

Psychometric AI Mapping of Engineering Outcomes: Supporting College–Industry Dialogue Between ABET Outcomes and Workforce Skills

Dr. Lilianny Virgüez, University of Florida

Dr. Virgüez is an engineering educator who teaches foundational electrical engineering courses for students across multiple disciplines and class standings, with prior experience teaching first-year engineering students. Her work includes curriculum development and program-level coordination, and her research focuses on student motivation, workforce alignment, and the role of emerging technologies, including AI, in engineering education. She brings prior industry experience in the telecommunications sector and holds a Ph.D. in Engineering Education and a Master's degree in Management Systems Engineering from Virginia Tech, as well as a bachelor's degree in Telecommunications Engineering.

Dr. Sreyoshi Bhaduri, Public Corporation

Dr. Sreyoshi Bhaduri leads at the intersection of Generative AI, customer-centric innovation, and global business scale. A recognized voice in tech, Dr. Bhaduri is an award-winning leader, global speaker, mentor, and advisory board member. She is deeply committed to democratizing and demystifying AI. She has delivered 100+ talks worldwide, breaking down complex topics and sharing insights on human-centered development. As a founder of ThatStatsGirl, she amplifies the importance of multi-disciplinary collaborations and lifelong learning in technology.

Dr. Debarati Basu, Embry–Riddle Aeronautical University, Daytona Beach

Dr. Debarati Basu is an Assistant Professor in the Engineering Fundamentals Department in the College of Engineering at the Embry-Riddle Aeronautical University, Daytona Beach campus. She earned her Ph.D. in Engineering Education from Virginia Tech. She received her bachelor's and masters in Computer Science and Engineering. Her research is at the intersection of Engineering Education (EE) and Computing Education Research (CER) for enhancing individualized experiences, specifically focused on educational technologies including GenAI (for learning, engagement, self-directed learning), student-centered curriculum and pedagogy, and support systems for student and faculty success. She primarily teaches freshmen computing students with active learning techniques and focuses on bringing EE and CER into practice.

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Abstract

Engineering programs are increasingly expected to articulate how accreditation-driven student outcomes relate to workforce capabilities valued by industry. In college–industry partnership contexts, these conversations often unfold informally, leaving differences in vocabulary and underlying competence logic implicit and difficult to revisit. Our work-in-progress paper introduces *Psychometric AI Mapping*, a human-in-the-loop methodological framework for interpretive comparison of text-based outcome frameworks. Drawing on the unified view of construct validity, the method treats accreditation outcomes and workforce skill statements as observable indicators of underlying competencies, and operationalizes their comparison through a transparent workflow of thematic aggregation, interpretive alignment, and matrix construction. Large language models are positioned as structured analytic instruments within this workflow rather than as autonomous interpretive authorities.

We demonstrate the method on the ABET EAC Student Outcomes (Criterion 3, outcomes 1–7) and workforce skills from the World Economic Forum’s *Future of Jobs Report 2025*. A researcher-generated alignment matrix surfaces patterns of conceptual concentration, overlap, and absence revealing, for example, strong alignment around cognitive problem-solving alongside gaps in adaptability and operational capabilities. The contribution is methodological: a transparent, reproducible workflow that supports more systematic dialogue among faculty, assessment leaders, and industry partners.

1. Introduction

“The bird wishes it were a cloud. The cloud wishes it were a bird.”

—Rabindranath Tagore, *Stray Birds* (1916)

Tagore’s imagery captures a tension that quietly shapes engineering education today. Universities and industry partners often look across at one another with a similar mutual longing, each wishing to speak the other’s language. Accreditation frameworks aim to anticipate the agility of the workplace; workforce frameworks look back to the structure of formal education. Yet the words each uses (like communication, design, adaptability, problem-solving, teamwork) do not always mean the same thing on either side of the conversation.

Engineering programs are increasingly asked to articulate how accreditation-driven student

outcomes relate to workforce capabilities valued by industry [1, 2, 3, 4, 5]. While ABET outcomes provide a stable articulation of educational priorities, workforce skills frameworks emphasize evolving expectations shaped by technological change and labor market dynamics [6]. Bridging these perspectives remains a persistent challenge during curriculum discussions, advisory board meetings, and accreditation preparation, where stakeholders seek shared understanding of workforce readiness.

In practice, comparisons between academic outcomes and workforce skills are conducted informally through discussion and professional judgment. Although valuable, such approaches are rarely documented as systematic procedures, making assumptions implicit and difficult to revisit [7]. The challenge is not merely lexical: outcome and skill statements are short, abstract texts that index broader latent competencies, and comparisons relying on surface-level keyword overlap risk obscuring the conceptual structure each framework encodes.

Recent advances in generative artificial intelligence (AI), and large language models (LLMs) in particular, offer new opportunities to support structured analysis of such text-based artifacts. Within engineering education research, AI is increasingly positioned as methodological support for qualitative and interpretive workflows, provided that human oversight and transparency are maintained [8, 9, 10, 11, 12, 13]. These developments suggest the potential for AI-supported methods to make outcome–skill comparisons more explicit and reproducible without displacing expert judgment.

In this work-in-progress paper, we introduce *Psychometric AI Mapping*, a human-in-the-loop framework for interpretive comparison of accreditation and workforce skills frameworks. The approach is distinguished from keyword-based or curriculum-mapping methods by treating outcome and skill statements as observable indicators of underlying latent constructs, drawing on the unified view of construct validity in which interpretive judgments must be supported by both theoretical rationale and evidence [14]. As an illustrative case, we examine the ABET Engineering Accreditation Commission Student Outcomes (Criterion 3, outcomes 1–7) and workforce skills drawn from the World Economic Forum’s *Future of Jobs Report 2025* [6]. The contribution of this work-in-progress is primarily methodological - our paper articulates the assumptions and workflow of Psychometric AI Mapping and presents a conceptual alignment matrix as an analytic artifact. Consistent with its work-in-progress scope, it does not report AI-generated outputs or quantitative results, but establishes the methodological foundation for subsequent empirical implementation and validation.

2. Background

Accreditation Outcomes and Workforce Skill Frameworks

ABET student outcomes serve as a stable, accreditation-driven articulation of the knowledge, skills, and professional competencies expected of engineering graduates. Designed to apply across institutions and over time, these outcomes prioritize consistency, broad applicability, and assessability within academic programs[15]. In contrast, workforce skill frameworks—such as those published by the World Economic Forum—are explicitly future-oriented and responsive to evolving labor market conditions, technological change, and organizational practices. These

frameworks often emphasize adaptability, systems thinking, and continuous reskilling, reflecting industry concerns about workforce readiness in rapidly changing contexts.

In college–industry partnership settings, these differing purposes can complicate interpretation. Industry partners may expect educational outcomes to directly reflect emerging skill priorities, while academic programs must balance such expectations against accreditation requirements and curricular stability. As a result, discussions about workforce alignment frequently rely on translation between outcome language and industry skill discourse[16], underscoring the need for methods that support shared sensemaking rather than prescriptive evaluation.

Psychometric Framing of Outcome Language

This study adopts a psychometric framing to conceptualize the relationship between accreditation outcomes and workforce skills. Drawing on the unified view of construct validity articulated by Messick [14] and codified in the *Standards for Educational and Psychological Testing* [17], the framing treats short text artifacts (e.g., a workforce skill description) as observable indicators of broader latent competencies. Under this view, no single sentence fully captures a competency such as communication or adaptability; instead, each framework expresses such competencies through a particular configuration of language, emphasis, and omission. Comparing the language used across frameworks therefore allows examination of how different educational and workforce perspectives represent and prioritize similar underlying capabilities.

This framing carries explicit assumptions and associated limits. It does *not* assume equivalence between textual similarity and curricular implementation, instructional emphasis, or actual student learning, and it does not treat alignment between frameworks as evidence of workforce readiness. Instead, it supports interpretive examination of how constructs are distributed, concentrated, or implicitly encoded across frameworks, and where one framework foregrounds capabilities that another leaves tacit. Used in this way, the psychometric perspective enables systematic comparison while preserving human judgment as the primary interpretive authority. This is a positioning consistent with emerging practice in which large language models help render expert knowledge into structured representations without replacing the experts who validate them [18].

Generative AI as Methodological Support in Engineering Education Research

Recent work in engineering education research has begun to explore the use of generative artificial intelligence as methodological support for research workflows involving qualitative and text-based data [12, 19, 20]. Rather than positioning AI as an autonomous analytic authority, this body of work emphasizes the importance of human-in-the-loop approaches, transparency, and theory-guided interpretation when integrating large language models into research processes [8]. Related studies have demonstrated how generative AI can assist with scaling and structuring qualitative analyses while retaining human interpretation as the central analytic driver[9].

Positioning of the Present Study

Building on these perspectives, this work positions Psychometric AI Mapping as a methodological contribution that articulates a workflow for interpretive comparison of accreditation outcomes and workforce skill frameworks. The approach combines a psychometric framing of outcome language with a proposed AI-supported semantic analysis, which is described conceptually in this work-in-progress manuscript rather than implemented empirically.

The method is intentionally non-prescriptive and does not seek to evaluate curricula, measure student learning, or determine workforce readiness. Instead, it provides a documented and transparent workflow that supports clearer articulation of how accreditation outcomes and workforce skill frameworks may be related at the level of language and constructs, establishing a foundation for informed discussion in college–industry partnership settings and for future implementation and validation.

Method

Analytic Scope and Inputs

This study adopts a work-in-progress, methods-focused design to articulate a transparent workflow for comparing text-based accreditation outcomes and workforce skill frameworks in college–industry partnership contexts. The analytic scope is intentionally bounded to demonstrate the structure, assumptions, and interpretive use of the proposed method rather than to report AI-generated outputs or validated quantitative results.

Two publicly available frameworks are used to illustrate the method. The first is the ABET Engineering Accreditation Commission (EAC) Student Outcomes, Criterion 3, outcomes (1) through (7), as defined in the 2019–present accreditation criteria. These outcomes represent a stable, accreditation-driven articulation of educational expectations. The second is the World Economic Forum (WEF) Top 26 Skills for 2025, which provide an industry-facing account of workforce capabilities responsive to technological change and labor market dynamics. These frameworks were selected to reflect distinct but complementary perspectives—educational standards and workplace capacities—commonly negotiated in college–industry partnership discussions.

Researcher-Led Thematic Aggregation of Workforce Skills

To support interpretability and fit within space constraints, the WEF Top 26 skills were thematically aggregated through researcher-led interpretive synthesis into eight higher-order workforce capability themes. This aggregation was guided by conceptual proximity and functional similarity among skills, with attention to preserving the industry-facing logic of the WEF framework rather than mirroring accreditation outcome language.

The resulting themes reflect workplace capacities, organizational roles, and adaptive behaviors (e.g., operational quality, digital fluency, physical and sensory work capabilities) and are used as analytic lenses for comparison. This thematic aggregation is an interpretive step intended to make

differences in representational logic visible; it is not presented as a formal restructuring of the WEF framework nor as an AI-generated categorization.

Psychometric AI Mapping Workflow (Proposed)

Psychometric AI Mapping is conceptualized as a human-in-the-loop analytic workflow that combines interpretive comparison with the potential for AI-supported semantic analysis. In the fully implemented version of the method, pre-trained large language models (LLMs) could be used as analytic instruments to support systematic comparison of outcome and skill statements. For example, LLMs may generate semantic representations or provide structured categorical judgments regarding conceptual correspondence between accreditation outcomes and workforce capability themes.

In this manuscript, the AI-supported components of the workflow are described conceptually rather than implemented empirically. The purpose is to articulate how such tools could be integrated transparently into outcome–skill comparison while preserving human judgment as the primary interpretive authority. This positioning allows the assumptions, decision points, and intended use of the method to be examined prior to implementation.

Conceptual Alignment Matrix as an Analytic Artifact

To illustrate the form and interpretive use of the method’s output, a conceptual alignment matrix is presented in Figure 1. The matrix is constructed through researcher-led interpretive synthesis and presents ABET student outcomes as rows and WEF-derived workforce capability themes as columns. Qualitative alignment levels (High, Moderate, Low) indicate conceptual correspondence based on outcome language and workforce skill framing.

As shown in Figure 1, the matrix is intended to make visible patterns of conceptual concentration, distribution, and absence across frameworks. It is illustrative and non-evaluative: the matrix is not presented as an AI-generated result, nor does it report computed similarity values. Instead, it functions as a representation of how competencies are represented differently in accreditation standards and workforce frameworks.

Planned Implementation and Validation

Future work will implement the proposed workflow using pre-trained LLMs as structured analytic coders and will compare AI-generated alignment matrices across models and against human-generated matrices. Agreement metrics and qualitative analysis of discrepancies will be used to examine stability, interpretive differences, and conditions under which AI-assisted alignment supports or complicates college–industry dialogue. These steps will move the method from conceptual articulation toward empirical evaluation.

Table 1: Conceptual Alignment Matrix Between ABET Student Outcomes and WEF Workforce Capability Themes.

Cell shading indicates qualitative alignment level: ■ High, ■ Moderate, ■ Low.

ABET Student Outcomes (Criterion 3)	Cognitive Problem Framing & Reasoning	Digital & Computational Fluency	Work Design, Operations & Quality	Leadership, Influence & People Mgmt.	Communication & Human Interaction	Professional Judgment, Ethics & Responsibility	Adaptability, Motivation & Self-Regulation	Physical & Sensory Work Capabilities
SO1: Problem Solving	High	Moderate	Moderate	Low	Low	Low	Moderate	Low
SO2: Engineering Design	Moderate	Moderate	High	Moderate	Low	Moderate	Moderate	Low
SO3: Communication	Low	Low	Low	Moderate	High	Low	Low	Low
SO4: Ethics & Responsibility	Low	Low	Low	Moderate	Low	High	Low	Low
SO5: Teamwork & Leadership	Low	Low	Low	High	Moderate	Low	Low	Low
SO6: Experimentation & Data Analysis	Moderate	High	Moderate	Low	Low	Low	Low	Low
SO7: Adaptive Learning & Knowledge Acquisition	Low	Low	Low	Low	Low	Low	High	Low

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