TOWARDS SOCIALLY LEGITIMIZED TRUST IN AI-LEARNING SYSTEMS

Sanket Ramchandra Patole[1], Rob E. Carpenter[1], Reed M. Milewicz[2], Rose M. Baker[3], and John R. Turner[4]

[1]Soules College of Business, University of Texas at Tyler, Tyler, Texas, USA
[2]Computer scientist and software engineering researcher, USA
[3]University of North Texas, Denton, Texas, USA
[4]TexasA&M University, College Station, Texas, USA

ABSTRACT

AI-enabled learning technologies are rapidly becoming institutional infrastructure. In this context, "trust" cannot be treated as a simple user attitude or a byproduct of technical performance. We argue that durable trust in AI-enabled learning systems is fundamentally a legitimacy outcome: stakeholders must judge AI-mediated practices as appropriate, credible, and defensible within the normative and governance structures of learning environments. Building on socio-technical systems scholarship and institutional legitimacy theory, we introduce Socially Legitimized Trust (SLT), a framework that helps us understand adoption stability and contestation through alignment among three foundations: technocratic validation (credible evidence of capability, limits, and reliability), social validation (shared normative judgments among instructional actors regarding appropriateness and credibility), and institutional authorization (formal governance, policy, and accountability mechanisms that allocate decision rights and responsibility). Further, we argue that SLT predicts recognizable instability patterns under misalignment, including contested use despite high technical performance, fragile informal practices under weak authorization, and compliance without confidence when authorization outpaces validation. We formalize five propositions to guide empirical research on stability, contestation, cross-boundary credential credibility, and design orientations that favor learning augmentation over task substitution. By shifting the unit of analysis from individual users or artifacts to the learning system, SLT provides an integrative agenda for studying how trust is constructed, challenged, and repaired as AI becomes embedded in learning infrastructures.

KEYWORDS

Artificial Intelligence, Education, Socio-Technical Systems, Technocratic, Digital Learning

1. INTRODUCTION

What does it mean for digital technologies in learning environments to be trustworthy? This is an interesting question because the answer is necessarily multimodal, because "trust" is not a single judgment but a composite of beliefs about competence, reliability, integrity, and care, formed across technical performance, institutional governance, and everyday user experience [1]. Accordingly, trust should not be treated as a single attitude toward "technology" in the abstract, but as a socially legitimized judgment produced within a specific digital learning environment. In this view, trust is shaped by interacting technocratic, social, and institutional foundations that jointly influence what stakeholders regard as appropriate, credible, and acceptable [2,3].

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Digital learning technologies are no longer peripheral aids; they are institutional infrastructure. Empirical research documents the widespread institutionalization of learning management systems, digital assessment platforms, and data-driven instructional tools as the core systems through which instruction and skill formation are organized [4,5]. As these systems become embedded, they increasingly mediate how learning activities are designed, delivered, evaluated, and credentialed across educational and professional contexts [6]. This shift raises the stakes of trust: judgments about a tool's reliability or usefulness are simultaneously judgments about the legitimacy of the learning practices and institutional decisions the tool operationalizes.

This is most clear and evident in the case of generative artificial intelligence (AI), which has expanded what learning technologies do and where they sit in the learning system. For example, generative AI now supports automated feedback, content generation, assessment assistance, and adaptive learning processes at scale [7, 8]. These capabilities are being introduced rapidly across learning environments, often without aligned oversight, shared standards, or clear coordination across institutional levels [9]. As a result, AI is increasingly encountered less as a discrete instructional tool and more as an embedded layer of learning infrastructure that shapes decisions, workflows, and outcomes across the learning lifecycle [9]. This infrastructural embedding intensifies the trust problem by distributing agency across systems, people, and policies, which complicates responsibility when AI output is contested, consequential, or wrong [10,11]. In other words, technical reliability may be necessary for trust, but it is rarely sufficient for legitimacy in learning systems [12,13]. Across higher education —in classrooms, departmental meetings, and administrative governance— generative AI has sparked debate and challenged existing norms around how we learn and how we teach. Indeed, in the history of learning technologies, few innovations have provoked such immediate, vigorous, and pervasive controversies around everything from academic integrity and professional authority to the very roles of students and teachers vis-à-vis technology.

One visible manifestation of this is outright opprobrium towards the use of AI, even as the technology now enjoys widespread use. Giray, for instance, has called attention to "AI shaming", which involves "dismissing the validity or authenticity of AI-assisted work, suggesting that using AI is deceitful, lazy, or less valuable than human-only efforts"[14]. Among students, there can be "stigma and judgment" towards those using AI to complete their assignments[15]; to quote two students, "I feel as though a lot of people are using it secretly and it makes me angry" and "anyone can go and type things into a bot or AI, but not every human has the capacity or willingness to think critically and come up with interesting ideas."

Similar tensions are at work among academics. Barnes and Tour note that educators may conceal their usage of AI as "a dirty little secret"[16]; one interviewee, Andrew, reflected on this, saying "A lot of teachers are very funny about it. They feel like it's an existential threat to the industry and to them morally and professionally. I see it as an inevitability and something that we need to work with rather than against. So, yeah, I'll continue to use it. I might not be as open in my use of it as I am with you right now." In another study, Kumar describes the thought processes of one professor (Dr. Case), who must navigate concerns around legitimacy in the use of AI as a grading tool: "First, is the use of AI technology to mark papers legally permissible? Second, what attitudes are prevalent amongst institutional administrators and colleagues who would decide whether or not to renew [my] contract? Third, the public's positive or negative views on university professors' use of AI to grade student papers would have a tremendous influence on university administrators' decision to renew [my] contract"[17].

Meanwhile, even among the most ardent supporters of AI usage in the classroom, there remain many unsettled questions around the functions of learning and teaching in a world where intelligence is increasingly "on tap". An excellent recent analysis by Dishari suggests that AI for some educators is currently a source of significant cognitive dissonance, inviting rapture and terror in equal measure[18]. To quote several of their sources…

- “It’s exciting, but I also wake up at night worrying what this means for my job.”
- “It’s exhilarating to witness this level of computation. But in that exhilaration, there’s also grief. Grief for what it might replace—not just skills, but the role we play.”
- “There’s a strange beauty to how it synthesizes information. But that beauty comes with dread—it’s like watching a new species evolve that doesn’t need us.”

Scholarly discourse increasingly suggests that the rapid embedding of AI into learning infrastructure is producing disagreement rather than convergence on what “trustworthy use” looks like [19-21]. Educational technology research documents persistent tensions over authorship, assessment integrity, and the delegation of cognitive work to automated systems [4,8,22,23]. Importantly, these tensions are not resolved by technical refinement or clearer user guidance alone [24]. They instead signal a more fundamental contest over authority and accountability, including who has the right to define legitimate learning practice, who is responsible for AI-mediated decisions, and what counts as acceptable delegation in educational settings [25].

Much of the literature on technology in education has examined adoption through lenses centered on effectiveness, usability, and risk mitigation. These approaches generate valuable evidence about system performance and learning outcomes, but they are less equipped to explain why adoption remains contested, uneven, or unstable even when tools appear to “work” [26,27]. In particular, acceptance-oriented models often treat trust as an individual attitude shaped by perceived usefulness, rather than as a collectively produced judgment that depends on institutional conditions, social norms, and governance arrangements [27]. The result is a theoretical gap: legitimacy questions, whether technology use is appropriate, credible, and defensible within a learning system, are often left implicit or treated as secondary to performance. This paper argues that trust in digital learning technologies is best understood as a legitimacy outcome produced within socio-technical and institutional conditions, not merely a technical feature or an individual attitude. For clarity, we use the terms digital learning technologies and AI-enabled learning technologies interchangeably throughout the paper. In this study context, both refer to platform-based learning infrastructures in which AI capabilities (for example, generative support, automated feedback, analytics, or assessment assistance) are embedded within the tools, workflows, and governance arrangements that organize instruction, evaluation, and credentialing.

We advance this argument by introducing *Socially Legitimized Trust* (SLT), which conceptualizes trust as emerging when three foundations align: technocratic validation of AI capabilities and limits, social validation through shared norms and credibility judgments among instructional actors, and institutional authorization through governance, policy, and accountability mechanisms [2,29,30]. Centering legitimacy reframes adoption as an institutional process in which technical design, social interpretation, and formal authority jointly shape what is considered trustworthy and acceptable in practice [31,32]. The purpose of this paper is to develop SLT and advance a set of propositions to guide future empirical and conceptual research on AI-enabled learning technologies across educational environments where concerns about skill formation, credential credibility, and learning system integrity converge.

The rest of this paper is organized as follows. First, we specify the problem and conceptual gap by explaining why technocratic accounts of trust are insufficient for AI-enabled learning technologies embedded in digital learning infrastructures and why legitimacy dynamics are required to explain stability, contestation, and repair. Next, we develop the conceptual foundations of SLT by integrating institutional legitimacy and socio-technical perspectives and defining SLT's three constituent foundations: technocratic validation, social validation, and institutional authorization. We then articulate implications for learning technologies and educational governance, emphasizing how alignment and misalignment across these foundations shape system-level trust trajectories. Finally, we advance research directions and analytical propositions to guide future empirical and conceptual work, followed by limitations and a concluding discussion of SLT's contribution to understanding trust as an institutional outcome in AI-enabled learning systems.

2. THE PROBLEM AND CONCEPTUAL GAP: WHY TECHNICAL TRUST IS INSUFFICIENT IN LEARNING TECHNOLOGIES

Research on AI-enabled learning technologies has expanded rapidly, with much of the field organized around questions of effectiveness, efficiency, and personalization. This work has clarified important dimensions of system performance and pedagogical potential. Yet it also tends to carry an implicit theory of trust that is narrower than the phenomenon at stake. Across many studies, trust is operationalized as confidence in technical functionality, predictive accuracy, or instructional utility, which effectively treats trust as a property of the artifact or as a proximal response to system outputs [4]. That framing is incomplete for digital learning environments because educational institutions do not merely *use* digital learning technologies; they authorize AI-enabled capabilities within those technologies to participate in normatively consequential practices, including instruction, assessment, progression, and credentialing.

This limitation is reinforced by the dominant influence of technology acceptance and adoption frameworks. Technology acceptance models and related approaches typically explain adoption through perceived usefulness, ease of use, and behavioral intention [22,33]. These models are valuable for understanding individual-level evaluations, but they are structurally ill-suited for explaining why digital learning technologies become normalized, persistently contested, or quietly abandoned after initial uptake, especially once AI-enabled capabilities are embedded into routine instructional and evaluative workflows. In educational and training settings, adoption is rarely reducible to individual choice because participation is organized through roles, professional jurisdictions, and institutional rules that shape what counts as appropriate practice [34,35].

Empirical evidence increasingly shows that technically functional AI-enabled learning technologies can still produce resistance and instability in educational contexts. Studies of automated assessment, learning analytics, and feedback systems report disputes that persist even when systems demonstrate reliability or accuracy [36]. The point is not that technical performance is irrelevant, but that technocratic validation operates as a necessary condition that does not resolve the deeper question learning environments must answer: whether AI-mediated actions are legitimate, accountable, and consistent with educational purposes. When AI-enabled capabilities enter evaluative and consequential domains, they generate governance questions that exceed the scope of performance metrics, including explainability and oversight [37] and the institutional politics of standards, accountability, and audit cultures [38].

Digital learning environments make these limits particularly visible because they are normatively structured systems. Educational practice is organized around socially stabilized expectations regarding authorship, evaluation, progression, and credentialing, not simply the efficient completion of tasks [5]. When AI-enabled learning technologies alter how these practices are enacted, they can disrupt tacit agreements about what constitutes authentic work, fair assessment, and credible learning outcomes. These disruptions are not reducible to "implementation issues" that disappear with clearer training materials; they are legitimacy disputes over the boundaries of acceptable delegation and the meaning of educational accomplishment [39]. Technical assurances can reduce uncertainty about what a system does; they cannot, by themselves, settle disagreements about what the system should be permitted to do within a learning institution.

Socio-technical systems scholarship provides a stronger analytic lens by treating trust as an emergent property of systems-in-use rather than as an internal attitude or a technology attribute. In information systems and organizational studies, trust in complex technologies is understood to arise through the interaction of technical design, social interpretation, and institutional arrangements that shape how tools are embedded into routines, roles, and accountability structures [40,41]. On this view, trust is an ongoing accomplishment: it is produced, stabilized, challenged, and repaired as digital learning technologies become entangled with organizational work. Applied to AI-enabled learning technologies, this perspective shifts attention from whether AI "works" in a narrow technical sense to how AI is interpreted, governed, and institutionally situated in ways that make its use defensible over time.

Institutional theory further clarifies why this defensibility is central to sustained integration. Legitimacy theory argues that practices endure when they are perceived as appropriate within socially constructed systems of norms, values, and rules [32]. Subsequent work shows that legitimacy judgments shape whether innovations are embraced, contested, or abandoned, and that these judgments are multi-actor, context-dependent, and often decoupled from technical superiority [12,42]. In professionalized domains such as education and workforce training, legitimacy is not optional; it is the basis on which authority is recognized, credentials are trusted, and institutional decisions are accepted as rightful. Accordingly, trust in AI-enabled learning technologies cannot be reduced to "confidence in outputs," because the consequential question is whether AI-mediated practices remain consistent with educational purpose and institutional responsibility.

Despite these theoretical resources, legitimacy remains under-integrated in much of the trust discourse surrounding AI-enabled learning technologies. Many studies acknowledge context, governance, or ethics, but they often stop short of theorizing how legitimacy is constructed, maintained, contested, and repaired as AI becomes infrastructural [43,44]. The result is a recurring explanatory failure: the field can describe adoption, satisfaction, or performance, yet still lacks a coherent account of why AI use remains fragile even when accuracy improves and policies exist. This constrains theory-building and weakens the practical interpretability of empirical findings by treating instability as residual rather than as a predictable outcome of legitimacy dynamics.

The conceptual gap addressed in this paper is therefore not simply "missing variables" in adoption models; it is the absence of an integrative framework that links technocratic validation to the social and institutional processes through which trust becomes legitimate and sustainable. Without such a framework, trust is repeatedly modeled as a psychological disposition [45] or a user evaluation rather than as an organizational outcome produced through negotiated authority, professional jurisdiction, and institutionalized standards [46,47]. In digital learning environments, credibility and accountability are collectively produced. Trust must be socially ratified and institutionally authorized to endure, especially when AI-enabled learning technologies participate in assessment and credentialing decisions. The next section elaborates SLT's conceptual foundations and prepares the reader for the propositions that guide future empirical and conceptual research.

3. CONCEPTUAL FOUNDATIONS OF SOCIALLY LEGITIMIZED TRUST

3.1. Why Legitimacy Is The Right Starting Point

Institutional legitimacy theory provides a direct lens for explaining why technically capable innovations can still fail to stabilize in organized systems. Legitimacy refers to the generalized perception that an action, practice, or arrangement is appropriate within socially constructed systems of norms, values, and rules [32]. Legitimacy judgments matter because they condition endurance: practices persist not only when they perform well, but when they are recognized as proper, defensible, and aligned with what relevant stakeholders believe the institution is for [12,42]. This is especially consequential in professionalized and rule-bound domains such as education and workforce training, where credibility and continuity depend on shared standards and recognized authority.

Digital learning technologies sit inside precisely these legitimacy-laden environments. Learning systems are structured by institutionalized expectations about authorship, evaluation, progression, and credentialing, which function as social guarantees that educational outputs mean what they claim to mean [5]. When AI-enabled capabilities become embedded in the infrastructures that administer these practices, they do more than optimize delivery. They alter how instructional work is done, how evidence of learning is produced, and how the credibility of outcomes is established. As a result, adoption hinges on whether AI-mediated practices are interpreted as consistent with educational purposes and professional standards, not merely whether they are technically functional [9, 21].

3.2. How Socio-Technical Conditions Produce Trust And Contestation

Socio-technical systems scholarship sharpens this point by specifying how legitimacy and trust are formed in practice. Technologies are not adopted as standalone artifacts; they are embedded into routines, role relations, governance structures, and interpretive frames that determine what the technology is taken to be "doing" and what it is allowed to do [13]. Trust in complex technologies is therefore not reducible to performance metrics. It emerges through interaction among technical design, social interpretation, and institutional arrangements that distribute authority and accountability [48]. In learning environments, this interaction becomes visible in disputes that persist despite high technical performance because the disagreement is often about educational meaning, responsibility, and institutional credibility rather than system accuracy per se.

This is where many prevailing models in educational technology under-specify the phenomenon. Acceptance-oriented models provide useful leverage on individual experience and intention, but they tend to treat trust as an individual perception rather than a collectively produced judgment stabilized by authority and institutional endorsement [7,33]. In learning systems, however, "use" is an unreliable proxy for trust: participation may be required, unevenly enforced, or strategically complied with while legitimacy remains contested. A legitimacy-centered account is therefore needed to explain stability, contestation, and repair over time.

4. DEFINING SOCIALLY LEGITIMIZED TRUST

Building on these foundations, we conceptualize trust in AI-enabled learning technologies as SLT. This is because SLT refers to the extent to which AI-enabled practices are regarded as appropriate, credible, and sustainable within a learning system. SLT is not reducible to technical accuracy, usability, or compliance with stated policy. It is an institutional outcome that emerges when three foundations align: technocratic validation, social validation, and institutional authorization [2]. Figure 1 summarizes this alignment logic and links these foundations to the core SLT outcomes of perceived appropriateness, credibility, and adoption stability. To avoid taxonomy drift, we use the following terms consistently in the SLT model: 1) technocratic trust corresponds to technocratic validation: evidence that the system is reliable, sufficiently transparent, and aligned with instructional goals, 2) social trust corresponds to social validation: shared credibility judgments and normative interpretations among instructional actors, and 3) institutional trust corresponds to institutional authorization: formal governance, policy, and accountability mechanisms that confer legitimacy and allocate responsibility.

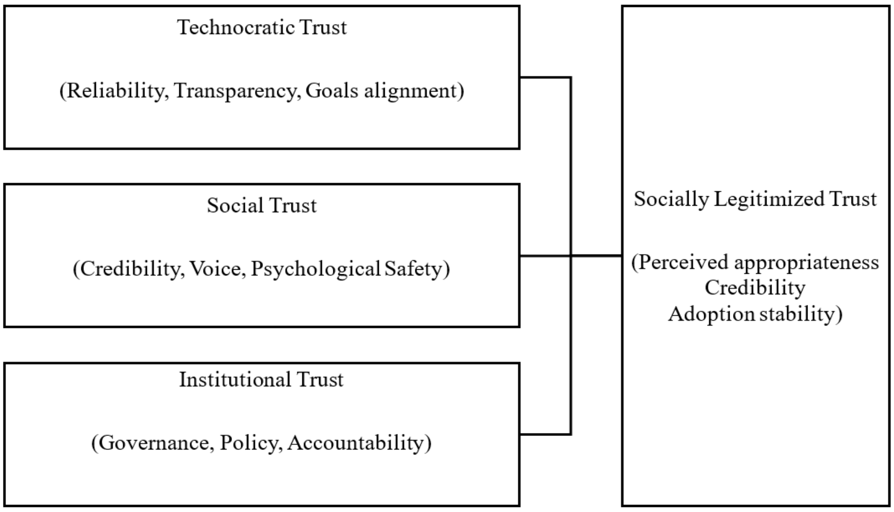

Figure 1.*Socially Legitimized Trust (SLT) framework for AI in learning technologies*

4.1. Component 1: Technocratic Validation

Technocratic validation refers to credible evidence that AI-enabled capabilities function reliably within their intended scope and known limitations. In learning systems, this includes performance and robustness, transparency appropriate to the stakes of use, and alignment with instructional objectives and assessment requirements [49,50]. Technocratic validation is necessary because without it, contested outputs are easily interpreted as arbitrary or unsafe. However, technocratic validation does not determine whether a practice is educationally defensible. A tool can be accurate and still be judged inappropriate for a given learning aim, assessment regime, or credentialing standard.

4.2. Component 2: Social Validation

Social validation refers to collectively produced judgments among instructors, learners, administrators, and other relevant actors that AI-enabled practices are appropriate and credible in context. These judgments are formed through professional norms, peer interaction, shared interpretive frames, and ongoing sensemaking about what counts as legitimate learning activity [42]. Social validation is especially salient where AI-enabled capabilities touch authorship, assessment integrity, and the delegation of cognitive work, because these are precisely the domains where educational meaning is socially negotiated and guarded [24]. A system may meet technocratic standards yet remain contested if it conflicts with prevailing understandings of authentic performance, fairness, or pedagogical responsibility.

4.3. Component 3: Institutional Authorization

Institutional authorization refers to formal endorsement and stabilization through governance structures, policy frameworks, and accountability mechanisms. Authorization signals not only that AI use is permitted, but that it is institutionally owned: aligned with institutional purposes, supported by rules, and accompanied by enforceable responsibility assignments [51]. Authorization matters because learning environments distribute authority across multiple levels (program, department, institution, accreditor, regulator, employer), and ambiguity at any level can keep AI-enabled practices fragile even if users have adapted to them. When authorization is inconsistent or symbolic, locally "accepted" practices can remain vulnerable to reversal, scandal cycles, or credibility shocks.

4.4. Alignment, Misalignment, And Why SLT Predicts Stability

Socially Legitimized Trust emerges when technocratic validation, social validation, and institutional authorization converge within the same learning system (Figure 1). Misalignment among these foundations produces predictable instability patterns. First, strong technocratic validation with weak social validation tends to yield ongoing contestation, workaround behavior, or selective uptake. Second, strong social validation with weak institutional authorization often yields fragile practices that persist informally but remain vulnerable to policy shifts and accountability failures. And third, strong institutional authorization with weak technocratic validation risks compliance without confidence, producing brittle adoption that fails under scrutiny. This alignment logic is what distinguishes SLT from acceptance-based accounts: SLT explains why adoption can be coerced yet unstable, and why high-performing tools can remain illegitimate in practice.

4.5. Positioning SLT Among Trust Conceptions

Table 1 further differentiates SLT from adjacent trust conceptions by specifying each conception's primary focus, unit of analysis, and typical limitation in learning technology contexts. The key distinction is that SLT treats trust as a learning-system outcome grounded in legitimacy judgments, not as a property of the artifact or a proxy inferred from use. This is consistent with the depiction in Figure 1 of three interacting foundations converging on perceived appropriateness, credibility, and adoption stability.

4.6. Bridge To Propositions

Together, these conceptual foundations position SLT as an analytical framework for explaining variation in adoption stability, contestation, and repair across digital learning environments in higher education and workforce development. The next section leverages this framework to develop propositions that specify how alignment and misalignment among technocratic validation, social validation, and institutional authorization should shape trust trajectories over time.

Table 1. Limitations of traditional trust conceptions in AI adoption

Trust conception	What it treats as "trust"	Unit of analysis	What it explains well in learning systems	Where it breaks down (the SLT gap)
Technocratic trust	Confidence that the system performs as intended	Artifact / feature	Whether outputs seem dependable; whether users can	Cannot explain legitimacy disputes when systems "work" but remain

Trust conception	What it treats as "trust"	Unit of analysis	What it explains well in learning systems	Where it breaks down (the SLT gap)
	(reliability, transparency, goal alignment)		rely on system behavior	unacceptable for assessment, authorship, or credentialing
Interpersonal trust	Confidence in another person's intentions and competence	Dyad (person–person)	Instructor–student trust dynamics; trust in human judgment	Mis-specified when agency is distributed across platforms, models, vendors, and policy; does not locate responsibility for AI-mediated actions
Organizational trust	Confidence in organizational routines, procedures, and safeguards	Organization	Local adoption conditions (training, support, process reliability)	Assumes coherent routines and authority; cannot explain cross-boundary contestation (department vs institution vs accreditor vs employer) or legitimacy shocks
Institutional trust	Confidence in formal authority, rules, and governance	Institution / field	How policy, accreditation, and formal accountability shape permissibility	Under-specifies how legitimacy is negotiated in practice (classroom norms, professional judgments) and why "authorized" tools can still be contested
Acceptance-based trust	Willingness to use the technology (intention, satisfaction, continued use)	Individual user	Early uptake patterns; user experience and perceived usefulness	Conflates use with legitimacy; cannot distinguish voluntary trust from compliance, coercion, or fragile adoption that collapses under scrutiny
Socially Legitimized Trust (SLT)	A legitimacy judgment that AI-enabled practices are appropriate, credible, and sustainable	Learning system (socio-technical + institutional)	Stability vs contestation vs repair across contexts; why adoption persists, fragments, or reverses over time	Not a limitation but a scope claim: SLT is designed to explain trust as an institutional outcome produced by alignment across technocratic validation, social validation, and institutional authorization

Note: SLT differs from prior conceptions by shifting the unit of analysis to the learning system and by treating trust as an institutional legitimacy outcome rather than an attitude or a performance inference.

By shifting the unit of analysis from the individual user or the technology artifact to the learning system, SLT makes visible a recurring pattern in AI-enabled learning technologies: widespread use can coexist with contested legitimacy. This move aligns with socio-technical scholarship that conceptualizes technologies as embedded in broader socio-technical systems rather than as standalone tools evaluated solely on performance [13,52].Infrastructural tools may be adopted through policy, procurement, or convenience while remaining disputed in practice because the central question is not only whether the system performs, but whether its use is appropriate, credible, and institutionally defensible. This also clarifies why trust trajectories can change without any change in technical performance: legitimacy is a multilevel process in which judgments shift with changing norms, authority structures, and accountability expectations [42]. Legitimacy can erode when governance signals become inconsistent or accountability failures occur, and it can be repaired when technocratic validation, institutional authorization, and professional interpretation are realigned [53]. These dynamics move trust from a usability problem to a governance problem, with direct implications for how AI-enabled learning technologies are designed, implemented, evaluated, and regulated within educational institutions.

5. IMPLICATIONS

5.1. Implications For Learning Technologies And Educational Governance

Socially Legitimized Trust reframes what it means to "adopt" AI-enabled learning technologies by treating adoption stability as an institutional accomplishment rather than a discrete decision. Instead of asking whether a tool is effective or whether users intend to use it, SLT directs analytic attention to the conditions under which AI-enabled practices become routinized, remain contested, or are withdrawn as legitimacy shifts over time. This is consistent with socio-technical accounts that locate technology outcomes in the interplay of artifacts, routines, and governance, and with research showing that educational technology trajectories are shaped as much by organizational arrangements and authority structures as by instructional effectiveness [5,52]. In this view, digital learning technologies operate as institutional infrastructures in which trust is continuously produced, challenged, and repaired rather than simply "held" by individual users.

5.2. Implications For Learning Technology Design And Evaluation

For designers and evaluators, SLT clarifies that technocratic validation is necessary but not dispositive. Evidence of reliability, transparency appropriate to use-stakes, and alignment with instructional goals remains foundational to credibility claims about AI-enabled capabilities [54,55]. Yet, the literature also shows that technically functional systems can destabilize practice when they alter established instructional and evaluative arrangements, particularly around assessment and feedback [56,57]. SLT implies that evaluation regimes should treat performance metrics as only one input to trust, pairing technocratic evidence with analysis of how AI reshapes workflows, redistributes responsibility, and interacts with existing standards of authorship, fairness, and credential meaning.

5.3. Implications For Professional Practice And Social Validation

Socially Legitimized Trust also foregrounds the central role of social validation in determining whether AI-enabled practices are interpreted as legitimate instructional supports or as inappropriate substitutions for learning activity. In professionalized domains, credibility is socially produced: educators rely on shared norms, peer judgments, and professional jurisdictional boundaries to interpret whether new practices are acceptable and to defend those interpretations in contested settings. When AI-enabled learning technologies align with prevailing understandings of pedagogical responsibility, authorship, and assessment integrity, trust can stabilize. When they conflict with these normative expectations, legitimacy can erode even in the presence of strong technical performance [24]. The implication is direct: trust work must include professional sensemaking and normative alignment, not just user training or interface guidance.

5.4. Implications For Educational Governance And Institutional Authorization

From a governance perspective, SLT distinguishes institutional authorization from both technical performance and local acceptance. Authorization is not merely permission to use a tool; it is the formal allocation of accountability, decision rights, and enforceable standards that signal institutional ownership of AI-enabled practice [9,32]. Where authorization is ambiguous or inconsistent, adoption is likely to fragment across units, creating uneven practice, contested enforcement, and fragile credibility claims. This aligns with socio-technical governance work emphasizing that oversight requires clarity about roles, responsibilities, and decision authority, especially when technologies become infrastructural [13]. Under SLT, governance is a trust mechanism: it stabilizes or destabilizes legitimacy by shaping what is institutionally defensible when AI output is disputed, consequential, or wrong.

5.5. Implications Of Alignment And Misalignment Across Institutions

Socially Legitimized Trust further explains why similar AI-enabled learning technologies can produce divergent trajectories across institutions. Alignment among technocratic validation, social validation, and institutional authorization increases the probability that AI-enabled practices will become normalized and sustained. Misalignment predicts recognizable instability patterns: systems that are technically validated but lack social validation remain contested; practices that are socially accepted but weakly authorized remain fragile; policies that authorize AI without credible technocratic validation invite compliance without trust, producing brittle adoption vulnerable to credibility shocks [39,52,53]. This alignment logic offers a principled basis for comparative research on adoption stability across higher education and workforce development contexts where credential credibility and skill formation are shared concerns, but governance regimes differ [58].

5.6. Why This Reframing Matters

By situating trust within institutional legitimacy, SLT reframes debates about AI-enabled learning technologies from “should we use it?” to “under what conditions is its use legitimate, credible, and sustainable?” This reframing provides analytic leverage by shifting attention from individual attitudes and artifact performance to the learning-system arrangements through which authority, accountability, and credibility are collectively negotiated and institutionally enforced [32,46]. Accordingly, SLT’s implications extend beyond individual tools to the governance of learning systems themselves: how institutions authorize AI-mediated practices, how professional communities validate or resist them, and how legitimacy is maintained as learning technologies become infrastructural. Table 2 maps SLT alignment configurations to predicted system-level adoption patterns, previewing the logic formalized in Propositions 1–5.

Table 2. Predicted adoption stability patterns under SLTalignment conditions

Alignment condition (SLT foundations)	Predicted system-level adoption pattern	Observable indicators in learning environments	Proposition(s) most directly supported
Full SLT alignment: technocratic validation + social validation + institutional authorization are mutually reinforcing	Stable adoption and normalized use; AI practices become routinized, defensible, and sustained	Low variance across courses/departments; consistent assessment and authorship norms; clear policy and enforcement; disputes adjudicated through formal governance channels; credential credibility remains stable	P1 (alignment → stability)
Technocratic validation strong; social validation weak; institutional authorization	Technically “working,” socially contested adoption; selective use and	Instructor-level workarounds; uneven adoption by discipline; recurring boundary disputes over authorship and assessment integrity;	P2 (reliability without social validation → lower sustained trust)

Alignment condition (SLT foundations)	Predicted system-level adoption pattern	Observable indicators in learning environments	Proposition(s) most directly supported
mixed/unclear	recurring legitimacy disputes	“shadow policies” emerge informally; trust depends on local champions rather than shared norms	
Social validation strong; technocratic validation adequate; institutional authorization weak/ambiguous	Locally accepted but institutionally fragile adoption; high vulnerability to shocks and reversals	High uptake within communities of practice but weak institution-wide standardization; inconsistent rule enforcement; uncertainty about accountability for errors; rapid shifts after incidents, media attention, or audits	P3 (authorization moderates social validation → durability)
Institutional authorization strong; technocratic validation weak or contested; social validation mixed	Compliance without legitimacy; brittle adoption that collapses under scrutiny	Mandated usage with low professional confidence; elevated appeal rates or dispute frequency; reliance on exception-handling; visible mismatch between policy claims and observed tool behavior; erosion of credibility after errors	P1 + P3 (misalignment predicts fragility; authorization alone does not stabilize trust)
Education-to-work misalignment: local SLT may be high internally, but downstream stakeholders do not validate outcomes	Credential credibility risk and cross-boundary contestation; legitimacy disputes extend beyond the institution	Employer skepticism; increased verification demands; friction in placement or licensure pathways; public/industry questioning of skill claims; divergence between institutional assessment and workforce expectations	P4 (downstream misalignment undermines credibility)
Design orientation toward learning-to-learn with alignment across SLT foundations	More durable legitimacy; AI viewed as supportive augmentation rather than substitution	Stable policies emphasizing metacognition, formative feedback, skill transfer; assessment designs emphasize process evidence; lower concern about shortcutting; sustained legitimacy across cohorts	P5 (learning-to-learn orientation → stronger SLT association)
Design orientation toward task substitution even if technocratically strong	Higher legitimacy volatility; recurring disputes about bypassing learning processes	Persistent arguments about authenticity and authorship; stricter policing and reactive governance; higher risk of moratoria/bans in assessment-heavy contexts; greater cross-unit variance	P5 (task substitution → weaker SLT association)

Note: Unit of analysis: learning system (not individual user). Outcome focus: adoption stability and legitimacy (not short-term uptake).

Building on these predicted patterns, we formalize Propositions 1–5 to guide empirical tests of how alignment and misalignment across SLT foundations shape adoption stability, contestation, and repair across learning contexts.

6. RESEARCH DIRECTIONS AND ANALYTICAL PROPOSITIONS

The SLT framework is intended to guide future research on AI-enabled learning technologies by specifying the institutional conditions under which trust becomes legitimate and stable. Current models often treat trust as an individual attitude or a proxy inferred from usage metrics [55,56]. In contrast, SLT conceptualizes trust not as a static trait, but as a learning-system outcome—one produced through legitimacy judgments that are socially constructed and institutionally enforced. This move is consistent with socio-technical and institutional scholarship showing that technology outcomes depend on how artifacts are embedded in routines, interpreted by professional communities, and authorized through governance arrangements, not on technical performance alone. Accordingly, SLT offers an analytical structure for explaining variation in adoption stability, persistent contestation, and repair across learning contexts. The propositions below translate this logic into testable claims that can organize empirical study and conceptual refinement of trust in AI-enabled learning technologies.

6.1. Proposition 1. Alignment And Adoption Stability

The stability of AI-enabled learning technologies will be positively associated with alignment among technocratic validation, social validation, and institutional authorization.

Institutional legitimacy theory suggests that practices endure when they are widely perceived as appropriate within a normative and rule-governed environment, and when authority structures make that appropriateness defensible over time [57]. Socio-technical scholarship similarly indicates that stability emerges when technical capabilities, interpretive frames, and governance arrangements cohere rather than contradict one another [13,52,62]. Applied to learning systems, SLT predicts that adoption becomes normalized when evidence of capability and limits (technocratic validation), professional and stakeholder judgments of appropriateness (social validation), and formal accountability structures (institutional authorization) mutually reinforce each other. Conversely, misalignment should predict recognizable instability patterns: selective use, recurring disputes, compliance without confidence, or reversal even in the presence of functional effectiveness. Empirical work can operationalize alignment as cross-level congruence (artifact performance evidence, normative consensus, and governance clarity) and test whether it predicts adoption persistence and variance across units and time.

6.2. Proposition 2. Technocratic Validation Is Insufficient Without Social Validation

AI-enabled learning technologies that demonstrate technocratic validation but lack social validation among instructional actors will exhibit lower levels of sustained trust and greater contestation.

Professionalized systems rely on collective judgments to determine what counts as legitimate practice, particularly when innovations touch core jurisdictional domains such as evaluation and credentialing [42,46]. In learning environments, instructors' and administrators' shared interpretations shape whether AI-enabled practices are seen as credible instructional supports or as illegitimate substitutions that threaten authorship norms and assessment integrity. SLT suggests that technical reliability and transparency may be sufficient to show an AI-enabled learning system functions, but not sufficient to stabilize trust. Trust remains fragile when the professional community does not recognize the practice as pedagogically appropriate, ethically defensible, and aligned with accepted norms. Research can test this proposition by examining settings where validated tools (for example, analytics dashboards or automated feedback) remain unevenly adopted, generate persistent boundary disputes, or prompt policy workarounds.

6.3. Proposition 3. Institutional Authorization Moderates Social Validation And Durability

Institutional authorization will moderate the relationship between social validation and adoption stability, such that socially validated AI-enabled practices will be more durable when governance is clear, consistent, and enforceable.

Legitimacy is not only negotiated at the practice level; it is stabilized by institutional structures that allocate decision rights and accountability, thereby transforming local acceptance into system-level defensibility [42]. In educational settings, formal policies and governance mechanisms signal whether AI use is recognized as consistent with institutional purpose, what boundaries apply, and who bears responsibility when outcomes are disputed. Where authorization is ambiguous or inconsistent, socially accepted practices may remain fragile, vary across units, and become vulnerable to reversal after incidents, audits, or external scrutiny. This proposition can be tested by comparing institutions with similar social norms but different governance clarity, examining whether clarity predicts lower variance in practice, fewer legitimacy disputes, and more stable integration over time.

6.4. Proposition 4. Cross-Boundary Legitimacy And Education-To-Work Credibility

Misalignment between AI-enabled practices in educational settings and downstream workforce expectations will undermine perceptions of learning credibility and weaken trust in credentials.
Learning systems do not legitimate themselves in isolation; they are embedded in broader fields that include employers, professional bodies, accreditors, and regulators who evaluate whether credentials reliably signal competence [13]. Workforce development and organizational learning research emphasizes that credible learning systems cultivate adaptability and learning capacity, not merely task completion [58]. SLT therefore predicts that even when AI-enabled practices are locally aligned within an institution, legitimacy can be destabilized if downstream stakeholders interpret those practices as bypassing learning processes or diluting performance signals. This proposition invites cross-sector analyses that trace legitimacy judgments across the education-to-work transition, examining how employer interpretations, professional standards, and credential evaluation practices shape trust trajectories across institutional boundaries.

6.5. Proposition 5. Design Orientation And Legitimacy Durability

Socially Legitimized Trust will be more strongly associated with AI-enabled learning technologies designed to support learning-to-learn capabilities than with technologies oriented toward task substitution.

Institutional legitimacy in learning environments is anchored to claims about developing durable capability: metacognition, skill transfer, and adaptive performance across contexts [13]. Technologies that primarily substitute for cognitive work risk being interpreted as undermining authorship norms and the evidentiary basis of assessment, thereby increasing legitimacy volatility even when technocratically validated [26]. In contrast, AI-enabled designs that foreground scaffolding, feedback that preserves learner agency, and supports for reflective practice are more likely to align with institutional educational purposes and be defended as credible over time [7,54]. Empirical work can test this proposition by classifying AI-enabled features by design orientation (learning augmentation vs substitution) and assessing whether augmentation-oriented designs correlate with stronger social validation, clearer authorization pathways, and more stable adoption.

6.6. Integrative Contribution

Collectively, these propositions position SLT as a legitimacy-centered framework for analyzing AI-enabled learning technologies across higher education and workforce development. They convert the framework's core mechanism, alignment among technocratic validation, social validation, and institutional authorization, into testable expectations about stability, contestation, and repair. By locating trust at the learning-system level, SLT provides a foundation for future research that can connect educational technology studies with human resource development and organizational scholarship without collapsing their distinct concerns: credential credibility, skill formation, and governance of legitimate learning.

7. LIMITATIONS

This manuscript advances SLT as a conceptual framework and set of propositions; it does not provide empirical tests of the model. Accordingly, the claims are theory-driven and intended to guide subsequent operationalization and hypothesis testing rather than to demonstrate effect sizes, boundary conditions, or causal mechanisms in situ. Empirical evaluation will be required to assess the explanatory adequacy of SLT relative to acceptance-based, organizational trust, or institutional trust models across learning contexts.

A second limitation concerns construct delineation and measurement. SLT is defined at the learning-system level, but its three foundations are likely to be measured using indicators that originate at different levels of analysis (for example, system performance evidence, instructor norms, policy clarity, and accountability structures). This creates risks of construct overlap with adjacent concepts such as institutional trust, organizational trust, or governance quality, and it raises challenges for specifying alignment or misalignment in a way that is both reliable and comparable across settings. Future work will need to develop validated measures for technocratic validation, social validation, and institutional authorization, and to define alignment metrics that do not collapse distinct processes into a single index.

Third, SLT foregrounds legitimacy dynamics, which may not capture the full range of factors shaping adoption trajectories. Resource constraints, vendor lock-in, infrastructural dependencies, and compliance requirements may produce stable use even when legitimacy is weak, or unstable use even when legitimacy appears strong. In such cases, "adoption stability" may reflect coercion, path dependence, or sunk-cost dynamics rather than socially legitimized trust. Future studies should therefore model SLT alongside institutional pressures, material constraints, and economic dependencies to avoid over-attributing outcomes to legitimacy processes alone.

Fourth, the framework is developed at a level of abstraction intended to span higher education and workforce development. This breadth is a strength for generalization, but it limits specificity regarding domain differences in governance regimes, professional norms, and credential stakes. For example, regulated professional programs, open-enrollment community colleges, corporate training environments, and credentialing bodies differ in accountability structures and in the consequences of assessment decisions. These variations are likely to condition how social validation forms and how institutional authorization is enacted. Future research should specify boundary conditions, including sector, discipline, and regulatory context, that moderate the SLT alignment–stability relationship.Future research should specify boundary conditions and assemblages [63-65], including sector, discipline, and regulatory context, that moderate the SLT alignment–stability relationship

Finally, SLTcenters institutional authorization as a stabilizing mechanism, but authorization itself may be contested, unevenly enforced, or strategically symbolic. Policies can be adopted without meaningful accountability, and governance can function as legitimation theater rather than as a mechanism of responsibility allocation. The framework anticipates these dynamics through misalignment logic, but it does not yet specify how symbolic compliance, decoupling, and enforcement variability interact with social validation and technocratic validation over time. Longitudinal and multi-actor designs will be necessary to capture how SLT is constructed, challenged, and repaired as AI-enabled learning technologies evolve.

8. CONCLUSION

AI-enabled learning technologies now operate as institutional infrastructure, shaping how learning is designed, evaluated, and credentialed. In this context, trust cannot be reduced to technical performance or individual willingness to use a tool. The central problem is legitimacy: whether AI-mediated practices are regarded as appropriate, credible, and defensible within a learning system. This paper introduced SLT to address that problem. SLT conceptualizes trust as a learning-system outcome that emerges through alignment among technocratic validation, social validation, and institutional authorization. By shifting the unit of analysis from users and artifacts to the learning system, SLT explains why technically capable tools can remain contested, why adoption can be widespread yet fragile, and how trust can erode or be repaired without changes in model performance.

The propositions offered here provide a research agenda for studying stability, contestation, and repair across educational and workforce learning systems. Taken together, SLT reframes AI adoption as a governance challenge as much as a design challenge and offers a rigorous foundation for empirical work that can strengthen learning integrity while clarifying when, why, and for whom AI-enabled practices become legitimate over time.

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AUTHORS

Sanket Ramchandra Patole holds a PhD in Human Resource Development fromSoules College of Business, The University of Texas at Tyler. Dr. Patole's research explores trust in AI as it becomes embedded in organizations.His research grounded in technology-mediated teams shows how performance-oriented, data-driven systems can unintentionally reproduce inequities unless technical design, team practices, and governance structures are intentionally aligned. Dr. Patole is currently working as a Senior Analyst of Human Capital Management at a leading U.S. healthcare organization.

Rob E. Carpenterholds a PhD in Human Resource Development from the University of Texas at Tyler where he currently serves as the Soules College of Business Executive in Residence. He is also Community of Practice Faculty in the Department of Cellular and Molecular Biology at the University of Texas at TylerSchool of Medicine. His professional concentration is in the healthcare sector while his academic pursuits include teaching and conducting interdisciplinary research in both the physical and social sciences.

Reed M. Milewicz, PhD, is a computer scientist and software engineering researcher whose work focuses on developing better practices, processes, and tools to improve software development in the scientific domain. This is a course of research that straddles the line between systems and human factors, ranging

from technologies such as compilers and formal verification tools to direct engagement with software teams through evidence-based software process improvement. His current interests include the trustworthiness of complex, AI-enabled systems and developing a better understanding of how to best incorporate the roles of different stakeholders (such as system developers, users, and governance entities) in assuring that trustworthiness.

Rose M. Baker, PhD, PMP is an Associate Professor at the University of North Texas, where she directs the Learning Technologies Bachelor of Applied Sciences degree. With more than 30 years of experience in project management, instructional design, and higher education, her work centers on advancing learning technologies and artificial intelligence in educational and organizational settings. Her research focuses on human–AI teams, AI integration for teachers, workforce learning, performance improvement, and program evaluation. Dr. Baker partners with government agencies, academic institutions, corporations, and nonprofits to promote human-centered, evidence-based approaches that enhance teaching, learning, and data-informed decision-making.

John R. Turner, PhD, is an Associate Professor at Texas A&M University in the College of Education and Human Development for the Department of Educational Administration and Human Resource Development. He also serves as the EHRD Program chair for the department. Professor Turner has published over 90 articles in various journals and book chapters. He presented his research at prestigious conferences, including but not limited to the Academy of Human Resource Development (AHRD), the International Society for Performance Improvement (ISPI), and the International Network for the Science of Team Science (INSciTS). Dr. Turner’s research resides at the intersection of leadership, team science, complexity, decision-making, and human-AI teams.