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Characterizing the Curricular Complexity Faced by Transfer Students: 2+2, Vertical Transfers, and Curricular Change

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Abstract

This paper reviews a method for quantifying the accessibility of a curriculum for transfer students. When first conceptualized, the Curricular Analytics framework implicitly described the trajectory of a first-time-in-college student. Accordingly, using the metrics within the framework for transfer student pathways does not appear to have the same predictive power for estimating completion rates as they do for first-time-in-college pathways. Thus, we adapted metrics inspired by the literature and previous work in quantifying the complexity of curricula to better capture issues more commonly faced by transfer students from a structural perspective. To highlight how the metrics operate, we purposefully selected three engineering programs and then formed plans of study by selecting a feeder school for each and concatenating the curricula – using information from course catalogs to confirm the timing of offerings and prerequisites. Our three examples are a 2+2 program, a program within a statewide community college system, and a program that underwent a large curricular change. Through these examples, we highlight how practitioners and researchers can do substantial curricular analyses, both retrospective and forward-looking, with only available data.

Introduction

The complexity of engineering programs has emerged as a substantive area of study. Some efforts have involved developing visualization techniques for understanding dependencies in curricula [e.g., 1]. Authors have also begun defining metrics for what we mean by “complex” when describing curricula [e.g., 2,3], predicting graduation rates using these metrics [e.g., 4,5], and correlating the metrics with other outcomes like program quality [e.g., 6]. These effects have culminated in the *curricular complexity metric* or *curricular complexity framework* (i.e., referring to the variables composing the overall metric), including a webtool called *Curricular Analytics* [7]. This webtool allows users to import a plan of study as a spreadsheet, visualize the prerequisite networks inherent in the course organization, and calculate the structural properties of the network that impact student persistence. As shown through experimentation [e.g., 2,8] and empirical work [e.g., 5], there is a negative correlation between curricular complexity and completion rates.

Because of the new insights that quantifying a curricular structure could bring, authors have begun using the curricular complexity framework to assign values to the accessibility of curricula [e.g., 9,10,11]. There are two components of the framework, instructional complexity and structural complexity [2]. Instructional complexity refers to the latent characteristics of the curriculum, such as the quality of instruction. Currently, the instructional complexity is proxied by pass/fail rates; little work has been done to expand this metric, with some exceptions like Hilliger et al.’s [12] mixed methods grounded theory study on what makes engineering courses demanding. Still, pass/fail rates appear sufficient for simulation studies [2,8].

Next, structural complexity involves representing a plan of study as a network, where each vertex is a course and the edges connecting them are the pre- and corequisites. Each course is assigned a delay factor, the longest prerequisite chain it belongs to, and the blocking factor, the number of courses inaccessible to a student if the course in question is failed. Summing the blocking factor and delay factor together yields the course cruciality [8]. The crucialities provide vertex level information about how central a course is to a plan of study by assigning a number to how entangled the course is within the broader prerequisite structure. Summing all of the crucialities together yields the structural complexity of the curriculum.

An example of calculating a course cruciality is shown in Figure 1.

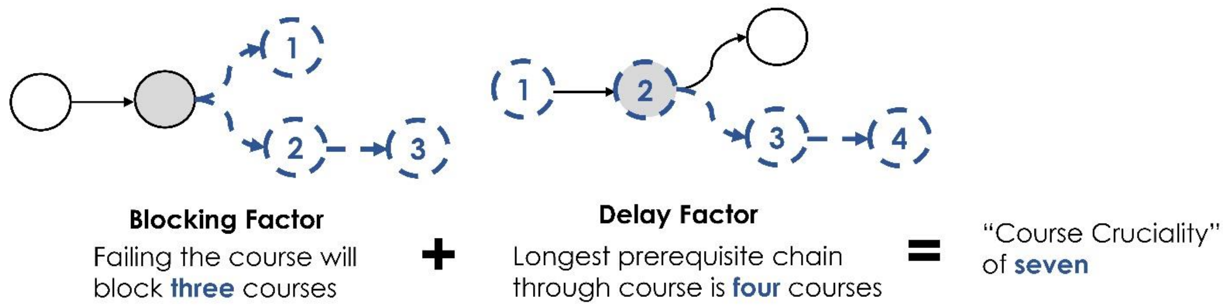

Figure 1. Example calculation of a course cruciality using the delay and blocking factors

As noted by Heilemen et al. [2], the blocking and delay factors perform well as measures of the interconnectedness of a curriculum's prerequisite structures, with other proposed metrics like a course's reachability (i.e., the number of courses that must be completed to take a course) and a curriculum degrees of freedom (i.e., number of ways to rearrange courses in a curriculum while respecting prerequisties) being linearly dependent on the blocking and delay factors.

The Gap, Applying Curricular Complexity to Analyze Transfer Student Persistence

Most of the work involving curricular complexity rests on the assumptions that students follow the curriculum as laid out by the faculty, which is often not true [13], and perhaps more tacitly, that the students matriculate directly into the program. Stated differently, the typical application of the curricular complexity framework assumes a student body that started at the institution in question. This assumption might lead one to wonder how the curricular complexity framework translates to address research questions about the success of transfer students in terms of persistence and graduation rates.

From the limited literature on the intersection of curricular complexity and transfer students, there are several avenues for reconceptualizing what curricular complexity means for non-first-time-in-college students. For example, previous work has examined how curricular complexity changes during a substantial curricular revision [14,15] on the scale of seven new courses and a new program structure. The course crucialities were examined to pinpoint potential bottlenecks in student progress as a forecasting tool despite not having graduation data. In this example, the authors identified that Digital Systems was a potential issue to student progress because of its position in the curricular structure.

We can further highlight the issue of the Digital Systems (ECE 2544) course using DeRocchis et al.'s [10] "term-weighted cruciality" (TWC) – an extension of the "cruciality" idea in Figure 1. For a course with cruciality *c* offered in term *t*, its TWC is simply *ct.* In the original paper, it was found that the cruciality of Fundamentals of Digital Systems was 32, and its prerequisite, Introduction to ECE Concepts (ECE 1004), was 33 (Figure 2). When unweighted, Digital System's prerequisite seems to be more of a barrier than Digital Systems itself; however, by incorporating term information as a weight, the potential impact of failing Digital Systems is starker, from 1 point less ECE 1004 than to 27 points more than ECE 1004. This example shows how curricular complexity can be used as a forecasting tool for both FTIC and transfer students.

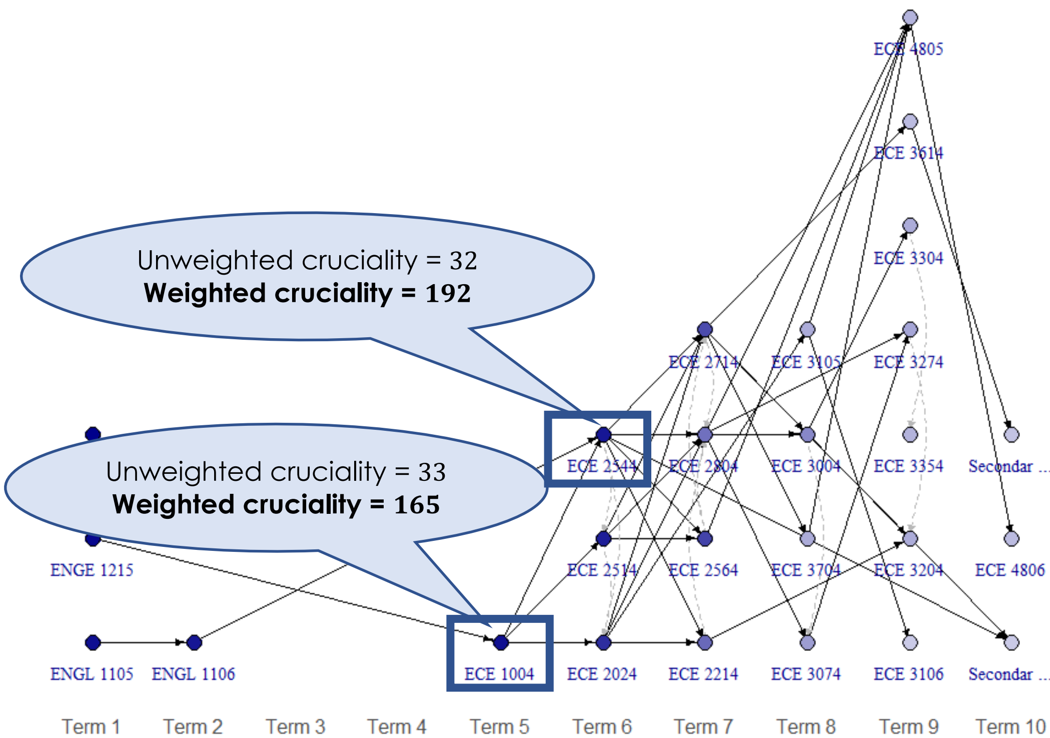

Figure 2. An example of weighted cruciality in analyzing bottlenecks in student progress

Despite the advantages of the curricular complexity framework, there is some predictive weakness in estimating completion rates. The structural complexity metric works well in predicting four-, five-, and six-year completion rates for first-time-in-college students [2,8]; however, the relationship appears to be less evident for transfer students [5].

Moreover, transfer-specific issues are not captured as directly as a transfer persistence researcher or practitioner might like. For example, unlike constructing a plan of study for first-time-in-college students, which is often readily available as a document through an institution's catalog or department's website, a transfer plan of study carries more data requirements and features. To elaborate, a transfer plan of study is two concatenated plans of study, one from the community college or previous institution and one from the four-year institution, which involves checking for course equivalencies to simplify the prerequisite structures.

Because the transfer pathway is the concatenation of two plans of study, one example of a shortcoming in the original framework concerns credit loss. Courses may not be applied to the requirements at the four-year institution; Simone [16] outlines the wide range of factors that contribute to credit loss, such as GPA and open admissions versus selective admissions, with an average of 13 credits lost on average. However, this complication of the transfer student experience is not incorporated into the curricular complexity framework through any discernable metric.

Accordingly, we developed a revised framework, called Transfer Student Structural Complexity (TSSC), with metrics that directly incorporate the difficulties transfer students face: timing of course offerings (inflexibility factor), sequencing causing courses to extend beyond the intended time to degree (transfer delay factor), and credits that are not applied to course requirements (lost credits) [17]. Moreover, these metrics are readily calculated using an R package that we have developed and tested with previous work to validate its functionality.

Research Aim

This paper aims to demonstrate our method for quantitatively describing the complexity of a plan of study for engineering transfer students. We highlight course-level and curriculum level metrics that incorporate transfer-specific issues like timing of course offerings and unfavorable sequencing of courses. This paper leans toward a descriptive aim; therefore, the inferences are not meant to be broadly generalizable for all program types described here.

Transfer Student Structural Complexity

In our previous work, we illustrated three metrics that account for curricular factors that are more relevant for transfer students: the inflexibility factor, the transfer delay factor, and credit loss [17] – in which the theoretical basis for their formulations was discussed. We will review them here and discuss how the metrics have evolved.

Inflexibility Factor

The premise of the inflexibility factor is to incorporate timing information into courses. In the original conceptualization of structural complexity, it is implicitly assumed that a student can take a course at any time. However, this is often not the case, especially for upper-level courses. Our previous paper leaned heavily on the idea of a curriculum's degrees-of-freedom, the number of ways the courses can be rearranged while respecting prerequisite structures [2]. The measure considered the sum of how many terms were ineligible for each course to move divided by the number of possible terms courses could move without restrictions. There were also penalties for crucial foundational courses not available at the community college and courses that extended the student's time to degree. As we experimented with a wider range of test cases than shown in [17], it was recognized that the measure was measuring several dimensions of inflexibility that did not capture the spirit of the rationale for its creation.

Accordingly, we opted for a simpler metric that more directly captures the idea of course offering timing. Figure 3 demonstrates the inflexibility factor using the delay factor and penalties for courses that are not offered every term. For each course with a limited offering, such as Fall-only, Spring-only, or Alternating-Spring, we shift the course to its next possible offering time and shift any following courses by the same amount. We then determine how many terms the prerequisite structure extends the student's completion time. In the case of Figure 3, the grey course's subsequent courses would extend the completion time by two terms after waiting two terms to take the course. These waiting times serve as the basis for penalties on the delay factor.

In other words, given the course's delay factor, we want to add a weight based on a penalty for delays in timing and graduation. Here we will take the penalty to be the sum of the original term number, the time needed to wait to take the course if missed, and the number of terms beyond the expected completion time when the subsequent courses are shifted by the wait time. In Figure 3, we have a starting delay factor of 4, taken in the second term, with two penalties of 2 each; this yields (2+2+2)*4 = 24.

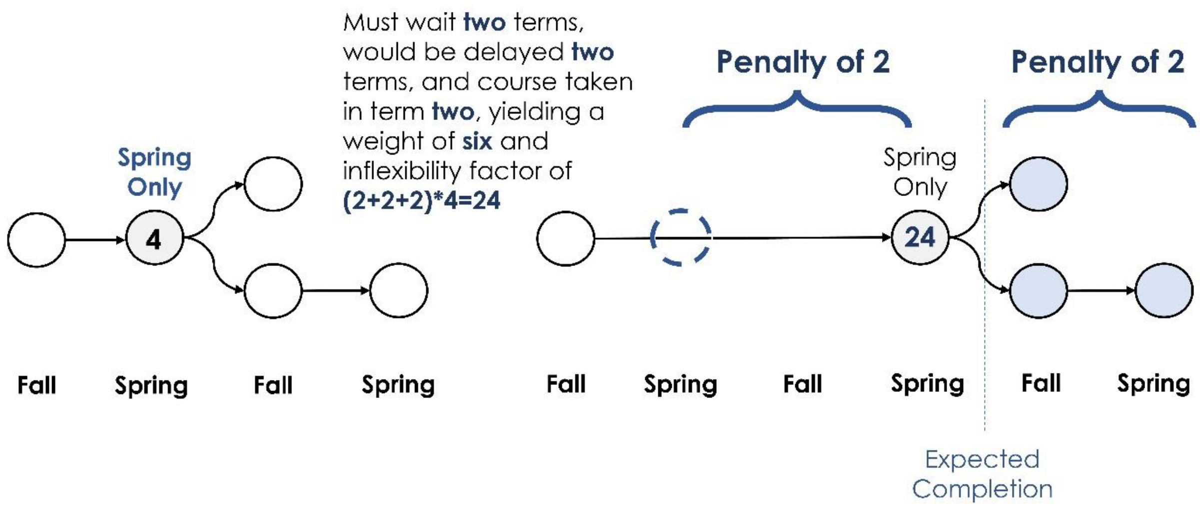

Figure 3. Inflexibility factor using the delay factor as a basis with penalties for limited offering courses

When phrased as an equation, let $d(v_{ij})$ be the delay factor of the ith course in the jth term. Similarly, let $o(v_{ij})$ be the frequency of a course's offering over T terms (e.g., two years of Fall/Spring/Fall/Spring). Heileman et al. [2] write, $v_a \rightsquigarrow_s v_b$, to denote a sequence s of courses $< v_a, \dots, v_b >$ with the property that each pair of courses is a valid edge in the graph (i.e., they all belong to the same prerequisite chain), starting at v_a and ending at v_b. Let $t_w(v_{ij})$ be the number of terms a student must wait to take a course if missed and t_e be the expected time to degree. Finally, define the indicator functions:

$$I_s(v_a, v_b) = \begin{cases} 1, & v_a \rightsquigarrow v_b \\ 0, & \text{else} \end{cases}$$

where I_s is an indicator if a valid sequence of courses starting at v_a and ending at v_b exists. And,

$$I_o(v_{ij}) = \begin{cases} 1, & \text{if } o(v_{ij}) < T \\ 0, & \text{else} \end{cases}$$

where I_o is an indicator if a course is not offered every term. We'll formulate the penalties based on the time a student must wait, $t_w(v_{ij})$, and the number of terms delaying the course would push course-taking beyond the expected time to degree, $p(v_{ij})$. The second penalty would be expressed as:

$$p(v_{ij}) = \max_{k>j} \left\{ \left(k + t_w(v_{ij})\right) I_s(v_{ij}, v_{*k}) - t_e, 0 \right\}$$

This means the inflexibility factor for a course is:

$$I_f(v_{ij}) = d(v_{ij}) \left(j + p(v_{ij}) + t_w(v_{ij}) \right)$$

To summarize the timing sequencing issues, we'll sum up the course inflexibility factors for the courses that have limited offerings (using the indicator function I_o) to get the total inflexibility factor $I_f T$.

$$I_f T = \sum_{(i,j)} I_o(v_{ij})\, I_f(v_{ij})$$

Note that the delay factor itself is calculated as follows [2]:

$$d(v_{ij}) = \max_{a,b,l,m} \left\{ \left| v_{*a} \rightsquigarrow_l v_{ij} \rightsquigarrow_m v_{*b} \right| \right\}$$

where |.| denotes the length of the sequence. In essence, the formula $d(v_{ij})$ fetches the longest path including v_{ij} bridged by arbitrary sequences of courses *l* and *m* from v_{*a} to v_{*b} (which is the longest requisite chain flowing through the course under consideration).

Transfer Delay Factor and Transfer Delay Subcomplexity

The Transfer Delay Factor T_d intends to capture the type of delay where transfer students' expected time to degree is pushed through curricular factors alone; in other words, the sequencing of courses simply does not permit the student to finish within the constraints of an X-year program. This metric was further motivated by a previous study with 56 transfer pathways into engineering at Virginia Tech, where only 11% were possible to complete in four years [5]. Moreover, egregious delays could occur if the receiving institution has courses that block the student from several later offerings, such as new requirements resulting from a substantial curriculum revision. The transfer delay factor is the sum of the delay factors for the courses beyond the expected time to degree, which is calculated using the following sum:

$$T_d = \sum_{(i,j):j>t_e} d(v_{ij})$$

where v_{ij} represents the *i*th in course in term *j*. One could also divide T_d by the number of courses beyond the expected-time-to-degree and find the average length of the prerequisite chains.

Another quantity to examine is the Transfer Delay Subcomplexity, ST_d. When considering the courses that extend a student's completion time, we can visualize how dense the prerequisite chains leading up to them are and quantify them. Recall that the total term weighted cruciality (or term-weighted structural complexity, TWSC) is:

$$TWSC = \sum_{(i,j)} jc(v_{ij})$$

where $c(v_{ij})$ is the cruciality of the course v_{ij}. The expression that captures the sequencing using the term-weighted crucialities from DeRocchis et al. [10] is:

$$ST_d = \sum_{(i,j)} jc(v_{ij}) I_s(v_{ij}, v_{*j>t_e})$$

In essence, $I_s(v_{ij}, v_{*j>t_e})$ indicates if there is a requisite chain that the course flows into later in the program that extends the student's time to degree.

The formulas are almost identical, with the exception that all of the courses are included in TWSC instead of only the courses related to extending the student's time to degree in ST_d. To examine how much of the structural complexity is explained by sequencing issues extending time to degree, we can form the following ratio:

$$Complexity\ Explained = \frac{ST_d}{TWSC}$$

This idea has a convenient parallel with the notion of explained variance in statistical analyses and can be used to evaluate how interconnected the prerequisite chains are that cause delays. An example of the Transfer Delay Factor and Transfer Delay Subcomplexity is shown in Figure 4.

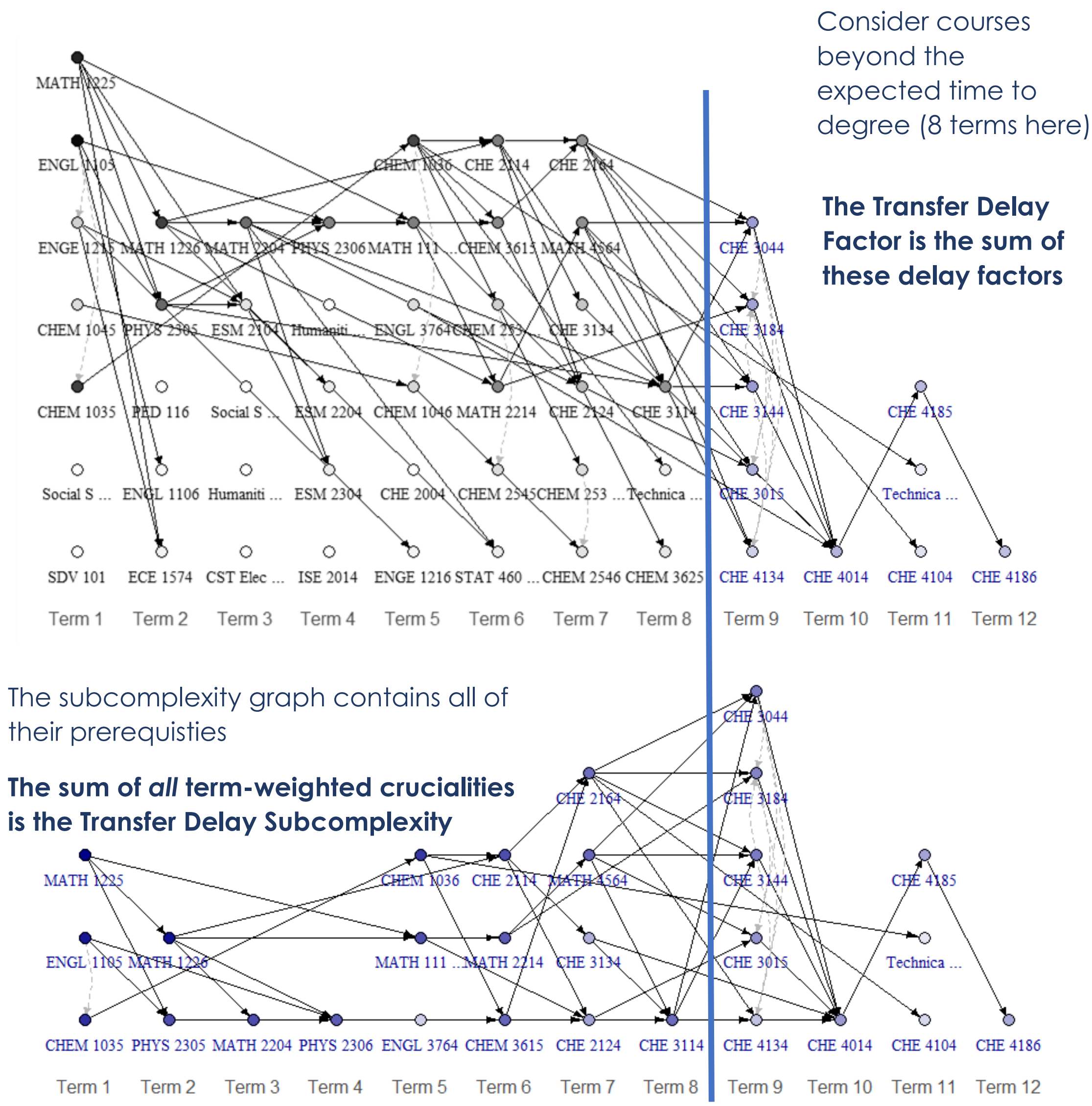

Figure 4. Calculation of the Transfer Delay Factor and the Transfer Delay Subcomplexity

Credit Loss

The last metric, credit loss C_l, concerns courses that are included in the plan of study but do not count toward the degree program's requirements. These courses could be relegated to elective credit or not counted at all. Credit loss tends to decrease the likelihood of graduation [18], so we consider the inclusion of lost credits as a valuable factor in the Transfer Student Structural Complexity model. We sum the number of credits from the community college that do not apply to the student's degree program requirements for this metric. For this paper, we will be focusing on the structural differences between curricula.

Application of Transfer Student Structural Complexity

Now that we have reviewed the components of the Transfer Student Structural Complexity framework, let's apply it to a selection of real curricula.

Context of Our Examples

To demonstrate our method for the broader two-year college community, we purposefully selected an intentionally streamlined program for transfer, i.e., a 2+2 engineering program, a program that does not have a specified transfer pathway, and a program that underwent a curriculum overhaul to highlight different features of our metrics. We collected the course data for a feeder community college for each of the three institutions and the four-year institution plan of study data, which included prerequisites, corequisites, and course equivalencies. Then, we constructed the plans of study based on the suggested pathways at the institutions. Course equivalencies available through the institutional websites were used to eliminate redundancies in prerequisites.

A Deliberately Sequenced Mechanical Engineering 2+2 Program

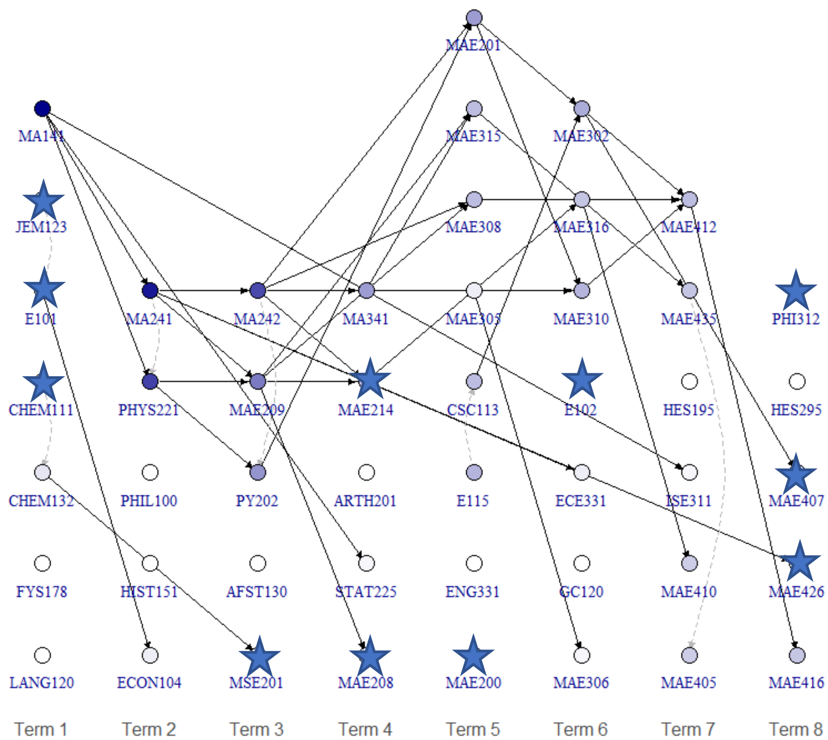

Figure 5. Plan of study for a sequenced 2+2 program, horizontal transfer; stars denote limited offering courses.

The plan of study in Figure 5 derives from a partnership between two four-year institutions that offer a joint program in engineering, which makes these students horizontal transfers. The overall structural complexity of this curriculum is 343, with a term-weighted structural complexity of 1351.

What can be seen in Figure 5 is a set of limited offering courses scattered throughout the plan of study. What we can capture using the inflexibility factor is a measure of how severe sequencing delays could be if a student misses or fails a limited offering course – or fails a course in the sequence of a limited offering course. By summing up the delay factors and associated penalties of the limited offering courses (denoted by stars). The resulting value is 268.

If we compare the results of the course-level inflexibilities with the weighted crucialities, we can see how courses in longer prerequisite chains can suddenly become much more crucial than others that are a more fundamental linchpin of a denser set of requirements. Consider MA341 and MA214 in the fourth term. The term weighted cruciality of MA341 is the highest of all five courses (Table 1), with MA214's term weighted cruciality being 31% less than MA341. If we examine the delay factor's contribution to the cruciality, we see that they are equivalent – the difference is in the number of courses each one blocks. Next, if we apply the inflexibility factor calculation, MAE208's delay score that incorporates timing now exceeds MA341's delay score. In fact, now MAE214's delay is only 3 points away from MA341's weighted cruciality, underscoring how a limited offering course can impact a student's progress if the prerequisite chain is not followed as scheduled.

Table 1. How individual course inflexibilities can be compared to weighted crucialities, course-level measures of fourth term courses in the 2+2 program

Course	Weighted Cruciality	Weighted Delay Factor	Inflexibility Factor
MA341	**52**	**28**	
MAE208	20	20	**30**
MAE214	36	28	**49**
STAT225	8	8	
ARTH201	4	4	

Note: Shaded rows are limited term offerings.

At this point, we should note that because the 2+2 program is specifically designed to be done in four years, there are no courses that actually extend the student's time to degree on paper. Therefore, the transfer delay factor is zero. Despite the transfer delay factor being zero, the inflexibility factor captures the potential for delays. Examining the weighted delay factors and inflexibility factors of individual courses can help identify timing issues in sequences for students. Although the aggregate measure of the inflexibility factor provides a summary of the sequencing issues, disaggregating by analyzing individual crucialities, delays, and inflexibilities is recommended.

A Mechanical Engineering Program in a Statewide Community College System

The plan of study in Figure 6 is a general vertical transfer program supported by a statewide community college system that is designed to streamline transfer. The overall structural complexity of the curriculum is 367, and the term-weighted structural complexity is 1500. In this case, the recommended courses result in an additional year to the student's plan of study. Note that the structural complexity is 24 points (+7%) more than the last curriculum, whereas the weighted structural complexity is 149 (+11%) to account for the additional terms. The weighted crucialities allow us to punish these additional terms directly using the standard metrics at the aggregate level.

We can single out those courses extending the student's time to degree using the transfer delay factor. Figure 7 shows the courses that are related to the ones extending the student's time to degree.

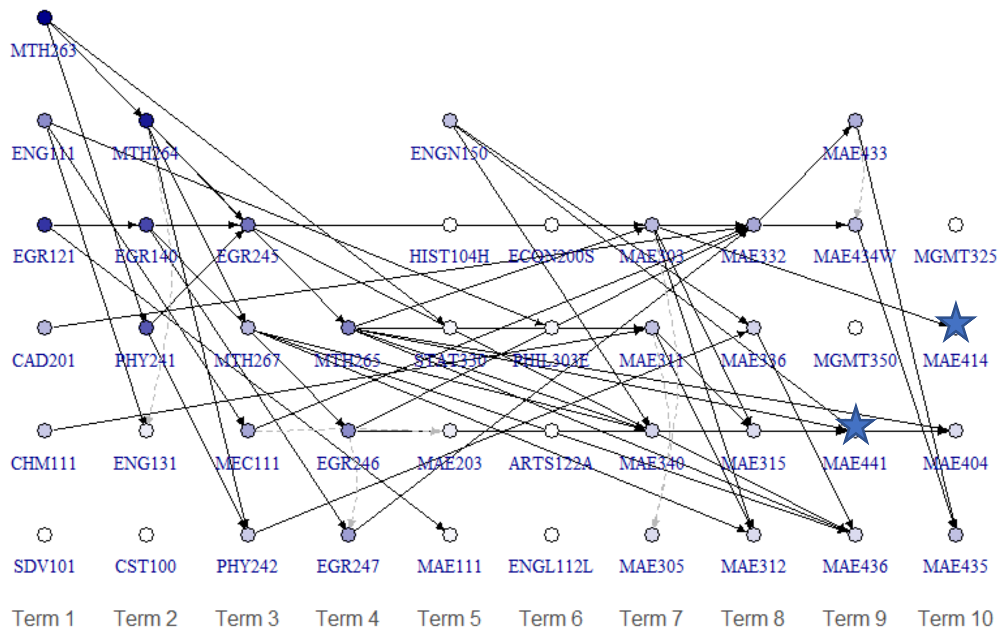

Figure 6. Plan of study for a general vertical transfer program; stars denote limited offering courses.

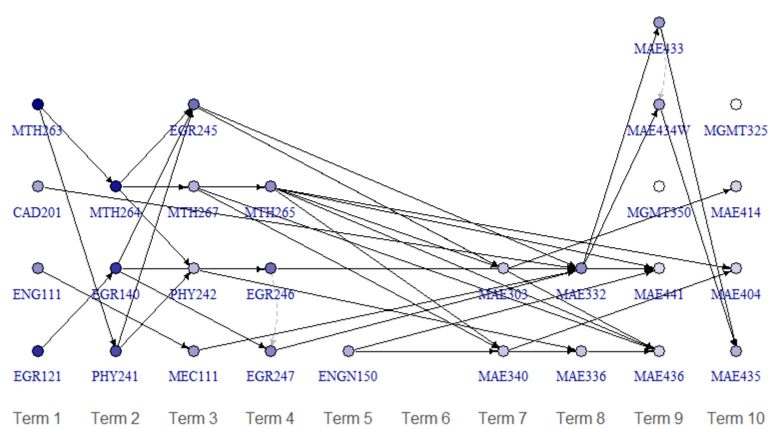

Figure 7. Courses that are extending the student's time to degree in the program

The structural complexity of the subgraph in Figure 7 is 283, and its term weighted structural complexity is 1156. Therefore, we can calculate that the complexity contributing to the student's extended time to degree is 77% of the overall weighted and unweighted complexity. Looking at the total delay factors of the courses in the 9th and 10th terms, we can deduce the transfer delay factor is 45. On average, the sequencing pushing these courses beyond the eighth term is five courses long (45/9 courses = 5). These three figures – explained complexity, transfer delay factor, and average sequencing – allow us to quantify the messy web of prerequisites the students must navigate through that are impeding timely degree completion.

In terms of timing, only two courses are limited offerings in mostly unsurprising locations – near the end of the curriculum. Because they are in the 9th and 10th terms, they are subject to both penalties as described in the prior section on calculating the inflexibility factor. After performing the calculation, we find that MAE441 has a delay factor of 4 and could extend completion until term 11 (a penalty of 3), whereas MAE414 has a delay factor of 5 and could extend completion until term 12 (a penalty of 4). In total, we have $I_f = 4(2 + 3 + 9) + 5(2 + 4 + 10) = 136$.

Compared to the other curriculum, which had an inflexibility factor of 275 – a little more than double the inflexibility factor here – we can highlight how the placement of limited-term offerings makes a tremendous difference in the resulting value. The first curriculum has 11 limited offering courses scattered throughout the curriculum, but the prerequisite structures were a little more forgiving in the previous curriculum. Here, the courses that could extend time to degree further are already beyond the eighth semester. Therefore, missing these courses can have a tremendous effect, hence the value of the inflexibility factor. This simple comparison highlights the value of the inflexibility factor in unearthing timing issues that are currently not captured in the current framework.

A Significantly Revised Electrical Engineering Program

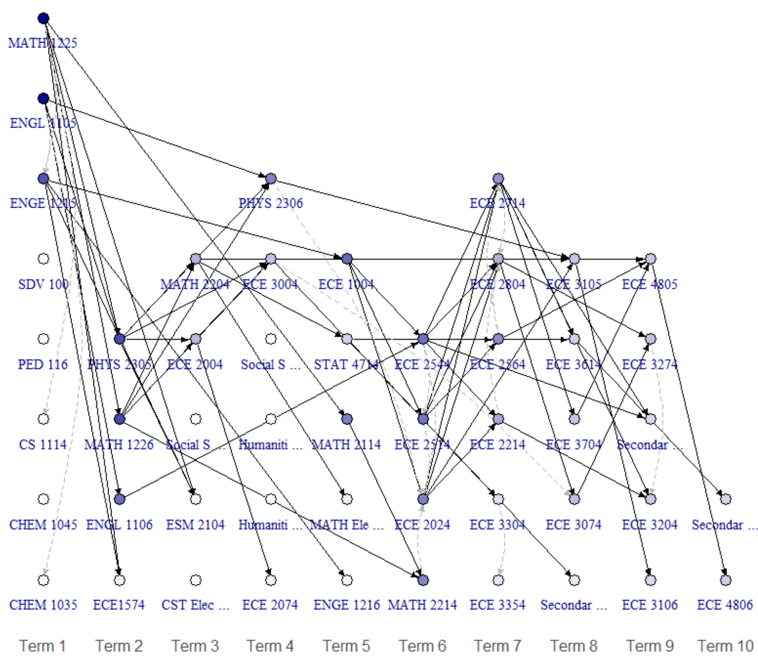

Figure 8: An example of a significantly revised program in Electrical and Computer Engineering for vertical transfers

In contrast with the previous program, consider a pathway into the Electrical and Computer Engineering program significantly changed as part of a curricular renewal mentioned in the background to this paper. The structural complexity is 698, and the term-weighted structural complexity of 3265 – more than double the previous curriculum.

Its transfer delay factor is 67, compared to 45 in the last case (49% larger). Thus, on average, the sequencing is 67/7 = 9.6 courses – making the sequencing much less forgiving than the previous 5-course average sequencing. Unlike the previous curriculum, all seven courses are connected to a prerequisite structure earlier in the network. In contrast, nine courses in the other curriculum extended beyond the expected time to degree but not all depended upon other coursework.

The comparative power of the Transfer Delay Subcomplexity comes into play when we calculate the corresponding value of the graph in Figure 9. Its Transfer Delay Subcomplexity totals 2972, implying that 91% of the explained complexity for delays arises from the courses extending the student's completion time.

Taken together, we see how the suite of measurements can vary considerably across programs and can identify potential pain points for transfer students.

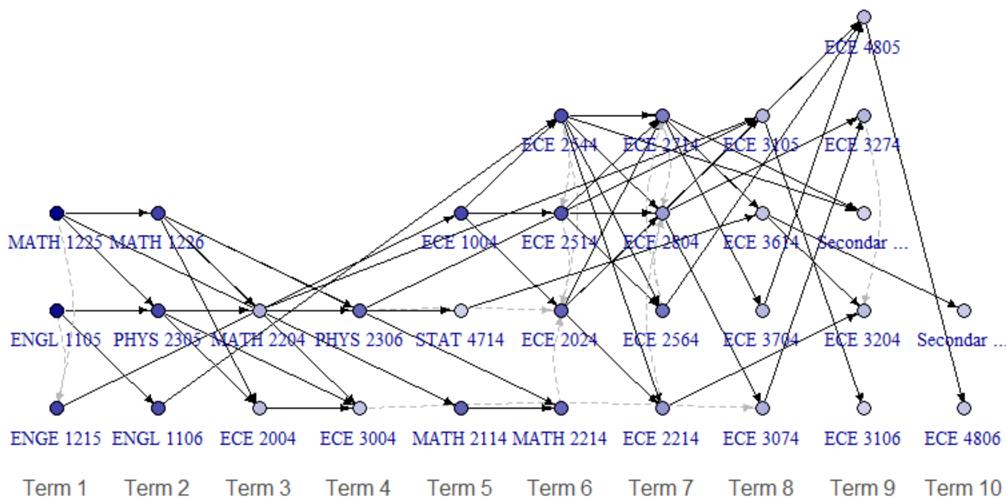

Figure 9: Transfer Delay Subcomplexity graph for the significantly revised program

Conclusions and Future Work

In this paper, we highlighted the descriptive power of the curricular complexity framework when modified to consider issues related to transfer students. As a whole, the term-weighted structural complexity, term-weighted crucialities, inflexibility factor, transfer delay factor, average sequencing, and transfer delay subcomplexity have the potential to provide a comprehensive view of sequencing and timing issues for vertical and horizontal transfer students. Each component offers different levels of information that can signal issues for hypothetical or actual transfer pathways.

We expect our method to be useful for researchers and practitioners alike. For researchers, studying persistence in transfer student pathways can be complemented by one or more of these metrics intended to capture the predicted completion rate for those individuals. Moreover, studying curricular policy for transfer students can be accomplished using proposed plans of study, allowing the implications of decisions to be quantified and forecasted using all available data. These analyses can also be combined with a method proposed by Slim et al. [19] that uses Bayesian Networks to evaluate the impact of changes to curricula on graduation rates. Finally, our method empowers practitioners like advisors to visualize hypothetical pathways for students and consult with them about decisions they must make to have a successful transfer.

Because curricula are dynamic, we can think of the metrics here as *implied* or *forecasted.* Students often do not follow the curriculum as described [13], such as retaking courses multiple times [20] or switching majors [21]. These behaviors are captured to an extent by the instructional complexity metric. However, there is still work to be done to cover the broader scope of student decision-making and institutional factors that impact curricula. Headway in incorporating student behaviors into the curricular complexity framework is seen in Slim et al. [22,23], who introduced a Markov model to provide closed-form solutions describing how students flow through a curriculum. Their example was with a subset of courses in a plan of study, but the authors plan to expand the Markov models to complete curricula.

To continue refining our Transfer Student Structural Complexity model, we are currently in the midst of a project to collect more face and construct validity for our measures by soliciting feedback from transfer stakeholders, including faculty, advisors, administrators, and students themselves. We aim to contextualize a broader theory of Transfer Student Curricular Complexity to complement the instructional complexity in Heileman's [2] framework. Moreover, we plan to collect more plans of study to explore the variation in the measures provided here.

Finally, we have an alpha version R package that we are using to conduct the analyses that we plan to make available to the community. As a result, we aim to make this work accessible as a tool for researchers and practitioners.

Acknowledgments

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