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Analyzing Curriculum Structure and Student Navigation Using Graph Theory in Engineering Education

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Leveraging Graph Theory to Analyze Curriculum Structure and Student Navigation in Engineering Education

Abstract

In engineering education, curriculum design quietly structures every student's journey. It shapes what knowledge they encounter, how they build expertise, and who ultimately succeeds. Yet, despite its centrality, curriculum often remains a static map rather than a system open to analysis and redesign. This work-in-progress paper proposes a graph-based learning analytics framework that models curriculum as a multi-layer network of courses, learning objectives, assessments, and digital resources. The framework is developed in the context of a graduate engineering certificate program at a large R1 university in the southern United States and is grounded in constructive alignment theory, backward design, and network-based learning analytics.

The framework organizes curriculum analysis into two complementary layers: structural analysis of curriculum design such as examining how courses, learning objectives, assessments, and digital resources are connected, and behavioral analysis of enacted student experience through LMS interaction data. Together these layers form an analytical pipeline linking design intent to student navigation and outcomes. The contribution is a replicable, theoretically grounded approach for examining how curriculum structure shapes learning pathways, one that complements existing outcomes-based evaluation and positions curriculum as a dynamic system open to evidence-based redesign.

Introduction

A graduate engineering certificate program was recently established at the College of Engineering at a large R1 university in the southern United States following a rigorous, structured curriculum design process. The program's degree plan was developed through market analysis, labor market data review, and stakeholder survey to define program-level learning outcomes, which were subsequently validated by an advisory board of industry practitioners and disciplinary experts. Faculty curriculum committees applied constructive alignment principles [1] to ensure coherence among program-level outcomes, course-specific objectives, and corresponding assessments.

Despite these systematic efforts, a critical gap remained. The process established internal coherence among defined learning outcomes, course objectives, and assessments—but did not employ methods to examine how curriculum *structure* itself shapes student learning pathways. Structure here refers to the arrangement of courses and their prerequisite relationships, the sequence in which students encounter content, the linkage between course-level learning objectives and artifacts, and how those artifacts connect upward to program-level outcomes. These structural properties are consequential: they determine which knowledge students encounter when, which courses are load-bearing for program progression, and where gaps between intended and enacted curriculum are most likely to emerge.

Existing program evaluation approaches in engineering education address outcomes measurement but not structural analysis. ABET's student outcomes framework provides a well-established mechanism for evaluating whether graduates achieve defined competencies, but does not offer methods for examining how curricular structure produces or constrains those outcomes [2]. Curriculum analytics, an emerging subfield of learning analytics, offers precisely this structural perspective. Recent systematic reviews document a growing body of work applying network methods to course enrollment sequences, degree audit data, and LMS interactions to surface structural properties that periodic program review cannot [3, 4].

This work-in-progress proposes a graph-based learning analytics framework that addresses this gap by modeling curriculum as a multi-layer network. The framework investigates three questions: (1) How does the prerequisite and sequencing structure of the curriculum network shape the pathways available to students? (2) How well do course-level learning objectives and artifacts align to program-level outcomes across the curriculum? (3) Are students who engage more with aligned course artifacts performing better?

Background and Conceptual Framework

Curriculum Design Foundations

Contemporary curriculum design in engineering education integrates constructive alignment and backward design as complementary organizing principles. Constructive alignment, introduced by Biggs and Tang, holds that learning is driven by the coherent connection of course outcomes, assessments, activities, and content [1]. Backward design, articulated by Wiggins and McTighe, operationalizes this logic by specifying desired outcomes first, then determining acceptable evidence of their achievement, then designing instruction accordingly [5]. At the program level, scaffolding theory, grounded in Vygotsky's Zone of Proximal Development, extends these principles through prerequisite sequencing and progressive complexity, ensuring students encounter new material within reach of what they already know [6]. Together these frameworks establish the design logic that the present study takes as its analytical starting point: a well-aligned curriculum is one in which program outcomes, course objectives, assessments, and resources are explicitly and verifiably connected.

These frameworks, however, are qualitative. They specify what a well-designed curriculum should accomplish but do not provide empirical methods for examining whether a given curriculum's structure actually achieves that alignment in practice, or how its arrangement of courses and prerequisites shapes the pathways students can take through the program.

Graph-Based Curriculum Analytics

Network science provides the analytical foundation for treating curriculum as a system. Course-prerequisite networks (CPNs), in which nodes represent courses and directed edges represent prerequisite dependencies, enable computation of centrality metrics, critical path length, and modularity [4, 7, 8]. Betweenness centrality identifies load-bearing courses whose disruption would most affect student progression; longest-path analysis reveals the minimum sequence required for program completion. Comparative CPN studies across institutions have shown that structural properties vary systematically with disciplinary conventions, suggesting that analysis of curriculum structure can surface design decisions that are otherwise invisible to curriculum committees [8].

Beyond prerequisite structure, curriculum analytics has been extended to the alignment between learning design and student behavior. Lockyer, Heathcote, and Dawson established a foundational framework distinguishing checkpoint analytics—whether students completed designed activities—from process analytics—the sequences and patterns of engagement those activities produce [9]. The present framework applies this distinction at program scale: analysis of curriculum design structure addresses the checkpoint dimension, while LMS navigation analysis addresses the process dimension. De Silva and colleagues' systematic review of curriculum analytics identifies integration of these two modes as the critical unmet need in the field [3], which the present framework directly addresses.

Proposed Methodology

The proposed methodology conceptualizes curriculum as a multi-layered network system in which instructional design decisions, structural constraints, and student behaviors jointly shape learning opportunities and outcomes. The framework organizes analysis into two complementary layers. The first layer examines designed curriculum structure: how courses are sequenced through prerequisite dependencies, how program-level outcomes are distributed across course objectives and assessments, how course artifacts link to those objectives, and where the resulting network is structurally vulnerable. The second layer examines enacted student experience: how students navigate digital learning resources within and across courses through their LMS interactions, and whether engagement patterns are associated with performance outcomes. Together these two layers form an analytical pipeline from design intent to student experience.

Table 1 maps the six analytical constructs that operationalize this framework to their corresponding metrics, learning analytics techniques, data sources, and supporting references.

#	Construct	Analytic metrics	LA technique	Data sources	Refs.
01	Design alignment across instructional levels. Tripartite network linking program outcomes, course assessments, and digital learning resources.	Objective coverage ratio; outcome–assessment linkage density; gap and redundancy detection	Tripartite network; alignment gap analysis	Syllabi; LMS outcomes tools; assignment metadata; module structures	[3, 9, 10]
02	Curriculum prerequisite structure and sequencing. Directed network of formal course dependencies governing student progression.	In- and out-degree centrality; betweenness centrality; longest path	Directed prerequisite network; centrality analysis	Program catalog; degree audit records; curriculum maps	[4, 7, 8]

#	Construct	Analytic metrics	LA technique	Data sources	Refs.
03	Program coherence and modularity. Structural proximity of thematically related courses; descriptive in pilot, algorithmic at scale.	Within- and between-cluster edge density; modularity score	Syllabus-derived topic tagging; Leiden community detection (at scale)	Course metadata; outcome and topic tags; prerequisite network	[11–13]
04	Curricular efficiency and structural vulnerability. Network robustness to course disruption; bottleneck identification.	Bottleneck load; critical path length; node-removal impact	Network robustness simulation	Course offering histories; prerequisite graph; enrollment data	[4, 7]
05	Student navigation in digital learning environments. LMS interaction data modeled as directed sequence networks; enacted pathways compared to designed structure.	Transition probabilities; sequence entropy; navigation density	Sequence networks; process mining	LMS clickstream logs; timestamps; module completion events	[14–16]
06	Integration of engagement and performance with structure. Structural position and navigation behavior examined in relation to student outcomes.	Centrality–performance associations; navigation density vs. outcomes	Weighted graph overlay; correlational modeling	Grades; assignment completion; LMS engagement records	[15, 17, 18]

Note. Constructs 1–4 operate on designed curriculum structure; Constructs 5–6 operate on enacted student behavior. Community detection in Construct 3 requires program-scale data and will be applied as the certificate expands beyond the pilot phase.

Future Work and Expected Contributions

This work-in-progress contributes a theoretically grounded and methodologically specified framework for analyzing engineering curriculum as a multi-layer network system. The framework's primary contribution is integrating two analytical traditions that curriculum analytics research has largely kept separate: structural analysis of curriculum design, examining course sequencing, prerequisite dependencies, and outcome-to-artifact alignment, and behavioral analysis of enacted student experience through LMS interaction data [4, 8, 14, 15]. By bridging these levels within a single pipeline, the framework enables a question neither tradition alone can answer: where does the gap between designed and enacted curriculum most affect student experience?

A second contribution is the use of a tripartite network to model design alignment, simultaneously linking program outcomes, course assessments, and digital resources, which extends prior bipartite approaches and makes alignment gaps structurally visible [1, 9]. Third, the framework is designed for replication: the required inputs, syllabi, LMS logs, and program catalogs, are available at most institutions operating graduate programs through a learning management system.

Planned empirical work will apply the framework to the graduate certificate program described above, reporting CPN structural characterization, tripartite alignment gap analysis, and LMS navigation patterns. Longer-term extensions include temporal network analysis to track curriculum evolution across program iterations and multi-program comparative analysis to examine how structural properties vary across disciplines and institutional contexts. The framework is designed to complement existing accreditation-driven evaluation infrastructure [2], positioning structural curriculum analytics as a continuous improvement tool alongside ABET outcomes assessment.

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