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Curriculum Modelling and Learner Simulation as a Tool in Curriculum (Re)Design

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Abstract
Learning analytics (LA) provides tools to analyze historical data with the goal of better understanding how curricular structures and features have impacted student learning. Forward-looking curriculum design, however, frequently involves a degree of uncertainty. Historical data may be unavailable, a contemplated modification to curriculum may be unprecedented, or we may lack data regarding particular learner populations. To address this need, we propose using curriculum modelling and learner simulation (CMLS), which relies on well-established modelling theory and software to represent an existing or contemplated curriculum. The resulting model incorporates relevant research-based principles of learning to individually simulate learners and estimate their learning achievement as they move through the modelled curriculum. Results reflect both features of the curriculum (e.g., time allocated to different learning outcomes), learner profiles, and the natural variability of learners. We describe simulations with two versions of a college-level curriculum, explaining how results from simulations informed curriculum redesign work. We conclude with commentary on generalizing these methods, noting both theoretical and practical benefits of CMLS for curriculum (re)design.

Notes for Practice

- Curriculum Modelling and Learner Simulation (CMLS) is a method for making principled quantitative projections of the impact curricular structures and arrangements will have on student learning.
- CMLS draws on general principles of curriculum design, human learning, and simulation modelling, with assumptions that are explicit, transparent, and easily adjusted.
- We implement CMLS in this work as coloured Petri nets using CPN Tools, a widely used and freely available simulation development environment.
- CMLS can be applied both to test novel curriculum designs and to inform redesign work by simulating how modifications to a curriculum are likely to impact student learning.
- The CMLS methods we describe both support existing methods in learning analytics and significantly extend our capacity for theoretically motivated work in curriculum design and development.

Keywords
Computer-based modelling, simulation, curriculum design

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1. Introduction

A central risk in curriculum design is that design solutions cannot be empirically evaluated until well after stakeholders have made significant commitments. Large-scale curricular design efforts usually begin with broad philosophical and pedagogical principles, but these commitments typically leave many questions unanswered. This is especially true when it comes to evaluating specific modifications to a proposed or existing curriculum. Even a knowledgeable designer may be hard-pressed to forecast the ultimate impact of a given modification. For example, stakeholders might want to put greater emphasis on a specific learning outcome in a curriculum. In response, a designer might propose using assessment data to reallocate instructional time to the target outcome. Before implementing a modification, stakeholders may want to explore both whether a modification is likely to achieve the intended goal and to what extent achievement on other learning outcomes will be reduced. Moreover, instructional dependencies are influenced both by general principles of human learning and student attribute-treatment interactions (e.g., Cronbach & Snow, 1977; Snow, 1989), further complicating forecasting. For example, if we consider the principle that unreinforced learning decays over time (e.g., Arthur et al., 1998; Pilotti et al., 2009), it becomes clear that the same curricular modification (e.g., additional instructional time) can have quite different effects on achievement depending on where in the curriculum it is implemented. If a target skill is allocated additional instructional time early in a course of study, student achievement is likely to increase in the short-term, but long-term achievement may be greater if the additional time is allocated in two lessons or courses spaced in time, one early in the course of study and a second later on (e.g., Carpenter et al., 2012).

To cope with this challenge, curriculum designers and other stakeholders have traditionally looked to experimental and quasi-experimental education research. Scouring the literature may sometimes turn up a study that investigated a curricular modification closely matching the one being contemplated. More frequently, designers and other stakeholders must extrapolate from studies that do not exactly match the details of their particular scenario, so, while these studies may be generally relevant, and may provide some general guidance, they will not support the detailed forecasts of impact that would be most helpful. More recently, designers have also been able to turn to the emerging field of learning analytics (LA) that has developed methods to analyze available historical data to shed light on possible or likely future effects of a contemplated modification (e.g., Brown et al., 2018; Hilliger et al., 2020; Munguia & Brennan, 2020; Salazar-Fernandez et al., 2021). As a post-hoc research design relying on existing data, however, learning analytics do not support tests of theory-based causal hypotheses.

In situations like this, we propose that curriculum designers and other stakeholders consider the more systematic and formal approach to forecasting provided by curriculum modelling and learner simulation (CMLS). With CMLS, stakeholders build a virtual replica of a curriculum incorporating specifically relevant principles of learning (e.g., unreinforced learning decays over time). In addition, simulated students can be defined with learning profiles to reflect specific populations of learners. CMLS therefore has the capacity to reflect features of the curriculum, learner characteristics, and the natural variability of learners, and how these variables can interact. For example, a curriculum redesign effort that seeks to reorganize the sequencing of courses could compare multiple versions of a program based on the quasi-empirical data generated by simulations (Winsberg, 2010). Two benefits of this kind of modelling are especially important. One benefit is that simulations can support both general and specific research questions exploring possible curriculum designs as stakeholders consider different options and make critical design decisions. The second benefit is that CMLS provides a shared systematic framework for stakeholders to anchor discussion and decision-making. CMLS therefore has the potential to address the problem of inadequate or unavailable data while simultaneously supporting predictive analytics (Chou et al., 2017) that are both theoretically motivated and can support iterative investigations of specific design options.

The remainder of this paper consists of the following sections. We begin with an overview of curriculum design concepts and general learning principles that serve as theoretical and empirical foundations for CMLS. We then present a detailed explanation of the CMLS approach. Starting from the fact that modelling and simulation methods are not currently included in the average curriculum designer's toolkit, we explain the key concepts and methods that make modelling possible, and how models work to produce forecasts. As part of this unpacking of CMLS, we explain why and how we rely on coloured Petri nets to develop simulations, and present basic principles behind Petri net modelling using the CPN Tools development environment (AIS Group, 2019). Next, we describe the process we relied on to create two proof-of-concept CMLS simulations comparing alternative curriculum designs as part of a curriculum redesign effort at a large Midwestern university. We then present the results of our analyses comparing the two versions of the curriculum to highlight how our simulations helped us explore the potential impact of program structure on student learning. Finally, in the last two sections we discuss the applications and benefits of CMLS and conclude with the limitations and implications of the CMLS approach for thinking about curriculum more broadly.

2. Background

CMLS is not a theory of curriculum design, it is a practical tool for quantitative investigation of curricular designs that draws on well-established curriculum design frameworks and theories of human learning. These concepts, frameworks, and theories are reviewed in the following subsections. Regarding technical aspects of model building and simulation, we apply existing tools and techniques based on coloured Petri nets (Jensen & Kristensen, 2009) and the CPN Tools development environment (AIS Group, 2019). Finally, to contextualize the unique contribution of CMLS in relation to existing scholarship aimed at informing curriculum design, we briefly contrast the guidance provided by CMLS with work based on experiments, quasi-experiments, and LA studies of historical data.

2.1. Curriculum

We use the term *curriculum* to refer to an "academic plan" based on a specific institutional context (e.g., a school of education) and comprising four macro-curricular elements: purpose, content, sequence, and learners (Lattuca & Stark, 2009). We define *purpose* in terms of program-defined learning outcomes, *content* in terms of courses, *sequence* in terms of temporal dependencies between courses (e.g., prerequisites), and *learners* in terms of general attributes that define populations of learners we are interested in modelling (e.g., high- vs. low-proficiency learners). Moreover, our work abstracts micro-curricular instructional elements (e.g., specific materials, pedagogical strategies, assessments) so we can focus on simulating a curriculum as a complete instructional system rather than lesson-, activity-, or assignment-level events experienced by individual learners. As is necessarily the case with any simulation, we have made deliberate choices about what to model and how to abstract elements that are not modelled. Moreover, because our work was motivated by a specific college-level curriculum redesign effort, the language we adopt conforms with common usage in college and university settings. We have, however, chosen to anchor our intentionally familiar curricular terminology in three broader conceptual frameworks that will better contextualize our work: 1) outcomes-based education that serves to define our thinking about purpose, 2) curriculum mapping that defines our thinking about sequencing and structural aspects of curriculum, and 3) learning progressions, a framework central to defining the curriculum redesign effort that motivated our work.

Outcomes-based education (OBE) is an approach to curriculum design that prioritizes the learning outcomes that students are expected to attain at the conclusion of their studies (Spady, 1994; Spady & Marshall, 1991), as opposed to short-term objectives teachers tend to focus on in individual activities or lessons. Recently, OBE has been widely adopted, particularly in professional domains such as engineering (Besterfield-Sacre et al., 2000; ABET, 2018; Chou et al., 2017; Tshai et al., 2014), nursing (Hsieh & Hsu, 2013; Tan et al., 2018), and teacher education (Ball & Forzani, 2011; Forzani, 2014; TeachingWorks, 2019) where professional organizations often work to define standards for entry into professional fields. Furthermore, with exit outcomes more clearly articulated, instructors are better able to address instructional design at the micro-curricular level to align with and support program-level outcomes. Clarity about exit outcomes also means that student progress can, at least in theory, be mapped in terms of how far students have come, and how far they still need to go, toward achieving mastery. The result is a high level of cohesion, transparency, and accountability across an entire program. CMLS, as we implement it in this work, fully embraces OBE's focus on learning outcomes. In modelling curriculum, therefore, simulations should be rooted in clearly stated learning outcomes that are shared across program courses. As simulated learners progress through a series of courses in a modelled curriculum, their growth toward mastery of these learning outcomes is estimated and tracked. In the proof-of-concept demonstration of CMLS we present in this paper, for example, the shared learning outcomes are seven "high-leverage teaching practices" (HLPs; TeachingWorks, 2019) that all pre-service teachers in a teacher-preparation program were expected to master (e.g., "eliciting and interpreting individual student's thinking"; "leading a group discussion"). Every course in the program addressed two or more of these HLPs (see Table 3 for a list of these learning outcomes).

Curriculum mapping (CM) shares OBE's focus on learning outcomes. However, where OBE emphasizes the importance of "outcome specification" (Morcke et al., 2013, p. 853), CM adopts a more explicitly structural perspective (e.g., Heileman et al., 2017) that puts priority on providing a bird's-eye view of a program with the potential to yield insights about areas for improvement (e.g., Fuchs et al., 2014; Hale, 2008; Jacobs, 2004). In CM, more attention is paid to the sequencing and relationships of curriculum components. Perhaps most relevant in the present context is that CM, like CPN Tools, capitalizes on visualization to both convey the "big picture" and help contextualize more specific curricular elements within that larger picture. As we describe later, this and several other key CM concepts are central to the CMLS approach we have adopted in this work.

Finally, learning progressions (LPs) are a framework for conceptualizing the stages of engagement and understanding that students move through as they progress from novice-level encounters with content to expert-level applications of concepts and skills (Otero, 2006). In effect, LPs typically define categorical levels of complexity and sophistication in thinking about a domain and, for that reason, often serve as a tool to "sort" lower-level learning objectives extracted from individual course syllabi as a first step in defining or confirming the sequencing of activities, topics, and courses in a curriculum. As we will describe later, LPs turned out to be particularly important in our work because this kind of sorting was precisely the way our colleagues had begun the curriculum redesign effort prior to the time we began our modelling and simulation work.

2.2. Principles of Learning

CMLS also makes use of what we know about general principles, patterns, and regularities of human learning and cognition. For example, it is now well established that possessing topic-relevant prior knowledge has a significant positive influence on learners' comprehension and recall of unfamiliar text (e.g., Kendeou & van den Broek, 2007; Kostons & van der Werf, 2015; Pearson et al., 1979), that the capacity of learners' working memory is limited (e.g., Burin et al., 2018; Leong et al., 2008), that first-learned and last-learned information is better recalled than information learned in the middle of a study session (e.g., Follmer et al., 2018; Guéraud et al., 2018), and that temporally "spaced" and "interleaved" study sessions are more conducive to deep learning and retention of information than "massed" study time, also known as "cramming" (e.g., Janes et al., 2020; Weinstein et al., 2018). Moreover, CMLS is not simply loosely "based on" or "aligned with" this large body of empirical findings and theory. Rather, the CMLS approach involves intentional selection of a small subset of learning principles of particular relevance to a target scenario. For example, when modelling student progression through a series of courses, obvious candidate learning principles might include the principle that, on average, more time on task with new content correlates with higher levels of achievement (e.g., Fredrick & Walberg, 1980; Gromada & Shewbridge, 2016), and the principle that, unless reinforced over time, new learning will gradually decay and newly acquired skills will fade (e.g., Pilotti et al., 2009). Building a CMLS model involves explicitly identifying a short list of relevant principles and then coding these into the algorithms that estimate achievement as simulated students move through a given curriculum. The specific learning principles built into our proof-of-concept curriculum model are detailed in the following section.

2.3. Modelling and Simulation

Modelling methods and tools are well established and widely used outside the field of curriculum design. For example, computational chemists use simulations to discover novel approaches to chemical synthesis (Jensen, 2007) and astronomers test competing models for what occurs when galaxies collide (Mapelli & Mayer, 2012). Recently, epidemiological modelling of COVID-19 transmission in higher education settings has helped institutions make decisions about when and how to reopen campuses (Gressman & Peck, 2020). In the areas of learning and instructional design, there is also a long history of model building in research on perception (Minsky & Papert, 1969), cognitive processes (Wetherick, 1992), learning (Gogate & Hollich, 2013), and social interaction (Thalmann & Musse, 2013). In short, outside of curriculum design, there is longstanding and growing appreciation of models and simulations as tools that operate in a "middle ground" (Winsberg, 2010) between theory and empirical observation. As classroom access to digital technology has grown, some educators have adopted simulation technologies as teaching tools to help students learn about political decision-making (Bursens et al., 2018) and scientific hypotheses (Kuang et al., 2020), among other topics, and to support more effective collaborative learning (Gijlers & de Jong, 2013). Application of simulation technologies to support curriculum design, however, is rarely described. We found no published scholarship specifically targeting curriculum simulation, nor did we find colleges offering courses to teach educators about this kind of work. With a few notable exceptions (e.g., Gonzalez-Brenes & Huang, 2015; McEneaney, 2016; Pelánek et al., 2016; Lomazova et al., 2021), it appears that the potential of computer-based modelling and learner simulation to inform curriculum design has rarely been considered. As we will show, however, concepts, techniques, and tools to support modelling and simulation can be readily adapted to support curriculum design.

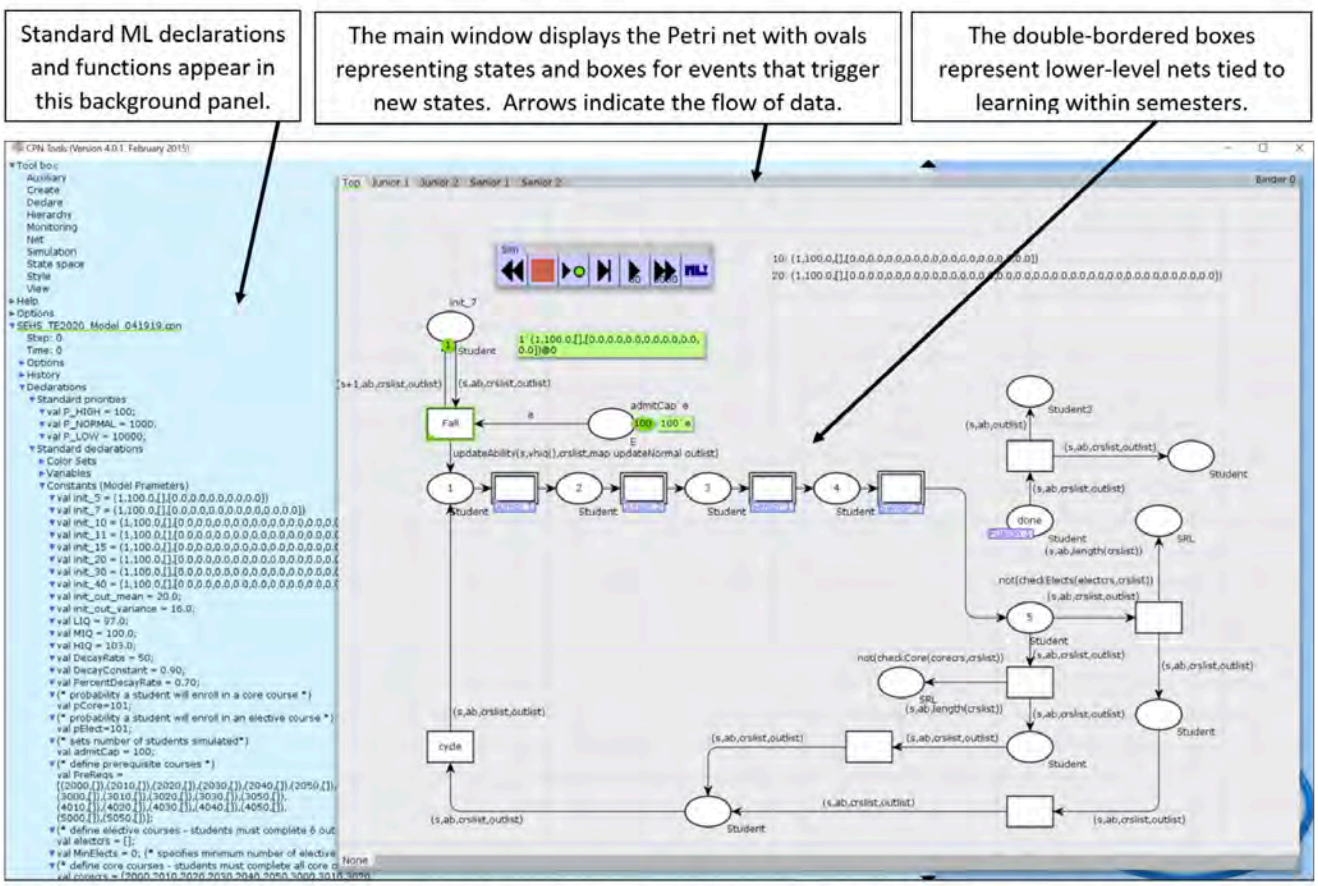

Figure 1. An annotated screenshot of the initialized CPN environment ready to begin a simulation. The "init_7" and "admitcap′e" ovals at the upper left initialize a simulation based on 100 students.

We selected CPN Tools (AIS Group, 2019), a programming environment based on coloured Petri nets (CPNs; Jensen & Kristensen, 2009), to build our models and run simulations. Figure 1 presents the model building and simulation interface for our curriculum models. The graphical part of the simulation appears as a grey window with oval nodes representing system states, rectangular transitions representing points in the simulation where system states change, and arrows indicating the flow of data within the model. Green highlighting of two nodes and one transition at the top of the window indicates that the model is initialized and ready to run a randomized sample of 100 simulated students. Oval nodes 1, 2, 3, and 4 represent student learning states prior to the start of each of the four semesters in the modelled curriculum, represented by the four rectangular transitions. Programming code appears in the background window in a pale blue panel on the left that defines constants, variables, and functions that drive the simulation. Core simulation processing occurs in four rectangular transitions Junior 1, Junior 2, Senior 1, and Senior 2, representing each of the four terms in the curriculum. Nodes and transitions that follow the Senior 2 transition address circumstances where a student fails a course or a prerequisite. When a simulation is completed, student data records are extracted from the Student and Student2 output nodes.

Table 1 presents simulated learning data for six students after completing the four-semester curriculum. The first and second values in each record are a unique student identifier (ID#) and an individual learning proficiency parameter (LP). The learning proficiency variable is assigned randomly by a Standard ML normal distribution function and influences both a student's rate of learning and learning decay. The third data value in each record is an ordered list reporting simulated learning across seven learning outcomes targeted in the curriculum. Students start with outcomes initialized to [0,0,0,0,0,0,0]. As students progress through the curriculum, outcome values are incremented up to a maximum of 100 based on both a student's learning proficiency and the relative emphasis learning outcomes receive in each course. Outcome values are also decremented to simulate learning decay in the absence of reinforcement. Finally, the "Term" data value (@4) represents the number of semesters completed. Although higher learning proficiencies are associated with greater achievement, the simulation is probabilistic, so individual student performance varies, with less proficient students sometimes outperforming more proficient peers (compare, for example, students 1 and 2).

Table 1. Six simulated student records after four semesters with an overall average outcome score.

(Student ID#, LP, [Current Scores on Seven Objectives])	Term	Avg Score
(1, 107, [68,86,85,93,82,77,71])	@4	80
(2, 113, [76,79,87,84,70,76,69])	@4	77
(3, 113, [75,77,92,89,88,91,77])	@4	84
(4, 124, [72,85,89,91,84,89,72])	@4	83
(5, 116, [84,80,95,94,87,85,73])	@4	85
(6, 122, [76,78,95,95,93,81,80])	@4	85

Student records like those illustrated in Table 1 can be examined at any point in the simulation. Moreover, student records can also be modified by functions representing particular learning principles (e.g., learning decay). In addition, although not examined in the simulations we describe, the models we have developed can also use student records to enforce curricular requirements restricting, for example, whether or not a student can enroll in a class depending on a minimum grade or completion of a prerequisite course. In Figure 1, for example, some arrows have associated filters that appear as short text segments in parentheses (e.g., "(s, ab, crslist, outlist)") that can block or otherwise modify the flow of data by sending a student back to a prerequisite course rather than allowing them to enroll. Modification of data records within transitions are carried out by functions serving as the primary data processing mechanism. In CPN Tools all traditional programming elements, including constants, variables, filters, and functions are defined in the CPN ML programming language, based on Standard ML (Milner et al., 1997; Ullman, 1998).

Table 2. Three sets of records for three simulated students (Students #14, #53, and #11) with different learning proficiencies (LP) at the conclusion of each term in the curriculum.

(Student ID#, LP, [Current Scores on Seven Objectives])	Term	Avg Score
(14, 92, [15,15,57,73,54,57,19])	@1	41
(14, 92, [43,43,64,80,67,65,27])	@2	56
(14, 92, [61,55,69,85,75,71,50])	@3	67
(14, 92, [74,68,75,87,82,81,68])	@4	76
(53, 107, [19,25,73,68,57,74,24])	@1	49
(53, 107, [53,60,84,80,62,76,36])	@2	64
(53, 107, [71,77,87,87,70,81,61])	@3	76
(53, 107, [79,79,90,90,72,82,63])	@4	79
(11, 121, [27,19,76,86,33,39,28])	@1	44
(11, 121, [55,47,83,92,55,55,51])	@2	63
(11, 121, [69,63,86,95,58,67,71])	@3	73
(11, 121, [83,77,90,95,80,71,80])	@4	82

Table 2 presents a finer-grained view of individual learning in the simulation, with data for three simulated learners with different learning proficiencies (lower, average, and higher) across the four semesters in the curriculum. This data also illustrates the stochastic character of the simulation where, on average, students with higher learning proficiency tend to perform better than those with lower proficiency, although this is not a deterministic relationship, as evidenced by the higher average performance at the end of term 3 by student #53 over student #11 who has a higher learning proficiency. In most cases, a simulation study will rely on multiple simulations that depend on either different simulation parameters such as learner characteristics (higher versus lower learning proficiency) or modifications to the curriculum that adjust the emphasis courses put on learning outcomes (e.g., to provide more reinforcement of prior learning). In summary, each student in the simulation is individually modelled, with dependent variables representing learning achieved for each learning outcome and a time stamp incremented each semester. In addition, when the semester is incremented, a random decay function reduces learning achievement by a small amount. At any given point in time, therefore, a student's data record represents the current level of learning in a way that accounts for prior performance, opportunities for learning, and learning decay.

2.4. Unique Aspects of CMLS

The potential contributions of CMLS to the work of curriculum design become clearer when CMLS is considered alongside other well-established branches of scholarship intended to inform curriculum designers such as quasi-experimental studies, learning analytics, and its recent offshoot of curriculum analytics. As we noted earlier, it may be difficult to identify prior studies that clearly address specific curriculum design questions and, apart from only very small-scale designs, ethical issues would usually preclude studies of hypothetical curricula with human learners. Even when relevant prior studies can be found, designers must undertake complex extrapolations from past correlations and trends, adjusting for different settings and learner populations. Simulation, by contrast, affords a tool for precisely the kind of iterative "informed exploration" Hilliger and colleagues (2020, p. 183) call for in continuous curriculum improvement. CMLS also aligns with some recent efforts defining curriculum analytics (Chou et al., 2017; Hilliger et al., 2020; Munguia & Brennan, 2020) that focus on the level of programs and curricula while avoiding the labour-intensive and course-specific work typical of more traditional learning analytics approaches (Gottipati & Shankararaman, 2017).

3. Methods

In this section, we describe a proof-of-concept study conducted in support of a curriculum redesign effort in an undergraduate teacher education program at a large Midwestern university in the US. Work on the redesign began in 2016 and formal analysis and modelling began in 2018 after a preliminary curriculum proposal had been developed. During the formal analysis needed to develop the simulation, a number of questions arose that suggested a modification to the original proposal. In response to these questions, we developed a modified version of the curriculum that focused on the relative emphasis courses put on specific learning outcomes. The study we present addresses two questions comparing the alternative curricula. The first quantitative question tested whether simulated students exhibited statistically significant differences in predicted learning achievement despite the "natural" probabilistic variability of the simulations. Secondly, if the quantitative analysis indicated differences, a follow-up qualitative question would examine how student learning achievement differed and what these differences might suggest about the relative suitability of the two curriculum designs within the broader commitments and goals of the redesign effort. Our simulations adopted a fully crossed 2 × 2 analytic design comparing the two different curricula and two categories of simulated students of high and low proficiency. Because both programs focused on seven distinct learning outcome goals, we relied on MANOVA to address our initial broader question with follow-up univariate analyses to assess where differences arose if the omnibus test was significant. In the event of statistically significant differences, we would follow up with a qualitative examination.

3.1. Developing the Simulations

The first steps in simulating curriculum are deciding on elements to model and then creating an abstracted version of that curriculum. In our case, work began with a preliminary curriculum map developed by a faculty committee. The proposed design made mastery of seven high-leverage teaching practices or HLPs (TeachingWorks, 2019) the central focus of an 18-course curriculum spanning four semesters. HLPs adopted in the curriculum are presented in Table 3. The preliminary curriculum was developed from a learning progressions perspective that distinguished four kinds of instruction tied to levels of student understanding related to the HLPs: introducing the HLP (i), developing and deepening understanding (d), independent practice (x), and providing opportunities for coaching and reinforcing (c) in a seminar setting. In addition, the preliminary curriculum identified a specific mapping, of the course, its sequences, and a preliminary time-on-task specification in terms of credit hours allocated to each course. Our goal in this first stage of formalization was to capture these specific elements in our curriculum model.

Table 3. High-leverage teaching practices (HLPs). (The numbering of the seven HLPs is not consecutive because they are taken from the full list of nineteen HLPs.)

HLP #	Description
HLP #1	Leading a group discussion
HLP #2	Explaining and modeling content, practices, and strategies
HLP #3	Eliciting and interpreting individual student's thinking
HLP #9	Setting up and managing small group work
HLP #10	Building respectful relationships with students
HLP #12	Learning about students' cultural, religious, family, intellectual, and personal experiences
HLP #15	Checking student understanding during and at the conclusion of lessons

As we studied the proposed curriculum (Table 4), some of the elements we needed to model were clear. Since the seven HLPs had been adopted as program-level learning outcomes, we selected cumulative learning achievement on these outcomes as dependent variables in our simulations. We also noted that time-on-task across the program as a whole had been roughly defined by assigning credit hours to each course (as shown in the second column of Table 4), although it was not clear how time-on-task for different program outcomes should be allocated within courses. Also, while the proposed curriculum distinguished developmental steps in a four-stage learning progression (namely, the stages indicated i, d, x, and c), it was not clear how we should assign more specific time-on-task weights depending on these categories. Should relatively more time-on-task be allocated to learning outcomes at particular stages of development? Building simulations, therefore, required us to go back to our colleagues who had developed the preliminary proposal so that we could begin to make plausible decisions about translating the conceptual model into quantitative terms that would support simulations.

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Table 4. Proposed objectives-based teacher education curriculum.

Term	Course # (credits)	Program Objectives (HLPs) Addressed (i = introduce; d = develop; x = independent practice; c = reinforce, connect, and coach)						
		HLP #1	HLP #2	HLP #3	HLP #9	HLP #10	HLP #12	HLP #15
Pre-program	EED 1000/2000(1/2)			i		i & d	i & d	
Junior 1	Equity & Diversity (3)					d	d	
Junior 1	Emrg Lit/ELA 1 (3)			d	i			
Junior 1	Math 1 (3)			d	i			
Junior 1	Soc Studies 1 (3)			d	i			
Junior 1	Seminar 1 (3)			c	c	c	c	
Junior 2	How People Learn (3)					d	d	i
Junior 2	Literacy/ELA 1 (3)	i	i	d	d			
Junior 2	Math 2 (3)	i	i	d	d			
Junior 2	Science 1 (3)	i	i	d	d			
Junior 2	Seminar 2 (3)	c	c			c	c	
Senior 1	Fluent Literacy (3)	d	d	x	d	x	x	d
Senior 1	Social Studies 2 (3)	d	d	x	d	x	x	d
Senior 1	Math 3 (3)	d	d	x	d	x	x	d
Senior 1	Science 2 (3)	d	d	x	d	x	x	d
Senior 1	Seminar 3 (3)		c		c	c	c	c
Senior 2	Student Teaching (10)	x	x		x			x
Senior 2	Seminar 4 (2)	c	c	c	c			c

It was at this stage in our work that we began to appreciate how our modelling and simulation work could be especially helpful in supporting ongoing stakeholder conversation and analysis about the goals of the redesign effort. When we sat down to talk with colleagues, we saw that our questions brought to light unstated assumptions and design details that had not yet been considered. Do all program outcomes deserve equal time-on-task emphasis, or should some be weighted more heavily? We found that questions like this led to conversations that might not have occurred in less concrete contexts. As a result of these conversations with colleagues, we decided on the following four principles to guide simulation development:

1. Time-on-task values are based only on the seven HLPs (with zero time-on-task assigned to blank cells).
2. Total time-on-task available for outcomes within a course is determined by the total course credit hours.
3. Unless otherwise specified, time-on-task is equally distributed across outcomes for different types of instruction.
4. Independent practice (x) is allocated a ½ relative weighting compared to other types of instruction.

In cases where an HLP was not addressed in a course (assumption 1), the weight assigned is zero (0.000). In cases where multiple comparably weighted objectives occur in a course (e.g., d and i in the Math 1 course), weights are simply the total course weight (in credits) divided by the number of outcomes emphasized (assumptions 2 & 3). Independent practice (x) as an instructional type is accorded a relative weight of ½ compared to other types of instruction (assumption 4). In the Science 2 course, for example, d values are accorded a unit weight while x values are accorded ½ of a unit weight, resulting in 0.546 time-on-task devoted to HLP #2 and 0.273 time-on-task for HLP #3. Note that in the weight column to the far right, the value is based on the credit hours assigned to the course and summing across columns within a course results in the total course credit hours within rounding. Finally, the last row reports on the overall weighting by outcome for the curriculum as a whole.

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This last row therefore reflects the relative priority of outcomes across all courses in the curriculum with some outcomes allocated considerably more time-on-task (e.g., HLP #9, at 13.184 units) than others (e.g., HLP #15, at 6.684 units).

Table 5. First numerical interpretation of the objectives-based curriculum.

Term	Course # (credits)	Program Objectives (HLPs) Addressed							Weight
		#1	#2	#3	#9	#10	#12	#15	
Pre-program	EED 1000/2000(1/2)	0.000	0.000	0.600	0.000	1.200	1.200	0.000	3.000
Junior 1	Equity & Diversity (3)	0.000	0.000	0.000	0.000	1.500	1.500	0.000	3.000
Junior 1	Emrg Lit/ELA 1 (3)	0.000	0.000	1.500	1.500	0.000	0.000	0.000	3.000
Junior 1	Math 1 (3)	0.000	0.000	1.500	1.500	0.000	0.000	0.000	3.000
Junior 1	Soc Studies 1 (3)	0.000	0.000	1.500	1.500	0.000	0.000	0.000	3.000
Junior 1	Seminar 1 (3)	0.000	0.000	0.750	0.750	0.750	0.750	0.000	3.000
Junior 2	How People Learn (3)	0.000	0.000	0.000	0.000	1.000	1.000	1.000	3.000
Junior 2	Literacy/ELA 1 (3)	0.750	0.750	0.750	0.750	0.000	0.000	0.000	3.000
Junior 2	Math 2 (3)	0.750	0.750	0.750	0.750	0.000	0.000	0.000	3.000
Junior 2	Science 1 (3)	0.750	0.750	0.750	0.750	0.000	0.000	0.000	3.000
Junior 2	Seminar 2 (3)	0.750	0.750	0.000	0.000	0.750	0.750	0.000	3.000
Senior 1	Fluent Literacy (3)	0.546	0.546	0.273	0.546	0.273	0.273	0.546	3.003
Senior 1	Social Studies 2 (3)	0.546	0.546	0.273	0.546	0.273	0.273	0.546	3.003
Senior 1	Math 3 (3)	0.546	0.546	0.273	0.546	0.273	0.273	0.546	3.003
Senior 1	Science 2 (3)	0.546	0.546	0.273	0.546	0.273	0.273	0.546	3.003
Senior 1	Seminar 3 (3)	0.000	0.600	0.000	0.600	0.600	0.600	0.600	3.000
Senior 2	Student Teaching (10)	2.500	2.500	0.000	2.500	0.000	0.000	2.500	10.000
Senior 2	Seminar 4 (2)	0.400	0.400	0.400	0.400	0.000	0.000	0.400	2.000
	Total weighting of each outome:	8.084	8.684	9.592	13.184	6.892	6.892	6.684	60.012

As we considered the time-on-task allocation shown in Table 5, however, we also found ourselves wondering whether the original proposal accurately represented the intent of the curriculum. We questioned, for example, why the coaching planned for seminars would exclude some HLPs that had been addressed in concurrent courses supported by the seminar (e.g., HLPs #3 and #9 in Seminar 2) while addressing others, given that student interest might lead to discussion on any one or all HLPs addressed during the term. It seemed to us plausible to think that all outcomes addressed in a semester would be eligible for coaching in seminar courses. A possible alternative time-allocation scheme might, therefore, provide coaching for every outcome addressed in a block, and by this assumption the time-on-task weights for Seminar 2 should be equally distributed across outcomes since all had been addressed in the block. Finally, we had the same kind of questions when we looked at time allocation in the student teaching course where, presumably, all outcomes (i.e., all the high-leverage teaching practices) would be expected to be addressed in some way. In response to these questions, we proposed an alternative modified curriculum displayed in Table 6 that reflects these ideas, with changes to the original curriculum highlighted in yellow. In the modified curriculum, overall constraints remain the same, with course weights still determined by course credit hours. What differs is that some outcomes that had zero weights in the first quantitative interpretation now are accorded larger weight values as a result of shifting time-on-task from other outcomes. Perhaps the most notable difference, however, is the way the modified weighting scheme changed the overall allocation of time to outcomes across the curriculum as a whole.

Table 6. Alternative modified interpretation of the objectives-based curriculum, with differences from the original curriculum highlighted in yellow.

Term	Course # (credits)	Program Objectives (HLPs) Addressed							Weight
		#1	#2	#3	#9	#10	#12	#15	
Pre-program	EED 1000/2000(1/2)	0.000	0.000	0.600	0.000	1.200	1.200	0.000	3.000
Junior 1	Equity & Diversity (3)	0.000	0.000	0.000	0.000	1.500	1.500	0.000	3.000
Junior 1	Emrg Lit/ELA 1 (3)	0.000	0.000	1.500	1.500	0.000	0.000	0.000	3.000
Junior 1	Math 1 (3)	0.000	0.000	1.500	1.500	0.000	0.000	0.000	3.000
Junior 1	Soc Studies 1 (3)	0.000	0.000	1.500	1.500	0.000	0.000	0.000	3.000
Junior 1	Seminar 1 (3)	0.000	0.000	0.750	0.750	0.750	0.750	0.000	3.000
Junior 2	How People Learn (3)	0.000	0.000	0.000	0.000	1.000	1.000	1.000	3.000
Junior 2	Literacy/ELA 1 (3)	0.750	0.750	0.750	0.750	0.000	0.000	0.000	3.000
Junior 2	Math 2 (3)	0.750	0.750	0.750	0.750	0.000	0.000	0.000	3.000
Junior 2	Science 1 (3)	0.750	0.750	0.750	0.750	0.000	0.000	0.000	3.000
Junior 2	Seminar 2 (3)	0.429	0.429	0.429	0.429	0.429	0.429	0.429	3.000
Senior 1	Fluent Literacy (3)	0.546	0.546	0.273	0.546	0.273	0.273	0.546	3.003
Senior 1	Social Studies 2 (3)	0.546	0.546	0.273	0.546	0.273	0.273	0.546	3.003
Senior 1	Math 3 (3)	0.546	0.546	0.273	0.546	0.273	0.273	0.546	3.003
Senior 1	Science 2 (3)	0.546	0.546	0.273	0.546	0.273	0.273	0.546	3.003
Senior 1	Seminar 3 (3)	0.429	0.429	0.429	0.429	0.429	0.429	0.429	3.003
Senior 2	Student Teaching (10)	1.430	1.430	1.430	1.430	1.430	1.430	1.430	10.010
Senior 2	Seminar 4 (2)	0.286	0.286	0.286	0.286	0.286	0.286	0.286	2.002
	Total weighting of each outome:	7.008	7.008	11.766	12.258	8.116	8.116	5.758	60.027

In the original curriculum design (Table 5), outcomes are dominated by HLP #9. After the principled adjustments to create a modified curriculum (Table 6), however, attention to outcomes is more evenly balanced across HLPs, with objectives #3 and #9 now receiving the most instructional attention, objectives #10 and #12 receiving significant attention though distinctly less than #3 and #9, objectives #1 and #2 in a third tier, and outcome #15 receiving least attention. In effect, the modified curriculum appears to provide a more systematic hierarchy of learning that might help guide faculty in their efforts to work out the many details that would next need to be fleshed out in course syllabi. If nothing else, it appears that the formalization of developing a learning outcome grid is useful as a basis for discussion and continued planning. But the modified curriculum design, while suggestive, does not provide the kind of analysis that a simulation can. Specifically, given the probabilistic variation built into the simulations, it is not apparent whether the differences we see in outcome weights across the curriculum would actually make a difference for student achievement. Do the relative priorities of total outcome weights lead to statistically significant differences across populations of simulated students and do these differences evince large enough effect sizes to be meaningful in a practical sense? This was the question we sought to answer by running a simulation in which 200 simulated students progressed through each of the two program models we built — one representing the initial program redesign and the other representing the modified program redesign.

4. Results

Results of an omnibus multivariate F test (Table 7) of simulated students' end-of-program achievement indicated a statistically significant difference in the achievement variable vector across the four cells of the study design (Hotelling's Trace, $F(7, 390) = 70.811$, $p = .000$, $\eta^2 = .560$), with a large effect size and excellent observed power. Planned follow-up univariate tests (Table 8) comparing achievement scores for each learning outcome across the two different curriculum designs also showed statistically significant differences for every HLP, with a small effect size for HLP #9 and medium to large effect sizes for all other HLPs (Ferguson, 2009). In short, the comparison of these two curriculum designs (original versus modified) indicate statistically significant differences after accounting for variability in simulated student learning–differences sufficiently large to suggest practical significance for learners. Not surprisingly, differences in student learning of individual HLPs across the two models depended on whether the overall outcome weight for a given HLP increased or decreased as a result of modification. Specifically, outcome scores in the modified curriculum indicated reduced learning for HLPs #1, #2, #9, and #15, while learning increased for HLPs #3, #10, and #12. Overall, as indicated in Table 9, student learning aligned as expected both with ability grouping and with the overall curriculum weight assigned to an HLP.

It appears, however, that the more general pattern of changes in learning achievement may be more important than the changes to individual outcomes. In reviewing changes in weights between Tables 5 and 6, we noted that the modified curriculum led to a more readily interpretable hierarchy of HLPs across the curriculum as a whole. Whereas the original curriculum was dominated by very heavy emphasis on a single outcome (HLP #9), the modified curriculum establishes a clearer hierarchy of tiers consisting of three outcome pairs with a single trailing outcome (see the Total Outcome Weight row in Table 6). Although each HLP represents an important goal, a multi-year teacher education curriculum is likely to prioritize outcomes in different ways that reflect the values and core professional principles of the program. Whereas the original curriculum presents a somewhat scattered organizational framework, the modified version seems to better organize the curriculum. HLPs receiving high or medium emphasis in the modified curriculum seem to focus on social and individual foundations of learning whereas the less emphasized HLPs seem to focus on more specialized instructional practices (Table 10). Moreover, although all HLPs are interconnected, these distinctions between a social/personal emphasis and a more practical pedagogical emphasis may help students in this program achieve a more coherent understanding of the objectives and principles supporting the curriculum.

Table 7. Omnibus multivariate F test assessing whether the vector representing seven HLP measures as a single latent variable differs by curriculum. As the model assures equality of variance between groups, only Hotelling's trace is reported.

Multivariate Tests								
Test	Value	F	Hypothesis df	Error df	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Hotelling's trace	1.271	70.811[a]	7.000	390.000	0.000	.560	495.675	1.000

The F test evaluates the multivariate effect of the curriculum based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Exact statistic
b. Computed using alpha = .05

Table 8. Follow-up one-way ANOVAs assessing whether curriculum weighting influences learning, analyzing each of the seven objectives (HLP#1-HLP#7) in separate ANOVAs.

Univariate Tests									
Dependent Variable		Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[a]
HLP #1	Contrast	3678.526	1	3678.526	56.942	.000	.126	56.942	1.000
	Error	25582.110	396	64.601					
HLP #2	Contrast	5535.221	1	5535.221	96.571	.000	.196	96.571	1.000
	Error	22697.836	396	57.318					
HLP #3	Contrast	3086.160	1	3086.160	88.409	.000	.183	88.409	1.000
	Error	13823.511	396	34.908					
HLP #9	Contrast	485.421	1	485.421	17.101	.000	.041	17.101	.985
	Error	11240.604	396	28.385					
HLP #10	Contrast	2267.236	1	2267.236	46.044	.000	.104	46.044	1.000
	Error	19499.482	396	49.241					
HLP #12	Contrast	3556.609	1	3556.609	64.734	.000	.141	64.734	1.000
	Error	21757.086	396	54.942					
HLP #15	Contrast	3931.436	1	3931.436	48.084	.000	.108	48.084	1.000
	Error	32377.406	396	81.761					

The F test evaluates the effect of curriculum. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Computed using alpha = .05

Table 9. Achievement means and standard errors by curriculum (original vs modified), proficiency levels of simulated learners (low vs high), and HLP.

		HLP #1	HLP #2	HLP #3	HLP #9	HLP #10	HLP #12	HLP #15
Default	Low Mean	67.432	69.602	71.711	81.141	62.249	60.529	62.431
	Std Error	.804	.757	.591	.533	.702	.741	.904
	High Mean	83.887	85.102	86.508	93.346	77.226	77.333	79.158
	Std Error	.804	.757	.591	.533	.702	.741	.904
Modified	Low Mean	61.116	61.634	78.757	78.765	65.700	66.755	55.280
	Std Error	.804	.757	.591	.533	.702	.741	.904
	High Mean	78.063	78.109	90.576	91.316	83.298	83.034	73.768
	Std Error	.804	0.757	.591	.533	.702	.741	.904

Table 10. HLPs grouped by their relative priority in the modified curriculum design (as indicated by simulated students' achievement scores).

Priority	Objectives
	Social and Individual Foundations of Learning
High	HLP #9: Setting up and managing small group work HLP #3: Eliciting and interpreting individual student's thinking
Medium	HLP #10: Building respectful relationships with students HLP #12: Learning about students' cultural, religious, family, intellectual, and personal experiences
	Instructional Practices Supporting Learning
Low	HLP #1: Leading a group discussion HLP #2: Explaining and modeling content, practices, and strategies
Lowest	HLP #15: Checking student understanding during and at the conclusion of lessons

5. Discussion

In the previous section, we described a two-stage approach to building a computer-based curriculum model and running a simulation that begins with the kind of curriculum map traditionally used by educators when designing or modifying a curriculum. In this first stage, the initial curriculum map is analyzed with the goal of highlighting key elements to be modelled and then tentatively assigning quantitative descriptors for these elements. Analysis of the curriculum may continue with further informal analysis by consulting with the curriculum design team to see if other elements or quantitative descriptors should be considered. Ultimately, an explicitly formal approach is adopted. In this more formal approach, gaps in the conceptual and quantitative framework are filled by means of assumptions drawn from research findings and recommendations of the curriculum design team. When all key elements of the model are defined and principles that determine student learning are coded, the model is ready to be used. Typically, model-based simulation studies will be designed to compare two or more alternative curricular models of special interest (e.g., McEneaney, 2016). Our work focused on comparing two distinct populations of simulated learners in two different curriculum designs focused on the same seven learning outcomes. Our first model represented a curriculum as proposed by program faculty. A second model introduced changes that were suggested by our first-stage curriculum analysis, while retaining the same overall course and program time-on-task constraints. In effect, we held overall time-on-task constant while we varied the allocation of time across learning outcomes within courses.

Results of the simulation study we ran showed significant differences even after accounting for the variability built into the models. Because our study was based on seven dependent variables, our first analysis relied on a MANOVA showing significant differences. We followed up with a series of univariate ANOVAs focusing specifically on differences between the curriculum designs and learning achievement means for the seven HLPs across all students. Results showed that means for every learning goal differed significantly between the two curriculum designs, although some outcomes showed greater effect sizes than others. We did not test for differences in performance between high- and low-proficiency groups since this was a difference we had effectively embedded in our simulations in defining these learner populations. The results support the conclusion that even small modifications in a curriculum design can lead to measurable and practically meaningful student learning differences over the course of a multi-year curriculum.

Lastly, when examining overall learning by simulated students across the two curricular designs, we found a reorganization of the curriculum's de facto priorities, as expressed through levels of learning achievement. The original curriculum indicated a rather lopsided hierarchy with significantly greater learning gains for HLP #9 than for other HLPs. In the modified curriculum, however, we found that learning goal gains seemed to group in more conceptually meaningful tiers. Four HLPs (#3, #9, #10, and #12) that emphasize social and individual foundations of learning showed the greatest simulated learning gains, while three HLPs (#1, #2, and #15) that focus on more technical aspects of instructional practice reflected a lower priority in the modified curriculum design. This arrangement of priorities was not evident in the original curriculum but it appeared to more accurately reflect the social-justice orientation embraced by program faculty than the disproportionate emphasis on HLP #9. Colleagues on the curriculum design team not involved in the simulation work seemed especially interested in our forecasts of the modified curriculum's impact on cumulative student achievement across outcomes, leading to further conversation about the relative importance and chronological prioritization of particular HLPs over others. It seemed to us that our curriculum redesign effort benefitted from both our predictive modelling and from the iterative informal discussion and analyses it supported.

5.1. Benefits of CMLS

Our proof-of-concept illustration of CMLS in action in the context of one program's curriculum redesign effort showcases several key features and benefits of this approach. In this section we highlight what we see as the most important of these benefits and elaborate on key implications for stakeholders taking up the work of curriculum design and improvement.

Regarding the practical challenges in curriculum design and continuous improvement, a first benefit of CMLS is the way it engages stakeholders in a collaborative process focused on the big picture of program improvement. Without imposing any particular protocols for collaboration, the CMLS approach in effect requires that stakeholders work together to clarify important global aspects of their program — things like shared learning outcomes and the allocation of time to outcomes in each course. Furthermore, CMLS requires that stakeholders quantify aspects of their curriculum — most notably time-on-task — for the sake of achieving a better collective understanding of students' overall in-program experience. CMLS thereby centres the reality that, through their individual decisions about how much time to devote to particular learning outcomes, faculty collectively shape their students' overall learning trajectories and their end-of-program levels of achievement — in both obvious and also not-so-obvious ways. These insights are, of course, not unique to the CMLS approach. That said, CMLS is unique regarding its capacity to directly show stakeholders — via simulations — big-picture consequences for students' overall end-of-program learning achievement of even relatively minor changes in time-on-task allocation. This aspect of CMLS may have the effect of motivating diverse stakeholders to consider a broader whole-system perspective when making decisions about their individual courses.

Beyond its centring of the basic importance of time-on-task, a related second key benefit of the CMLS approach is the way it foregrounds for stakeholders how decisions about sequencing and spacing courses influence student learning. Here again, no claim is made that insight into the importance of sequencing and spacing is unique to CMLS (e.g., Carpenter et al., 2012; Kang, 2017; Méndez et al., 2014; Pavlik & Anderson, 2005). As was the case regarding time-on-task, however, CMLS concretely shows stakeholders how general learning principles and assumptions may play out. The CMLS approach thus provides helpful grounding for conversations among stakeholders about a program's structure, and the pros and cons of modifying that structure in specific ways. This grounding may be especially helpful when, as is often the case, faculty and other stakeholders involved in a (re)design process do not all have deep experience or training in curriculum design (Lattuca & Stark, 2009).

Once curriculum design or redesign work is launched, a third benefit of CMLS is the way it can support sustained thinking through iterative testing of alternative options. When a promising program modification has been identified, CMLS provides a tool to evaluate pros and cons using constructs and metrics (e.g., student learning achievement) that are universally meaningful. Here again, it is important to underscore that, in the context of a curriculum (re)design effort, simulation results should not be seen as providing definitive answers. Rather, these results should be seen as providing support for specific theory-based hypotheses (e.g., "Given learning decay, achievement may be enhanced if sequencing assures outcomes are periodically reinforced") or, on the other hand, as alerting stakeholders to possible problems and/or raising questions for further investigation. In our proof-of-concept case study, for example, simulation results show how a few minor adjustments in weighting of outcomes in a handful of courses would result in an overall rebalancing of student learning across the program's seven major outcomes — a rebalancing shown to be not only statistically significant but also practically meaningful, based on the magnitude of the measured effects (Ferguson, 2009). Determinations of effect size are, of course, especially informative in situations like this one where the general direction of effects appears easy to predict (e.g., more time-on-task yielding higher achievement). Moreover, as we noted, the new hierarchy of learning outcomes better reflects the social-justice orientation of the program, a finding that could support further discussion and investigation.

Finally, a fourth practical benefit worth underscoring is the fact that, even as the CMLS approach shows how program design decisions are likely to impact student learning, it remains transparent and open to inspection, adjustment, and correction in ways a mathematical black-box model is not. CMLS's assumptions, rules, and algorithms are both explicitly stated and easily adjusted. Indeed, we suggest that the transparency and adjustability of CMLS invites stakeholders to think even more deeply about the factors being modelled (e.g., learning decay, learner proficiency) and about the interplay of these factors in their local context regarding how they might impede or enable student learning. CMLS therefore addresses concerns expressed by Hershkovitz et al. (2017) that "the use of any [simulated] data must be carefully considered, rigorously analyzed, interpreted through a strong theoretical framework and actioned with care and caution." CMLS can therefore facilitate and inform many of the tasks and processes familiar to stakeholders who participate in curriculum design and improvement efforts, while also providing a new methodological footing. CMLS gives stakeholders a new type of tool with a capacity to provide principled forecasts of the impact on learning of different curricular arrangements, a tool that may be potentially transformative in a wide range of curriculum design tasks, processes, and lines of inquiry.

5.2. Limitations of CMLS

As with any other methodology, the CMLS approach to curriculum design and improvement has limitations. Primarily, CMLS depends on simplifying the complexities of human learning by focusing on just a handful of key features of curriculum (e.g., time on task), learners (e.g., learner proficiency), and learning processes (e.g., learning decay). For example, the two models we describe do not address a potentially relevant learner attribute such as prior knowledge, though research indicates that, in some domains, high prior knowledge can enable less proficient learners to outperform more proficient learners who lack prior knowledge (e.g., Pearson et al., 1979; Schneider et al., 1989). At the same time, the power of CMLS lies precisely in its capacity to generate useful forecasts based on a circumscribed set of chosen inputs. Ultimately, the purpose of CMLS modelling is not simply to predict learners' achievement scores but to explore patterns of effects on student learning trajectories across program outcomes. Moreover, it is important to note that the calibration and application of curriculum models depends in a critical way on the reliability and validity of the learning assessments actually used with real students since this kind of assessment data is what anchors a model in reality and makes its predictions most meaningful and actionable.

A second important limitation is that the work we describe here is in its early stages. Although based on prior work modelling smaller-scale issues in instructional design (McEneaney, 2016; McEneaney, 2019), as far as we know, this is the first published study that applies curriculum design modelling and learner simulation on the scale of a multi-year curriculum. Moreover, since the actual curriculum our model is based on was only implemented in practice in the fall of 2021, we do not yet have data available to calibrate and test the model, so our present work remains a proof-of-concept rather than a validated model. The real power of simulation-based research, however, lies in its capacity to be developed across time in an iterative way to give it an ever-firmer grounding in the realities it seeks to model. As a result, our work represents a promising theoretical and methodological beginning rather than a definitive empirical test.

Lastly, CMLS models, like all forecasting models, are open to legitimate criticism for simplifying reality and relying on assumptions. In this regard it is important to remember that the goal of CMLS models and simulations is not to make predictions of student achievement like a regression model. Rather, the CMLS models we present allow us to make theoretically grounded estimates of potential positive or negative impacts on learning achievement that a particular curricular arrangement may produce. The question to ask about CMLS models and their forecasts is therefore not, "Are they true?" Rather, from a more pragmatic perspective, the question to ask is this: Are CMLS models and their forecasts useful for advancing the work of curriculum design and continuous improvement by alerting stakeholders to potential and perhaps unanticipated benefits and downsides of particular curricular modifications, generating productive questions for further exploration, and supporting well-informed decision-making?

6. Conclusions

We opened this article by observing that curriculum designers, program administrators, and other stakeholders sometimes find themselves in situations where there is insufficient historical data to answer questions about the likely effects on student learning of a contemplated curricular change. Modifications being contemplated may be unprecedented and/or complex and entangled. Or it may be the case that, before implementing change, stakeholders want to do their due diligence in terms of investigating the full range of intended and possibly unintended effects on student learning that the contemplated changes may have. Further, when a plausible program modification is identified, stakeholders may face hurdles that include a lack of shared language, metrics, and methodology for estimating and evaluating the likely impact of the modification. As we have illustrated, CMLS can help stakeholders address these hurdles and concerns. More broadly, CMLS methods have the potential to expand the stakeholder toolset for curriculum design and continuous-improvement work. CMLS provides a conceptual framework, procedures, and analytical methods for identifying possible areas for improvement and then supporting stakeholders in estimating with impressive granularity and specificity the likely consequences for student learning of a contemplated modification based on factors that are clearly stated and easily reviewed and adjusted. In sum, CMLS offers a methodology for making theoretically principled and detailed projections of the impact of contemplated curricular changes on student learning across multiple learning outcomes as well as for students with different learner characteristics. CMLS in no way replaces other sources of guidance, such as relevant experimental and quasi-experimental studies and LA studies, from which designers may try to extrapolate the likely impact of a change they are contemplating. CMLS should instead be seen as an additional and complementary source of guidance with unique benefits.

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