Emerging Technologies as Sociotechnical–Immersive Systems: Qualitative Validation of a Framework

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Abstract: Artificial intelligence now sits at the center of emerging technologies discourse in K–12 digital learning. Based on DLAC survey and focus group data, this study pilot-tests the Emerging Technologies Sociotechnical–Immersive Systems Framework (ETSIS) to examine how AI is being imagined and enacted in practice. Practitioners describe both pragmatic adoption and deep concern, particularly around authenticity, assessment, and equity. Using framework-to-data mapping and misfit analysis, we analyze how sociotechnical conditions shape environment design and everyday pedagogical routines. Findings suggest that AI is not simply another tool layered onto digital systems but a participant in evolving learning ecologies, raising questions about educator preparation, data infrastructures, and the reconfiguration of agency in online learning environments.

Introduction

K-12 online and blended learning now includes AI, AR/VR, learning analytics, and other emerging tools layered onto established systems such as LMSs and virtual programs. Yet access to these innovations remains uneven due to persistent disparities in funding, infrastructure, and support. Our previous theoretical work (Beck, et al., in press) authored the Emerging Technologies Sociotechnical–Immersive Systems Framework (ETSIS) as a means to show how decisions that occur in the sociotechnical realm influence design constraints and affordances in the environment design of an emerging technology; the narratives that they create and develop; and the agency that teachers and students experience. And while environment design produces a more abstract configuration of system, narrative, and agency, they translate into real life pedagogical routines and rationales as the Immersive Learning Brain is utilized, specifying the how and why of giving feedback, organizing collaboration, handling authenticity and assessment, and whether presence and socio-emotional learning are foregrounded or sidelined. Those practice and strategy patterns, in turn, generate the data, stories, and outcomes that travel back to the top of the spiral.

Although there appears to be some promise in how ETSIS can be used to help researchers and practitioners understand the implementation and uses of emerging technologies, it remains untested. However, focus groups with leaders and teachers at the Digital Learning Consortium's (DLAC) 2025/26 conferences discussed emerging technology implementation. Teachers particularly discussed their desire to use AR/VR and LA, but said that their current difficulties with more basic issues such as bandwidth, staffing, and time made their adoption desires nearly impossible to implement. In other words, optimism about what emerging technologies might do for learning parallels very real sociotechnical limitations on who can deploy them, how consistently, and for which students.

Emerging technologies as a moving target

Across the literature, emerging technologies are not defined as a fixed list of new tools. Instead, they are often described as technologies and practices that are still taking shape and whose meaning and value depend on context (Veletsianos, 2016). This perspective shifts attention away from technical features and toward the systems that surround a technology. It also helps explain why the same technology can function very differently across districts and programs, which is confirmed in historical analyses (Duran, 2022) and systematic reviews of literature in the areas of emerging technologies (Almufarreh & Arshad, 2023) and STEM education (Chng et al., 2023). It is also confirmed in broader taxonomies on how emerging technoolgoies reshape core educational decisions (Garg et al., 2025), research on teacher adoption of technology post COVID (Chalkiadakis & Noguera, 2024) and immersive technologies (Beck et al, 2023; Morgado et al, 2025). These perspectives are pulled together by Schlemmer and Morgado's (2024) argument stating that many so-called emerging technologies are layered onto older platform models that preserve established roles and power structures. They call for infrastructures that support ecological and cognitive ecosystems in which agency is distributed across humans and non-humans. From this perspective, technologies including AI are not neutral containers for instruction but active participants that shape learning processes.

Guiding questions

1. How are emerging technologies imagined and enacted in K–12 online learning?
2. How do practitioner perspectives align with or challenge current research?
3. How can sociotechnical, immersive-design, and educational-process lenses be integrated into a workable analytic framework?

Methods - Pilot Qualitative Validation of the ETSIS Framework

This research draws on DLAC Phase Two survey responses and a set of focus groups and convenings with K-12 online and blended educators, leaders, and partners. The approach combined an online survey (n=43) with focus groups held at the 2025 DLAC conference (n=87 total across 10 groups). The original purpose of the survey and focus groups was to have participants examine the K-12 Digital Learning themes discovered in Phase 1 (Barbour et al., 2025a; 2025b) and to refine, and revise them while commenting on their usefulness or problematic nature. Survey and conversation data was then analyzed together using the ETSIS framework and eventually transformed this manuscript. (Editor1, Executive Committee Focus Group).

We conducted a pilot qualitative validation (Heaton, 2008) of ETSIS framework using framework-to-data mapping plus misfit analysis. In this approach, ETSIS functioned as an a priori analytic lens to assess (1) how well the framework fits practitioner discourse, (2) where it shows conceptual overlap or ambiguity, and (3) what recurring ideas fall outside the framework and therefore indicate boundary conditions or needed refinements. Because practitioner references to "emerging technologies" were overwhelmingly dominated by AI in the DLAC inputs (reported in the manuscript as roughly 95% of coded comments under that theme), we treated the pilot as a stress test of ETSIS under an AI-saturated discourse environment while still attending to less-frequent references to AR/VR and analytics/dashboards.

Analytic procedure

Following DeCuir-Gunby et al. (2011) approach, we first operationalized ETSIS as a structured codebook reflecting its three linked lenses: (1) Macro level sociotechnical conditions; (2) Meso level environment design via system/narrative/agency; and (3) Micro educational activities via ILB-informed practice/strategy clusters. Each construct was defined with inclusion and exclusion rules and examples derived from the manuscript language used by Beck, et al (in press). Second, all meaning units relevant to emerging technologies were coded deductively to ETSIS constructs using the method laid out by Hsieh & Shannon (2005). During coding, each excerpt was tagged with a fit designation: (a) Direct fit; Partial fit; Competing fit; No fit.

Third, we produced two primary analytic artifacts, a fit matrix showing our ETSIS constructs and the frequency/strength of supporting excerpts), and a misfit log capturing excerpts that resisted coding, the reason for misfit, and proposed framework revisions. Fourth, all "no fit" and unresolved "competing fit" excerpts were analyzed inductively to identify themes. Themes were then sorted into one of three bins: (1) Out of scope for ETSIS;

Definition/boundary refinement needed; and framework revision needed. Finally, based on recurring misfit patterns and themes, ETSIS was revised by clarifying construct boundaries, refining relationships across the spiral, or adding decision rules for ambiguous cases. The revision rationale was documented by linking each change to specific misfit patterns.

To reduce confirmation bias inherent in validating an author-developed framework, we emphasized (a) explicit documentation of negative or resisting cases via the misfit log, (b) inductive analysis to ensure important content was not dismissed simply because it did not fit the framework, and (c) a transparent audit trail from excerpts to coding decisions to proposed revisions. We also note that this study used secondary analysis of existing practitioner inputs. Use of the dataset for this pilot validation followed the original data governance and consent procedures associated with the DLAC collection activities, with analysis limited to the purposes described above and reported in aggregate.

Results

Sociotechnical Circle

In the DLAC data, AI is doing most of the work in the emerging technologies category. When programs talked about new or future-facing tools, they were almost always talking about AI, particularly generative and assistive systems. Across the coded survey responses, roughly 95 percent of the comments tagged as “emerging technologies” were about AI (Editor2). These data tell us something about the current sociotechnical moment: AI has become the primary way districts and vendors imagine personalization, productivity gains, and innovation. When leaders say they want to “leverage emerging technologies,” AI is usually the default approach.

The way educators talked about AI combined everyday pragmatism and unease. One leader joked but was quite serious, about using AI every day and how Magic School AI was their “best friend.” along with Canva and other AI tools. They went on to muse about why we as educators punish children for using the same tools that educators are using (Unnamed participant, Executive Committee Focus Group). At the same time, Editor1 relayed an email from an online teacher who described it as “heartbreaking” to feel like she was “spending all her time grading AI-generated papers.” (Editor1, Executive Committee Focus Group).

Concerns about authenticity and assessment were especially strong in the SE Asian network. One participant explained that their teachers are trying to give students “the skills to be able to do good prompting, and to be able to utilize the tools, effectively, without breaching authenticity” in high-stakes assessments. (Participant 3, New Zealand Focus Group). Another added that “teachers… can have massive concerns about authenticity” when AI tools enter the picture. (Participant 5, New Zealand Focus Group). Teachers in this group imagined AI as a way to support differentiation and offload routine work, but educators worry about how much it “knows” about students, how recommendations are generated, and how its use intersects with cheating and academic honesty.

From a sociotechnical perspective (Veletsianos, 2016), AI adoption is not neutral. It embeds assumptions about teachers as overseers of automated recommendations and students as continuous data sources for optimization. These macro-level beliefs shape environment design and pedagogical practice downstream. As AI tools become widely integrated into business and social life, educational goals may shift—from producing original rhetoric to critically evaluating machine-generated arguments—reshaping teachers’ workload, professional identity, and district expectations. In this sense, AI links school-level decisions to broader societal transformations (Floridi, 2015; Schlemmer & Morgado, 2024).

Environment Design circle

To bridge the sociotechnical circle with the Environment Design circle, we thus need to go beyond “AI as data infrastructure”. In this framing we utilize the Immersive Learning Cube (ILC; Beck, et al, 2020; Morgado et al., 2025) to examine system, narrative and agency in a learning environment. It reframes AI adoption from a matter of “including an emerging technology” into an orchestration problem: designing immersive conditions where human and AI participation develops.

Whether AI appears as a generative assistant or as a data-driven dashboard, the ILC prompts three design questions: (1) System: What data sources and tools does the AI draw upon? (2) Narrative: What information sequence shapes its outputs and recommendations? (3) Agency: What degree of decision-making latitude does it exercise, and how constrained are its responses? These dimensions shift attention from AI as a tool to AI as a configured participant within the learning environment.

DLAC executive committee discussions provide data to flesh out these ILC dimensions. JF asked about "the systems that we need in place in order to produce… the kinds of data we need," and how to "structure it in a larger way to be able to ask more powerful kinds of questions, at scale." Another participant in the same session tied that to issues of representation and validity, describing "data at scale" as difficult because "there's just not a data set that's representative… to be able to… tell stories… that represent the true picture of… what's going on… across the country and even in the state."

Teacher focus groups also showed how system-level issues show up in day-to-day work. In the Monday, DLAC 2025 focus group, one teacher explained that their AI dashboard allowed for them to filter by "grade or race or gender, ethnicity… [so] you can see, like, okay, my program is mostly this type of student" (Speaker 2, Monday DLAC 2025 Focus Group). Their explanation continues by explaining that all dashboards are alike in this ability: "really just… so many data… assessment data… it's not specific to digital learning." This is a key point in that systems constructed to answer larger level questions at the state or national level may not be useful for handling the needs of a specific program. Another participant in a different group was concerned that innovative models such as ESAs and micro-schools were continuing, yet without any real thought to how to measure their success: People are "not… thinking about what are the data points that you would need to have to prove that that is working the way you intended it to." (Editor2, Monday DLAC leader focus group). Thus, AI is not just about the design of an interface, but about their interactions with policy and funding decisions.

The DLAC data illustrate how environment design mediates between macro-level policy pressures and micro-level classroom practice. Whether AI reinforces existing accountability narratives or enables more practice-centered inquiry depends on how system, narrative, and agency are configured.

Educational Approaches Circle

Within the third circle, we can now use the Immersive Learning Brain (ILB) to look at actual pedagogical practices and strategies with AI to promote learning. DLAC participants were clear that AI would not work without serious support for educators. In the executive committee meeting, Participant 3 listed "Educator Preparation and Development" among the most useful themes, and Participant 5 noted that in their state "there's no preparation [for learning emerging technologies] as part of teacher preparation programs… or even administrator preparation programs," calling for attention to this gap. (Participant 3 & 5, Executive Committee Focus Group). Participant 8 described a "severe need… for onboarding quickly, teachers who need to have some experience in this area," especially as modalities and technologies "go hand in hand" and keep changing. (Participant 8, Executive Committee Focus Group). The DLAC survey and focus groups paint a practitioner landscape where AI is front and center and everything is refracted through questions of equity. Within the ILB framework, AI applications, such as adaptive tutoring, automated feedback, dashboards, or generative tools, map onto clusters like Engagement & Scaffolding, Multimedia Learning, and Collaboration. The key analytic move is not listing every possible tool, but asking how AI participation reshapes feedback routines, collaboration structures, authenticity judgments, and professional learning. In each case, educators must still consider how AI's configured system, narrative, and agency influence classroom practice.

Conclusion

In this article, we've shown that qualitative data gathered from the DLAC conference focus groups and surveys help us to approach qualitative validation of the SYSFET framework. Thus, the idea that we should treat emerging technologies as artifacts within sociotechnical–immersive systems, and not merely as a list of tools that just show up in classrooms, is valid. Linking these perspectives to DLAC survey and focus group data, and to recent reviews on emerging technologies and teacher appropriation, provided us a more complete picture than any one lens on its own.

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