighi et al., 2022; Smith, 2019; Wäschle et al., 2014). In line with psychological models of workload, course workload can be regarded as the amount of time, mental effort, and psychological stress a course imposes on a student through course work, instruction time, and other attributes of a course (Reid & Nygren, 1988). Yet, the metric that is routinely used to convey course workload to students at the time of course selection, credit hours, is conceptualized based only on weekly time spent on a course (Heffernan, 1973). This time-based metric has been empirically shown to be a poor proxy of students' actual undergraduate course workload experiences (Pardos et al., 2023).

In response to a lack of representation of mental effort and psychological stress in institutional metrics of course workload in course catalogues, past work has developed analytics that can predict these attributes of courses at scale using learning management system (LMS) records and enrolment data (Borchers & Pardos, 2023). These data are increasingly available for researchers and administrators in higher education institutions and can be trained on end-of-semester student course evaluations (Evrard et al., 2023). Hence, these analytics, which may provide students and academic advisors with low-cost, scalable supplemental course information that prior work has deemed relevant for students' undergraduate course selection (Chaturapruek et al., 2021), could potentially improve educational effectiveness. It is also conceivable that these analytics could already be useful if integrated into existing course catalogues or course recommendation systems (Pardos et al., 2019), which would require no human supervision.

However, research guiding the integration of learning analytics into course catalogues is rare. Existing studies have tended to centre on advisor-facing dashboards (Vemula & Moraes, 2024), or—when examining student perspectives—have often been limited to assessing students' general intentions to use learning analytics in academic advising (Bahari et al., 2023). In contrast, our work on course load analytics (CLA) presents a novel contribution: the intervention we investigated can be seamlessly integrated into widely used course catalogues. Unlike many other learning analytics tools, this approach could directly serve students, both independently and in combination with academic advisors, thus enhancing and broadening the potential impact of learning analytics in higher education.

The psychological mechanisms underlying student course selection in higher education concerning workload are understudied. Past research investigated course selection via surveys, focus group interviews, and machine learning, focusing on social, logistical, and content factors in course selection (Othman et al., 2019; Towers & Towers, 2020). None of these studies investigated the effect of perceived workload on course selection, except perceived difficulty (Babad & Tayeb, 2003), often based on expected grades or pass rates (Srivastava et al., 2024). Yet, since workload is a crucial moderator of outcomes in higher education (Huntington-Klein & Gill, 2021; Smith, 2019), understanding course selection in relation to workload could be one pathway toward improving academic outcomes in higher education through learning analytics. Therefore, one objective of the present research is to study how student course selection decisions are moderated by course load information. Along with credit hours, a potentially poor workload indicator (Pardos et al., 2023), we follow methodologies of past work in learning analytics on producing advanced course workload estimates (Borchers & Pardos, 2023). Given the lack of studies investigating what factors underlie student decision-making in course selection when given access to advanced CLA, we set up an experimental scenario that, unlike high-stakes in vivo experiments, allows for accurate quantification of different analytics on student course selection decisions alongside conventional course catalogue information in higher education. We contribute to the literature on how students weigh different analytics and sources of information, specifically on workload, when selecting courses in higher education.

The success condition of our presented intervention would be to see measurable relationships between CLA and course selection, including what workload facets contribute most to selection. Analytics of course load that highlight dimensions of workload going beyond time-based workload estimates might prompt students to pay more attention to these workload dimensions when selecting a course. Specifically, this is because students describe mental effort and psychological stress as less manageable than time load (Pardos et al., 2023). Further, if CLA prompt students to pay more attention to workload in general or to deliberate on workload more at the time of course selection, this could help mitigate some of the adverse factors of workload on grades and well-being identified in prior work (Huntington-Klein & Gill, 2021; Smith, 2019). Hence, *desirable* course selection strategies prompted by analytics interventions include paying more attention to workload dimensions neglected in institutional, time-based credit hour metrics (Reid & Nygren, 1988; Pardos et al., 2023) and reducing excessive amounts of workload (Borchers & Pardos, 2023).

As learning analytics research programs mature toward real-world implementation (Wise et al., 2023), it is worth noting that CLA have hitherto not been evaluated or even shown to students or academic advisors. Rolling out advanced CLA as part of real-world catalogues has high stakes. Influencing student course selection decisions could have unexpected and adverse effects on student course workload decisions. Therefore, a secondary goal of this research is to gauge up front, in a scenario-based, experimentally controlled, and low-stakes environment, how the display of such analytics influences student course selection decisions (Figure 1). Such an evaluation of advanced CLA is the logical next step in the real-world realization of such analytics support. Next to studying psychological mechanisms of course selection, effect sizes of a current analytics design allow researchers and practitioners to gauge how much student course decisions are influenced by analytics (i.e., whether they are persuasive or even persuasive to an undesirable degree such that students neglect other considerations of course selection, such as degree requirement satisfaction), and open-ended feedback in these settings can be used to refine analytics design. This is especially important since little is known about how students may factor different facets of workload (i.e., time load, mental effort, and psychological stress) into their course decisions. Taken together, experimental evaluations of analytics in higher education prior to high-stakes interventions can inform whether such analytics are ready and suitable for real-world deployment.

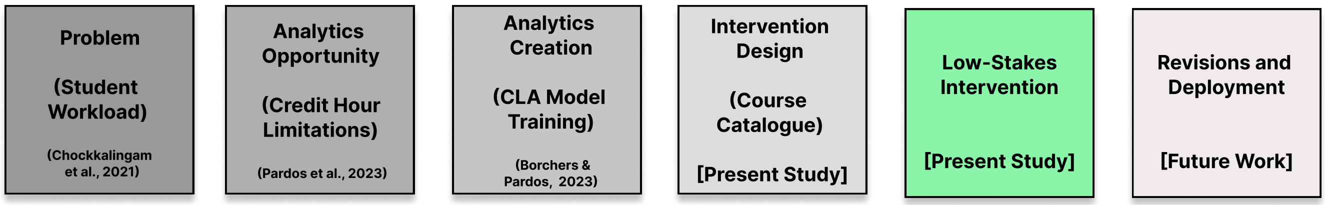

Figure 1. Summary stages of developing advanced course workload interventions in higher education. The present study (green) constitutes a low-stakes intervention, which is a crucial but often neglected step toward realizing real-world deployment of validated analytics. As indicated by a fade-out of the grey scale, few research applications of analytics go beyond their initial offline validation to their end user.

1.1 The Present Study

Our study lays out results from an experimental evaluation of the effect of the presentation of advanced CLA on student course selection decisions. Specifically, we present an initial design of such analytics to students in a pairwise binary forced-choice experiment, which asks students to choose between two courses satisfying the same requirement. CLA are then integrated into an existing course catalogue design and compared to a baseline condition in which they are not presented. Students' binary decisions across conditions then allow for the statistical estimation of the effect of the presentation of CLA on students' course selection decisions and what workload dimensions (i.e., time load, mental effort, and psychological stress) have the highest effect on students' decision-making. In other words, to gauge how much students currently take workload into account, one can consider workload as expressed in credit hours as a baseline comparison. It is worth noting that many analytics developed in the past for higher education have not made that crucial step (Larrabee Sønderlund et al., 2019), and our study describes an initial design for presenting CLA to students at scale in an experimental manner, which could serve as a blueprint for future studies dealing with similar analytics.

Our experiment is preregistered and hypothesis driven. We generated hypotheses regarding the general effect of providing CLA to students and considerations of differential effects of specific course workload dimensions. We also have some basis for hypothesizing about these factors. For example, prior work shows that when asked, students weigh mental effort most highly in their course selection decisions and find psychological stress least manageable (Pardos et al., 2023). Our hypotheses are as follows:

H1: Effect of workload expressed in credit hours on course decisions: We predict that students will more often choose courses with lower credit hours when they satisfy the same requirement.

H2: Effect of workload expressed in CLA on course decisions: We predict that students will significantly more often choose courses with lower CLA when they satisfy the same requirement.

H2a–d: This pattern is generally consistent across CLA expressed in predicted time load, mental effort, psychological stress, and their average (i.e., combined CLA).

H3: As students expressed that mental effort has the highest importance for them when choosing courses in our past work, we expect the effect of mental effort in H2a–d to be significantly larger than any other effect of CLA.

H4: When both CLA and credit hours are available to students, we predict that students will give more weight to CLA than credit hours when selecting courses; that is, the marginal effect of credit hours on course selection decisions when conditioning on CLA is non-significant.

H4a–d: This pattern is generally consistent across CLA expressed in predicted time load, mental effort, psychological stress, and their average (i.e., combined CLA).

Our contributions are threefold. First, we gathered empirical evidence from a randomized controlled experiment that the presentation of advanced CLA was related to students being more likely to choose courses that are lower in predicted workload. Second, CLA influenced student decision-making more strongly than credit hours, which, in the control condition, were not associated with student course selection decisions. Therefore, our findings suggest that the presentation of such analytics generally leads to students reflecting more on course workload and its facets (i.e., time load, mental effort, and psychological stress), which prior work has found to be associated with student academic outcomes (Karimi-Haghighi et al., 2022; Smith, 2019). Third, we gathered additional evidence that students care most about mental effort compared to time load and psychological stress when presented with advanced CLA, emphasizing prior findings highlighting that a time-based metric only (e.g., course credit hours) is insufficient to encapsulate higher education students' course workload experiences (Pardos et al., 2023).

2. Literature Review

2.1 Workload in Higher Education

In higher education, the credit hour now serves as a standardized proxy for course workload, indicating how much time students should expect to invest in a class. Its origins trace back to Harvard in the late 19th century, when Charles Eliot's introduction of the elective system created a need for standard measures of student progress, initially tied to classroom contact hours (Heffernan, 1973). The concept expanded through the adoption of the Carnegie unit, which linked faculty retirement funding to an institutional standard of 120 hours of instruction, further cementing time as the basis of measuring academic credit (Shedd, 2003). Around the same period, metrics like the "student hour" emerged to quantify productivity, costs, and outputs based on student engagement (Cooke, 1910). These time-based measures influenced current international standards, including the European Credit Transfer and Accumulation System (ECTS), which similarly uses expected student workload as its foundation (Silva et al., 2015). The US Department of Education defines a credit hour as one hour of classroom instruction plus two hours of out-of-class work per week (Laitinen, 2012). Although historically tied to instructor hours, the credit hour now reflects the student's perspective as well, serving as the primary official signal of expected effort and a proxy of the overall course workload, as opposed to contact hours only. Indeed, students often rely on credit hours when choosing courses, balancing workload, and managing academic success. Research shows that students with higher GPAs often attempt more credits, and institutions with fixed-term tuition structures may prompt students to enrol in more courses to reduce time and cost to degree (Cummings & Knott, 2001; Bound et al., 2007).

Notably, all of the historical roots and contemporary uses of credit hours to describe higher education workload are *time-based* representations of work. However, psychological research recognizes workload as a multidimensional construct (Reid & Nygren, 1988). Therefore, credit hours may not fully capture the complexity of a course's workload, for which there is empirical evidence based on studying undergraduate perceptions of course workload along multidimensional lines through surveys (Pardos et al., 2023). Past research emphasizes the multidimensional nature of workload, including time load, mental effort, and psychological stress (Reid & Nygren, 1988). While mental effort relates to the difficulty of learning complex tasks (Paas et al., 2010), psychological stress is routinely measured through self-assessment of excess workload (Ilies et al., 2010).

Inadequate consideration of course workload in undergraduate students' course selection is one source of adverse academic outcomes. Yet, previous research on higher education workload and outcomes primarily relied on time-based metrics despite prior work treating workload as a multidimensional construct. A recent study suggested that reducing academic workload in credit hours could lower dropout risk (Karimi-Haghighi et al., 2022). Another study noted increased time spent on coursework before deadlines (Ruiz-Gallardo et al., 2011). Limited research explores how known factors in STEM degree attainment, for example, math and English preparedness in community college transfer students, may be explained by differences in resulting mental workload (Zhang, 2022). Similarly, regarding psychological stress, limited research explores students' coping mechanisms for high workloads and resulting psychological stress. Some students may sacrifice leisure to manage their time load and avoid low grades (Huntington-Klein & Gill, 2021), potentially impacting their well-being (Smith, 2019). Mismatches between course workload and student course selection may also indirectly relate to outcomes via procrastination (Wäschle et al., 2014) in relation to academic outcomes. An open question remains whether adjustments to student course decisions and their resulting course loads may improve the outcomes that have been found to relate to suboptimal or excessive "workload packages" (Borchers & Pardos, 2023). The present study paves the way for a real-world intervention of CLA that tentatively encourages students to reflect on and change their course selection decisions related to the expected workload by studying how CLA change students' course selection decisions.

2.2 Analytics-Based Higher Education Interventions and Course Selection

Analytics play an increasingly important role in the landscape of higher education interventions (Fischer et al., 2020). One class of such interventions is course decision-support systems. Multiple systems to date have used large-scale, rich institutional data to create and scale such systems. The CARTA project offers students course-related data, including past grade distributions and overall evaluation ratings, to support course selections (Chaturapruek et al., 2021). The ATLAS system provides students with enriched course information built through volumes of institutional data, including student composition, grade histories, student evaluations of learning, and subsequent courses taken. ATLAS integrates features such as a schedule builder and collection creation, further aiding course selection decisions, with design features co-designed with instructors and academic advisors (Evrard et al., 2023). Similarly, AskOski leverages institutional enrolment data and machine learning to aid course selection decisions by recommending to students courses to enrol in based on personalized topical interest and considerations of requirement satisfaction (Pardos et al., 2019). Finally, Pathways has been proposed as a tool to visualize course enrolments as “academic pathways” to support student course selection by offering students unique insights into the academic choices of previous students and their resulting academic course sequence (Chen et al., 2022).

Some of these systems have examined the short-term impact of informational interventions when deployed in student course catalogues or digital course selection infrastructure. While CARTA found no improvements to academic outcomes for students gaining access to advanced course catalogue information (Chaturapruek et al., 2021), AskOski has conducted experiments investigating the effects of different course selection algorithms on student-reported course relevance to their goals (Jiang et al., 2019). Consequently, the current scientific understanding of how informational interventions relate to course selection and subsequent academic outcomes is limited. This is partly because course selection in higher education has a considerable impact on student careers and, ultimately, life outcomes (Chaturapruek et al., 2021), making the stakes high. Therefore, any intervention deployed in the real world ought to be carefully tested and analyzed in a low-stakes setting via experiments with fictional course selection environments, which is at the heart of the present study. Furthermore, a gap exists between the conceptualization and real-world impact of learning analytics in this context. In higher education, only 11 out of 689 surveyed studies in a systematic review have specifically measured the effectiveness of learning analytics interventions in terms of academic outcomes as opposed to outcome prediction and capability building (Larrabee Sønderlund et al., 2019). Similarly, interventions might not be well integrated into the administrative structure of higher education institutions or there may not be much intervention-based experimentation for the validation of analytics effectiveness for student academic outcomes (Wise et al., 2023). For evaluations of real-world impact, low-stakes interventions are necessary to eventually transition to high-stakes interventions with tangible improvements to academic outcomes (Figure 1). The present study presents a low-stakes intervention in the context of advanced CLA in higher education.

2.3 Course Decisions in Higher Education

The elective system in the US and its large-scale adoption in that country have granted millions of students considerable freedom over their course choice (Heffernan, 1973). Two emerging strands of literature have since shaped the study of how students choose their academic courses: what motivates students to choose courses and how predictable these choices are. First, past work has discerned factors underlying student motivation in higher education: quality of instruction, quality of curriculum, interactive classrooms and effective management practices, progressive assessment, and timely feedback (Sogunro, 2015). Prior work also confirms that these factors play a role in student course selection, at least in more advanced college courses (Babad et al., 1999). Other studies have documented that students tend not to select hard courses unless they have to and that learning value and lecturer style are the most influential student course selection decisions (Babad & Tayeb, 2003). However, while it is, therefore, likely that various course factors also play a role in micro-level course selection decisions, there is a lack of research into analytics-based interventions representing novel course attributes (e.g., predicted workload) in that context, which the current study allows for by studying course selection as an experimental, binary choice scenario where students select between two courses satisfying the same requirement.

Second, regarding course selection prediction, nascent work demonstrates that the prediction of academic course selection becomes increasingly feasible based on rich institutional data records. A recent study indicates that a student’s initial enrolled course strongly predicts their eventual major declaration, using natural-language methods and vector embeddings for forecasting (Lang et al., 2022). Similar results have been reported in Chaturapruek and colleagues (2021).

3. Methods

All methodologies, including hypotheses, were preregistered, and all data analysis code is publicly available[1].

3.1 Sample

We surveyed $N = 61$ undergraduate students at a large public university in the US, the University of California, Berkeley (UC Berkeley). All participants were currently enrolled undergraduate students in the university’s largest college in terms of student body. This college provides over 80 majors across disciplines in the arts, humanities, natural sciences, and social sciences. Further, the college student body is about 30% White/Caucasian, 37% Asian, 15% Hispanic, 4% African American/Black, and 1% Native American, and includes 13% international students. Sampling from one college was performed to ensure standardized requirement categories during the course selection experiment. Participants were $M = 20.49$ ($SD = 1.13$) years old, with 36 participants being female, 23 being male, and two being non-binary. The median university standing of the sample was the third semester. Participants were recruited through mailing lists, social media, and university-wide recruitment channels for behavioural research. Participants completed the survey in their own time, online and unsupervised, with each survey taking approximately 45 minutes to complete. Each participant received a $45 Amazon gift card for successful survey completion.

[1] Preregistration: https://osf.io/4kqyr/; code: https://github.com/CAHLR/course-selection-JLA/

3.2 Experimental Design

The present study employed a randomized controlled within-subjects design measuring student course selection decisions as a binary, forced-choice experiment. Specifically, students were tasked to repeatedly choose between two university courses, with displayed course catalogue entries for each. In addition, each course pair would satisfy the same requirement category. This ensured that the courses were comparable, as choosing between courses to fulfill the same requirement is a common task students perform during academic planning. Course pairs were sampled from university-wide requirements ($N = 30$) and college-specific requirements ($N = 25$), such that the 61 participants in the present study's sample rated a total of $N = 3355$ course pairs. A prompt accompanying each course pair asked students to choose one of the two courses, assuming they would need to take one. The prompt further specified the requirements that both courses would fulfill.

The course selection experiment consisted of two conditions, with random assignment performed on the level of individual course pairs: the control and the intervention conditions. The *control condition* was modelled after a standard course catalogue entry at the study site university. Students consult that course catalogue when looking for courses to enrol in. Catalogue entries include, among others, a course title and name, instructor name, number of credit hours, and a short description. At the study site, one credit hour is defined as one hour of in-class instruction per week as per campus policy[2], with the expectation that students devote an additional two to three hours of study time outside of class for every credit hour earned. They also include administrative course attributes such as the time and place the course meets, the number of seats, textbooks, and through what period the course is offered. However, these administrative attributes were omitted from course catalogue entries in the present study for brevity and because we did not expect them to systematically alter student course selections in our experiment. The *intervention condition* represented an augmented course catalogue entry, adding advanced analytics of course workload to the traditional, time-based credit hour metric. The design rationale for adding additional analytics to credit hours, rather than replacing credit hours, is that CLA are unlikely to replace credit hours in real-world course catalogues, as credit hours fulfill essential administrative functions such as measuring and ensuring a minimal amount of enrolment for each student. The design of the intervention condition is further described and visualized in Section 3.4.

3.3 Sourcing of CLA Predictions

To produce relevant and valid CLA, we followed methodologies from prior work using courses in the study site's course catalogue. First, ground-truth labels of student workload perceptions of courses at the end of the semester were collected from students taking the courses along the dimensions of time load, mental effort, and psychological stress, based on the Subjective Workload Assessment Technique (SWAT) (Reid & Nygren, 1988). Further, we used an adapted survey of SWAT relevant to higher education contexts as described in Pardos and colleagues (2023). Having collected $N = 332$ ground-truth course load ratings from 128 students on 5-point Likert scales of each construct and their average, we trained four machine learning models for cross-validated and out-of-sample validation, leveraging institutional LMSs and enrolment data features following prior work on machine learning workload predictions and their validation described in Borchers and Pardos (2023). We ensured satisfactory out-of-sample accuracy of our machine learning model, as documented in Borchers and Pardos (2023). We then generalized our machine learning models to all courses at UC Berkeley, except for courses introduced after spring 2022 ($N = 6150$). From these courses, we took CLA predictions for $N = 145$ unique courses in our sample for the paired-choice experiment. Based on these raw CLA estimates, we computed summary statistics of each course and their relative differences, as described in the next section.

3.4 Intervention Design

The intervention condition (see Figure 2) included analytics of predicted time load, mental effort, psychological stress, and overall course load, equal to the average of the three individual course workload subdimensions for real courses at the study site (see Section 3.3) to ensure a naturalistic decision-making context while preserving the benefits of estimating effect sizes in experimentally controlled settings. We emphasize that our intervention was not designed to steer students into a specific kind of course choice, that is, toward choosing courses with lower or higher workloads. Instead, our goal was to offer an overall assessment and comparison of the workload as indicated by CLA and credit hours. Each of the three subdimensions (time load, mental effort, and psychological stress) was visualized using a continuous diagram, placing each of the two courses of a course selection pair on a standardized scale with a mean of zero and a standard deviation (*SD*) of three, chosen to provide students with a standardized scale across all three subdimensions, with standardization performed on all 6150 courses at the study site. Visualizations indicated that the mean of the distribution corresponded to an average course load. In addition to these subdimensions, course catalogue entries in the intervention condition included a credit hour estimate based on the predicted overall course load. That estimate was computed by (1) computing how many standard deviations above or below the mean a given course's overall predicted workload analytics is (out of all courses offered at the institution with such predicted metrics, averaging standardized predicted time load, mental effort, and psychological stress) and (2) assigning the credit hour

[2] https://academic-senate.berkeley.edu/coci-handbook/2.3.1

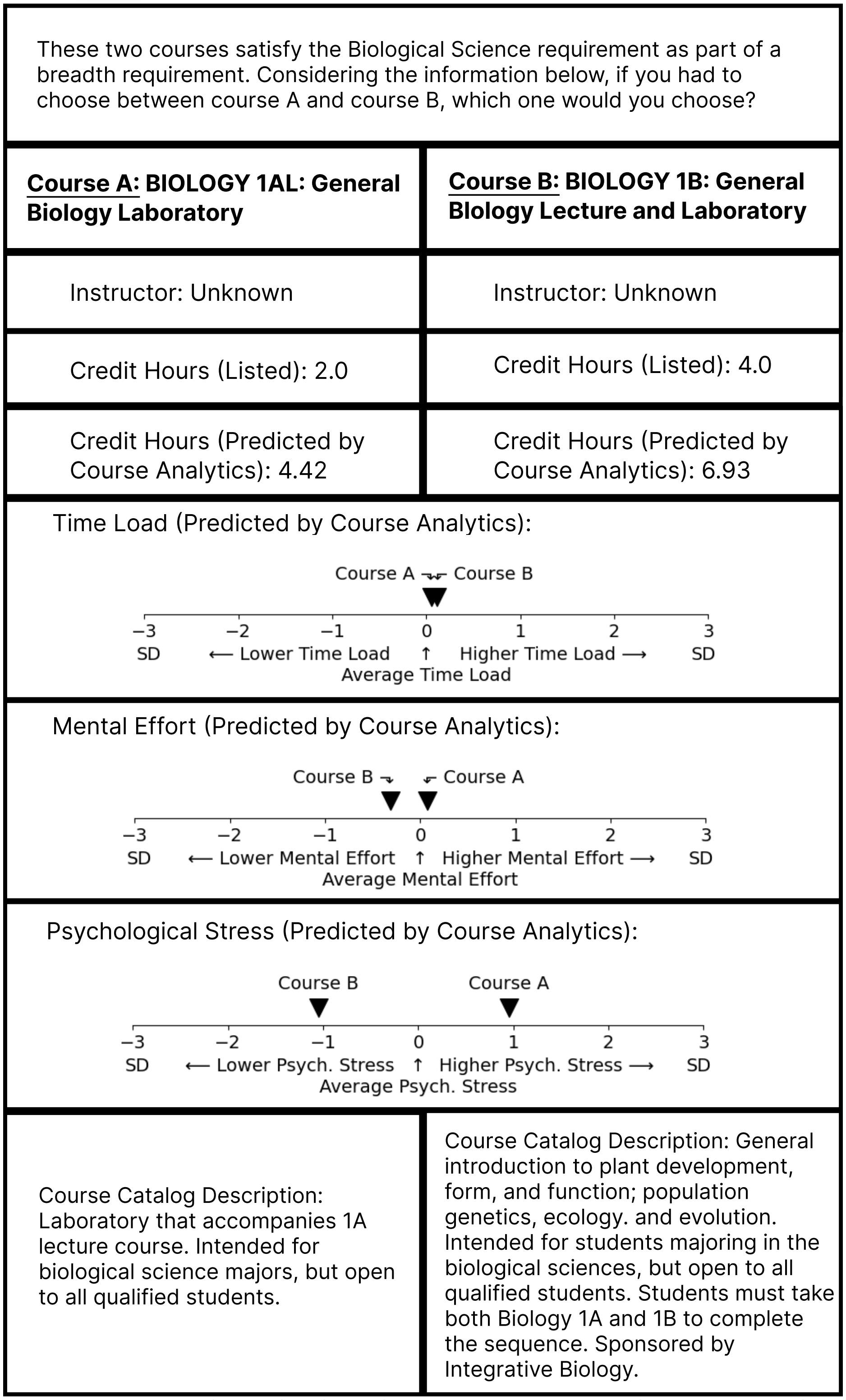

Figure 2. Intervention design, including the prompt accompanying the course pair.

designation that corresponds to that number of standard deviations in the distribution of credit hours. For example, if a given course had a predicted overall course workload of +1.45 *SD*s, then the corresponding credit hour conversion is the value corresponding to +1.45 *SD*s above the mean of the credit hour distribution.

3.5 Procedure

Participants were guided to a virtual survey environment in Qualtrics. The experiment began with a brief introduction to the experimental task and CLA. Specifically, the dimensions of time load, mental effort, and psychological stress were explained in line with the SWAT workload model (Reid & Nygren, 1988). Further, students were told that CLA are machine-learned predictions that leverage course-level data from the campus LMS and enrolment records (e.g., grade data and co-enrolment sequences). Finally, an annotated example of the analytics similar to that shown in Figure 2 ensured consistent understanding across students. Specifically, these annotated examples explained the relative predicted workload (i.e., *SD*s). The expressed *SD*s were defined as relative to all courses at the university, with the university-wide average being zero. The experimental task asked students to choose between two courses based on course catalogue entries, given that they would satisfy the same course requirement category. The instructions asked students to choose among courses as if they were planning their academic semester, that is, what courses they would be more likely to enrol in if they had to make a choice. Students chose among 60 course pairs, with predetermined assignments to either the intervention or control condition. This ensured that 30 course pairs per student were part of the control and 30 part of the intervention condition. All students ranked the same course pairs but in a randomized order, such that the order of the conditions was also randomized.

3.6 Measures

For each binary course selection response, the target variable represented whether students selected course A (on the left) over course B (on the right). That outcome is defined as a binary indicator variable of whether course A has been chosen, which allows for logistic regression modelling of course selection decisions, as is common in the analysis of forced-choice experiments (Brown, 2016). To estimate the effect of predicted CLA and credit hours on these course selection decisions, we similarly computed binary indicator variables representing whether or not course A has a strictly lower workload as expressed in credit hours or CLA (including their subdimensions) than course B. This allows an estimate of the extent to which students' course selection decisions corresponded to the workload alignment between both courses, that is, whether students follow the relative course ranking in terms of their credit hours or predicted workload. Finally, a binary indicator variable representing the experimental condition was coded to model the interaction effects of workload with the intervention condition, with the control condition as the reference category.

3.7 Analytical Methods

3.7.1 Modelling

Linear mixed model logistic regression with random effects (i.e., individualized participant intercepts for repeated measurements) was used to analyze the impact on student course selection decisions of CLA and the relative rankings of courses regarding their workload. As the modelled outcome for each paired course selection decision was whether students would choose course A, the models included individualized student intercepts that estimate the bias of individual students to select course A over course B. Mixed modelling is crucial to control for that bias and adequately estimate *p*-values given repeated observations per student (Bolker, 2015). We introduce three model formulas.

The first model (equation 1) represents a null model without any effect of course workload but only an individualized student intercept τ_s on the outcome of choosing course A (Y_A):

$$Y_A \sim \tau_s. \tag{1}$$

A credit hour model (equation 2) adds a fixed effect (β) for whether the credit hours of course A are strictly smaller than those of course B:

$$Y_A \sim \tau_s + \beta_{CH_A < CH_B}. \tag{2}$$

A CLA model (equation 3) adds a fixed effect (β) for whether the overall predicted course workload, that is, the average of time load, mental effort, and psychological stress of course A, is strictly smaller than that of course B. This model is fit to data of the intervention condition only:

$$Y_A \sim \tau_s + \beta_{CLA_A < CLA_B} \mid \text{Intervention}. \tag{3}$$

Similarly, relative effects for each workload subdimension (timeload or TL, mental effort or ME, psychological stress or PS; equation 4) can estimate their relative importance and weight on student course selection decisions:

$$Y_A \sim \tau_s + \beta_{TL_A < TL_B} + \beta_{ME_A < ME_B} + \beta_{PS_A < PS_B} \mid \text{Intervention}. \tag{4}$$

Finally, a comparative model (equation 5) of credit hours and CLA can estimate the relative weight of both alternative workload metrics on student course selection decisions via an interaction of both β terms with the experimental condition:

$$Y_A \sim \tau_s + \beta_{CH_A < CH_B} * \beta_{intervent.} + \beta_{CLA_A < CLA_B} * \beta_{intervent.}. \tag{5}$$

All effect sizes (β) are reported in terms of odds ratios (*OR*s). *OR* represents the ratio of two odds ($\frac{p}{1-p}$) of choosing course A over course B given an independent variable (e.g., the credit hours of course A being lower than those of course B). For example, an *OR* of 2 indicates that the odds of choosing course A are twice as large if course A's credit hours are lower, while an *OR* of 0.5 suggests that the odds are half as large. We conducted likelihood ratio and coefficient tests of different model complexities to test our hypotheses (see Section 1.1), as described next.

3.7.2 Hypothesis Tests

The likelihood-ratio test between model 1 and model 2 corresponds to H1. Wald-tests of whether course A's credit hours are smaller than course B's investigated the specific direction of the association. The likelihood-ratio test between model 1 and model 3 corresponds to H2a. Wald-tests of whether the CLA of course A are smaller than those for course B investigated the specific direction of the association. This procedure was replicated three times with models featuring the individual CLA subdimensions for tests of H2b–d.

Three pairwise linear hypotheses regarding the equivalence coefficients in model 4 were used to establish whether individual coefficients are significantly different, corresponding to H3. Wald-tests were also used to confirm the specific direction of the association. Wald-tests in model 5 were used to test if the marginal effect of credit hours is non-significant in the intervention condition but not in the control condition and if the effect of CLA is significant in the intervention condition but not in the control condition (as students do not have access to the CLA in that condition). If all of these tests aligned with these predictions, H4a would be confirmed. We also performed a likelihood-ratio test between models 2 and 5 to further interpret model fits. This procedure was replicated three times with models featuring the individual CLA subdimensions for tests of H4b–d.

For sample size planning, R simulations were used to conduct a power analysis to obtain a .95 power to detect a small effect size, a 5% increase in the probability of choosing a course with a lower workload based on credit hours and CLA (in the intervention condition) at the standard alpha error probability of .05. The standard $p < .05$ to determine the effect of each of the predictors in the model was used.

4. Results

4.1 Effect of Credit Hours on Course Selection

Our first hypothesis (H1) states that students would choose the course with lower credit hours more often. In line with H1, overall, a credit hours model described students' course selection decisions significantly better than a baseline model with just a student-level intercept ($\chi^2(1) = 13.12, p < .001$). Students, overall, chose the course with lower credit hours more often: $OR = 1.41, CI_{95\%} = [1.17, 1.69], p < .001$. However, we performed a follow-up analysis, fitting separate models by condition, and the direction of association differed by condition. In the control condition, there was no significant association between credit hours and students' course selection decisions: $OR = 0.98, CI_{95\%} = [0.72, 1.33], p = .889$. However, in the intervention condition, where advanced CLA were presented, students indeed chose the course with lower credit hours more often: $OR = 1.65, CI_{95\%} = [1.30, 2.09], p < .001$. If the predicted course load correlates with credit hours, then a unidimensional effect of credit hours could be explained by students choosing the course with a lower predicted course workload more often. However, that was not the case, as credit hours and CLA in our sample have a negligible correlation of $r = -0.07$ based on 145 courses sampled for this study.

4.2 Effect of CLA on Course Selection

Our second hypothesis (H2) states that students are more likely to choose the course with a lower predicted course load in the intervention condition. In line with H2, a predicted course load model described students' course selection decisions significantly better than a baseline model with just a student-level intercept ($\chi^2(1) = 17.42, p < .001$) based on data in the intervention condition. The effect of the overall predicted course load was considerably large, with the odds of choosing the course with a lower predicted course load being around three times as large as in the control condition, where those odds were about 1:1, $OR = 3.18, CI_{95\%} = [2.60, 3.88], p < .001$. This pattern was also consistent when modelling individual subdimensions instead of the effect of the overall predicted course load, as shown in Table 1.

Table 1. Estimated effect sizes of individual predicted course load subdimensions as expressed as the *OR*s of choosing course A if course A has less workload according to those dimensions based on $N = 3355$ rated course pairs.

Coefficient	*OR*	$CI_{95\%}$	*p*
Intercept	0.37	0.30–0.46	**<.001**
Time Load Smaller	1.34	1.08–1.67	**.007**
Mental Effort Smaller	2.85	2.25–3.60	**<.001**
Psych. Stress Smaller	2.03	1.63–2.53	**<.001**

In line with Table 1, each course load subdimension led students to significantly more often choose the course with a lower predicted course load when the predicted load of a given course was smaller. Descriptively, mental effort had the largest marginal effect, estimated to be $OR = 2.85, CI_{95\%} = [2.25, 3.60], p < .001$.

What predicted course load did students choose in both conditions? Figure 3 visualizes the distribution of the predicted workload of chosen courses in terms of their standardized CLA. Overall, students exhibited a course selection behaviour that is in line with the desired intervention goal of reducing overall CLA. Specifically, students in the intervention condition chose not only an overall lower predicted workload but also a workload that is more centred around zero, that is, an average workload of courses at the study site. In the control condition, the median predicted workload of selected courses (which students were unable to see as no analytics were presented) was well above zero. However, Figure 3 also reveals that the predicted workload distribution of chosen courses in the intervention condition was bimodal, with local minima of about -0.3 *SD*s and 0.3 *SD*s of CLA. The higher CLA also corresponded to higher credit hours, with an average credit hour of selected courses of $M = 3.87$ for the higher CLA maximum and $M = 3.76$ for the lower maximum. These averages were based on aggregating the average credit hours of selected courses within the histogram bins corresponding to the two minima: -0.37 to -0.04 and 0.30 to 0.63, respectively, rounding to two decimal places. This difference in credit hours between the two intervals was statistically significant based on a simple t-test, $t(1761) = 5.92, p < .001$. As further analyzed in Section 4.3, this bimodal distribution maps onto the desirability of high credit hours at the occasional expense of higher workload courses.

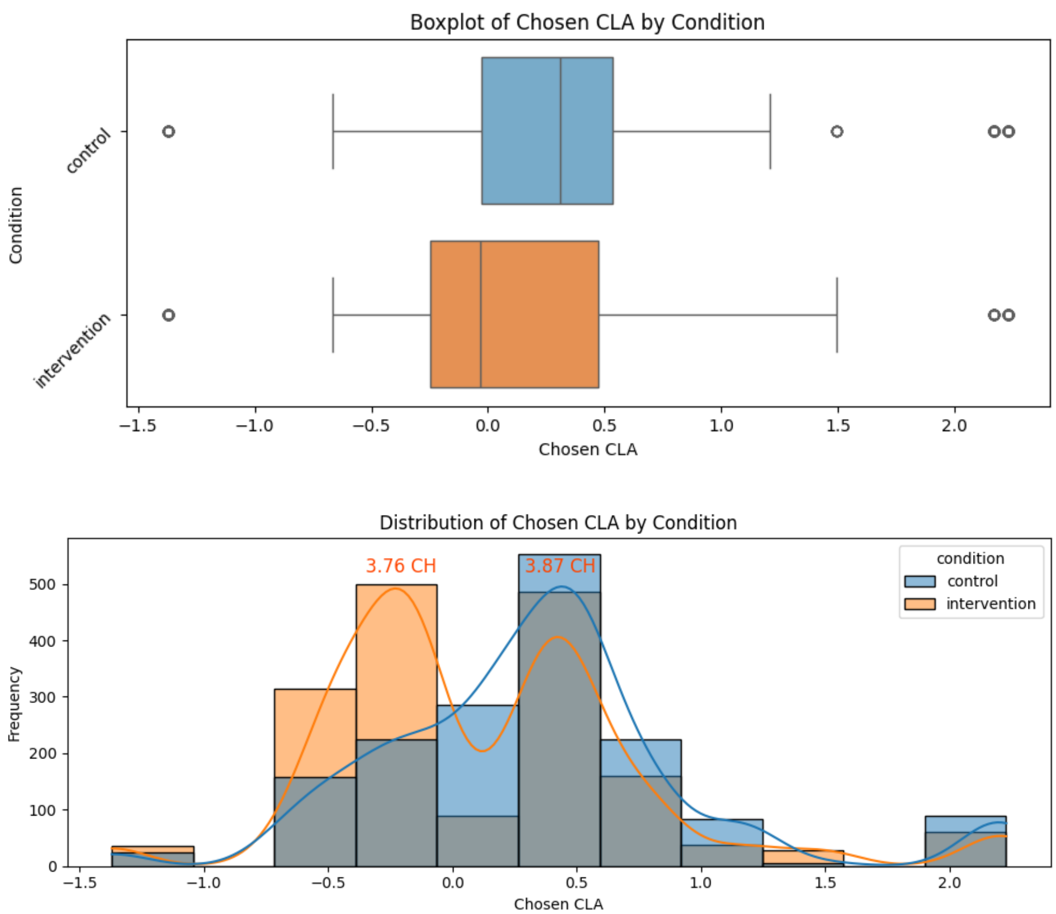

Figure 3. Boxplot (top) and histogram with estimated density distribution and average credit hours (CH) at local maxima (bottom) visualizing the standardized chosen CLA by condition standardized to a mean of zero and a standard deviation of one.

Our third hypothesis (H3) says that mental effort would be significantly larger than the effects of time load and psychological stress, which we estimated in Table 2.

In line with Table 2, we indeed find that mental effort had a significantly larger effect on student course selection decisions than time load ($p < .001$) but was only marginally significantly larger than the effect of psychological stress ($p = .078$). However, the effect of time load was also significantly smaller than that of psychological stress ($p = .007$), confirming that time load was the least important dimension in student's course selection decisions within the overall effect of predicted course load.

Table 2. Linear hypothesis tests of coefficient equivalence of time load (TL), mental effort (ME), and psychological stress (PS) to ascertain the significance of whether mental effort had the largest coefficient among all estimated effect sizes. Significance indicates that the hypothesis is rejected.

Hypothesis	χ^2	df	p
TL = ME	28.49	1	$<$.001
TL = PS	7.39	1	.007
ME = PS	3.10	1	.078

4.3 Joint Modelling of Credit Hours and CLA

The analysis of H1 (see Section 4.1) revealed that credit hours were significantly associated with students' course selection decisions. Expanding on the model featured in that analysis, H4 predicted that if the effect of CLA and credit hours was jointly modelled, the effect of credit hours would become insignificant when both credit hours and advanced CLA were available to students in the intervention condition. First, in line with H4, a model featuring CLA in addition to credit hours, including the hypothesized interaction between condition and both workload metrics, described the data significantly better than the credit hour model of H1, $\chi^2(4) = 151.13, p < .001$. Table 3 gives an overview of the fitted model parameters.

Table 3. Estimated effect sizes of different workload metrics as expressed as the *OR*s of choosing course A if course A has less workload according to those dimensions, including interaction effects of condition (with the control condition as reference category) based on $N = 3355$ rated course pairs.

Coefficient	OR	$CI_{95\%}$	p
Intercept	1.10	0.96–1.26	.171
Credit Hours Smaller	1.21	0.87–1.68	.268
Condition [intervention]	0.63	0.52–0.76	**<.001**
CLA Smaller	0.70	0.57–0.86	**.001**
Credit Hours Smaller × Condition [intervention]	0.52	0.33–0.82	**.005**
CLA Smaller × Condition [intervention]	5.68	4.09–7.88	**<.001**

As displayed in Table 3, in line with H4, credit hours have no significant effect on student course selection decisions in the control condition ($OR = 1.21, p = .268$). However, even more so, students were *less* likely to choose the course with the lower credit hours in the intervention condition, where both credit hours and CLA were available to students ($OR = 0.52, p = .005$) when adjusting for CLA. At the same time, in line with findings for H2, students were significantly more likely to choose courses with lower CLA in the intervention condition ($OR = 5.68, p < .001$). Notably, when CLA were not present, students' baseline behaviour was associated with courses having higher CLA ($OR = 0.70, p = .001$). To make these associations more intuitive, the probability of students choosing course A in the intervention condition based on the relative ranking of workload expressed in credit hours and overall predicted workload is visualized in Figure 4.

In line with Figure 4, in the intervention conditions, students' choices were always aligned with whether CLA were smaller or not. Specifically, when course A's predicted workload was smaller but credit hours larger, students were even more likely to choose the course with a lower predicted workload than when credit hours aligned with the predicted load. In other words, students generally chose the course with a lower predicted workload, but the prospect of receiving more credit hours while also taking the course with a smaller predicted workload had an even stronger effect on students' course selection decisions.

Figure 3 indicates a bimodal distribution where chosen courses with higher credit hours also had higher CLA. How much more predicted workload are students willing to spend to gain additional credit? To this end, we use the model parameter estimates of the H4 model (equation 5) to average the predicted workload for chosen courses with and without higher credit hours for course pairs where course A had a lower predicted workload. We estimated that students are willing to work an additional 21.2% (0.22 *SD*) predicted workload if a course offers more credit than if it does not. This corresponds to a reduction of 10% in the average predicted workload of one credit hour. This means that students' decision-making aligns with spending *more* predicted workload to gain more credit but *less* workload than the average credit hour, meaning that students tended to try to minimize expected workload while maximizing credit, putting more weight on the former.

Credit hours were not associated with course selection decisions compared to overall CLA in the intervention condition. We tested if that was consistent for time load, mental effort, and psychological stress (H4b–d). Results generally aligned with the main results for the overall predicted course load, with two exceptions. First, there was no significant interaction between the intervention condition and time load when adjusting for credit hours ($OR = 1.19, p = .221$). Students did not choose courses based on predicted time load, except when it aligned with credit hours. In other words, the intervention effect of CLA was

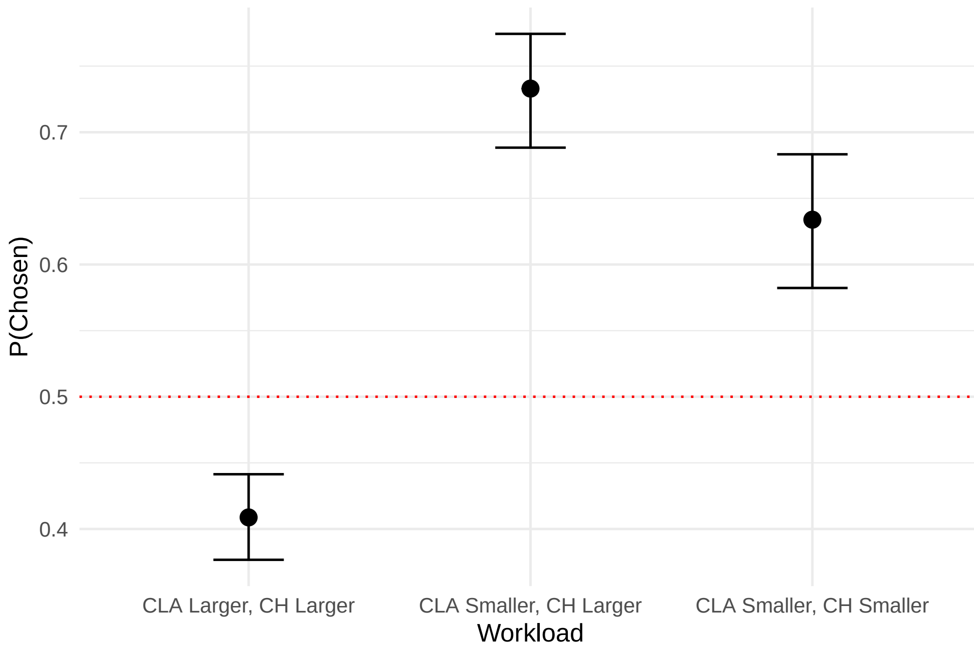

Figure 4. Probability of students choosing course A over course B by whether the workload of course A expressed in credit hours (CH) and predicted workload is smaller than course B's in the intervention condition, including 95% confidence intervals. Note: No course pair included course A with strictly lower credit hours but a larger predicted workload.

specifically associated with mental effort and psychological stress ratings. Second, when the credit hours of a course were strictly smaller but the predicted workload was not, students' course selection decisions were generally not associated with the predicted workload, except for higher psychological stress. The correlations between predicted workload and credit hours were $r = -0.30$ for time load, $r = -0.13$ for mental effort, and $r = 0.07$ for psychological stress, based on 145 courses sampled for this study.

4.4 Exploratory Analysis of Differential Effects of Student Standing

More senior standing students might have had more experiences in perceiving discrepancies between credit hour designation and actually experienced workload, which only weakly correlate with one another (Pardos et al., 2023). Therefore, we investigated if the effect of CLA might be more pronounced in more senior standing students, as they might perceive more value in alternative metrics to credit hours. A natural split in our data is between first-year students ($N = 11$) and students in at least their second year ($N = 50$). Students at the college from which the sample was taken are often admitted undeclared and do not have to declare their major until around the end of their second year or beginning of their third. We note that incoming transfer students are treated as being in their third year when they enter the university.

There was a regularity in the effect of CLA on the intervention condition between first-year and more senior standing students. A linear mixed model of course choice as an interaction of condition, CLA, and student standing did not fit the data better than a model without the interaction term of student standing (which is analogous to the CLA model in Section 4.2) based on a likelihood-ratio test, $\chi^2(8) = 2.01, p = .981$.

4.5 Open-Ended Feedback on the Analytics Design

An open-ended question at the end of the survey asked students about general feedback of the intervention design, reading "Please add 2–3 sentences on what you thought about the display of additional course load analytics and any feedback you may have." We highlight three improvements to our current intervention design that emerged from students' responses based on an informal analysis. First, there were prevalent concerns and suggestions regarding the clarity and visual appeal of the interface. Students expressed a desire for a clearer display of analytics, with one participant suggesting, "I think it was a bit bland, needs more design work to be user-friendly." Second, concerns and skepticism were voiced regarding the reliability and validity of the data and produced analytics. Some students deemed the course analytics as untrustworthy, citing personal disagreements, as expressed by one participant: "Course analytics felt untrustworthy since I personally disagreed with ratings on multiple courses." Furthermore, one student assumed that the analytics were trained based on student course evaluations (which they are not), which they perceive to be unrepresentative of the student population, stating, "I would be concerned over the type of people who provide data that create the course load analytics. I know that there aren't many people who fill out course evaluations, and the ones who do only fill them out if they really loved the class or really hated it [...].” Therefore, better explanations of the produced analytics could help alleviate some of those student concerns. Third, participants proposed including grade distribution information related to courses and introducing more interactive features to enhance user experience. Overall, students perceived the intervention as useful and relevant in supporting their course selection: “The course analytics is a great system of support for students who are unsure about which classes to take.” Another participant emphasized how the intervention augments traditional course descriptions, noting, “I think it was helpful since the status quo of just the description is not enough information.”

5. Discussion

The present study investigated the efficacy of novel and scalable analytics of course workload in higher education in a low-stakes, experimentally controlled environment. Prior work suggests that credit hours, a time-based course workload metric, are a poor proxy of student course workload experience and that analytics of course mental effort and psychological stress are additional components relevant to student course workload experiences (Pardos et al., 2023; Borchers & Pardos, 2023). However, such advanced analytics of course workload are predictable via institutional data at scale, but they have not been formally evaluated with students concerning their influence on course selection decisions, a necessary step to integrate them into academic advising and institutional course catalogues, unlocking their potential to improve student educational outcomes. Our results contribute to the emerging area within learning analytics of advanced, analytics-based course recommendation and catalogue systems that can support higher education students (Chaturapruek et al., 2021; Evrard et al., 2023; Pardos et al., 2019; Chen et al., 2022).

In this preregistered experiment, we hypothesized that students would generally choose courses with lower predicted workloads when presented with advanced analytics about them (H2). Our results strongly support this hypothesis, with the odds of selecting courses in line with the overall lower predicted workload being estimated at about three times as likely as in the control condition. The effect was consistent across individual facets of predicted course load (time load, mental effort, and psychological stress) and regular across first-year and more senior standing students. The regularity of the intervention effect across students is desirable to avoid heterogeneous effects of the intervention on subpopulations, for example, historically disadvantaged students (Yu et al., 2021). However, more investigations of student-level attributes are needed to further support this hypothesis.

Students also generally chose the course with lower credit hours (H1). However, contrary to H4, they did not disregard institutional credit hours in their decisions when advanced CLA were presented to them. Rather, we gathered evidence that students paid *more* attention to credit hours when such analytics were present. Specifically, when the predicted course load was lower, students favoured a course more strongly if it had more credit hours. In other words, students not only tried to minimize the expected workload (in line with the finding that they ascribed CLA higher reliability in measuring workload than credit hours) but also tried to maximize credit. Specifically, we estimated that students are willing to expend around 20% more workload on a course if it will earn them additional credit hours. This decision may be influenced by the inherent value of credit hours as they relate to satisfying degree requirements. This decision-making model aligns with the notion that students prefer taking courses that are easier in order to preserve resources: students need a certain amount of credit hours to graduate and maintain student status[3]. Therefore, if students can earn more credit toward their educational goals with less effort, they prefer preserving additional resources that they would need to expend for attaining the same goal. This finding is also desirable because it shows that CLA do not simply persuade students to automatically choose courses with lower workload and avoid high-workload courses; rather, they prompt students to be more strategic about their resources and workload, including facets of workload relevant to student experience that institutional, time-based credit hours do not convey (Pardos et al., 2023; Huntington-Klein & Gill, 2021; Smith, 2019). Past work pointed out that students generally avoid taking hard courses unless they have to (Babad & Tayeb, 2003) and prefer taking easier electives (Srivastava et al., 2024). However, the present study adds nuance to that observed pattern by showing that this tendency might be related to the rational use of resources rather than avoiding effortful courses more generally. Similarly, our finding that students do not simply avoid difficult courses when they know which courses are difficult aligns with prior research finding that when students receive access to analytics of past course GPA, the average difficulty of courses students choose, as measured in courses' prior fraction of A's, does not change (Chaturapruek et al., 2018). The finding also adds credence to recent work that posits that students may cope with higher workload by cutting into their leisure time (Huntington-Klein & Gill, 2021). Therefore, one hypothesis for future work is to estimate the optimization function that students employ when trading expected workload with credit hours. Our results offer one data point for such future work: students, on average, were willing to spend around 90% of the predicted workload related to the average credit hour, putting more weight on minimizing workload than maximizing credit, in line with our main CLA intervention effect. However, more refined statistical modelling could fit utility functions in future work.

[3] https://lsadvising.berkeley.edu/policies/unit-minimum-maximum-semester

We also hypothesized that mental effort would be the course workload facet most strongly associated with student course selection decisions (H3). Our findings align with this hypothesis but primarily highlight that it is predicted time load that students considered *less* than mental effort and psychological stress in the intervention condition. This finding adds evidence to prior work finding limitations in a time-based workload metric in higher education, specifically the time-based credit hour metric (Pardos et al., 2023; Chockkalingam et al., 2021). Advanced CLA make students think about mental effort and psychological stress during course selection, which might improve their subsequent academic outcomes, as both factors have been linked to such outcomes in prior work (Smith, 2019; Parker et al., 2006). Another reason students did not pay much attention to predicted time load is its small marginal utility beyond the time metric implied in credit hours (i.e., a certain number of expected hours per week spent on course load). Time load, in contrast to mental effort and psychological stress, is intuitive because students bargain in terms of time when selecting courses, for example, when balancing education with leisure time (Huntington-Klein & Gill, 2021).

Students not only chose courses with lower predicted course workload but also chose courses with *higher* predicted course workload when advanced analytics were not present. In fact, students in the control condition, but not the intervention condition, tended to choose above-average courses in terms of their predicted workload. Why is that the case? Naturally, students have various prior beliefs about courses, instructors, and domains that influence their baseline course decision behaviour in the control condition, with prior work linking student beliefs about knowledge and learning to major choice (Paulsen & Wells, 1998). Prior work motivates the hypothesis that excessive experienced (i.e., predicted) workload in contrast to the expected (i.e., credit hour-based) workload is especially common in first-year students and negatively related to academic outcomes (Borchers & Pardos, 2023). Therefore, the presentation of advanced CLA could potentially level the playing field and support students with little experience in managing higher education workloads. Prior work supports that differences in managing workload relate to first-year students' academic outcomes (Cheung et al., 2020). However, other students with maladaptive strategies to procrastinate on difficult academic tasks could also benefit from setting more realistic course selection goals using CLA (Wäschle et al., 2014). More work is needed to explicate the potential positive effects of CLA interventions on academic outcomes that could stem from such analytics, making students more prepared for the workload they sign up for at the time of course selection (Dika & D'Amico, 2016).

5.1 Limitations

We see three limitations to the present study. First, we observed student course selection in a low-stakes environment, which may differ from real-world decision-making. To be sure, the objective of this experiment was to test whether CLA affect student course workload decisions such that the resulting, desirable course selection behaviours tend to favour (a) a lower predicted workload that could lead to excessive effective load (Borchers & Pardos, 2023) and (b) increasing considerations of workload dimensions other than time encoded in institutional credit hours, such as mental effort and psychological stress (Reid & Nygren, 1988; Pardos et al., 2023), which is expected to relate to student experiences and outcomes, including mental health (Huntington-Klein & Gill, 2021; Smith, 2019; Ruiz-Gallardo et al., 2011). Our results align with both desirable course selection outcomes. Hence, our study objective was fulfilled. However, we acknowledge that high-stakes follow-up interventions are the next step to confirm the effectiveness of CLA interventions on meso-level and mid-term student outcomes like GPA and late course drops that we could not gauge in this study (Fischer et al., 2020). Such interventions could close the loop between CLA trained on student workload *perceptions* and improved real-world student workload *experiences*. These meso-level outcomes could encompass studies of mental health related to excessive psychological stress as observed in past research on higher education workload, especially in the context of the COVID-19 pandemic (Yang et al., 2021). While it is likely that interventions with advanced CLA would also influence student add and drop decisions in real-world settings similar to findings implied by our experiment (e.g., increased consideration of credit hours and avoidance of unintended overload by considering previously inaccessible facets of workload such as mental effort), more work is needed to investigate student decision-making through that lens. In CLA interventions, which we generally deem ready for prime time based on our findings, future work could compute semester loads based on different predicted workload facets to study student outcomes (Borchers & Pardos, 2023).

Second, for the sake of straightforward statistical modelling and estimation of intervention effects, course selection decisions were operationalized as a paired forced-choice experiment, which is less complex than real-world decision-making, where students consider adding and dropping courses from an overall set of courses or basket (Hagedorn et al., 2007). While potential inter-course dependencies exist that could lead to different decision-making outcomes than those implied in our experiment, we note that UC Berkeley generally does not enforce any prerequisites, such that this type of inter-course dependency can be partially ruled out. Still, follow-up studies could explore additional factors that may influence students' course selection behaviour during semester planning, including long-term career goals, schedules, personal preferences, and degree requirements. It is plausible that, when adding courses to their baskets, students compare each course to others already selected. However, modelling such decision-making processes remains a task for future studies, as our current findings only allow for speculations about this behaviour. More generally, given the differences in enrolment constraints at non-US or non–liberal arts institutions, our findings warrant replication and further exploration of their generalizability to other higher education contexts, such as community colleges and universities outside the US, where course selection often involves less elective choice. This will ensure that CLA interventions are effective and equitable for diverse student populations across different institutional contexts.

Third, open-ended feedback from students regarding the intervention suggests that a subset of students distrusted the present analytics, which calls for further refinements to the intervention in terms of conveyed explainability beyond the standardized introduction to the analytics offered to participants in the present study (De Laet et al., 2020). Some students said their course experience did not align with the predicted course load ratings. These misalignments could be a further source of validation for CLA (van Haastrecht et al., 2023) but also may speak to the need to personalize analytics to student attributes, as individual students' course workload experience can differ from the average course-level prediction. Future work could explain to what extent student-level calibration of analytics, as is common in higher education recommendation systems (Jiang et al., 2019), is desirable for supporting course decision-making. Based on prior work, individualization of course workload inference is expected to have significant, although small, accuracy gains (Pardos et al., 2023). One potential factor calling for individualization is the overall workload students selected during a semester, as workload capacity is limited per student (Huntington-Klein & Gill, 2021).

5.2 Implications and Future Work

A pressing question for future work is whether advanced CLA are ready to be integrated into real-world course catalogues for intervention studies on academic outcomes. We discuss implications and considerations for how higher education stakeholders other than students could benefit from and work with these analytics to support their potential to improve academic outcomes.

CLA interventions could support academic advising and curriculum analytics. Analytics could be evaluated with academic advisors and implemented during advising sessions to qualitatively study how students engage with CLA. Collaboration with advisors on intervention and analytics design could also mitigate against too much emphasis being placed on analytics over other considerations of course selection (e.g., ensuring adequate prerequisite knowledge and requirement satisfaction). For example, CLA could be shown to students when their predicted semester workload exceeds a certain threshold. Further, future work could study what differences manifest over time in student course selection when exposed to CLA and the resulting differences in pathways (Chen et al., 2022). Research on academic outcomes and trajectories is also crucial to confirm positive impact and assess the effectiveness of CLA interventions. Prior studies have shown that not all analytics-based interventions in higher education improve student outcomes. For example, displaying grade distributions to students has been found to reduce GPA, although access to such analytics did not change student course selections systematically (Chaturapruek et al., 2018). Finally, researchers could further explore which factors of courses, in the presence of CLA, contribute to student course selection and which data sources further refine CLA constructs. CLA models could potentially be leveraged to inform curriculum redesign by explaining why some courses exhibit over-enrolment while others suffer from under-enrolment. CLA interventions could then shine a light on whether better matching of students to courses happens when advanced CLA are available in course catalogues or other information or recommendation systems at the institution.

CLA could be portable to other higher education institutions. Complementing prior validation work (Borchers & Pardos, 2023), the present study adds confidence that CLA as a methodology has utility for other institutions. The results, therefore, encourage replication work of CLA and their interventions to other higher education institutions. In particular, future work could investigate CLA at two-year community colleges, which historically have a low retention rate—the academic outcome most in need of remedy (Wheeler, 2019). These replications could also estimate whether the decision point for working more for additional credit (i.e., a 20% increase in predicted workload) varies by institution. As collecting ground-truth data on student workload perceptions and sourcing institutional data types for workload prediction (e.g., enrolment and LMS data) are costly, future work should investigate if (a) CLA models trained on one institution can generalize to predict students' perceptions of surveyed workload at other institutions and (b) conduct ablation studies to estimate what data types are essential and useful to make such predictions. In the ideal case, CLA models could generalize across institutions, and course workload perceptions could be collected through integration into routine student course evaluations. These considerations would improve the accessibility and scalability of analytics.

A final application area of advanced CLA interventions could be course recommender systems (Pardos et al., 2019). Course recommender systems could help students plan their semester and have less conflict with other educational objectives, such as requirement satisfaction, as students are not primed to pay more attention to workload, as in the present study's design. A comparison of dashboards to recommender systems suggests fruitful future work regarding resulting course selection behaviour in high-stakes settings and resulting academic outcomes. More generally, course recommender settings could support students in their goal of preserving resources (i.e., minimizing workload) while maximizing credit toward degree satisfaction, a strategy students engage in, as suggested by our results. Besides hedging against students taking comparatively predicted workload courses (as observed in the control condition), they can help students avoid excessive course workloads related to adverse academic outcomes, such as late drops (Borchers et al., 2025). Finally, course recommender systems could pose an opportunity for more tempered institutional adoption, where CLA are an optional feature in recommenders, without revising official course catalogues to include analytics.

Bridging the gap between research and practice in learning analytics remains a critical challenge in educational technology research (Wise et al., 2023). A close-the-loop experiment (Liu & Koedinger, 2017) demonstrating improved student outcomes based on design recommendations from our study might involve integrating our analytics into a real-world course catalogue. During course enrolment periods, students could utilize CLA to consider factors beyond time load and obtain more accurate workload estimates in their decision-making process. Based on this study's findings, we hypothesize that access to CLA will (a) encourage students to consider a broader range of workload facets beyond time, (b) lead to more balanced and manageable semester workloads, which in turn may (c) enhance academic achievement (Wäschle et al., 2014) and student well-being (Smith, 2019). Accordingly, redesign of our current mockups should emphasize all three workload facets—time load, mental effort, and psychological stress (Reid & Nygren, 1988)—and consider highlighting cases where credit hours over- or underestimate the effective workload predicted by CLA. A randomized controlled trial assigning students to CLA access would serve as a rigorous test of its effectiveness in real-world course selection settings, providing empirical evidence to bridge the gap between research and practice.

6. Conclusion

The present study established, via a low-stakes intervention experiment, that CLA effectively change student course selection decisions. This effect was comparable across first-year students and students of higher academic standing, suggesting that different subgroups (at least those investigated in this study) have similarly strong receptivity to such analytics. The described CLA intervention was a success as it fulfilled all prior objectives: lowering effective workload, having students pay more attention to workload facets other than time encoded in credit hours, and supporting student reflection on workload rather than prompting them to reflexively choose low-workload courses. We document a strategy regarding students being more likely to take a higher credit hour course that minimizes the expected workload associated with each credit hour. This decision-making pattern aligns with a theoretical model of students attempting to preserve resources while working toward satisfying degree requirements, a deliberation enabled by CLA. Further, students' course decision patterns confirmed intuitions of prior work that showed that mental effort and psychological stress were significantly more weighted than time load by students. Notably, students in the control condition selected comparatively high workload courses, showing their baseline predispositions in course selection. This highlights the potential of CLA interventions to lower students' effective course workload and improve academic outcomes. Taken together, we conclude that CLA interventions are primed for real-world deployment in future work, where allowing students to manage and select the courses according to CLA could improve subsequent academic outcomes.

Declaration of Conflicting Interest

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