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Diagnosing Epistemic Frames in Digital Learning Environments: A Scoping Review

Mr. Jobin Varughese, Texas A&M University

Jobin Varughese is a doctoral student in the College of Engineering at Texas A&M University, where he also serves as Senior Educational Data Analyst at the Center for Teaching Excellence. He holds an M.S. in Management Information Systems with an emphasis in Data Science from Oklahoma State University and a B.S. in Electronics and Communication Engineering from Christ University. His research draws on learning analytics, AI in education, and human-computer interaction to observe, build, and study systems that learn how people learn. In this work, he partners closely with faculty, instructional staff, and students — believing that the most meaningful scholarship emerges not from research alone, but from collaborations with the people closest to the learning experience.

Dr. Gibin Raju, Texas A&M University

Gibin Raju is a Postdoctoral Researcher in Engineering Education in the Department of Multidisciplinary Engineering at Texas A&M University. He earned his Ph.D. in Engineering Education from the University of Cincinnati and is a recipient of the ASEE Educational Research and Methods (ERM) Division Apprentice Faculty Grant. His research focuses on transformative learning, creativity, critical thinking skills, spatial skills, and engineering design, with particular attention to cognitive stress, cognitive load, and STEM accessibility. By integrating these strategies into a holistic framework, Dr. Raju enhances workforce development, strengthens engineering pathways, and broadens participation in STEM fields. His work equips educators with tools to personalize instruction and foster professional identity, ultimately preparing future engineers to thrive in a rapidly evolving global landscape.

Dianna Morganti, Texas A&M University

Prof. Dianna Morganti is an Instructional Associate Professor at Texas A&M University teaching research-informed writing and publication practices to PhD students throughout the College of Engineering. She brings a focus on information literacy to the critical review of scholarly communication practices in the classroom.

Dr. Kristi J. Shryock, Texas A&M University

Dr. Kristi J. Shryock is the Frank and Jean Raymond Foundation Inc. Endowed Associate Professor in Multidisciplinary Engineering and Affiliated Faculty in Aerospace Engineering in the College of Engineering at Texas A&M University. She also serves as Director of the Craig and Galen Brown Engineering Honors Program. She received her BS, MS, and PhD from the College of Engineering at Texas A&M. Kristi works to improve the undergraduate engineering experience through evaluating preparation in areas, such as mathematics and physics, evaluating engineering identity and its impact on retention, incorporating non-traditional teaching methods into the classroom, and engaging her students with interactive methods.

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Abstract

Online higher education is expanding rapidly, with U.S. institutions navigating rising enrollment demands, uneven readiness, and the emergence of artificial intelligence in teaching and learning. These conditions shift raises critical questions about how students construct and justify professional knowledge in digital learning environments (DLE), particularly within engineering education. This scoping review examines research at the intersection of epistemic frame theory (EFT) and learning analytics (LA), mapping how EFT, a model of professional reasoning grounded in the interplay of knowledge, skills, values, identity, and epistemology, has been applied to study how learners "think like engineers" in online contexts.

Despite growing methodological sophistication, applications in engineering-specific contexts remain sparse. Most studies operationalize EFT through Epistemic Network Analysis (ENA) to model co-occurrence patterns among epistemic elements in student discourse, simulation logs, or design artifacts. Emerging techniques, including ordered network analysis, sentiment modeling, and automated discourse tools, are increasingly used to capture temporal and affective dimensions of epistemic development. Yet few studies adapt EFT constructs to engineering-specific practices such as spatial reasoning, failure analysis, or design under constraint, and fewer still embed epistemic analytics into instructional systems in ways that inform real-time feedback.

The findings suggest that EFT-informed analytics hold significant promise for diagnosing and supporting epistemic development in engineering education. Realizing this potential requires closer alignment between cognitive theory and data science practice, integration that can shape not just how learning is measured, but how students learn to think as engineers.

Introduction

The most recent Changing Landscape of Online Education (CHLOE) 10 report [1] signals that many U.S. institutions are expanding online learning offerings while grappling with uneven institutional readiness, rising competition, and the rapid emergence of artificial intelligence (AI). This development aligns with Flaherty's [2] observation that higher education institutions are under mounting pressure to improve the quality and reach of online offerings, as student demand and competitive dynamics continue to reshape the postsecondary landscape. These conditions expose both the gaps in how online learning is currently structured and the urgency of closing the distance between institutional preparedness and student readiness.

Within these expanding digital learning environments (DLE), understanding how engineering students construct and justify knowledge, and how they professionally reason among their peers is a dimension that can be explored to shape instruction. Learning analytics (LA) offers one avenue for addressing this challenge. According to the Society for Learning Analytics Research (SoLAR) Learning Analytics Definition Task Force (2025), LA is "the collection, analysis, interpretation and communication of data about learners and their learning that provides theoretically relevant and actionable insights to enhance learning and teaching.” In engineering education, LA has been used to examine performance trends, engagement behaviors, and collaborative dynamics in DLEs, yet its potential for diagnosing epistemic frames within digital learning processes remains underexplored. Prior research cautions against treating digitalization as a matter of technological efficiency, highlighting instead the need to align analytic methods with pedagogical goals and meaningful epistemic development [3, 4].

Engineering professional practice requires learners to develop coordinated capacities for iterative design, systems thinking, risk assessment, and technical judgment in ill-defined, real-world contexts [5]. These demands are epistemologically distinct from other STEM fields, motivating the need for a targeted synthesis of how learning analytics has been applied within engineering education specifically.

Epistemic frames, understood as interconnected networks of professional reasoning, offer a powerful lens for examining how engineering students develop professionally in digital contexts. Epistemology, broadly defined as the study of the nature and justification of knowledge [6], provides a foundation for understanding how learners frame and evaluate what they know. Epistemic frame theory (EFT) posits that becoming a professional requires developing interconnected networks of knowledge, skills, values, identity, and epistemology, and understanding how these elements are activated in authentic problem-solving contexts. Analytical methods like epistemic network analysis (ENA) translate this theory into practice by modeling epistemic elements over time, enabling researchers to visualize and quantify how learners “think like” members of a profession within DLEs. Prior studies demonstrate the promise of combining EFT and LA to reveal nuanced patterns of reasoning, collaboration, and epistemic agency [7], but most applications have focused on general STEM or K-12 contexts, and some in medical education, rather than the unique cognitive and epistemic demands of engineering education.

This review was further motivated by the observation that artificial intelligence and large language models (LLMs) represent an emerging frontier for both conducting and automating learning analytics work. Prior studies have begun to explore how generative AI can support epistemic reasoning in student discourse, and conversely, how AI-driven coding and semantic analysis can scale the identification of epistemic markers in large datasets [8]. The extent to which current research has leveraged AI/LLM tools to conduct learning analytics, and whether studies have examined how students engage with AI as a tool for supporting epistemic development, remains an open question that this review seeks to address.

This scoping review traces how current research applies epistemic frame theory and learning analytics to engineering education in digital contexts, examining three research questions:

(RQ 1) What theoretical foundations and operationalizations of EFT are represented in online learning, particularly in engineering education contexts?

(RQ 2) What methodological advances, analytic techniques, research designs, and tools have been leveraged to diagnose epistemic frames?

(RQ 3) What gaps remain, and what directions do these suggest for applying EFT-informed analytics to engineering education?

These questions guide the review and reveal persistent tensions between theory, method, and practice. A scoping review is the appropriate design because the purpose is to map evidence, clarify concepts, and identify gaps rather than synthesize effect sizes [9, 10]. This review was conducted in accordance with PRISMA-ScR [11]. Progress in this area requires not just better methods, but better alignment between what can be measured, what engineering epistemology demands, and what instructors can act on.

Methods

Review Design

This study employed a scoping review methodology following the five-stage framework of Arksey and O'Malley [10] as updated by Peters et al. [12], and reported in accordance with PRISMA-ScR [11]. Scoping reviews are appropriate when the purpose is to map evidence on a topic, clarify key concepts, identify research gaps, and determine whether a systematic review is warranted—rather than to synthesize effect sizes or appraise study quality [9]. This review addresses all three conditions: the field of EFT-informed learning analytics in engineering DLEs is conceptually heterogeneous, methodologically diverse, and insufficiently mapped.

Eligibility Criteria

Studies were eligible for inclusion using a Population–Concept–Context (PCC) framework [12]. Table 1 summarizes the formal criteria applied during screening.

TABLE 1. Eligibility criteria using the Population–Concept–Context (PCC) framework

Element	**Inclusion**	**Exclusion**
Population	Postsecondary learners, instructors, or researchers in higher education; university-affiliated MOOC participants	K-12 students; purely K-12 contexts without transferable HE implications
Concept	Epistemic frame theory (EFT), epistemic network analysis (ENA), ordered or hybrid ENA variants, or learning analytics applied to epistemic development	Studies using "epistemic" only in a philosophical sense, without empirical application to learning data
Context	Digital learning environments (online, blended, or hybrid); postsecondary or university-affiliated platforms	Purely face-to-face contexts; informal learning settings without institutional affiliation
Study types	Peer-reviewed empirical studies, design-based research, mixed-methods studies, and systematic or scoping reviews	Conceptual-only papers; editorials; dissertations; performance-only metric studies without epistemic framing

Search Strategy

Literature was identified through three databases selected for their complementary disciplinary coverage. EBSCO Academic Search Complete provides broad multidisciplinary coverage with particular depth in education research. Web of Science covers high-impact social science and engineering content across indexed journals. IEEE Xplore offers specialized depth in engineering and engineering education literature beyond what the other two databases capture. Together these sources ensured coverage across the theoretical, methodological, and applied dimensions of the corpus. Search terms combined variations of ”epistemic frame theory”, ”learning analytics”,”educational data mining”,”digital learning environments”, and ”higher education”. Methodological terms such as “epistemic network analysis” or “ordered network analysis” were intentionally excluded from the primary search string to avoid biasing the corpus toward studies that happened to use specific tools rather than those substantively addressing epistemic frame diagnosis in digital contexts.

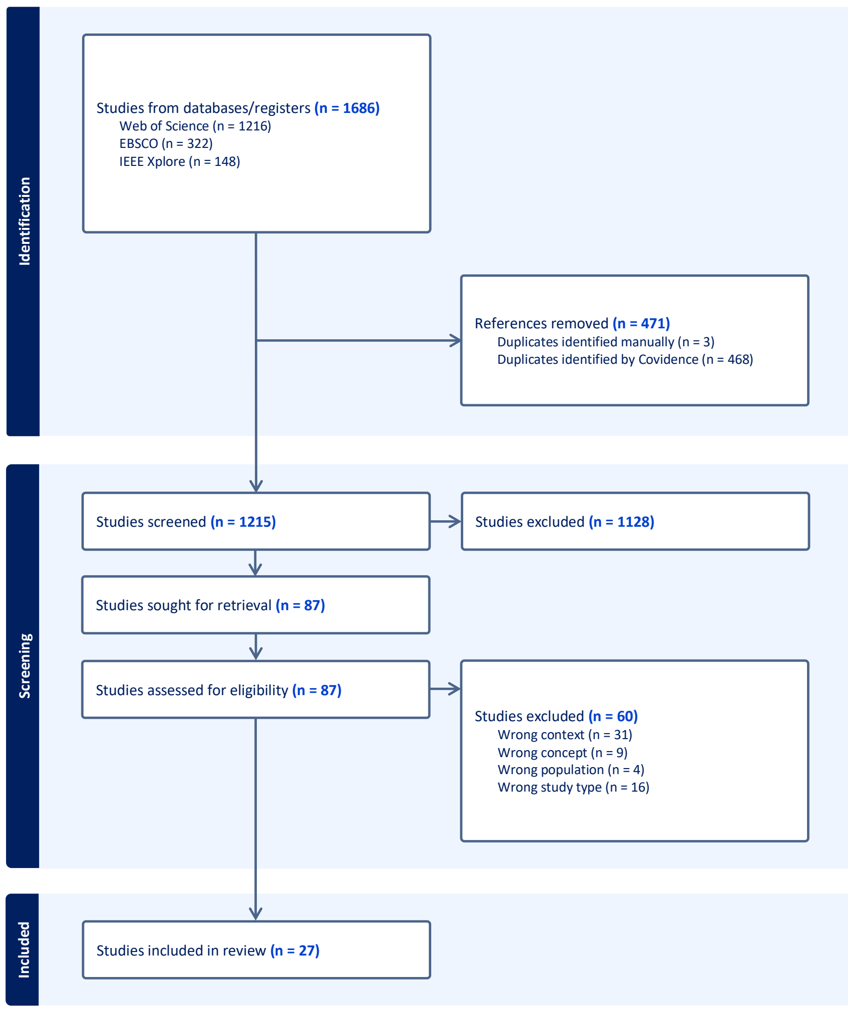

FIGURE 1. PRISMA-ScR flow diagram for the identification, screening, and inclusion of studies in the scoping review ($n = 27$).

Study Selection

Study selection proceeded in two stages following PRISMA-ScR guidelines (Figure 1). From an initial pool of 1,686 records identified across the three databases, 471 duplicates were removed — 468 identified automatically by Covidence and 3 identified manually — leaving 1,215 records for screening. In Stage 1, titles and abstracts of all 1,215 records were screened for relevance to epistemic frame diagnosis or assessment in a postsecondary digital learning context. Of these, 1,128 were excluded and 87 were sought for full-text retrieval, all of which were successfully retrieved. In Stage 2, full texts of all 87 records were reviewed against the formal PCC eligibility criteria. Sixty records were excluded at this stage: 31 for wrong context (not a digital learning environment), 16 for wrong study type (not empirical), 9 for wrong concept (no application of EFT or LA to epistemic development), and 4 for wrong population (not postsecondary). An additional 3 studies identified through citation chaining of included studies were added, yielding a final corpus of 27 included studies.

Data Charting

The charting process attended to how studies conceptualize epistemic development, what methods and data they employ, whether they address engineering-specific contexts, and how findings translate into practice. Specifically, the charting form examined: (a) how epistemic frames are defined and operationalized (e.g., coded themes, network nodes); (b) research designs employed (experimental, descriptive, design-based, mixed methods); (c) data sources and analytic techniques (ENA, topic modeling, natural language processing, sentiment analysis); and (d) whether analytics translated into instructional interventions or curriculum redesign. Charting was conducted by the primary author. To support consistency, the charting form was applied iteratively, with categories refined and reapplied across the corpus.

Results

Understanding how epistemic frames have been theorized, measured, and applied in digital learning environments requires examining both the theoretical foundations that anchor current work and the persistent gaps that emerge when generic frameworks encounter engineering-specific contexts. This section traces the evolution of EFT applications across three dimensions: how epistemic development is conceptualized, how methods for diagnosing it have evolved, and why these developments have not yet translated meaningfully into engineering education practice. Table 2 summarizes the 24 applied included studies by context, EFT operationalization, analytic method, engineering relevance, and translation to practice.

RQ1: Theoretical Foundations of Epistemic Framing

Across the 24 applied studies, EFT is operationalized predominantly through Shaffer's five-element framework of knowledge, skills, values, identity, and epistemology [7, 13], with ENA serving as the primary analytic vehicle for modeling co-occurrences among these elements in digital learning data [14–16].

A critical limitation, however, runs through the corpus: the five-element framework was designed to be discipline-agnostic, applicable across medicine, law, science, and engineering alike [7]. This generality enables comparative research across professions but risks treating engineering as a variant of generic professional development rather than attending to the epistemic practices that actually define engineering work. Engineering reasoning involves iterative design, constraint-aware judgment, failure analysis, model-based inference, and spatial visualization [5]. None of these appear as first-class constructs in the five-element framework, and few studies in the corpus attempt to introduce them. Tiwari et al. applied the five core EFT elements to engineering drawing education but did not extend the coding schema to capture spatial reasoning

TABLE 2. Summary of applied included studies by context, EFT operationalization, analytic design and method, engineering relevance, and translation to practice ($n = 24$). Three additional corpus studies serving as methodological anchors are cited throughout but omitted here as they define or review ENA rather than apply it diagnostically. *Eng. Rel.*: ✓ engineering-specific context or EFT adaptation; ~ partial (STEM context, no engineering-specific EFT adaptation); ✗ not engineering-specific. *Prac. Trans.*: ✓ instructional application demonstrated or tested; ~ practice implications discussed, not empirically tested; ✗ methods paper or no implications reported.

Study	**Context**	**EFT Operationalization**	**Analytic Design and Method**	**Eng. Rel.**	**Prac. Trans.**
Arastoopour et al. (2016) [19]	Undergraduate engineering design; virtual internship, HE	EFT five-element framework applied to engineering design discourse; ENA networks compared to professional engineer benchmarks	Design-based; ENA	✓	✓
Fougt et al. (2018) [20]	Literary analysis course, HE; 16 students	Keyword sets coded from written assignments; ENA networks used as formative and summative evaluation tool	Exploratory; ENA	✗	✓
Whitelock-Wainwright et al. (2020) [21]	Blended learning, HE; 6,040 course offerings, 10 faculties	Learning activities as ENA nodes; disciplinary differences in blended design patterns modeled	Descriptive, large-scale; ENA	✗	~
Wang et al. (2020) [22]	Online synchronous STEM collaborative learning; 131 learners	Interaction behaviors coded as ENA nodes; patterns compared across multimedia conditions	Quasi-experimental; ENA and lag sequential analysis	~	~
Arastoopour Irgens (2021) [23]	Undergraduate engineering design, HE; collaborative chat data	Connected design rationale model: design moves and rationale as ENA nodes; compared to professional engineer profiles	Design-based; ENA	✓	~
Zhang et al. (2021) [16]	Online collaborative learning; 45 student teachers, HE	Regulatory behaviors (content monitoring, evaluating, social-emotional regulation) coded as ENA connections	Descriptive, mixed methods; content analysis and ENA	✗	✓
Ye & Zhou (2022) [24]	Online collaborative learning, HE; 40 college students	Learning sentiments and cognitive processing co-modeled as ENA connections across engagement groups	Descriptive; ENA and sentiment analysis	✗	~
Fan et al. (2023) [25]	University-affiliated MOOC; 8,788 learners, 4M+ events	Learning tactic sequences as directed ONA networks; temporal ordering of epistemic acts captured	Descriptive, large-scale; ordered network analysis	✗	~
Guo et al. (2023) [14]	Online open course, HE; discussion forums	Cognitive engagement levels coded from forum text; co-occurrence patterns across interaction levels modeled via ENA	Mixed methods; text mining and ENA	✗	✓

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Table 2 continued

Study	**Context**	**EFT Operationalization**	**Analytic Design and Method**	**Eng. Rel.**	**Prac. Trans.**
Liu et al. (2023) [15]	Online course, HE; mind mapping quasi-experiment	Cognitive presence phases (CoI framework) as ENA nodes; connections compared across experimental conditions	Quasi-experimental; ENA, ANCOVA, and regression	✗	✓
Alzahrani et al. (2023) [26]	Learning analytics adoption; senior HE managers	Thematic interview codes (challenges and factors) modeled as ENA connections across adoption stages	Qualitative; thematic analysis and ENA	✗	✓
Ba et al. (2023) [27]	Online inquiry-based discussions, HE	Cognitive presence phases (CoI) coded via BERT classifier; temporal co-occurrences modeled as ENA networks	Descriptive, computational; BERT classifier and ENA	✗	✓
Rakovic et al. (2023) [28]	Flipped classroom; undergraduate engineering, HE ($N = 290$)	Learning strategies and time management from LMS trace data; ENA models connections across performance groups	Descriptive, mixed methods; ENA on LMS trace data	✓	✓
Luther et al. (2024) [29]	Hybrid and online courses, HE; asynchronous discussions	Discussion elements coded via automated text mining; ENA networks generated dynamically from instructor-defined codebook	Design-based; text mining and ENA (OnDiscuss)	✗	✓
Chan et al. (2024) [8]	Postgraduate engineering course, HE ($N = 37$)	Epistemic Cognition Inventory; five epistemic cognition aspects as predictors of GenAI prompting behavior and performance	Work-in-progress, mixed methods; ECI survey and statistical analysis	✓	✓
Alqahtani (2024) [30]	Blended course, HE; 43 students, 16 weeks	Reflection types coded as ENA connections; patterns linked to student performance differences	Descriptive; ENA	✗	~
Viberg et al. (2024) [18]	Large engineering course, HE; 231 students, 2,444 peer feedback messages	Peer feedback types coded inductively; ENA models connections between feedback categories and performance	Exploratory, mixed methods; ENA	✓	~
Ding et al. (2025) [31]	Online courses, HE; two real-world datasets	Cognitive states as latent topic clusters; ENA maps topic co-occurrences (SLPoK-ENA pipeline)	Computational; topic modeling and ENA	✗	~
Tiwari et al. (2025) [17]	Engineering drawing education, HE; three modality groups	Behavioral patterns coded across AR, video, and text modalities; ENA networks compared across conditions	Quasi-experimental; ENA and OpenFace analytics	✓	✓
Ko et al. (2025) [32]	HE online discussion forum; high vs. low performers	Epistemic orientation via conceptual engagement patterns; ENA and ONA model learning trajectories	Descriptive, mixed methods; ENA and ONA	✗	✓

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Table 2 continued

Study	**Context**	**EFT Operationalization**	**Analytic Design and Method**	**Eng. Rel.**	**Prac. Trans.**
Divjak et al. (2025) [33]	Undergraduate mathematics course, HE ($N = 169$)	Learning outcome mastery as ENA and SNA network; cognitive diagnostic models integrated for outcome interdependencies	Mixed methods; ENA, SNA, and cognitive diagnostic models	~	✓
Wang et al. (2025) [34]	Design thinking CSCL, vocational college; 40 students	Divergent and convergent creative thinking coded; ENA models discourse across design thinking stages	Mixed methods; ENA	✗	✓
Fan et al. (2025) [35]	Online course, HE; 98 participants, 2,470 texts	Deep learning cognitive levels coded; epistemic networks compared across learner groups and course phases	Descriptive, mixed methods; Delphi, content analysis, and ENA	✗	✓
Lai et al. (2025) [36]	HE online course with Socratic GenAI chatbot	SRL processes and chatbot actions as process-action ENA and ONA networks; correlated with learning measures	Descriptive, mixed methods; process-action ENA and ONA	✗	✓

or design iteration [17]. Chan et al. examined engineering students' epistemic cognition when interacting with generative AI yet employed generic epistemic cognition constructs rather than engineering-contextualized dimensions such as design trade-off reasoning or model evaluation [8]. Viberg et al. applied ENA to peer feedback in a large engineering course, revealing connections between feedback types and academic performance, but the coding categories reflected general feedback theory rather than engineering epistemic practices [18].

The most substantive engineering-specific adaptations in the corpus come from Arastoopour and colleagues. Arastoopour et al. used ENA to assess engineering design thinking in virtual internship simulations, comparing student discourse networks directly against professional engineer profiles, a move that grounds EFT operationalization in authentic engineering practice rather than generic professional development [19]. Arastoopour Irgens subsequently proposed a connected design rationale model that codes design moves and rationale as ENA network nodes, offering the closest approximation of an engineering-specific EFT coding schema in the reviewed corpus [23]. Critically, this work demonstrates that engineering-contextualized EFT operationalization is both theoretically coherent and empirically feasible. Yet these studies remain isolated contributions. No subsequent work in the corpus builds on the connected design rationale model or extends it to online engineering course contexts, and no study has validated an engineering-specific EFT codebook across multiple subdisciplines or institutional settings. The gap between what is theoretically possible and what has been systematically developed represents the field's most most important unmet need.

RQ2: Methodological Approaches in Learning Analytics

Methodological approaches for diagnosing epistemic frames have evolved across four identifiable stages, moving from manual coding toward computational, multimodal, and increasingly automated methods. Figure 2 illustrates this trajectory.

Stage 1: Foundational ENA (2016–2018). Early applications established ENA as the core paradigm for epistemic frame diagnosis in higher education DLEs. Arastoopour et al. demonstrated that ENA could detect meaningful differences between novice and professional engineering discourse networks [19], and Fougt et al. showed ENA could support formative and summative evaluation of written assignments [20]. These studies were largely manual, labor-intensive, and confined to small samples.

Stage 2: Hybrid and scaled extensions (2019–2021). Researchers began pairing ENA with complementary methods to capture dimensions that standalone ENA could not. Whitelock-Wainwright et al. applied ENA to 6,040 course offerings to model disciplinary differences in blended learning design at institutional scale [21]. Zhang et al. combined content analysis with ENA to trace regulatory patterns across collaborative learning stages [16]. Arastoopour Irgens introduced the connected design rationale model, extending ENA's interpretive scope to capture design move sequences in engineering contexts [23].

Stage 3: Computational and NLP extensions (2022–2024). Studies increasingly automated the coding step that ENA requires as input. Ba et al. used a BERT classifier to code cognitive presence phases before modeling them via ENA, achieving substantial human-coder agreement and significantly reducing manual effort [27]. Luther et al. introduced OnDiscuss, which generates ENA networks dynamically from instructor-defined codebooks applied to asynchronous

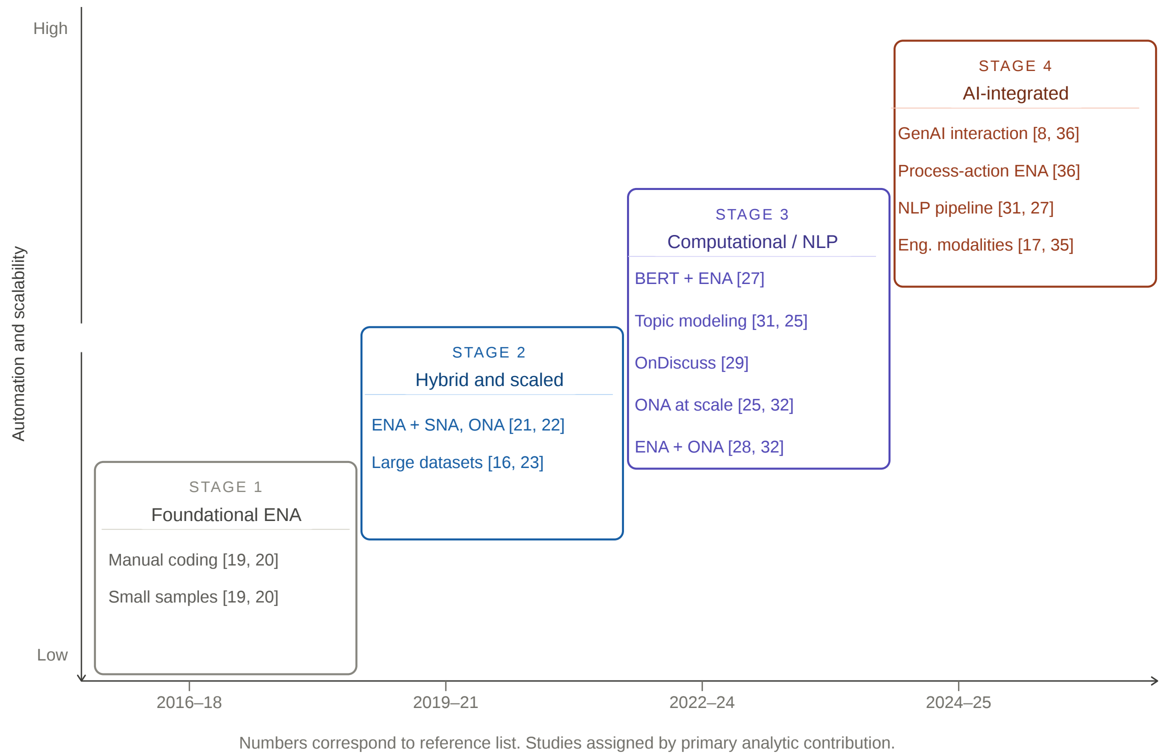

FIGURE 2. Evolution of analytic methods for diagnosing epistemic frames (2016–2025). Numbers in brackets correspond to references. Studies assigned to stages by primary analytic contribution.

discussion data, bringing epistemic diagnostics closer to real-time instructional use [29]. Ding et al. proposed SLPoK-ENA, integrating topic modeling with ENA to identify latent cognitive structures without requiring manual code development [31]. Fan et al. applied ordered network analysis to over four million MOOC learning events, demonstrating that ONA's temporal directionality surfaced learning tactic sequences that standard ENA could not detect [25]. Ko et al. extended this approach, using both ENA and ONA to model epistemic orientation across performance groups in HE online forums, showing that high-performing students established more interconnected epistemic networks earlier in the course [32].

Stage 4: AI-integrated frontiers (2024–2025). The most recent studies signal a shift toward AI-augmented epistemic analytics. Chan et al. examined engineering students' epistemic cognition when interacting with generative AI, finding that epistemic beliefs significantly predicted GenAI prompting behavior and academic performance [8]. Lai et al. applied process-action ENA combined with ONA to student interactions with a Socratic chatbot, demonstrating that SRL processes are recoverable from GenAI interaction logs and that temporal ordering of epistemic acts carries diagnostic information beyond what standard ENA captures [36].

Despite these innovations, a fundamental challenge persists. Most methods remain confined to research contexts. Computational approaches reduce coding labor but require technical expertise most instructors lack, and few tools integrate with learning management systems. The scalability gap between methodological sophistication and classroom deployment remains largely unresolved across the corpus.

RQ3: Gaps and Future Research Directions

Three fundamental gaps limit the field's impact.

The engineering specificity gap. The five-element EFT framework is discipline-agnostic by design, applicable across medicine, law, and engineering alike [7]. This generality becomes a liability in engineering contexts: no study in the corpus has validated a coding schema that captures iterative design thinking, failure analysis, constraint-aware reasoning, or spatial visualization as first-class epistemic constructs [5]. The connected design rationale model of Arastoopour Irgens [23] is the most developed attempt, yet it has not been replicated, extended to asynchronous online contexts, or validated across engineering subdisciplines. Chan et al. and Tiwari et al. apply ENA to engineering settings but use generic cognitive constructs rather than engineering-contextualized coding schemas [8, 17]. Viberg et al. similarly apply ENA to a large engineering course without adapting the framework to engineering epistemic practice [18].

The theory–practice translation gap. Across the corpus, studies diagnose epistemic patterns with increasing sophistication but rarely demonstrate how those diagnoses inform instructional action. Luther et al. bring ENA closer to real-time use through OnDiscuss [29], and Fougt et al. deploy ENA directly in summative evaluation [20], but neither reports a design-based research cycle in which epistemic visualizations are systematically used by instructors to modify curriculum. Elmoazen et al.'s systematic review confirms this pattern across the broader ENA literature, identifying a persistent gap between analytic capability and pedagogical application [37]. What should an instructor do when ENA reveals that engineering students are not connecting design iteration to failure analysis? Current research describes what epistemic patterns look like far more often than it demonstrates how instructors respond to them.

The scalability and AI integration gap. Manual coding remains the norm across the corpus, with only Ba et al. and Ding et al. introducing automated coding pipelines [27, 31]. Neither pipeline has been validated against engineering-specific EFT constructs. Only three studies engage generative AI directly [8, 31, 36], leaving two critical questions unanswered: how does student use of GenAI reshape epistemic demands in engineering DLEs, and can LLM-assisted coding pipelines scale EFT diagnostics to classroom deployment without sacrificing validity?

Discussion

The Diagnosis–Action Paradox

This scoping review identifies a fundamental paradox: the field has developed sophisticated methods for diagnosing epistemic frames yet struggles to translate those diagnoses into meaningful pedagogical change. Liu et al. and Alqahtani demonstrate that ENA can enable instructors to visualize epistemic development across learning tasks [15, 30], and Guo et al. show that combining log and discourse data can help diagnose epistemic stagnation in online learning cycles [14]. These studies describe what epistemic patterns look like and what they correlate with, but they do not report instructors systematically using those visualizations to modify instruction. The gap between measuring epistemic frames and responding to what is measured remains the field's most consequential unresolved problem.

Structural Insights: The Fragmentation Problem

Manual inspection of reference lists revealed that the corpus organizes into three largely non-communicating communities: foundational EFT and ENA methodologists, discipline-specific applications researchers, and computational extensions researchers. The most consequential gap is between the engineering-specific applications community and the computational extensions community, researchers developing more powerful analytic tools are not engaging with the applied engineering education literature, and vice versa. Engineering educators cannot easily access the analytic advances most relevant to their contexts, while computational researchers are building tools uncalibrated to engineering epistemic demands. Bridging these communities through cross-disciplinary venues, shared datasets, and tool interoperability represents a structural opportunity the field has not yet exploited.

AI as Both Challenge and Opportunity

Only three studies directly engaged with AI or generative language models [8, 31, 36], yet two distinct questions deserve attention the field has not yet separated clearly.

The first is AI as an *object of study*: how does student engagement with generative AI reshape epistemic demands in engineering DLEs? Chan et al. provide the most direct evidence, finding that engineering students' epistemic cognition predicted GenAI prompting behavior and performance, but that students applied generic rather than engineering-specific reasoning when evaluating AI outputs [8]. Knowing when to trust, interrogate, or override AI-generated outputs is itself an engineering epistemic competency that current EFT frameworks are not equipped to measure. More fundamentally, when a student delegates design iteration to a generative model, the epistemic frame being practiced may be that of a technology consumer rather than a design engineer, a shift with consequences that current EFT instruments cannot detect or measure.

The second is AI as a *methodological instrument*: can LLM-assisted pipelines automate epistemic coding at classroom scale? Ba et al. demonstrate that BERT classifiers can code cognitive presence phases with near-human agreement [27], and Ding et al. show that topic modeling can identify latent cognitive structures without manual code development [31]. Neither pipeline has been validated against engineering-specific EFT constructs, a gap that must be closed before automated diagnostics can be responsibly deployed in engineering education contexts.

Limitations

Data charting was conducted by a single coder, introducing the possibility of interpretive inconsistency. The review was restricted to English-language publications, which may underrepresent contributions from non-Anglophone ENA research communities, particularly in East Asia. The corpus includes both journal articles and conference papers; the latter undergo lighter review and may introduce quality variance not addressed by the charting process. Thematic organization was informed by manual reference list inspection rather than computational bibliometric analysis, which limits the precision of the three-cluster structure identified. The AI and LLM literature is evolving rapidly; the frontier described in RQ3 should be understood as a snapshot rather than a settled characterization.

Implications for Engineering Education

Implications for Practice

ENA-based tools are now sufficiently mature to pilot in higher education engineering courses, but deployment without a corresponding instructional protocol reproduces the diagnosis–action gap this review identifies as the field's central limitation. Practitioners should begin with design-based partnerships in which instructors and researchers co-develop response protocols grounded in engineering epistemic practice. Tools such as OnDiscuss [29] and ONA-based dashboards [25, 32] represent viable entry points, provided their outputs are paired with actionable rubrics rather than left as diagnostic visualizations without instructional follow-through.

Implications for Future Research

Three priorities stand out. First, developing and validating an engineering-specific EFT coding schema, one that treats iterative design, failure analysis, and constraint-aware reasoning as primary epistemic constructs rather than instances of generic knowledge and skills, is the field's most foundational unmet need. Second, bridging the computational extensions and engineering applications communities through targeted cross-disciplinary studies would yield the highest near-term leverage. Third, validating LLM-assisted EFT coding pipelines against expert coders using engineering-specific codebooks would test whether the scalability barrier that has confined EFT to research contexts can be substantially reduced.

Conclusion

Engineering education stands at a pivotal moment where online enrollment is expanding, analytic techniques are becoming more sophisticated, and generative AI is rapidly entering both professional and educational practice. Yet the core challenge remains unresolved: how to use these tools to support authentic epistemic development so that students learn not only course content but also how to think like engineers, in ways that reflect spatial reasoning, design under constraint, systems thinking, failure analysis, and iterative judgment.

This scoping review has mapped the available evidence across 27 included studies, traced a four-stage methodological trajectory from foundational ENA to AI-integrated analytics, and identified three gaps where the field's progress has stalled: the absence of engineering-specific EFT constructs, the persistent difficulty connecting epistemic diagnosis to instructional action, and the unvalidated potential of automated coding pipelines.

Progress will require three interrelated shifts. The field needs engineering-specific epistemic frameworks built for engineering contexts rather than retrofitted into them, frameworks that treat iterative design, failure reasoning, and constraint navigation as primary epistemic categories. Epistemic diagnostics must become multimodal, integrating discourse with design artifacts, simulations, and calculations so that the full range of engineering reasoning becomes visible to analytics. EFT based analytics must be embedded into instructional systems in ways that close the loop between measurement and pedagogical action. When these shifts converge, learning analytics grounded in epistemic theory can help cultivate engineers who not only know more but reason more critically and responsibly about the systems they design.

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