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Practitioner-Informed Learning Analytics Metrics for Measuring Curricular Complexity for Transfer Students

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Abstract

This study expands the concept of curricular complexity as defined in the Curricular Analytics framework (Heileman et al., 2018) by providing qualitative evidence of the suitability of three new metrics, concerning timing of course offerings, extended time-to-degree, and credit loss, that more adequately address curricular challenges encountered by transfer students. Curricular Analytics is a method for analyzing a curriculum that enables practitioners and researchers to quantify and systematically analyze the impacts of course sequencing in a plan of study on student outcomes. However, the original conceptualization falls short of capturing the substantive challenges faced by transfer students who enter an undergraduate program at various points in the curricular sequence. This study was guided by the following research question: "How do three new measures of curricular complexity (i.e., inflexibility factor, transfer delay factor, and credit loss) align with transfer professionals' perceptions of curricular barriers for transfer students?" Using a grounded theory approach, we conducted seven focus groups with 38 transfer professionals across the United States. We presented these transfer experts with each new measure and prompted them to reflect on its validity based on their experiences supporting transfer students. We found transfer professionals resonated strongly with all three new metrics, suggesting strong initial construct and content validity.

Notes for Practice

- Curricular Analytics in higher education has traditionally focused on first-time-in-college (FTIC) students, emphasizing the role of course sequencing and prerequisite structures. However, it is essential to recognize that transfer students encounter distinct challenges, such as credit loss and timing issues, which are not fully accounted for by existing curricular complexity metrics.
- This study extends the Curricular Analytics framework by introducing three new metrics tailored to transfer students: the inflexibility factor, the transfer delay factor, and credit loss.
- The new metrics enable researchers and practitioners to better understand and address the curricular barriers faced by transfer students, potentially leading to improved advising practices and academic planning. These improvements can be further enhanced by tailoring the metrics to specific student experiences.

Keywords: Curricular Analytics, transfer student, curriculum, higher education, STEM education, transfer agent

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1. Introduction

When considering the different elements of a learning experience that can be transformed into usable analytics, the curriculum is perhaps the most daunting. Even writing the phrase "curriculum analysis*"* can evoke different meanings for various groups; as Ariav (1986) wrote, "curriculum analysis is difficult to define because the term 'curriculum' is itself controversial and interpreted in different ways" (p. 139). As such, a variety of data streams have been used to quantify aspects of a program for the purposes of development, improvement, and comparison. For example, Méndez et al. (2014) provide an approach to measure dependencies between courses by correlating the final grades from each pair of courses and exploring curriculum coherence (i.e., the curriculum is structured around a set of competencies that students are supported in completing) by conducting an exploratory factor analysis on the same final grades to find groupings of courses. Aside from examining the impact of grades, they also propose using sequence mining to identify combinations of courses that lead students to drop out of their program. A similar analysis can be conducted using alluvial or Sankey diagrams to map student progression through key courses in the curriculum (Reeping et al., 2019). More broadly, Lord et al. (2019) advocate for ecosystem metrics to analyze programs, such as stickiness, which refers to the percentage of students who initially enroll in a program and ultimately graduate from it (Ohland et al., 2012). These varied approaches aim to contextualize an educational program quantitatively and explore dependencies on student success, which are often associated with retention and graduation rates.

Still, these different approaches metaphorically dance around the structures that students must engage with to complete their degree, the curriculum itself. Continuing with our first example, Méndez et al.'s (2014) approach to analyzing dependencies acknowledges the relationships between courses through prerequisites but does not directly incorporate them into the analysis. However, a method for systematically analyzing these kinds of relationships has been growing in popularity: *Curricular Analytics* (Heileman et al., 2018).

We know that gateway courses, such as Physics, Statics, Calculus, and Electric Circuits, have a considerable influence on student progress toward graduation in STEM fields (Alexander et al., 2009; Bloemer et al., 2017; Seymour & Hewitt, 1997). Because they contain foundational content, they are often assigned as prerequisites for later courses in a plan of study, which frequently impedes students' progress (Koch, 2017). How might we analyze a curriculum to more precisely quantify the impacts of such courses? Heileman et al. (2018) conceptualized Curricular Analytics as a way to understand plans of study as a network, where each course in the program is a vertex (or node) connected through pre- and corequisite directed edges (i.e., arrows) that define the hierarchical relationships between courses in a plan of study network. Mathematically, we describe these networks as $G = (V, E)$, a "graph" composed of a set of vertices V and edges E. By reformulating the curriculum into a network, we can measure the impacts of gateway courses on students' ability to navigate plans of study and understand a curriculum's relative complexity (i.e., interconnectedness).

Heileman et al. (2018) created two factors to measure a program's *structural complexity*: the blocking factor and the delay factor. Analogous to how we think about gateway courses, a course's *blocking factor* is the number of courses a student cannot access if they earn a failing grade in it. The *delay factor* captures how embedded a course is in the program's prerequisite structure. To calculate the delay factor, we identify the longest prerequisite chain to which the course belongs. The sum of a course's delay and blocking factor yields the course's *cruciality*; a high cruciality implies that a course is a barrier to many other courses in a plan of study and/or is part of a long prerequisite chain—both of which are generally indicative of a gateway course. An example of calculating a course's cruciality is given in Figure 1. Example calculation of a course's cruciality using the delay and blocking factors.

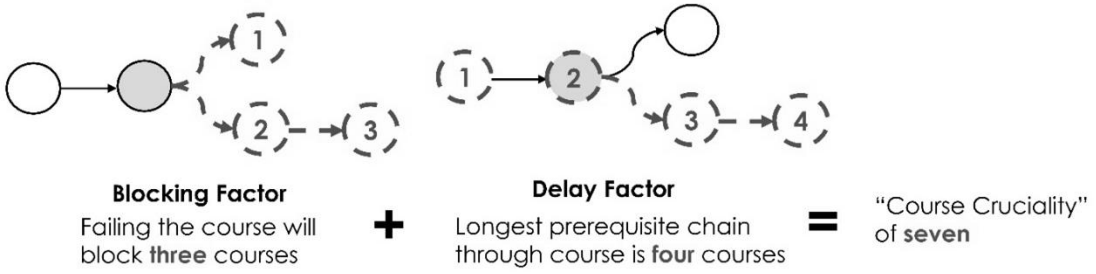


Figure 1. Example calculation of a course's cruciality using the delay and blocking factors

Finally, to calculate the *structural complexity* of an entire plan of study—an aggregate measure that describes the overall complexity of a curriculum—we sum the course cruciality scores for all courses in the plan of study. Using structural complexity as a tool to investigate curricular mapping alongside institutional data on student performance, it is plausible to predict the impacts of specific curricular design patterns on student outcomes (Heileman et al., 2017). Moreover, the structural complexity of a curriculum has been found to negatively correlate with completion rates in both simulations (Slim, 2016) and

empirical research (Grote et al., 2020; Hansen et al., 2024; Slim et al., 2021), suggesting that it may be of predictive value for programs to reconsider their curricular structures and remove unnecessary barriers to student progression.

2. Research Aims

Although curricular complexity appears to adequately characterize the relationship between a program's curricular complexity and the completion rates of first-time-in-college (FTIC) students, the correlation is less clear for other student pathways, such as community college transfer (Grote et al., 2020). In particular, the analytical framework does not explicitly account for issues that are salient for transfer students, such as (1) the timing of courses being offered, (2) sequencing causing students to delay their graduation by the simple virtue of how course prerequisites are established, and (3) credit loss for major courses for coursework that did not apply to their four-year degree program. This paper aims to extend the premise of Curricular Analytics by collecting practitioner-informed validity evidence for a set of transfer student-centered metrics that can complement existing metrics, such as the blocking and delay factors. By extending Curricular Analytics to incorporate transfer-centric issues, we provide researchers and practitioners with tangible ways to quantify the well-known problems in the literature. By achieving this aim, the metrics will enable learning analytics researchers and practitioners to study curricular factors that affect the learning and progress of transfer students, introducing a computational perspective on analyzing and improving curricula and policies for transfer students.

3. Expanding Curricular Analytics to Transfer Experiences

The Curricular Analytics framework relies on assumptions that, though sensible for FTIC students, obscure the challenges faced by students who do not enter the curriculum at its beginning (Reeping & Grote, 2021). To highlight the significant challenges these assumptions pose for the utility of curricular analytics as a tool for analyzing curricular complexity for the transfer student population, we will outline three primary considerations that are not currently accounted for in the conceptualization of Curricular Analytics.

3.1. Timing of Courses Being Offered

Unlike FTIC students, vertical transfer students may enter the four-year institution at varying points in the curriculum. For example, students may complete only the first year of introductory coursework at a community college before transferring to a four-year institution. Other students may seek to transfer via articulated degree pathways that require completion of an Associate's Degree at the community college, which are typically designed to be completed in two years. Other four-year institutions may offer spring admission for transfers or rolling admissions, allowing students to enter at any point. Simultaneously, prescribed plans of study for four-year degrees usually consider the timing of courses being offered by departments (i.e., fall, spring, summer). Although required courses in the first two years of a plan of study are often offered every semester, upper-level in-major courses may be offered less frequently, often because fewer faculty teach them, limiting when and how often they can be offered.

As currently constructed, the Curricular Analytics framework assumes that all courses are offered in every semester within a plan of study. However, transfer students who may arrive in a fall semester and need a course not offered until the spring, or one offered only in odd years, for example, will be forced to wait for one, two, or even three semesters. Therefore, this simplifying assumption in Curricular Analytics obscures a persistent challenge for all students, but particularly for transfer students.

3.2. Sequencing Issues Embedded in the Curriculum

Compounded by the frequency of offerings, prerequisite relationships embedded in curricula can make it impossible for a transfer student to complete a two-year graduation timeline once they reach the four-year institution. There is extensive evidence that transfer students take longer to graduate than FTIC students (Blash et al., 2012; Packard et al., 2012; Shapiro et al., 2016; Shirley et al., 2023; Yoon et al., 2015). Few prior studies have examined how curricular complexity contributes to the extended time-to-degree among engineering transfer students. For example, Grote et al. (2020) compared the most expedient pathways to graduation for 56 transfer pathways with 14 FTIC pathways in engineering at Virginia Tech, including pathways resulting from curricular changes in the Electrical and Computer Engineering degree programs (Reeping et al., 2021). They found that, by design, 93% of FTIC pathways could be completed in 4 years (8 semesters) compared with only 11% of transfer pathways across engineering disciplines. Despite the additional semesters, the aggregate curricular complexity scores for the transfer pathways were lower than those for the FTIC pathways, indicating that the current operationalization of curricular complexity failed to capture how course sequencing extends time-to-degree for transfer students, with significant financial implications and impacts on their completion rates. This misalignment suggests the need for an alternative metric to capture the structural elements of a curriculum that prevent the program from being completed on time.

3.3. Credit Loss for Major Courses

Finally, and perhaps most salient for the transfer population, is the issue of lost credit. Credit can be accounted for in three ways: 1) credits that do not transfer to the four-year institution; 2) credits that are transferred, wherein the student earns credit, but they count toward elective credits that do not advance degree progress; and 3) credits that were applied toward courses required for students to complete their degree at the four-year institution. Of all the elements not addressed in the current conceptualization of curricular complexity, credit loss is likely the most crucial; as Monaghan and Attewell (2015) have found that it decreases the likelihood of graduation. The loss of credit is widespread, and the educational research community is still grappling with how to reconcile the various reasons it occurs (Giani, 2019), such as misalignments between course outcomes and institutional standards (Hodara et al., 2017). Simone (2014) reported that students who began college in 2003–2004 lost an average of 13 credits when transferring between institutions, and approximately 40% of students had no credits transferred. Moreover, transfer students often face challenges in applying credits to major prerequisites (Spencer, 2021), and the resulting credits are frequently relegated to electives. In fact, Kadlec and Gupta (2014) describe courses that are transferred with the elective designation as an "academic graveyard where students essentially bury all those courses that transfer but do not meet any specific requirements in the new institution" (p. 7). This leads us to consider how credit loss could be included in our analysis.

Notably, credit loss is not a structural property of the curriculum at face value, like timing and sequencing. Instead, it is shaped by several external factors, including student decision-making and articulation policies. Still, when we consider the credits lost by students entering a four-year program, the number of credits that ultimately transfer has a nontrivial impact on the curricular structure they will face. For example, if a student decides to switch their major when they transfer from the community college to the four-year institution, they must essentially navigate the curriculum from scratch—or at least close to it. Whereas a student benefiting from a strong articulated pathway will be able to jump more readily into their upper division courses. Therefore, we consider credit loss a factor we cannot ignore when conceptualizing Curricular Analytics for transfer students.

4. Operationalizing Transfer-Centric Metrics

To address the analytical shortcomings of the original conceptualization of curricular complexity, we propose three additional measures for Curricular Analytics that capture challenges experienced by transfer students in navigating plans of study across institutions: 1) inflexibility factor, 2) transfer delay factor, and 3) credit loss. The inflexibility factor accounts for the possibility that a required course in a transfer plan of study is not offered during the semester in which a transfer student enters a curriculum at a university after completing a community college. The transfer delay factor accounts for any subnetwork of courses that extend a student's time-to-degree beyond the four-year (or 2+2) timeframe. Finally, credit loss refers to the number of credits not applied to a student's degree requirements at the four-year institution where they transfer. These metrics will comprise what we will refer to as *transfer student curricular complexity* (TSCC).

4.1. Standard Curricular Analytics Metrics

Because the transfer-specific metrics build upon the ideas from Heileman et al.'s (2018) original metrics, we will briefly review them here mathematically to further illustrate the concepts in Figure 1. First, let $d(v_{ij})$ be the delay factor of the *i*th course in the *j*th term, represented by v_{ij}. If one index in v_{ij} is not needed, we substitute it with an asterisk (*). With this in mind, our delay factor is found using the following:

$$d(v_{ij}) = \max_{a,b,l,m} \{ |v_{*a} \dashrightarrow_l v_{ij} \dashrightarrow_m v_{*b}| \} \tag{1}$$

Where |.| denotes the length of the sequence of courses. Heileman et al. (2018) write, $v_a \dashrightarrow_x v_b$, to denote a specific sequence of courses $x =< v_a, \dots, v_b >$ with the property that each pair of courses is a valid edge in the graph, starting at course v_a and ending at course v_b. In essence, the formula $d(v_{ij})$ fetches the longest path including v_{ij} bridged by arbitrary sequences of courses from v_{*a} to v_{*b} (Heileman et al., 2018). The other primary metric used in Curricular Analytics is the blocking factor. First, we'll define an indicator function, I_s, to build the blocking factor. Here, I_s tells us whether a valid sequence of courses starting at v_{*a} and ending at v_{*b} exists:

$$I_s(v_{*a}, v_{*b}) = \begin{cases} 1, & v_{*a} \dashrightarrow v_{*b} \\ 0, & \text{else} \end{cases} \tag{2}$$

From this, the blocking factor, $b(v_{ij})$, can then be found by summing all of the instances where some course v in the set of all courses, *V*, is linked to the course of interest v_{ij}. As such, this calculation captures the number of courses that have v_{ij} as a direct or indirect prerequisite:

$$b(v_{ij}) = \sum_{v \in V} I_s(v_{ij}, v) \tag{3}$$

The cruciality of a course, $c(v_{ij})$, is the sum of its blocking and delay factors, providing a measure of how essential that course is in the curriculum:

$$c(v_{ij}) = b(v_{ij}) + d(v_{ij}) \tag{4}$$

These crucialities can be summed to form a summary score for a curriculum, called the structural complexity, α_c:

$$\alpha_c = \sum_{(i,j)} c(v_{ij}) \tag{5}$$

4.2. Inflexibility Factor

With the standard Curricular Analytics metrics defined, we can now turn to incorporating transfer-specific issues. To explore the impact of courses with limited offerings, such as *fall-only*, *spring-only*, or *alternating spring*, we can shift the course to its next possible offering time and any subsequent courses by the same number of semesters. We can then determine how many terms the prerequisite structure extends the student's completion time, if at all. These waiting times can serve as the basis for our inflexibility factor.

Because sequencing is a core issue for transfer students in completing their degree in a timely fashion, we built the inflexibility factor from the delay factor. In this case, we can add weights to the course's delay factor based on the impacts of limited offerings on timing and graduation. Here, we will consider the weight to be the sum of the term the course is offered, the time needed to wait to take the course if missed, and the number of terms beyond the expected completion time when the following courses are shifted by the wait time.

We can build the formula using two indicator functions, the first of which we defined in (2). Next, we'll define an indicator function for whether a course is not offered each term, I_o:

$$I_o(v_{ij}) = \begin{cases} 1, & \text{if } o(v_{ij}) < T \\ 0, & \text{else} \end{cases} \tag{6}$$

Here, $o(v_{ij})$ is the frequency of a course's offering over T terms (e.g., two years of fall-spring-fall-spring). This indicator function essentially tells us if a course is not consistently offered each semester.

We'll consider two penalties. Our first penalty will be based on the time a student must wait to attempt a course with limited offerings again, $t_w(v_{ij})$. For example, a student who misses the timing for a course offered in the fall must wait only two terms to retake it. Next, we'll calculate our second penalty, $p(v_{ij})$, which will be the number of terms delaying the course would push the student's course-taking beyond the expected time to degree, t_e. The second penalty would be expressed as:

$$p(v_{ij}) = \max_{k>j} \{(k + t_w(v_{*k}))I_s(v_{ij}, v_{*k}) - t_e, 0\} \tag{7}$$

Here, $p(v_{ij})$ is finding the number of terms for which the student is now delayed because we shifted the course to its next possible offering. We check every course with a term k greater than the term of the course under consideration in term j. If shifting the course does not result in an extended time to degree, then $p(v_{ij}) = 0$.

Next, we'll apply these penalties to one of the existing Curricular Analytics metrics, the delay factor. We'll multiply the delay factor by the sum of our penalties, including the course's current term, to punish courses later in the curriculum. This process yields the inflexibility factor of an individual course, $I_{fc}(v_{ij})$:

$$I_{fc}(v_{ij}) = d(v_{ij})\left(j + p(v_{ij}) + t_w(v_{ij})\right) \tag{8}$$

To summarize the timing and resulting sequencing issues, we'll sum up the inflexibility factors for the courses with limited offerings to determine the total inflexibility factor by combining (6) and (8).

$$I_f = \sum_{(i,j)} I_o(v_{ij})\, I_{fc}(v_{ij}) \tag{9}$$

Figure 2 illustrates the inflexibility factor for a course, I_{fc}. For each course with a limited offering, such as fall-only, spring-only, or alternating spring, we adjust the course to its next available offering time and shift any subsequent courses by the same number of terms. We then determine how many terms the prerequisite structure extends the student's completion time. In the case of Figure 2, the grey course's subsequent courses would extend the completion time by two terms, assuming a two-term wait to take the course. These waiting times serve as the basis for penalties on the delay factor. Using (1), we find that we have a starting delay factor of 4, taken in the second term, with two penalties of 2 each from (7); this yields (2+2+2)*4 = 24 using (8) and (9).

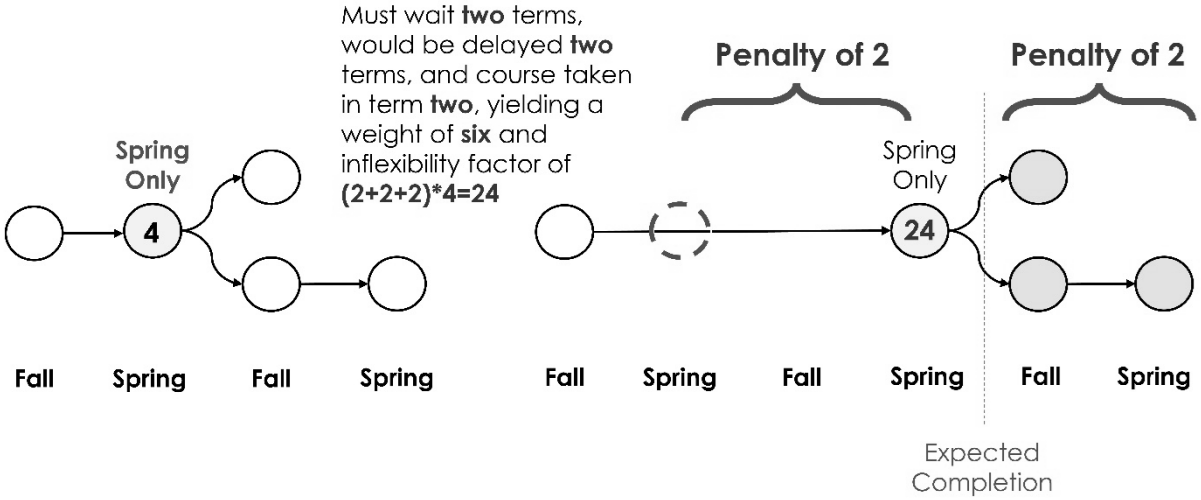


Figure 2. Inflexibility factor using the delay factor as a basis, with penalties for limited offering courses

4.3. Transfer Delay Factor

The Transfer Delay Factor T_d intends to capture situations when transfer students' expected time to degree is pushed back solely by curricular factors; in other words, the sequencing of courses does not permit the student to complete within the constraints of a four-year program. This metric was further motivated by a previous study of 56 transfer pathways into engineering at Virginia Tech, which found that only 11% could be completed within 4 years (Grote et al., 2020). Moreover, egregious delays could occur if the receiving institution has courses that block the student from later offerings, such as those following a 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:

$$T_d = \sum_{(i,j):j>t_e} d(v_{ij}) \tag{10}$$

Where, again, v_{ij} represents a course i in term j.

Another related 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 using the usual visualization tools in Curricular Analytics. We can also quantify them. The expression that captures this troublsome sequencing using term-weighted crucialities from DeRocchis et al. (2021) is:

$$ST_d = \sum_{(i,j):k\leq t_e<j} jc(v_{ij}) I_s(v_{*k}, v_{ij}) \tag{11}$$

Here, $c(v_{ij})$ is the cruciality of the course v_{ij}. Next, the total term-weighted structural complexity, TWSC, is:

$$TWSC = \sum_{(i,j)} jc(v_{ij}) \tag{12}$$

The formula is almost identical to (11), except that all courses are included in TWSC, rather than only those related to extending the student's time to degree. To examine how much of the structural complexity is explained by sequencing issues extending time to degree, we can form the following ratio:

$$Complexity\ Explained = \frac{ST_d}{TWSC} \tag{13}$$

This idea has a convenient parallel with the concept of explained variance in statistical modeling and can be used to evaluate how interconnected prerequisite chains contribute to delays relative to the overall structural complexity.

An example of the Transfer Delay Factor and Transfer Delay Subcomplexity is shown in Figure 3**Figure 3.** Calculation of the Transfer Delay Factor and the Transfer Delay Subcomplexity. Each vertex represents a course, and the shading indicates its cruciality (i.e., the darker, the more crucial). The solid arrows connecting courses represent prerequisites, whereas dotted arrows denote corequisites. In this figure, the course labels are irrelevant to our interpretation. As we described in the calculations, we establish a point at which we expect the student to complete their degree and retain any courses beyond that point, as well as any courses connected to them. From there, we can sum the delay factors for all courses to the right of the expected time to degree to obtain the transfer delay factor. Alternatively, we can multiply the individual crucialities in the second network by their respective term numbers and sum them to yield the transfer-delay subcomplexity.

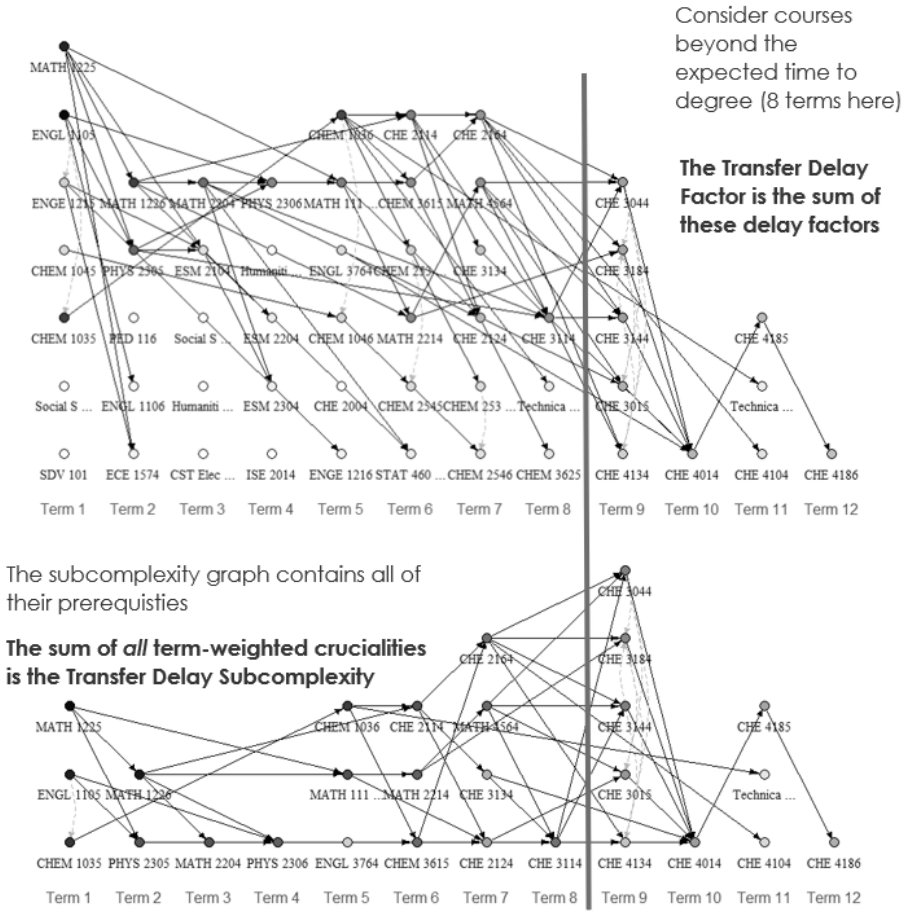


Figure 3. Calculation of the Transfer Delay Factor and the Transfer Delay Subcomplexity

4.4. Credit Loss

Unlike the other metrics, the credit loss metric's value is not derived from the network itself. Instead, we consider the set of courses V in the community college plan of study and the potential equivalencies V' at the four-year institution. We can assign each course a number of credits $c_r(v_{i*})$ and those at the community college $c_r(v'_{i*})$ as given by the plans of study. If no equivalent course exists for v_{i*}, then we say that $c_r(v'_{i*}) = 0$ because no credits can be used to offset the four-year program's requirements. We then sum the absolute difference between the credits earned at the community college and the equivalent course credits. If, for some reason, the number of credits for the equivalent course at the four-year institution exceeds those of the community college course, we use the max function to set the difference to zero. We do this because this negative credit is not lost; it is unfulfilled. Thus, our measure of credit loss, C_l, is:

$$C_l = \sum_{v_{i*} \in V, v'_{i*} \in V'} \max\{c_r(v_{i*}) - c_r(v'_{i*}), 0\} \tag{14}$$

Although credit loss is not an inherent property of the network, it has non-trivial impacts on the structure. When we account for equivalencies, we can remove one of the courses from the network rather than keeping the associated structure at both the community college and the four-year institution. As such, high values of C_l can often imply that students must navigate additional requirements, thereby increasing the network's number of vertices and edges—impacting other metrics. The value of this metric, unlike others that are currently available, enables users to ascribe aspects of curricular complexity to a combination of institutional processes or policies (e.g., articulation agreements, course-level requirements for applicability) and student decision-making—if the network is constructed for specific student cases.

4.5. Example Calculations

To illustrate how these metrics may be applied in a program, we will use the plan of study in Figure 4 as an example. We'll focus on the structural metrics, as credit loss is a straightforward tally. This plan of study is a general vertical transfer program supported by a statewide community college system designed to streamline the transfer process. The overall structural complexity of the curriculum is 367, as calculated from (4), and the term-weighted structural complexity is 1,500, as calculated from (12). In this case, the recommended courses result in an additional year to the student's plan of study. We can identify the courses that extend the student's time to degree using the transfer delay factor, as shown in Figure ***5.*** Courses that extend the student's time to degree in the program 5.

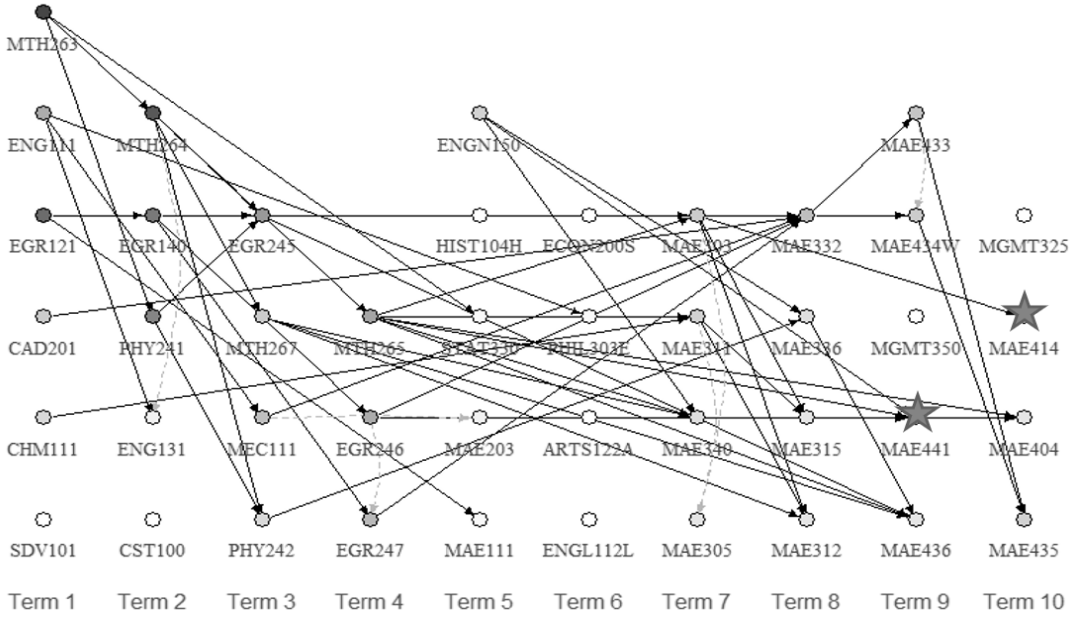


Figure 4. Example plan of study for a general vertical transfer program; stars denote limited offering courses; courses with darker shades have higher crucalities; output from author's R package (Reeping & Grote, 2022)

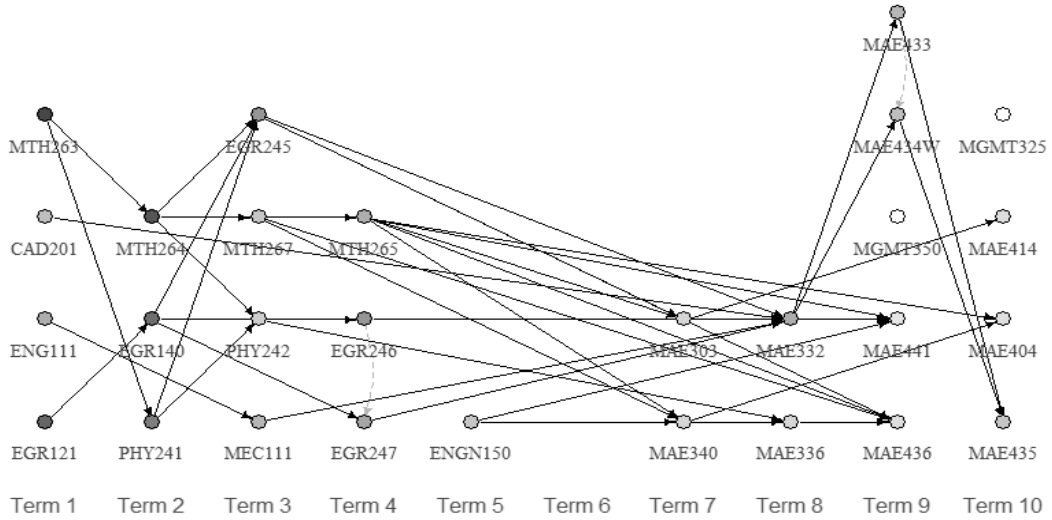


Figure 5. Courses that extend the student's time to degree in the program; courses with darker shades have higher crucialities; output from author's R package (Reeping & Grote, 2022; Reeping, 2026)

The structural complexity of the subgraph in Figure 5 is 283 by (4), and its term-weighted structural complexity is 1156 (12). Next, we can calculate that the complexity contributing to the student's extended time to degree accounts for 77% of the overall complexity, as calculated from (13). Examining the total delay factors of the courses in the 9th and 10th terms, we can infer that the transfer delay factor is 45, as calculated using equation (10). On average, the sequencing pushing these courses beyond the eighth term is five courses long (45/9 courses = 5).

In terms of timing, only two courses have limited offerings, mostly (unsurprisingly) 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 using (1) and could extend completion until term 11 (a penalty of 3 for extending the time to degree by three terms from (7)), whereas MAE414 has a delay factor of 5 and could extend completion until term 12 (a penalty of 4 from (7)). In total, we have I_f=4(2+3+9)+5(2+4+10)=136 using (9).

5. Research Design

Now, to what extent do these calculations accurately capture the curricular complexities that transfer students experience? To address this question, we employed constructivist grounded theory (Charmaz, 2014), which aligns well with theory-building (i.e., *conceptualizing what curricular complexity means for transfer students)* and helped us address the shortcomings of existing approaches (i.e., Curricular Analytics). This design also allowed us to synergize the current framework with preliminary metrics developed in consultation with the literature; as Timonen et al. (2018) note, grounded theory "can be used to deepen existing theoretical insights" (p. 5).

5.1. Data Collection

We used focus groups as our primary data source, which is compatible with grounded theory designs (Sargent et al., 2016). Our goal in conducting these focus groups was to refine the curricular complexity framework by collecting evidence of construct validity (i.e., the extent to which a measure accurately portrays the target construct (Heale & Twycross, 2015)) from practitioners and researchers regarding our TSCC measures.

We conducted seven 1.5-hour focus groups via Zoom, with 5 to 8 participants at each. One researcher facilitated the focus group, while another served as the notetaker. Five sessions included a third investigator whose role was primarily observational. Our total of seven sessions exceeded the minimum threshold for non-probability focus group sample sizes, as outlined by Guest et al. (2017), who found that 90% of themes were typically discoverable within three to six focus groups. Still, a range of five to eight focus groups seems to be common (Carlsen & Glenton, 2011).

During the focus group, we presented the new metrics, explained their premise with an example calculation in a PowerPoint presentation, and invited open discussion. We presented one metric at a time and asked the following question: "*How do these measures align with your perceptions of curricular barriers for transfer students?"* Follow-up questions included:

- What additional measures would help characterize curricular complexity for transfer students?
- What would you change about the existing measures?
- Is there a test case that we're not considering with the measures as they're currently defined?

All sessions were recorded using Zoom's recording functionality and later transcribed using Rev.com for analysis.

5.1.1. Sampling Design and Participants

We relied on several media to recruit transfer professionals from a broad array of institutional and state contexts across the U.S. In our context, a *transfer professional* is a person employed in a higher education setting who interacts with transfer students or the transfer process (e.g., creating policies) as a primary job responsibility including advisors, administrators, and faculty members. We initiated a broad call for participants across various social media platforms, promoted by the National Institute for the Study of Transfer Students (NISTS) accounts. Subsequent calls for participants were made through NISTS and the Council for the Study of Community Colleges (CSCC) email listservs, both of which are professional organizations dedicated to vertical transfer practice and research. These calls for participants yielded 61 email and social media responses from interested participants. Of those respondents, 38 participated in one of seven focus groups between March and May 2022. Table 1 summarizes the demographic characteristics of participants. Informed consent was obtained from all participants via a consent form over email, as approved by Weber State University (IRB-AY21-22-251).

Table 1. Summary of Participants

Category	*n*
Gender	
Man	5
Woman	33
Race	
Asian/Pacific Islander	2
Black/African American	3
Hispanic/Latine	3
White	29
Prefer not to disclose	1
Primary Role	
Advising	17
Administration	18
Faculty	2

Participants came from a wide range of two- and four-year institutions across 22 (dark-shaded) states (Figure 3), providing insights from both sending and receiving institutions and from various state policy contexts.

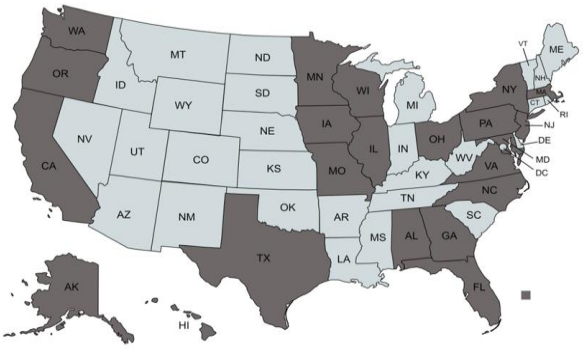


Figure 6. Distributions of participants across states, created with mapchart.net

5.2. Analysis

Consistent with the grounded theory analysis process described by Charmaz (2014), we analyzed the transcripts in a three-stage process: initial coding, which leveraged the constant comparative method (Boeije, 2002; Glaser, 1965; Strauss & Glaser, 1967); focused coding; and theoretical coding. Initial coding was completed by four researchers and included line-by-line coding for each metric, grounding our sequential comparisons between the challenges identified by participants and the metrics' intentions. These data-to-data comparisons yielded the first set of codes. After the initial coding was completed, focused coding was employed to refine the initial codes into more conceptual codes that explored the theory's underpinnings by comparing them to the data (Glaser, 1978). During this stage, we employed the constant comparative method extensively to reconcile our initial codes into meaningful categories by comparing codes to codes, codes to data, and focus groups to focus groups (Boeije, 2002). Finally, we engaged in theoretical coding by comparing codes with one another for the final integration into a coherent theory to support the underlying validity of the metrics.

While conducting focused and theoretical coding, our research team met for collaborative coding sessions, during which all authors contributed to developing a shared understanding of the data and to integrating a theory grounded in it. Our process for the collaborative coding sessions most aligns with Naganathan et al.'s (2022) description of Collaborative Zoom Coding, which involves live coding of select transcripts to foster a shared understanding of foundational concepts relevant to the study, consolidating initial codes into focused codes, and ultimately connecting these focused codes into a more comprehensive quantitative framework to measure curricular complexity for transfer students.

5.3. Limitations

This study is bound by a few notable limitations that can be addressed through further research. First is our choice of participants: transfer agents. Curricular complexity primarily affects students, so our focus on transfer agents may limit the salience of how the proposed measures capture students' lived experiences. For example, advisors or faculty may assume that course prerequisites or credit articulation policies are the main barriers, but students may face hidden hurdles such as misaligned schedules, financial pressures, or social-emotional challenges. However, we argue that, given the role transfer

agents play in helping students navigate curricular issues that the measures intend to capture, they can provide broader insights into program-level patterns through which they assist students. Readers should consider the validity evidence with caution when extrapolating concepts to specific student experiences, and future work will be conducted to address the lack of students' voices. Integrating student perspectives will be necessary to fully assess the validity of the TSCC measures in future work.

Despite our efforts to recruit across demographics, especially state contexts, there may be unrepresented perspectives, particularly from institutions or geographic regions not included in the sample. Although we did not specifically recruit participants from STEM disciplines, many of the examples used by the transfer professionals pertained to these programs. This is likely attributable to the highly sequenced nature of STEM program requirements (Heileman et al., 2017; Heileman et al., 2018). It is worth noting that the Curricular Analytics framework was developed within the engineering education field, given the dense prerequisite structures inherent to these programs. As such, programs outside STEM with fewer prerequisites might find less utility in some measures.

6. Results

We will split the results by metric, starting with the inflexibility factor. Narratively, we have organized our themes for each metric in the discussion section of Table 2.

6.1. Inflexibility Factor

The original conceptualization of the inflexibility factor was intended to incorporate the impact of course timing on curricular complexity. Heileman et al.'s (2018) model does not account for timing and implicitly assumes that courses are always available. However, this is not entirely true, as participants articulated a need to consider timing. For example, in the words of one of our focus group participants:

> *Let's face it, a lot of the direct entry programs are made for a student to start. A transfer student, they may come in spring semester, in summer semester or whatever else, and that causes a lot of problems with a lot of different programs because of sequencing of courses and things like that.*

With the difference in entry timing posing a unique problem for transfer students, one advisor at a small public school further elaborated that their institution only offered a selection of courses every other year (while reflecting on their experiences as a student), "So not only was it a penalization of not having the prerequisite done … I had to wait an additional year*."* The transfer professionals agreed that this metric was necessary to add to the Curricular Analytics framework.

Moreover, the timing of when students reach out to advisors and begin making transfer decisions was also a critical piece of this idea of inflexibility. As one transfer professional described:

> *There's many times when I will be working with the student and I'll say, "Okay, you're coming into this program at the university," and it's right before they graduate. And I'll say, "Do you have ... " Or let's say it's fall and I'll say, "Do you have pre-calc taken?" And they'll say, "No." Well, guess what? Pre-calc was offered at the community college in the fall semester when they first reached out to us, and it's not offered in the spring. That is delaying them before they even make that transfer just because of course sequencing at the college level not being aligned for them to be able to do that.*

Building on these considerations, participants frequently narrowed in on specific course sequences that are particularly troublesome for students, with one advisor explaining the possible delays in a physics sequence:

> *Especially the physics sequence, usually mechanics will be taught every semester, but then your E&M or your modern physics may not be taught. And then yeah, if you fail that class, now you're having to wait a whole other year. And then let's say E&M is then also taught in the fall, so now you're two years behind.*

The focus groups further elucidated other factors that could affect how transfer students engage with offerings at two- and four-year institutions. For example, courses could be offered at inconvenient times that conflict with students' schedules, especially for those who work part-time in addition to their studies. One advisor argued for a broader conceptualization of the inflexibility factor:

> *And the inflexibility that we also looked at wasn't just the sequencing [of] which semester, but also the modality of the course and the timing during the day. Some were in person [at] 8:00 AM, which isn't always feasible for, maybe, a working parent who needs evening classes, preferably online, that type of stuff. ... There is an additional layer of inflexibility as it relates to [the] modality of the teaching, the timing during the day, not just the course or the semester sequencing.*

This point was reiterated by another transfer professional who explained:

> *Sometimes there is a course offered each semester, but it's always offered in the evening, which then impacts anybody who can't do a[n] evening class. Or they alternate, so in the fall, it's in the evening. And the spring, it's in [the] day. But sometimes it's [in] a student[']s] schedule, especially at the community college, where they may be balancing two or three part-time jobs or full and part-time, family, etcetera.*

Similarly, the offering of courses is driven by faculty, and complications arise due to an understaffed department, as an advisor noted:

I was working with the transfer person in admissions, and she was trying to see what's going to be available summer and fall … to finish [a particular student's] degree. He only needs a handful of classes. And she said to me, "Oh my goodness, we're not offering any of those in the fall or in the summer." And part of that is being in that particular department, we've had some retirements, … one of the professors passed away. That's having, at least for us, a big effect. We have less faculty than ever.

The theme of faculty availability was salient in relation to the premise of the inflexibility factor, with another participant noting:

In the last couple of years, we've laid off faculty, we've offered buyouts to certain faculty who are at very high salaries, all in the interest of saving money. We're finding that we don't have the available faculty to teach these courses.

The discussion of the inflexibility factor suggested that the measure is well-supported with respect to construct and content validity from a practioner perspective.

6.2. Transfer Delay Factor

The transfer delay factor was presented to the focus groups as a means to capture unforgiving sequencing for transfer students. As an advisor remarked upon being introduced to the concept:

So, for example, we would hope to map it to a full-time eight semesters, assuming that the student would go full-time. And so, in that regard, because of the sequencing of the courses, whereas it might be even the prerequisites sequencing that would affect it. It actually brings it out to about a semester or two beyond the expected. Is that what I'm understanding from all of this? I think that's really important.

Like the inflexibility factor, the focus groups found value in this measure. Further discussion helped identify scenarios in which a study plan could not be completed within the expected eight semesters, regardless of how courses are arranged. One advisor commented on the availability of a specific course in several engineering programs at their institution, Dynamics, which amounts to a student taking a summer course to simply stay on track:

I know the schools, the community college, doesn't offer the Dynamics class, and that's so important. It's a course that we will offer in the summer. So they basically have that information, that they know that they have to do a summer class through us, or another four-year, in order for them to be kind of on track for the junior year.

Considering that Dynamics is a core course for many disciplines, such as Mechanical Engineering, if students do not follow this compromise, they will not be able to graduate within the expected timeframe. This example illustrates how the transfer delay factor distinguishes the availability of offerings from the inflexibility factor. Whereas the inflexibility factor is focused on the frequency of the course's offerings, the transfer delay factor captures what one advisor called a "prerequisite jam up" because of the need to wait until the student enrolls at the four-year institution to complete specific requirements:

Well, I have to agree with [Participant 1] and with [Participant 2] about the prerequisite jam up. The large institution in our state is [University 1], and our students, if they are admitted to the [University 1] programs, we don't even have the prerequisites for them to go in as juniors. So, the students are necessarily asked to take two classes during the summer before they advance to junior standing at the state institution.

Particularly crucial for the STEM disciplines was the concept of hidden prerequisites and how the students' enacted curriculum was severely more complex than what was presented in the degree requirements. Curricula are planned for students who arrive with certain competencies already mastered. A common pain point discussed by the transfer professionals was the calculus sequence. Students may not be calculus-ready; thus, they must take courses that solely prepare them for the first course in the sequence for the applicable credits. As stated by one of the participants:

So, for example, most of our STEM courses, our STEM programs require students already at Calc 1. And we know that for the students who are starting at our community college, they're not already at Calc 1. They're barely ready at college algebra, depending on where they're at. And so already from college algebra to Calc 1, there are three courses. So there's college algebra, two other courses, and then you can get into Calc 1. So that's four courses versus the way everything is truly mapped, would have them starting at Calc 1. So, that already provides where we're seeing this delay of the coursework here to actually get to where they need to go. And so I think it would be really helpful to see something like that.

These hidden prerequisites can be exacerbated by a student completing their degree part-time, as highlighted by the inquiries from the focus group participants: (1) "So I'm just wondering, is the delay factor specifically just focused on the sequencing? Will it account for that part-time enrollment that affects the sequencing as well?", (2) "Because our transfer students are, of course, mostly non-traditional students. So life happens, and is that being taken into consideration in the extension of the degree completion at all?", and (3) "If they're doing that part-time, then that affects how they move through even full-time or close to full-time." These questions yielded another assumption inherent to the Curricular Analytics models: the student is enrolled full-time. This consideration requires us to consider how we might adjust the models from full-time to part-time and explore the associated impacts of the measures. Still, the transfer delay factor was deemed an essential measure for assessing the curricular complexity of transfer students by the focus group participants.

6.3. Credit Loss

Perhaps the most robust discussion in our focus groups was around credit loss, where a student's previous coursework either does not transfer or does not apply to their degree. This metric resonated with all focus groups, yielding several instances in which students might lose credits during their transfer process. The validity of this metric was underscored by the experience of one focus group participant who articulated the surprise at how misaligned programs can be, even if the transfer occurs within the same major:

> *This is important. This is absolutely important. We recently participated in a Credit Loss Transfer study with one of the national organizations coming out for us and with four of our institutional partners. … It was a little bit of a, I don't want to say a wake-up call, but definitely an eye opener for folks to see that there's a lot of credits being lost that are left on the table for students who are moving from one institution to the next … But we're not necessarily expecting so much credit loss to occur when you're within the same major, within the same field, moving to that field at another institution.*

Further discussion enabled us to unpack the *why* behind the "eye opener*"* described by the participant. In particular, some transfer professionals focused on specific sets of courses that they have found impact transfer students disproportionately; for example, one issue with a Biology sequence was elaborated:

> *So we, through doing our major transfer maps, we've discovered a number of these issues. One of them, in particular, our Biology Department … They have put the three-course sequence together differently than almost any other school in the country. So if a student doesn't take that full sequence …, they force them to retake the entire sequence.*

The issue of customized courses was felt not only in Biology but also in other disciplines. For example, one transfer professional said there was a unique course about quantitative reasoning:

> *And now they have created a brand-new course specific to my college only. It's not going to be found elsewhere within the system. And now they just want to have students take this specific math course in order for them to take research methods or quantitative methodology.*

Because of the uniqueness, whether authentic or purported, the transfer professionals described how course credit can be articulated at the receiving institution. For example, students will "believe that they should have received credit for [a course], but there's not an 80% match. Or, it was two of the classes at [receiving institution] kind of combined into one class at their previous institution."

The course could also not be the right level, such as in engineering, where specific courses are required to progress into upper-division offerings: "students will come in having taken a lower-level chemistry than would be degree applicable or a lower-level physics that wasn't taught with calculus." Likewise, aligning pathways given the myriad programming languages in computer science can seem intractable. As one transfer professional remarked, "we've got institutions throughout the state that insist on Java. We've got one institution in the state that insists on C++. We've got some institutions that are like, oh, we'll take a combination of Java and Python." In one participant's experience, the institution-specific offerings are a push and pull for faculty. This tension not only impacts the transferability of courses from the two-year to the four-year but also reverse transfer:

> *I know, being at a community college, I keep having to fight back with our faculty because they want to make very specific degrees where there's no elective credit … it's going to create more issues when students transfer. But then, also, from a reverse transfer standpoint, it makes it very hard for us to do reverse transfer because we have such specific requirements no other school has.*

Confusion about applicability can become more complicated when students do not learn about the evaluation of their credits until they meet with their advisors and are confirmed as enrolled. One transfer professional described the applicability of credits in the case of block credit for Biology:

> *And so with that, usually, we know with our arts and sciences programs, they tend to accept block credit for natural science or math but some of our other colleges won't. And they won't find out until they're a confirmed student and meeting with their advisors. So I just want to add that, that's a big barrier because they're like, well how do I know if that means that I'm where I need to be in this engineering program? Or will I have to retake it again?*

Other transfer professionals echoed this delay, "Students when they're applying to transfer are not always told when their credits are going to be applied to their degree until registration day in July or August." Even in situations where degrees are not necessarily unique, as one participant described frequent conversations with students about their intended major. The transfer professional explained the difference between applicability and transferability, elaborating that "those programs, unfortunately, aren't very transfer-friendly." As detailed by this advisor:

> *For some of our curricularly complex programs like engineering, [the system] simply tags on those three credits, and that's unfortunately something that's difficult for a lot of faculty and staff to wrap their brains around. They often will argue to say, "Well, no, but that class transfers. It transfers as English elective." And it's like, well yeah, it transfers, but it's not applicable. And if there's no gen ed electives, it just gets bumped on as extra credit.*

The participants discussed cases like the previous example extensively across the focus groups, highlighting how credit can be treated differently depending on the course, college, institutional requirements, and the program. At best, the credits are applied to degree requirements. Still, these credits—especially electives—are often relegated to miscellaneous credits that have little to no impact on the student's degree progress. Throughout the focus groups, the credit-loss measure was well covered and vital to characterizing the curricular complexity of transfer students.

7. Discussion

This research aimed to develop new metrics to measure the curricular complexity experienced by transfer students and to understand their construct and content validity by seeking feedback from transfer professionals and practitioners nationwide through the NISTS and CSCC professional networks. As described by Moskal et al. (2002), construct validity refers to the extent to which a measure appropriately represents the construct of interest. Thus, the question of construct validity in this study concerns whether the inflexibility factor, for example, best captures the complexity faced by transfer students due to limited course offerings across various potential influences. By understanding the extent to which these metrics align with the realities of transfer from the perspective of professionals working in this space, we can better address broader questions in the literature, such as how to optimize transfer pathways (Zhang et al., 2024).

7.1. Expanding the Content Validity of the Metrics

This study provided initial construct validity for our metrics, which can aid transfer professionals in the field in analyzing different plans of study using a data-driven framework, especially once analyses can be automated using software. What we found in our focus groups was expanded *content validity* for our metrics as well, which concerns the breadth of the metrics in capturing different aspects of the construct (Moskal et al., 2002). For example, the original intent of the inflexibility factor was to contextualize when courses are offered. By introducing the idea of offering timing, we can explore the impact of a myriad of issues that may lead to a student not being able to access a course they can theoretically enroll in, such as course cancellations due to low enrollment or lack of faculty, inability to enroll because a course was too full, timing conflicts, or availability at a given institution. These considerations, and the necessity of this metric from an analytical perspective, align with Daddona et al.'s (2021) work on transfer student retention. In their work, the most common theme in response to the question "What would help you complete your degree sooner at (name of institution)?" was expanded offerings during the academic year and summer to avoid waiting for a course that is only taught once a year; this consideration is not only for the time of semester but also the time of day.

Similarly, the transfer delay factor produced a different angle to consider in these kinds of curricular analyses—whether a student is full-time or part-time. This distinction is another subtle assumption embedded in the original conceptualization of Curricular Analytics, where students can take whatever courses they like and in whatever quantity. Juszkiewicz (2020) astutely remarks that "the typical community college student has a profile that is almost diametrically opposite [to the perceived norm of recent high school graduates]—delayed entry to college, 24 or older, independent, often with dependents, and attends part-time" (p. 10). Thus, this perspective is non-ignorable analytically in the case of transfer students.

Additionally, the transfer delay factor captures other factors, including major uncertainties. Even though carefully constructed pathways exist for various majors, students cannot take advantage of them if they do not recognize their interest in completing their degree in that major early in their studies (Hodara et al., 2017). Coupled with existing misalignments between programs and unsatisfactory advising (Packard et al., 2012), restrictive prerequisite chains make it challenging for students to progress. Especially in programs with highly sequential coursework, the transfer delay factor can be used to explore the root causes of delays and help transfer advisors adjust a student's plan of study.

As more research has emerged on credit loss, we have gained a deeper understanding of the avenues transfer professionals can explore to understand why credits fail to apply to a student's degree requirements. For example, Richardson and Knight (2024) unpack the idea by describing credit loss as the sum of transfer credit and test credit accepted by the four-year institution, plus the credits earned at the four-year institution, minus the number of credits required for the degree. This calculation enables us to account for courses that do not apply, the typical focus of credit loss tabulations, and other unused credits that were accepted, expanding the credit loss measure.

We summarize the key points captured by each factor, based on our assumptions underlying their conceptualization and on how they relate to the considerations discussed in the focus groups, in Table 2. Our metrics were originally designed based on what a researcher or practitioner could do *without* student-specific data. For example, the transfer delay factor is based on an examination of sequencing issues that lead to an extended time-to-degree when degree programs, such as an AS and a BS, are combined using publicly available equivalencies. Similarly, the lost credits can be estimated by the extent to which courses in a particular program benefit from a broader articulation agreement. The participants in our focus group agreed that our metrics indeed measured what we intended from a practitioner perspective. However, our focus groups also added breadth, or content validity, by considering other circumstances in which the measures would be relevant. For example, the inflexibility

factor was originally conceptualized based on the availability of courses according to their general schedule, either historical or published frequencies at which they were or are offered. The focus groups expanded on other factors that could affect the course's availability, such as the time of day, which impacts a working student's ability to fit it into their course load. Regardless of the reason, the impact is the same. Therefore, practitioners can use the metrics to estimate the TSCC that a student will face, or could face, for a wide variety of common reasons.

Table 2. Expanding the content validity of the metrics from their original conceptualization

Metric	Original Conceptualization	Themes from Focus Groups Supplementing Metric Content Validity
Inflexibility factor	Limited offerings of courses based on department scheduling and their impact on time to degree	*Student-level factors:* modality, time of day, timing in contacting advisor *Department-level factors:* course cancellation stemming from understaffing, course buyouts, and low enrollment
Transfer delay factor	Sequencing issues that led to inevitable delays in time to degree	*Student-level factors:* Part-time and working students, major uncertainty *Department-level factors:* Unavailability of courses at the sending institution, Calculus-readiness assumption in curricula
Credit loss	Considers courses that students did not receive credit for in their transfer process	Types of credit, course level, timing of credit acceptance, transferability vs applicability, customized courses

7.2. Significance and Implications

Even well-intentioned and well-designed arrangements for course transfer between two-year and four-year institutions may be derailed by misaligned course sequences within academic plans when reconciling multiple articulation agreements (Nguyen et al., 2025). With TSCC, we quantify and visualize the complexities of curricular pathways for transfer students, providing faculty, advisors, and articulation policy administrators with concrete information on how pre- and corequisite structures affect transfer students' ability to navigate the curriculum. We believe that TSCC can help reduce the time-to-degree for vertical transfer students by shedding light on the curricular complexities inherent to these pathways. For example, instances where sequencing is not pedagogically necessary could be removed, reducing the curricular complexity that students encounter. In particular, further work could explore integrating learning outcomes into the network data to minimize the overall complexity (Heileman & Zhang, 2024).

The primary contribution of this work is methodological. The TSCC metrics extend beyond traditional indicators of transfer success by capturing the structural and sequencing features of curricular pathways that shape students' experiences. These metrics enable new forms of analysis, including cross-institutional and cross-major comparisons of pathway complexity, identification of curricular bottlenecks that disproportionately affect transfer students, and examination of how complexity accumulates across different transfer points. Crucially, this approach provides an empirical approach for casting transfer challenges as properties of curricular systems that can complement other individual student characteristics, yielding actionable insights for policy and curriculum design. This is the first effort to quantify the curricular issues transfer students face using network analysis, enabling comparisons across programs and institutions. In fact, comparisons or more general analyses can be conducted for both existing and proposed programs to forecast potential impacts.

Traditional learning analytics often focus on student data including engagement metrics, clickstream behavior, and assessment data. Our study drew upon curricular structures themselves and their associated analytics, including prerequisite chains, course availability patterns, and credit applicability, which can and should be analyzed to understand and support student learning and progression. By quantifying these structures, learning analytics can move upstream to inform institutional decisions that directly affect student opportunity and success. By operationalizing curricular complexity for transfer students through quantifiable metrics, this work lays the foundation for work in predictive models that can identify students at risk of extended time-to-degree or credit loss before registration or transfer. Additionally, these metrics offer diagnostic capabilities for institutional researchers and curriculum designers to optimize course sequences, advising strategies, and articulation agreements using data-informed methods. After additional testing of these metrics to establish stronger validity evidence, future work may integrate these approaches into adaptive degree-planning systems, curriculum visualization platforms, or simulations of programmatic reform impacts.

7.3. Applying the Metrics and Software Availability

To ensure the metrics discussed in this paper are usable, we have prepared an R package that enables users to calculate each metric, including the other standard Curricular Analytics metrics (Reeping, 2026). Additionally, an RShiny application will be available to run the necessary analyses in the reader's own context. By embedding the functionality into an RShiny application, barriers to use related to programming ability can be minimized.

8. Conclusion

This paper extends Curricular Analytics by collecting construct validity evidence for three new metrics (i.e., the timing of course offerings, sequencing that spans more semesters, and credit loss for major courses) that better capture the curricular challenges encountered by community college transfer students. Across all three metrics, transfer professionals provided real-life cases in which transfer students were impacted by the curricular challenges that the metrics sought to quantify. These real-life scenarios helped us ground and refine the new metrics, providing practitioner-informed evidence of their construct validity. This effort serves as a fundamental step toward developing an analytical framework that learning analytics researchers, transfer advisors, faculty, and policymakers nationwide can use to assess the curricular paths of transfer students and, ideally, reduce the complexities they encounter.

Declaration of Conflicting Interest

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