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Curriculum Analytics of Course Choices: Links with Academic Performance

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Abstract

In a higher education context, students are expected to take charge of their learning by deciding "what" to learn and "how" to learn. While the learning analytics (LA) community has seen increasing research on the "how" to learn part (i.e., researching methods for supporting students in their learning journey), the "what" to learn part is still underinvestigated. We present a case study of curriculum analytics and its application to a dataset of 243 students of the bachelor's program in the broad discipline of health sciences to explore the effects of course choices on students' academic performance. Using curriculum metrics such as grading stringency, course temporal position, and duration, we investigated how course choices differed between high- and low-performing students using both temporal and sequential analysis methods. We found that high-performing students were likely to pick an elective course of low difficulty. It appeared that these students were more strategic in terms of their course choices than their low-performing peers. Generally, low-performing students seemed to have made suboptimal choices when selecting elective courses; e.g., when they picked an elective course of high difficulty, they were less likely to pick a following course of low difficulty. The findings of this study have design implications for researchers, program directors, and coordinators, because they can use the results to (i) update the course sequencing, (ii) guide students about course choices based on their current GPA (such as through course recommendation dashboards), (iii) identify bottleneck courses, and (iv) assist higher education institutions in planning a more balanced course roadmap to help students manage their workload effectively.

Notes for Practice

- Analyzing students' choice of courses is a complex and challenging task. It is important that students be offered some assistance in course selection that can help them with their decision-making processes.
- Our study provides empirical evidence about the value of analytics that can be used for supporting program-level decision-making in higher education.
- The results can augment and support the roles of academic advisors and instructors and lead to students' success as well as institutional productivity.

Keywords

Curriculum analytics, learning analytics, course choices, course difficulty

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1. Introduction

In higher education, students are expected to take charge of their learning by deciding "what" to learn and "how" to learn (OECD, 2018). While the learning analytics (LA) community has seen increasing research on the "how" to learn part, where e.g., it is investigated how to support students in their learning journey by promoting their engagement (D'Mello et al., 2010), facilitating their meta-cognitive awareness (Matcha et al., 2020), designing feedback to promote positive affective experiences (Berland et al., 2014; Nawaz, Kennedy, et al., 2020), and designing the learning environments to be increasingly interactive (e.g., through the use of simulation-based (Nawaz, Srivastava, Yu, et al., 2020, 2022) and virtual reality–based (Nawaz, Alghamdi, et al., 2022) learning designs). The "what" to learn part (Dennehy et al., 2021), which mainly deals with students' curriculum choices, such as making a choice about which courses they want to take, is still under investigation.

The choices that students make can have a wide range of implications on their academic achievement, motivation, and employment pathways. When students enroll in a degree program, they usually have a variety of courses to select from. For instance, at the start of the degree program and then at the beginning of each semester, students need to make several decisions about which courses they should take. Analyzing students' choice of courses is a complex and challenging task (Ognjanovic et al., 2016). Several factors can influence these choices, e.g., the semester the course is offered in, the instructor, students' prior knowledge, and the course prerequisites. Based on the pathway model proposed by Kizilcec and colleagues (2023), students are active agents in their academic progress and their academic pathways are contingent on previous decisions; i.e., students, while progressing through their chosen curriculum, encounter a series of decisions related to their academic journey. For instance, for students to take multiple courses, they must choose between courses that can be taken concurrently so that the workload requirements can be met and students do not feel overwhelmed. The workload requirements are often defined based on the students' in-class contact hours as well as out-of-class preparation time—a metric often referred to as course credit hours information (Pardos et al., 2022). Recent research, however, has suggested that course load analytics (CLA), derived from learning management system (LMS) usage and enrollment data, may provide a more precise measure of actual course workload than the traditional credit hour metric (Borchers & Pardos, 2023). This task (of choosing a course) is further complicated by the depth and breadth of courses that are offered within a department and across other departments. Therefore, making *decisions* about which courses they should enroll in can often be overwhelming for students.

According to the rational decision-making model (Uzonwanne, 2016), people tend to make the best possible decisions from the available choices while incorporating the information at their disposal. It is also posited that the quality of information available to students is often insufficient or variable (Jin et al., 2011; Sutton & Sankar, 2011). Further, in a pressured setting (e.g., a fast-paced, high-pressure academic setting), individuals' decision-making and cognitive abilities can often be impaired (see Hilliger et al., 2019, for a detailed discussion on rational decision-making models in higher education).

The variability of the available information and the lack of quality information can result in students making poor choices with many-fold implications. For example, students often lose interest in science, technology, engineering, and mathematics (STEM) programs because of negative experiences in introductory courses (Crisp et al., 2009; Barr et al., 2008; Mervis, 2010). Possible reasons are that the courses are poorly designed and very difficult, the students are not yet ready to take the courses, or the sequencing of the courses needs to be adjusted to prepare students better (Sutton & Sankar, 2011). In addition to students' attrition or dropouts, students' choices of courses and instructors' sequencing of courses can also have financial implications, where students may not be able to complete their degrees in the expected time. For an institution, it can be problematic if a degree program does not meet its expected standards (where students complete their degrees late, change their program of study, or are unable to find future pathways in their area of specialty).

To mitigate these issues, it is important for students to be offered some assistance in course selection that can help them with their decision-making processes. While there are existing roles, such as academic advisors, that can offer some guidance and support to students, given the variety of degree programs that students can enroll in and the depth and the breadth of courses that students can choose from, it may not be possible or even efficient to provide individualized guidance to all students. Furthermore, the complexity of this task can often leave advisors feeling confused (Pechenizkiy et al., 2012), causing them to make worse academic advising choices (Allen & Smith, 2008; Ruffalo Noel Levitz, 2013).

Curriculum analytics (CA) aims to address some of these challenges. CA is defined as the collection, analysis, and visualization of administrative curricular data for supporting program-level decision-making (Ochoa, 2016). CA emerged as a sub-field of academic analytics (AA) and LA. Like AA, CA is used for decision-making purposes, and, like LA, it uses evidence-based data to "support curriculum decision-making and program quality improvement" (Greer et al., 2016). CA can offer methods and tools for teachers that allow them to analyze their learning design and delivery practices while incorporating students' evidence-based data for the purposes of reflection and improvement (Dennehy et al., 2021; Mor et al., 2015).

Previously, researchers have adopted a data-driven approach to assess which data-based indicators can be used for CA, to what level of analysis these indicators can be scaled down, and what sort of visual information can be provided to assess the difficulty of courses (Mendez et al., 2014). In an illustrative study, Ochoa (2016) proposed several metrics using students' academic data where their interaction with the curriculum can be considered while incorporating their academic progress. The Ochoa study highlighted the potential benefits of program-level data over course-level data in terms of their homogeneity between institutions and programs (Bouwma-Gearhart & Hora, 2016; Gottipati & Shankararaman, 2018). Following this, several applications of CA tools and dashboards have been explored. For instance, Yaginuma (2017) developed the visualizations of program syllabi based on the standard curriculum to see the commonalities and differences between various syllabi. Researchers have also applied process mining as a tool to analyze whether the timing at which students take a course in a semester matches with the timing for a given program or the curriculum model (Bendatu & Yahya, 2015). The results were mostly provided in terms of the individual courses, e.g., which courses are taken in line with the curriculum model and which courses are taken before or after the prescribed timing of the curriculum model. The possible effects of taking courses *on*, *before*, or *after* the time according to the suggested curriculum model were not analyzed in this study. Prior studies have also focused on the development of tools for academic advising (Hilliger, Laet, et al., 2020) and predicting early drop-outs (Simanca et al., 2019) or describing processes that lead to late dropout (Salazar-Fernandez et al., 2021).

Despite these advancements, more study is needed to develop an understanding of "actionable information" that can be used for decision-making (Hilliger, Aguirre, et al., 2020). Therefore, this study provides empirical evidence for some of Ochoa's illustrative metrics (Ochoa, 2016). In this study, we adopt a student-centred approach to analyze CA data. For analysis, we use LA techniques, since they can help provide insights into "learning-centred curricula" (Dawson & Hubball, 2014) and have the potential to lead to continuous curriculum improvement (Hilliger et al., 2019). We analyzed student academic data across an undergraduate degree program (in health sciences) and compared high- and low-performing students to develop a better understanding of students' choices and how these choices differ *temporally* and *sequentially*. The comparisons between students' choices were made in terms of course metrics proposed in previous studies (Mendez et al., 2014; Ochoa, 2016). The results of this study can assist researchers and practitioners in assessing the effectiveness of curriculum practices in terms of the learning outcomes. In addition, CA-based data can assist in the planning of instructional resources as well as the sequencing of instructions and learning activities. Furthermore, knowing how the choices differ between high- and low-performing students can also be beneficial in identifying bottleneck courses and developing course recommendation systems through a dashboard.

In sum, in this exploratory study, we aimed to address the following research questions:

- RQ1: Exploring the *temporal difference* between the course enrollments of high- and low-performing students:
  (a) To what extent does the difficulty of a course relate to its temporal position (i.e., the association of course difficulty with the semester when students complete that course)?
  (b) To what extent does the difficulty of a course relate to the time it takes for students to complete that course (e.g., whether students complete the course on their first attempt or require a re-enrollment)?
- RQ2: Exploring the *sequential difference* between the course enrollments of high- and low-performing students:
  (a) To what extent do difficulties of courses that students enroll in vary across semesters?
  (b) To what extent are course enrollments across different semesters associated with course difficulties (i.e., are difficulties of courses students take in one semester associated with those in the following semester)?

2. Methods

2.1 Dataset

In this section, we describe a simple case study of CA at one large public research-based university. We examined the curricular design of a large on-campus undergraduate program in the broad discipline of health sciences to develop a better understanding of students' choices, i.e., examine how different groups of students (high-performing students and low-performing students) make these choices, and how these choices vary between semesters.

2.1.1 Study Context

The program under study is a three-year undergraduate bachelor's program in health sciences (program name anonymized for ethical consideration) offered at a large public research university. In this program, students explore the foundations of life sciences, human anatomy, genetics, molecular biology, microbiology, immunology, pathology, pharmacology, and biochemistry. They also gain research skills and have opportunities to specialize in areas of interest. The program is three years of full-time study or six years of part-time study.

2.1.2 Program Structure

The program under study comprises 144 credit points, of which 96 credit points should be completed by enrolling in courses offered by the faculty of health sciences (also known as *core courses*), and the remaining 48 points could be completed by enrolling in courses within/outside the faculty (also known as *elective courses*). Students must complete the core courses to successfully complete their program. Based on the program structure, at the beginning of the program (year 1 and year 2), students are required to choose one elective course per semester (two semesters a year), and later in year 3, they have the freedom to choose two elective courses. Typically, a course is worth 6 credit points unless otherwise stated. This means, on average, a student is required to choose a minimum of eight elective courses during the complete duration of their program.

Because course-sequencing is a challenging task, a program progression map, which gives advice on the suitable sequencing of courses and guidance on how to plan course enrollment in each semester of study (see Figure 1), is provided to students by the university. However, the map does not contain any advice regarding what elective courses students should consider each semester according to learners' profiles.

Year 1 Semester 1	CORE101A (Topics include medical chemistry, basic development biology concepts, and biophysics)	CORE102A	CORE103A	Elective
Year 1 Semester 2	CORE106B (Topics include molecular biology, neurobiology, and public health principles)	CORE105B	CORE104B	Elective
Year 2 Semester 1	CORE201A (Topics include human body structure, biochemistry, body systems)	CORE202A	CORE203A	Elective
Year 2 Semester 2	CORE204B (Topics include human genetics, bioinformatics, study of microorganisms in health sciences)	CORE205B	CORE206B	Elective
Year 3 Semester 1	CORE303A (12-credit points includes group-learning)		Elective	Elective
Year 3 Semester 2	CORE305B (12-credit points includes group-learning)		Elective	Elective

Figure 1. Program progression map for 2016 commencing students. Here dark-blue blocks represent core courses and light-blue blocks represent elective courses. (Course names are redacted for anonymization.)

2.1.3 Data Collection and Pre-processing

Given that we were interested in understanding students' choices in a degree program, upon ethics approval of the Human Research Ethics Committee of [Anonymous] University (Project ID: 31325), we obtained the relevant program enrollment dataset from the student-information system stored in a relational database. We extracted the enrollment data for the batch of 2016 commencing students of an undergraduate program in health sciences. The extracted dataset contains 6,784 observations of 364 students enrolled in 310 different courses.

The dataset contained information about different categories of students—part-time, full-time, transfer, and drop-out students. However, since the motivation of this study was to understand what course choices students make while successfully completing a program, a few pre-processing steps were performed on the original dataset to *clean* it properly. First, we excluded the details of the students who discontinued the program before semester 2 of 2018 ($n = 49$) in our analysis. Second, we excluded the students who were enrolled as part-time in this program ($n = 5$). Third, we excluded the details of the students who were enrolled in undergraduate honours degree programs associated with the Department of Health Sciences ($n = 31$). Last we removed the details of the students who successfully completed the program but failed to complete the 144 credit-point requirements of this program ($n = 36$). We assume that these academic records belong to students who have previously earned credit-points in a different faculty (transfer students) or are pursuing this program as a double degree.

In total, our dataset consists of 5,419 observations of 243 students enrolled in 265 unique courses. The dataset spans a period of three years from semester 1 of 2016 to semester 2 of 2018. In terms of descriptive statistics, on average, each student enrolled in 22 courses ($M = 21.88, SD = 0.72$) to successfully complete their degree. The average GPA[1] of students for the 2016–2018 batch of students was 3.34 ($SD = 0.594, min = 1.51, max = 4.0$).

[1] The [University] GPA is calculated on a four-point grading scale, where 4.0 is the highest and 0.0 is the lowest.

2.2 Data Preparation

The extracted academic records contained the following information—student-id (anonymized), unit-code (the unique identifier for a course), semester-ID (semester when the course was offered), grade (individual grade of a student in a course), and course-status (PASS or FAIL). An example of the dataset is presented in Table 1. Every row of the dataset, as shown, contained information about the course in which a student was enrolled; details about the semester in which they enrolled; their grade in the specific course; and whether they failed, passed, or withdrew from the course.

Table 1. An example dataset representing students' academic records.

student-id	course-code	semester-ID	grade	course-status
S1	CORE101A	Semester 1	0.3	FAIL
S1	CORE102A	Semester 1	3.2	PASS
S2	CORE102A	Semester 1	0.3	FAIL
S2	CORE103A	Semester 1	2.9	PASS
S1	CORE111A	Semester 2	3.2	PASS
S2	CORE102A	Semester 2	3	PASS
S1	CORE112A	Semester 2	NA	WITHDRAW
S2	CORE101A	Semester 2	2.8	PASS
S1	CORE201A	Semester 3	2.9	PASS
S2	CORE201B	Semester 3	3.5	PASS

We converted the academic records into sequences of *course enrollment traces* for every student. Each enrollment trace includes a sequence of courses a particular student enrolled in during their program. Formally, a single enrollment trace of a student can be defined as follows:

Course enrollment trace: Let U represent the set of all courses offered at the university and C_i be the collection of courses taken by student i to complete the program. Also, let S be the ordered list of all semesters (e.g., semester 1, semester 2, semester 3, ...), $S = [s_1, s_2, \ldots, s_n]$. A *course enrollment trace* for student i is a collection of all course/semester pairs that a student has taken, $CT_i = \{(c, s_u^i)\} \forall c \in C_i$, where s_c^i represents the semester in which student i took course u.

For example, for the dataset presented in Table 1, the *course enrollment trace* for student S1 is $CT_{S1} = \{(s_1, \text{CORE101A}), (s_1, \text{CORE102A}), (s_2, \text{CORE111A}), (s_2, \text{CORE112A}), (s_3, \text{CORE201A})\}$, and similarly for S2 is $CT_{S2} = \{(s_1, \text{CORE102A}), (s_1, \text{CORE103A}), (s_2, \text{CORE102A}), (s_2, \text{CORE101A}), (s_3, \text{CORE201B})\}$. Next, we computed different sets of curriculum metrics to address our research questions. These metrics can be easily extracted from students' *course enrollment traces* and have been previously used to perform course-level detailed analysis (Ochoa, 2016; Mendez et al., 2014).

2.3 Utilizing Curriculum Metrics

Students' *course enrollment trace* or academic records contain information about two main interaction events: (1) the choice of courses during a given academic period and (2) students' performance or success within the chosen courses. Based on this motivation, Ochoa (2016) proposed two sets of curriculum metrics: *temporal metrics* and *difficulty metrics*, where temporal metrics are associated with the temporal information of the courses (such as position, duration, and distance) in the academic records, and the difficulty metrics are associated with the performance of students in a course (such as grading stringency (or difficulty)). He described a comprehensive list of curriculum metrics containing three temporal metrics (course temporal position (CTP), course duration (CDU), temporal distance between courses (TDI)), two difficulty metrics (grading stringency (β), multiplicative magnitude (α)), and three profile-based difficulty metrics (course passing profile (CAP), course performance profile (CPP), and course difficulty profile (CDP)). All of these metrics focus on course-level analysis and could provide deeper insights into students' choices.

1. **Temporal metrics:** As in a degree program, students have the flexibility to enroll in courses at different temporal points, so we utilize the following metrics to understand the *temporal* aspects of their choices:

   (a) *Course temporal position (CTP):* This metric represents a course's average position within course enrollment traces for all students who took a particular course. As indicated by Ochoa (2016), calculation of this metric requires calculation of *relative position (RP)* metric for each student, to account for different course enrollment times, where relative position of a course for a student is the relative value of the semester in which student S enrolled in course C. For instance, based on Table 1, the relative position of different courses for student S1 is RP(CORE101A) = 1, RP(CORE102A) = 1, RP(CORE111A) = 2, RP(CORE112A) = NA, and RP(CORE201A) = 3; i.e., all courses taken in the first semester of study would have relative position 1, while all courses taken the following term would have relative position 2, and so on. As represented in the example, only active periods, i.e., periods where the student was actively pursuing this course (i.e., course-status is not "WITHDRAWN") should be counted, in order to avoid inflating the RP metric. Once the relative position of a course was calculated for all students that actively completed the course (PASS or FAIL), the average temporal position of the course c was calculated according to the following equation:

$$CTP_c = \frac{\sum_{s=1}^{N} RP_s^c}{N}, \tag{1}$$

where N is the total number of students who took course c. For example, if out of the 20 students who enrolled in course CORE101A, 10 students took this course in their first semester of study, and the remaining 10 students took this course in their second semester of study, then the course temporal position for this particular course would be $(10*1+10*2)/20 = 1.5$.

(b) *Course duration (CDU):* For a specific course c, the course duration is the average value of the number of repetitions of the courses within the registration traces. In simple terms, course duration depicts the average value of the number of academic semesters that students need to take on average to pass a given course. Mathematically, we calculated the course duration of all the courses in the dataset using the following equation:

$$CDU_c = \frac{\sum_{s=1}^{N} D_s^c}{N}, \tag{2}$$

where N is the total number of students who took course c and D_s^c represents the number of repetitions of c in the *course enrollment trace* of student s. For example, in Table 1, the course duration of CORE102A is $(1+2)/2 = 1.5$, since student S1 took one ($D = 1$) semester to pass the course, and S2 took two ($D = 2$) semesters to pass the course.

2. **Difficulty metrics:** When estimating the difficulty of a course, some of the commonly used metrics are pass rate (PR) and average grade (AG). Although these metrics can be calculated with ease, they have some limitations, e.g., their value depends on the group of students who took the course (hence, they may not be considered comprehensive indicators of difficulty) (Ochoa, 2016; Mendez et al., 2014). For example, a course with high PR and AG might not necessarily be easier; it could be because it was always taken by highly motivated students or the students had prior subject knowledge that made it less challenging for them. To illustrate this point, we can consider Table 2. In this table, PR and AG for course CORE101A for the 2021 cohort are higher for the motivated students than for course CORE102A for the 2022 cohort of first-year students. Similarly, course CORE102A in 2021 had lower PR and AG than the 2022 cohort of CORE101A, where students had prior subject knowledge.

Table 2. An example demonstrating how difficulty metrics PR and AG may not take into account the difficulty of individual courses and hence individual students' course difficulty interpretation may be incomplete or inaccurate when only their PR and AG are considered.

Course-code	Cohort	Passing-rate (PR)	Average-grade (AG)	Student Group Characteristics
CORE101A	2021	85	3.4	Highly motivated
CORE102A	2021	75	2.8	Diverse academic backgrounds
CORE101A	2022	90	3.5	Prior subject knowledge
CORE102A	2022	65	2.6	First-year students

To address these limitations, Caulkins and colleagues (1996) proposed a difficulty metric—grading stringency (β), which was more robust than these simple difficulty metrics (AG and PR). β eliminates the potential bias that can be introduced by the group of students taking a course by considering their grade point average (GPA) in its computation as follows:

$$\beta_c = \frac{1}{N_c} \sum_{s=1}^{N_c} (GPA_s - r_{sc}), \tag{3}$$

where N_c is the total number of students who took the course c, GPA_s is the GPA of student s, and r_{sc} is the grade student s obtained on course c.

In other words, the difficulty of a course measured by the grading stringency (β) metric is an indicator of how much a given course *influenced* a student's GPA (or academic performance) (Mendez et al., 2014; Caulkins et al., 1996). More specifically, based on equation 3, the distance between the GPA and the particular course's grades (r_{sc}) can be seen as a measure of how much a course shifted (up or down) students' overall academic performance. When observed over time, on a set of several students, this distance might be considered an indicator of how much a given course usually moved students away from their GPA or brought them closer to it. For instance, if the course difficulty (β) was positive, the majority of students scored lower than their GPA in this course, i.e., the grading stringency of this course was high. On the other hand, if course difficulty (β) was negative, the majority of students scored higher than their GPA in this course, i.e., the grading stringency of this course was low.

3. **Profile-based metrics:** We divided the population of students into two groups based on their performance in the program (i.e., their GPA). For each group of students, we calculated the four curriculum metrics—course temporal position (CTP) per group, course duration (CDU) per group, and course difficulty (β and α) per group.

2.4 Data Analysis

At [Anonymous] University, students were allowed to take elective courses across any faculty within the university. Because of this, the number of unique courses in the dataset was large ($U = 265$). Therefore, a few filtration steps were performed on the dataset to present relevant findings in this paper. First, we excluded the core courses ($U_{core} = 14$) from our analysis, since these courses were mandatory for all students and did not represent students' unique choices. Second, we excluded courses that were offered in a non-standard teaching period ($U_{non-std} = 18$) from our analysis because a smaller number of students ($Mean = 8, SD = 10.07$) were enrolled in those courses per year. With this step, our dataset contained 1,920 academic records of 243 students enrolled in 243 elective courses.

Next, we calculated the different curriculum metrics defined in Section 2.3 for each unique offering of the elective courses for two groups of students—high-performing students ($N = 117$) and low-performing students ($N = 126$). *High-performing* students were those who scored above the median GPA of all students ($M = 3.83, SD = 0.15$), while students who scored below the median GPA of all students ($M = 3.00, SD = 0.51$) were considered as *low-performing* students. Due to the relatively small sample size (i.e., number of students) in this study, it was decided not to divide the students into three categories—low-performing, average-performing, and high-performing. This can be investigated in future studies where the patterns of the bottom 25% (as low achievers) and top 25% (as high achievers) students could be explored with a bigger dataset.

2.4.1 RQ1: Temporal Aspects of Course Choices

To address our first research question and explore the temporal difference between the difficulty of course choices of high- and low-performing students, we compared the curriculum metrics for the elective courses where the majority of students were enrolled in different semesters. We included the courses where more than 20 students (>8%) were enrolled ($C_{popular} = 19$). We posit that these were the popular courses, and analyzing the temporal aspects of these courses will help us understand students' course choices better. Next, we examined the difference in *course temporal position* and *course duration* of these popular courses between the two GPA groups. We further added course difficulty to the analysis and explored how the difficulty of a course relates to the shift in the temporal position and duration of courses.

2.4.2 RQ2a: Sequential Aspects of Course Choices

Because students' choices of courses differed between semesters, we analyzed the sequences of course difficulties for the low-performing and high-performing student groups in different semesters. As explained in Section 2.3, the course difficulty, represented by the grading stringency metric (or β), indicates the extent to which a specific course affects students' overall academic performance (Mendez et al., 2014; Caulkins et al., 1996). Specifically, a positive β value suggests that the majority of students in that course received grades lower than their overall GPA, indicating high grading stringency. Conversely, a negative β value implies that most students achieved grades higher than their overall GPA in that course, signifying low grading stringency. Based on this observation, we divided the courses into two sub-categories and calculated the sequences of course difficulties for different semesters:

- Low difficulty: If the difficulty of a course measured by grading stringency (or β) was less than the mean β value of all the courses offered in that semester, then we considered the course to be low difficulty.
- High difficulty: If the difficulty of a course measured by grading stringency (or β) was equal to or more than the mean β value of all the courses offered in that semester, then we considered the course to be high difficulty.

Next, we performed the Pearson chi-square test to compare how the distribution of course difficulties varies between high-performing and low-performing students for every semester of their studies (i.e., semester 1 to semester 6). The effect size of the association was also reported using ϕ_p.

2.4.3 RQ2b: Transitions of Course Difficulties

We observed that students transitioned between the two levels of difficulty (high and low difficulty) in every semester of their study. Therefore, we converted the *course enrollment trace* of every student into sequences of course difficulties. For example, if the course enrollment trace for student S1 contains $\{(s_1, c_1)$, (s_2, c_2), (s_2, c_3), (s_4, c_4), (s_5, c_5, c_6), and $(s_6, c_7, c_8)\}$, where c_i denotes courses and s_i denotes the ordered list of semesters, then the course difficulty sequences for student S1 will be β^L_{c1}, β^L_{c2}, β^L_{c3}, β^L_{c4}, $\{\beta^L_{c5}, \beta^L_{c6}\}$, $\{\beta^L_{c7}, \beta^L_{c8}\}$, where $\beta^L_{ci} \in \{\text{low difficulty}, \text{high difficulty}\}$ is the difficulty level of course c_i.

Once we had calculated the β^L sequences for all the students, we analyzed the transitions of course difficulties using D'Mello and colleagues' (2007) transition metric *L*. The *L* statistic is the most widely used metric in studying students' affective dynamics, i.e., examining how students transition from one affective state to the next during a learning session (D'Mello et al., 2007; Karumbaiah et al., 2021) or how students' learning difficulties change from one level of perceived difficulty to another (Nawaz, Srivastava, Yu, et al., 2020, 2022).

For analyzing such transitions, the use of the *L* statistic is preferred over conditional probabilities because these conditional probabilities do not take into account the base rate of a given state (i.e., in this case, a conditional probability would not take into account the base rate of courses with a high difficulty or the base rate of courses with a low difficulty). For example, consider a conditional probability $P[LD|HD]$, where LD is the current difficulty level of a course in which a student is enrolled given that the previously enrolled-in course had a difficulty level of HD. Formally, $P[LD|HD] = P[LD \cap HD]/P[HD]$. In this case, for each student, we count the number of times course difficulty LD followed course difficulty HD, and then we divide this by the number of times course difficulty HD was observed. This method of computing course difficulty transitions is problematic because it does not account for the base rate of course difficulty LD and, hence, it can lead to inappropriate conclusions.

Consider that for a particular student, $P[LD|HD] = 0.4$ and $P[HD|HD] = 0.6$. Based on these probabilities, we might conclude that a student enrolled in a course of high difficulty is more likely to enroll in another course of high difficulty than to enroll in a course of low difficulty. However, consider the case where the base rate of these transitions is as follows: students take a low-difficulty (*LD*) course 30% of the time and enroll in a high-difficulty (*HD*) course 70% of the time. In this case, the base rates or the prior probabilities are $P[HD] = 0.7$ and $P[LD] = 0.3$. Although we found that $P[LD|HD] < P[HD|HD]$, it may be more likely for students to enroll in a low-difficulty (*LD*) course after taking a high-difficulty (*HD*) course than to take another high-difficulty (*HD*) course. This happens because the probability of taking a low-difficulty (*LD*) course following a high-difficulty (*HD*) course is higher than the base rate of taking a low-difficulty (*LD*) course. Therefore, for a transition of sequences, the use of the *L* statistic is preferred over conditional probability because it takes into account the effect of base rate probabilities. Overall, the *L* statistic allows us to estimate whether a transition from one state to another is more likely than chance, less likely than chance, or just at chance level after correcting for the second state's base rate.

Calculating *L*-statistics The *L* statistic calculates the probability that a state (*past*) will transition to a subsequent state (*next*) after correcting for the base rate of the *next* state. Mathematically, this is expressed as

$$L(past \rightarrow next) = \frac{P(next|past) - P(next)}{1 - P(next)}.$$

Here $P(next)$ is the probability that difficulty level *next* occurs as a next state. In this regard, the first occurrence of any difficulty level is excluded from the calculation, since this occurrence cannot be considered for a next state. For instance, for a *course difficulty sequence* = $\{LD, LD, HD, HD\}$, the probability of the state (LD) as the next state, $P(LD\_next)$, is 0.33 instead of 0.5. Similarly, the calculation of *past* state excludes the last state in the sequence. The conditional probability *P(next|past)* is

$$P(next|past) = \frac{count(past \rightarrow next)}{count(past)}.$$

Here, $count(past \rightarrow next)$ is the number of times a difficulty level transitions from *past* to *next*, and $count(past)$ is the number of times the difficulty level *past* occurs as a previous state. For instance, in the example sequence $\{LD, LD, HD, HD\}$, count (HD_prev) is 1 (from $\{LD, LD, HD\}$) instead of 2 because the last state in the sequence cannot be a *past* state for any transition.

The value of L may vary from $-\infty$ to 1. For a given transition, $past \rightarrow next$, if $L \approx 0$, then we say that the transition occurs at chance level. If, however, $L > 0$, then we can say that the *next* state reliably follows the *past* state above chance level, and finally if $L < 0$, then the *next* state follows the *past* state below chance level (Nawaz, Srivastava, Yu, et al., 2020).

Statistical analysis To analyze the course difficulty transitions for high-performing students and low-performing students, the *L*-stat value was computed for all four possible transitions (low difficulty to low difficulty, low difficulty to high difficulty, high difficulty to low difficulty, and high difficulty to high difficulty) for each group of students. The *L*-stat value was computed individually per student based on the calculated course difficulty sequences. Those transitions where *L* was undefined were excluded from further analysis. Later, one-sample (two-tailed) t-tests were conducted on the calculated L values to measure whether each transition was significantly more or less likely than chance for each group. Then, Benjamini–Hochberg (BH) post-hoc correction was applied to control for false positives since the analysis involves multiple comparisons (Nawaz, Srivastava, Yu, et al., 2022).

3. Results

3.1 RQ1: Exploring the Temporal Difference between the Course Choices of High- and Low-Performing Students

To address our first research question and explore how course choices of high- and low-performing students differed *temporally*, we performed an exploratory comparison of the top 19 popular electives for the 2016–2018 students. The distribution of high achievers and low achievers in each of these top 19 elective courses is presented in Table 4 in the Appendix. The results of the exploratory comparison are presented in Figure 2 and Figure 3 and discussed in the following subsections.

3.1.1 RQ1 (a): To What Extent Does the Difficulty of a Course Relate to Its Temporal Position?

Figure 2 presents a visualization to explore the possible relationship between the difficulty of a course (β) and its corresponding temporal position. Since the aim was to analyze the effects of students' course choices, in this figure only the elective courses are presented. When we compared the course temporal position of the 19 elective courses between the two groups (high-performing students and low-performing students), no significant effect of group was found based on the Wilcoxon signed-rank test ($\mathrm{MD}_{low} = 5.15$, $\mathrm{MD}_{high} = 5.0$, $Z = 1.81$, $p = 0.0708$, $r = 0.29$). However, when we compared the course difficulty of these courses within each group, a significant effect of group was found with moderate effect size based on the Wilcoxon signed-rank test ($\mathrm{MD}_{low} = -0.25$, $\mathrm{MD}_{high} = -0.09$, $Z = -2.62$, $p < 0.005$, $r = 0.42$).

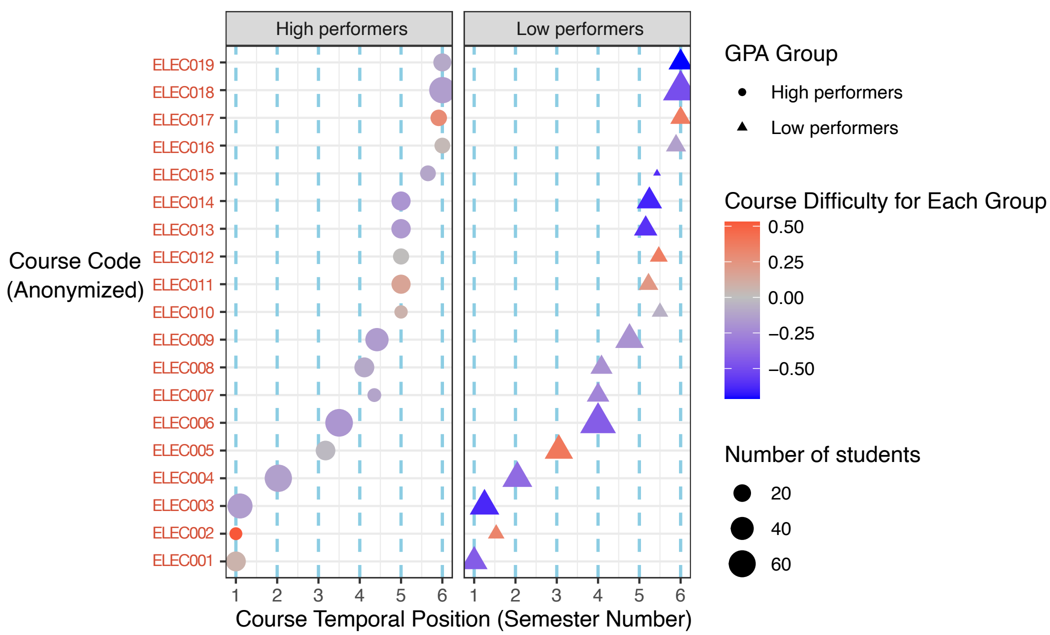

Figure 2. A figure showing the possible relationship between the difficulty of a course and its corresponding temporal position (CTP). The x-axis represents an average semester in which a student is enrolled in a course, and the y-axis consists of the code and name of the courses. The course difficulty and CTP are calculated per group. High-performing students and low-performing students are represented using circles and triangles, respectively. Red indicates high-difficulty courses and blue indicates low-difficulty courses.

3.1.2 RQ1 (b): To What Extent Does the Difficulty of a Course Relate to the Time It Takes for Students to Complete That Course?

Next, we analyzed the relationship between course duration (CDU) and course difficulty (β) to develop a better understanding of the effects of grading stringency (β) on the duration of the courses. When we compared the course duration of the 19 courses between the two groups (high- and low-performing students), no significant effect of group was found based on the Wilcoxon signed-rank test ($\mathrm{MD}_{low} = 1.0$, $\mathrm{MD}_{high} = 1.0$, $Z = 1.73$, $p = 0.25$, $r = 0.28$).

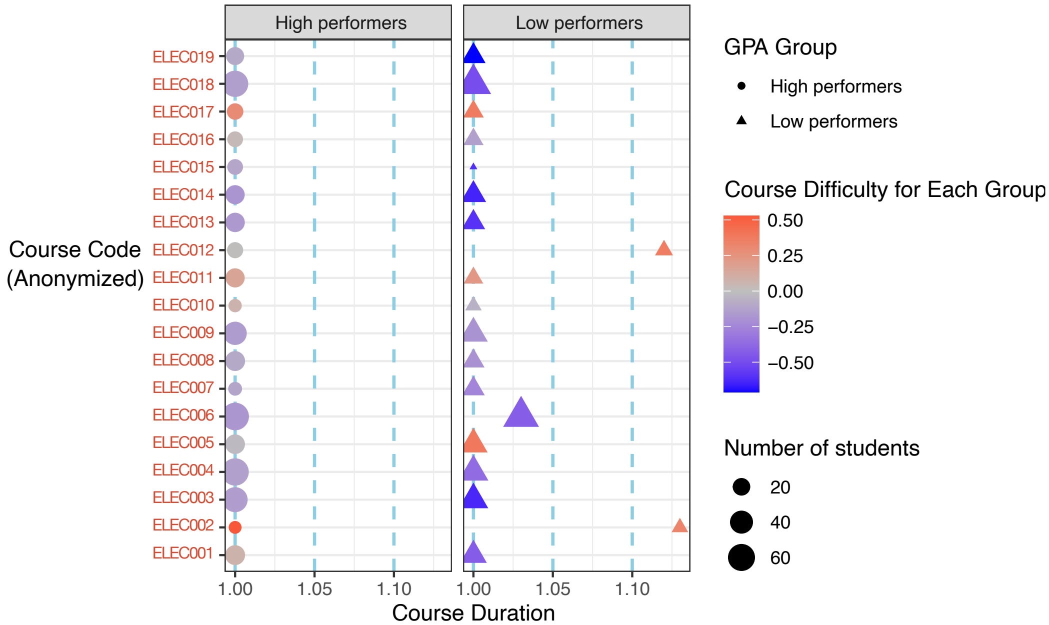

Figure 3. A figure showing the possible relationship between the difficulty of a course and its corresponding duration (CDU). The *x*-axis represents an average semester in which a student is enrolled in a course, and the *y*-axis consists of the code and name of the courses. The course difficulty and CDU are calculated per group. High-performing students and low-performing students are represented using circles and triangles, respectively. Red indicates high-difficulty courses and blue indicates low-difficulty courses.

3.1.3 Interpretation of the Results

When high- and low-performing students were compared—first in terms of course difficulty and course duration and second in terms of course difficulty and course temporal position—we found that some choices were common between the two groups; e.g., the temporal position of the course choices is broadly similar between the two groups. However, the estimated difficulty based on grading stringency (β) seemed to differ between them. For instance, from Figure 2, some courses are relatively difficult across both groups, such as ELEC002, ELEC011, and ELEC017. Based on the grading stringency, i.e., $\beta > 0$, it is expected that these courses could have negatively affected students' GPAs in both groups. But then there were courses that seemed difficult for one group but not so much for the other; e.g., ELEC005 and ELEC012 seemed difficult for low performers, while ELEC002 seemed difficult for high performers.

Similarly, in terms of course duration, as shown in Figure 3, we found that across both groups most of the courses required only one semester to be completed, indicating that students could pass or complete these courses within the expected duration. However, there were some courses, such as ELEC002, ELEC006, and ELEC012, on which the low performers seemed to spend longer than one semester, indicating that some of these students failed these courses and had to repeat them the next semester—as shown by a slight shift to the right for these courses. Upon combining the information from course difficulty and course duration, it appears that while ELEC002 and ELEC012 were difficult (as shown in red) and some students struggled to pass, ELEC006 did not appear to be a difficult course (in terms of its grading stringency, as shown in blue), and yet there were students who could not pass or complete this course within the expected duration. It could be that these students had prior beliefs about this course being easy and hence did not exert enough effort. However, to understand this better, this question would require further exploration.

Overall, the results of the statistical analysis of Figure 2 can be helpful in providing assistance to low-performing students in terms of managing their course load and also in terms of taking additional courses so that by the time they enroll in some of the advanced elective courses, they have the requisite prior knowledge, and hence the ability to manage the difficulty of such courses.

3.2 RQ2: Sequence Analysis of Course Difficulties

For RQ2, we analyzed the complete dataset of students, i.e., 1,920 records of 243 students enrolled in 243 unique courses.

3.2.1 RQ2(a): To What Extent Do Difficulties of Courses That Students Enroll in Vary across Semesters?

The distribution of high-performing and low-performing students enrolled in low-difficulty and high-difficulty courses in each semester is presented in Figure 4. A chi-square test was performed to investigate the association between GPA groups, and enrolled courses' difficulty for each semester of study showed statistically significant association at the standard 0.05 threshold with medium effect size for semester 1, semester 2, and semester 4, respectively (Cohen, 2013). However, no statistically significant association was found between GPA groups and course difficulty for semester 3, semester 5, and semester 6.

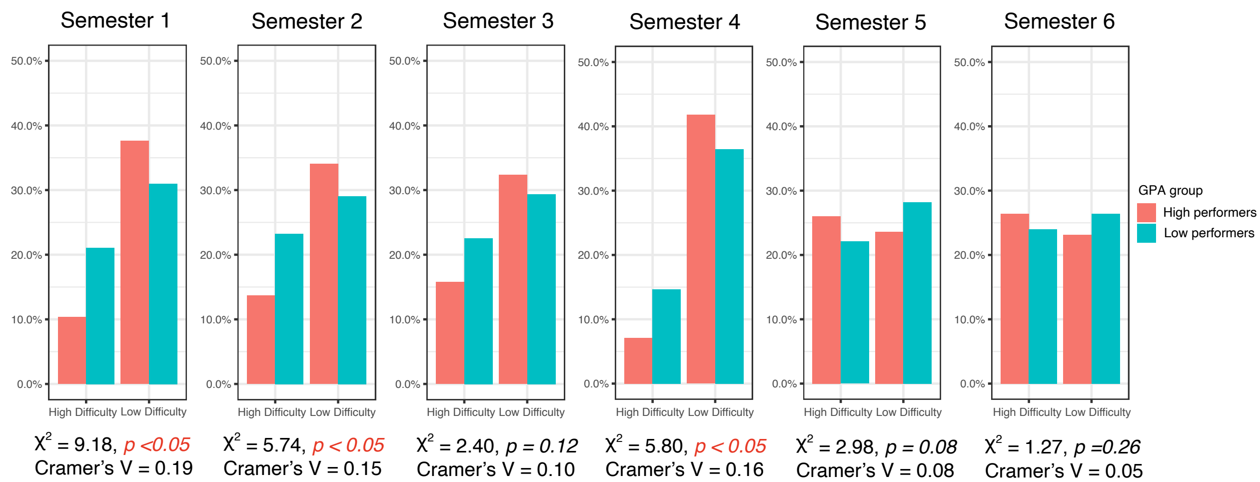

Figure 4. Comparison of course choice difficulty between high- and low-performing students.

3.2.2 RQ2(b): To What Extent Are Course Enrollments across Different Semesters Associated with Course Difficulties?

Table 3 presents students' transitions between electives, reflected in terms of the difficulty associated with those electives. As students progressed from one semester to another, they needed to choose elective courses, but how low- and high-performing students went about making these choices seemed to differ. For high-performing students, the transition from high- to low-difficulty courses is more likely than chance ($L_{mean} > 0$), while the transition from low- to high-difficulty and low- to low-difficulty courses is less likely than chance (i.e., $L_{mean} < 0$). The other transitions, i.e., from high to high difficulty, are not different than chance. For low-performing students, the transitions from high to high difficulty, from low to high difficulty, and from low to low difficulty are all less likely than chance, whereas the transition from high to low difficulty is not different than chance.

Table 3. Analyzing the sequences of course difficulties for high-performing and low-performing students using D'Mello's L-statistic. L_{mean} in bold indicates that the transition is more likely, and L_{mean} in italics indicates that the transition is less likely than chance.

	Transitions		Descriptives		One-sample t-test		
	from	to	N	L_{mean} (L_{sd})	T (df)	P-value	Sig after BH correction
High performers	High difficulty	High difficulty	115	−0.086 (0.550)	−1.675 (114)	$p= 0.097$	
		Low difficulty	115	**0.214 (0.784)**	2.928 (114)	$p< 0.05$	**
	Low difficulty	High difficulty	103	*−1.139 (1.343)*	−8.608 (102)	$p<0.001$	***
		Low difficulty	103	−0.088 (0.395)	−2.267 (102)	$p < 0.05$	**
Low-performers	High difficulty	High difficulty	116	*−0.192 (0.404)*	−5.129 (115)	$p < 0.001$	***
		Low difficulty	116	0.110 (0.989)	1.202 (115)	$p = 0.232$	
	Low difficulty	High difficulty	116	*−0.559 (1.289)*	−4.675 (115)	$p < 0.001$	***
		Low difficulty	115	*−0.171 (0.482)*	−3.824 (115)	$p < 0.05$	***

** $p < 0.05$, *** $p < 0.001$

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3.2.3 Interpretation of the Results

This question aimed to compare the sequential analysis of course difficulties between high- and low-performing students (i.e., between-group comparisons). First, from Figure 4, we find that there are some common trends across the two groups, where students in both groups (within-group comparisons) had an overall higher tendency to enroll in low-difficulty courses than in high-difficulty courses. Next, from Figure 4, it also appears that course choices in terms of being easy or hard seemed to differ between the two groups, where students in the high-performing group were more likely to select a course of lower difficulty than higher difficulty. By contrast, low-performing students were more likely to select an elective of higher difficulty than lower difficulty. While this trend is significant during the first, second, and fourth semesters, it seems to have impacted students' overall GPA, where those students who were selecting courses of high difficulty had lower overall GPAs (i.e., they were low performers). We also observed that toward the end of the program, i.e., in the fifth and sixth semesters, the choices between the high-difficulty and low-difficulty units were more balanced and high performers chose more difficult units than easier units compared to past semesters. The likely reasons for this trend could be that toward the end of the degree program, students were becoming more aware of their knowledge gaps and could be opting for courses that could address those deficiencies in their knowledge. Another reason could be that as they neared completion of their degree program, students could have opted for courses that were necessary to secure relevant jobs. This is further affected by the fact that students had more electives to choose from in the last year of their degree program than in the first two years.

After analyzing students' course choices between semesters, as shown in Figure 4, we next analyzed the likelihood of course difficulty transitions separately for each group, e.g., which course difficulty transitions are more likely than chance, are less likely than chance, or occur at chance level for high performers (and vice versa for low performers). The results are presented in Table 3. From this table, it appears that when high-performing students' current course is high in difficulty, they were more likely than chance to select a following course of low difficulty, and their likelihood of selecting a following course of high difficulty was only at chance level. Similarly, when the current elective of these high-performing students was low in difficulty, they were less likely than chance to select a following course of high difficulty or low difficulty, indicating perhaps a strong preference for low-difficulty courses (of the high-performing group) after the current difficulty had been high. But there was no preference for higher or lower difficulty when the current elective was low in difficulty.

Slightly different from this, the course choice behaviours seemed mixed for the low-performing group. For example, they were less likely than chance to opt for an elective of high difficulty regardless of whether their current elective was high or low in difficulty. They were also less likely than chance to opt for an elective of lower difficulty when their current elective was of low difficulty, and their likelihood of selecting a low-difficulty course after a high-difficulty course was only at chance level.

Overall, between the two groups, it appears that the high performers had a strong tendency to opt for low-difficulty courses and strong tendency *not* to opt for high-difficulty courses. While the low performers also had a strong tendency to avoid high-difficulty courses, their tendency to opt for low-difficulty courses is only at chance level. Could it be that the low performers have overly optimistic views of their knowledge and understanding, which motivates them to take highly difficult courses? If so, some guidance could be helpful for these students. Through interventions, these students could be enabled to become more meta-cognitively aware and could choose courses of optimal level—a difficulty that aligns better with their knowledge and skills.

4. Discussion

With reference to the research questions and the results presented earlier, we now discuss our findings.

4.1 RQ1: Exploring the *Temporal Difference* between Course Enrollments of High- and Low-Performing Students

Our results demonstrated that the proposed use of CA metrics can identify nuanced differences in how students with different performance levels tend to enroll in courses. In particular, our results showed that the estimated course difficulty based on grading stringency (β) is a promising indicator to unveil differences in the enrollment patterns between high- and low-performing students and pinpoints the specific courses in the curriculum that are difficult for some (low-performing students) but not for others. Likewise, our metric for the measurement of course duration can identify specific courses that a group of students typically had to retake while others did not. Moreover, combinations of some metrics can be particularly beneficial since our results demonstrated that the combination of course temporal position and course duration can help identify particularly difficult courses and provides a comprehensive understanding compared to a specifically dedicated metric (course-grading stringency (β)) for assessing course difficulty.

The above findings contribute empirical evidence about the value of metrics that were previously proposed in the CA literature (Ochoa, 2016) but received insufficient empirical research. Our results emphasize that while the previously proposed metrics can be useful for CA, it is very important to consider how the metrics can be combined to unlock their full potential. Although existing CA tools have been valued by relevant stakeholder groups (Hilliger et al., 2019; Yaginuma, 2017), our findings have implications for the design of next-generation CA tools. They emphasize the need to create visualizations and interfaces that can effectively support users (e.g., program directors) to sense-make combinations of CA metrics to identify and take actions for curriculum improvement (e.g., offer tailored support for groups of students when enrolling in certain courses). Future research should validate the extent to which combinations of metrics can be beneficial in other contexts (e.g., different subject areas, universities, and countries). Moreover, future user studies are required to examine and assess the usefulness of the proposed metrics for curriculum improvement.

4.2 RQ2: Exploring the *Sequential Difference* between the Course Enrollments of High- and Low-Performing Students

Our results demonstrate the potential of the novel approaches we proposed for the analysis of sequential enrollment patterns to inform curriculum improvement. Sequential analysis can reveal patterns that may have a negative impact on the performance of a group of students (e.g., low-performing students enrolling in highly difficult courses in the early semesters of their degree programs). We also showed that such analyses can even unveil particular points in the curriculum when certain issues stop playing an important role in the success of students (e.g., a semester when enrolling in courses with high difficulty is not associated with a decrease in the GPA of low-performing students). Finally, the sequential analyses we proposed can demonstrate effective strategies students can take to enhance their academic performance (e.g., they can consider enrolling in courses that can help them better manage their workload). This can help ensure success and better academic performance for students.

This empirical study provides evidence about the potential benefits of sequential analysis of students' course choices, since they can lead to curriculum improvement. Our research builds on and extends previous studies, such as the work by Pechenizkiy and colleagues (2012), who demonstrated how certain data analytic approaches (e.g., process mining) can be used to model sequences in course enrollments. Our study adds to the existing works on how the metrics can be used to identify actionable insights. When the approaches we proposed for sequential analysis are combined with metrics described in RQ1, they form a comprehensive foundation for building and implementing analytic tools for curriculum improvement in higher education. Future research is needed to understand how such complex analytics and metrics can be combined in effective user interfaces. Moreover, higher education institutions (HEIs) can inform the development of strategies that can help them support students with particular needs. For instance, our proposed CA can help HEIs to plan a more balanced course roadmap that wouldn't cause a high workload for students and thus potentially lead to low learning performance. And the difficulty transition metrics can potentially be used to help manage student workload; e.g., they could be used by learning advisors who can check individual students' profiles (performance and previous units that they take) and advise them which combination of units might be less challenging to them. However, future research is required to co-design such implementation strategies and evaluate the effects they may have on curriculum improvement.

Overall, our research has some implications for educators. For instance, this knowledge can help instructors assess the difficulty of their courses and also potentially restructure some of the course content so that the difficulty becomes more manageable for students (e.g., by having a clear delineation between the fundamental and advanced topics or courses). Additionally, the concept of course difficulty as presented in this study may be combined with other difficulty metrics, such as fail rate and average grade, to gain further insights. The aim of this study, however, is not to suggest that all course content should be made easier; rather, it is to suggest that courses be designed to optimize the difficulties for individual students, i.e., within the optimal zone for students, where they struggle a bit, but not so much that they fail or disengage (Nawaz, Alghamdi, et al., 2022; Vygotsky, 2012).

4.3 Limitations

We recognize two limitations to this study that may guide future work. First, the study was restricted based on certain empirical choices we made in terms of elective courses and data-cleaning practices in order to have a fair comparison and representation of data across different cohorts of students. For instance, the analysis in this study was restricted to optional or elective courses because the aim was to analyze students' course-taking choices or behaviours. In terms of analysis, one of the limitations of this study is that while analyzing a course's temporal position and its duration we only considered the popular courses. The definition of the popularity of a course was based on an empirical number (20 students, i.e., at least 8 percent of the students). Other researchers who have analyzed CA data have also adopted similar data-cleaning strategies, e.g., Mendez and colleagues (2014). Another limitation that was also associated with data processing and cleaning was that only those students who were enrolled full-time and were not transfer students were analyzed.

Second, the findings of this study were restricted to curriculum metrics derived from a dataset of academic records. Although the results presented in this study were supported by statistical and process-mining approaches, certain factors shaped by social norms (such as course advice from peers, parents, and professional advisors) and personal biases (such as favourite instructor or prior experience with the subject) were not considered. These factors can influence students' course considerations and choices, and future studies should investigate their relation with academic performance and course choices.

5. Conclusion and Future Work

In this study, we produced novel empirical evidence about the value of analytics that can be used for curriculum improvement. Our results can be used to inform the design of CA tools and the development of strategies for student support in higher education. This work can augment and support the roles of academic advisors and instructors and lead to students' success as well as institutional productivity. In the future, we plan to extend our model to include part-time and transfer students, so that we can ultimately develop a system that could offer individualized guidance to all students regardless of their study status. In addition, the model could also incorporate students' perceived usefulness or value of a course (Kardan et al., 2013) to make the course selection process more personal and individualized.

Declaration of Conflicting Interest

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Appendix

Table 4. *A table demonstrating the number of high achievers and low achievers per course for the top 19 elective courses in our dataset.*

unitcode	Low achievers	High achievers	Total students
ELEC1001	33	33	66
ELEC1002	12	11	23
ELEC1003	57	42	99
ELEC1004	70	43	113
ELEC1005	32	38	70
ELEC1006	72	66	138
ELEC1007	14	22	36
ELEC1008	33	21	54
ELEC1009	48	39	87
ELEC1010	13	11	24
ELEC1011	30	16	46
ELEC1012	20	13	33
ELEC1013	31	24	55
ELEC1014	30	29	59
ELEC1015	19	5	24
ELEC1016	19	17	36
ELEC1017	21	18	39
ELEC1018	64	64	128
ELEC1019	26	26	52