

# The AI Conceptual Learning Framework (AICLF): A Model for AI Learning Laboratories in Education and Organizations

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**Abstract:** This study introduces the AI Conceptual Learning Framework (AICLF), a conceptual model designed to support the development of artificial intelligence understanding through structured reasoning, sociotechnical awareness, and adaptive learning processes. The framework addresses limitations in traditional instructional approaches that often emphasize procedural skill acquisition over conceptual comprehension. The AICLF is organized around interconnected conceptual dimensions that collectively support learner engagement with AI-enabled environments, fostering interpretation, evaluation, and decision-making within complex contexts. By integrating principles from artificial intelligence education, adult learning, and sociotechnical systems, the framework provides a foundation for advancing conceptual understanding and applied reasoning. This study contributes a theoretically grounded model that may inform instructional design, workforce development strategies, and AI literacy initiatives across diverse educational and professional settings.

**Keywords:** Artificial Intelligence, Course Development, Experiential Learning, Laboratory, Teaching, Management

## 1. Introduction

The relentless escalation of cyber threats has made robust cybersecurity education an imperative for organizations seeking digital resilience. ELE ecosystems occupy a pivotal position in advancing digital resilience, as they are responsible not only for delivering technical expertise but also for fostering the discernment, flexibility, and adaptive reasoning required to engage with increasingly complex AI-enabled systems and data-rich environments (Baxter & Sommerville, 2011; Floridi et al., 2018; Long & Magerko, 2020; National Security Commission on Artificial Intelligence, 2021). AI plays an essential role in how ELE ecosystems pursue digital resilience, making AI literacy and AI-informed decision-making indispensable priorities for contemporary education, development, and training in the 21st century. ELE ecosystems reside in a pivotal position, tasked with delivering technical content as well as with fostering the discernment, flexibility, and adaptive rationalization necessary to connect with progressively complicated AI-enabled systems and data-rich environments.

This research progresses the viewpoint that a prudently designed, modular AI learning environment functions only as a technical training space however as a vigorous setting for experiential learning, interdisciplinary teamwork, and methodical knowledge development. These types of environments support the development of AI-related technical skills in addition to optimizing the collection, improvement, and sharing of institutional and organizational knowledge, as well as helping stakeholders acclimate within precipitously shifting digital and AI ecosystems. As highlighted in prior work (Dodla & Jones, 2023),

effective knowledge management strategies in technology-rich environments extend beyond information storage to include the structured interpretation, contextualization, and mobilization of knowledge for immediate application and sustained institutional value.

The current landscape exposes a considerable gap between conceptual instruction about AI and opportunities for authentic, practice-based engagement with AI tools, data, and scenarios (Long & Magerko, 2020; Luckin et al., 2018). Concentrating on this divide necessitates more than technology acquisition; the action requires a learning design orientation that distinguishes AI laboratories and simulations as engines for enduring learning, curriculum rekindling, and the nurturing of a durable learning ecosystem for learners of all types. The purpose of this conceptual study is to propose a comprehensive, adaptable framework for the design and stewardship of AI-focused laboratories and learning environments that aligns with evolving professional standards, addresses the needs of varied stakeholders, and embeds sound practices in teaching, adult learning, and knowledge management (Fantinelli et al., 2026; Kolb, 1984; Matsu, 2025).

To advance this intention, first, this article offers background on the evolution and contemporary demands of AI-related education, then it investigates central assumptions, key limitations, and the defined scope of the work. Succeeding sections give the identified research gap, describe the methodological orientation, review the literature, develop and critique the conceptual model, synthesize best practices, and then outline implications through discussion and concluding reflections. This movement supports a methodical treatment of the topic and provides readers a coherent route for comprehending the logic, structure, and contributions of the proposed AI-focused framework. While established programs offer significant theoretical foundations, they often fall short in preparing learners for authentic, applied challenges in AI-augmented operational contexts (Garzón et al., 2025). The central question, therefore, emerges: How can ELE ecosystems design and implement AI-focused laboratory and simulation environments that convert abstract understanding into demonstrable, practice-ready competence and innovation?

## 2. Background

The origin of AI laboratories can be traced to the mid-20<sup>th</sup> century. MIT's AI lab was founded in 1959 (Chiou et al., 2001). Stanford University's AI Lab was founded in 1962 (Stanford Engineering, 2023). Carnegie Mellon's AI developed as an essential research area beginning in the 1960s, with key institutional milestones in 1965, 1967, and 1979. These institutions were established against the flag of scientific discovery, to examine machine reasoning, symbolic logic, robotics, and computational models of human intelligence. From the 1980s through the 2000s, machine learning (ML) experienced significant advancement, transitioning from a style of AI that tries to model intelligence using explicit symbols, rules, and logic (symbolic AI) toward statistical and data-driven approaches.

The growth of deep learning and big data spurred the creation of specialized labs, including Google DeepMind, Google Brain, OpenAI, and Microsoft Research AI. Google DeepMind, an AI research arm of Alphabet Inc., concentrates on advancing general-purpose AI (e.g., deep reinforcement learning) and utilizing it across scientific domains and product ecosystems. Founded inside Google in approximately 2011, Google Brain's purpose was to make machines intelligent and enhance individuals' lives (Google Brain, 2011). OpenAI is an AI research and deployment organization devoted to safeguarding that artificial general intelligence (AGI) is developed in a manner that furthers all of humankind (OpenAI, 2025).

According to Microsoft Research (2025), Microsoft Research AI is the assemblage of Microsoft's AI research groups and labs that furthers core AI science and amalgamates those advances into Microsoft products and services. The overall goals grew to include making AI smarter and more capable in general, studying how to create AI that is safe and

used responsibly, and developing powerful AI systems that can understand language, interpret images, and help with robotics (Hu & Xu, 2025). The overall mission continues to be innovation-driven, and not threat-driven.

### ***2.1 Why the Emergence of Artificial Intelligence Laboratories?***

Different from traditional cybersecurity labs, AI labs subsist explicitly to train machine-learning models, high-performance computational experimentation, and serve as defined parameters for algorithmic evaluation (Otoum et al., 2025; Kucukkaya et al., 2024). Indirectly, the point of AI laboratories connects back to cybersecurity owing to their common focus on managed experimentation, resilience testing, and system refinement (Otoum et al., 2025; Kucukkaya et al., 2024). As given by Malatji & Tolah (2024) and Mamillapalli (2024), as artificial intelligence persists in being entrenched in defensive mechanisms, hazard detection, and automated mitigation systems, AI laboratories add to progressing cybersecurity research by patterning adversarial behavior, augmenting discovery accurateness, and enabling the creation of smart security architecture.

This information is significant because it clarifies that AI labs are not merely extensions of cybersecurity labs but distinct infrastructures whose design and capacity directly shape what is possible in AI-driven defense, detection, and response. This distinction helps educators, practitioners, and policymakers intentionally leverage AI laboratory capabilities for adversarial modeling, resilience testing, and intelligent security architecture instead of treating them as generic compute spaces. Comprehending the distinction between AI laboratories and traditional cybersecurity labs is momentous for the details that underline the manner in which AI-focused environments enable forms of defense, detection, and response that conventional labs cannot support. AI labs offer computational infrastructure differences (i.e., high-performance compute clusters and specialized data pipelines; Agarwal, 2024), controlled training environments (i.e., model-training environments; Apata et al., 2026), and adversarial modeling capabilities essential to build and evaluate machine-learning systems at scale (i.e., adversarial ML toolkits and controlled sandboxes for model-based attack simulation; Foundjem et al., 2025). Recognizing these differences ensures intentional use of AI labs for resilience testing, adversarial experimentation, and the development of intelligent security architectures. This clarity ultimately shapes how effectively AI-driven cybersecurity solutions can be researched, tested, and deployed.

### ***2.2 AI Laboratory Capabilities for Secure, Cyber-Aware Design***

AI-driven cyber defense, adversarial ML, and secure AI system design are precisely the types of synergistic domains that justify modular, shared lab spaces in higher education. In reality, AI and cybersecurity are no longer isolated (Al Siam et al., 2025). AI is essential for cybersecurity. Cybersecurity now also relies on AI. This further supports the need for a unified or cohesive AI laboratory framework (Okdem & Okdem, 2024). The background of the study clarifies that AI labs are distinctive infrastructures. Their design and capacity directly shape the possibilities for AI-driven defense, detection, and response (Roshanaei et al., 2024). Recognizing this discrepancy and indirect linkage helps educators, practitioners, and policymakers. They can purposely leverage AI laboratory capabilities for adversarial modeling, resilience testing, and intelligent security architecture, instead of treating labs as general-purpose computer areas. AI laboratories specifically bridge the gap between abstract concepts and applied, real-world experimentation.

As given by ISC2 (2023), the significance of AI conceptual laboratories is accentuated by the tenacious skills gap in applying AI to cybersecurity, a gap intensified by the rapid pace of AI and threat-landscape evolution. Also, the ELE ecosystems now

encounter the urgent concern of safeguarding that AI-focused programs, and their connected laboratory experiences, continue to be associated with industry mandates for AI-enabled defense, threat detection, and resilience (ICS2, 2023). The next sections will probe the assumptions, limitations, and delimitations of the planned approach, pinpoint the research gap, delineate the procedure employed, the literature review, a case study, the conceptual framework and its analysis, the uniqueness of the text, results, discussion, and conclusion, in addition to future research.

### **3. Assumptions, Limitations, and Delimitations**

This study is conceptual in nature and does not include empirical validation or statistical analysis. The framework is informed by theoretical integration and illustrative contexts, which may limit generalizability across diverse settings. Future research may explore empirical application and evaluation of the framework to further assess its effectiveness and adaptability. Numerous opening assumptions influence the development of an AI conceptual laboratory. The assumption exists that ELE ecosystems leadership encourages the initiative and provides adequate means for preliminary organization and continuing preservation (Karagiannis, 2024). The next assumption is that instructional personnel either already have, or can develop, the knowledge, skill, and capability required to design and run laboratory exercises effectively (Alshaikh, 2023).

Limitations are inherent in laboratory-based learning environments and conceptual framework development, particularly within complex and resource-dependent instructional systems (Kolb, 1984; Floridi et al., 2018). The proposed AI-focused conceptual laboratory may face capacity constraints, including limited access to graphical processing units, storage resources, and specialized AI platforms, which may restrict the complexity of models and tools available for instructional use (Sustainability Directory, 2024). Physical facilities and network infrastructure may also influence cohort size, the intensity of experimentation, and the realism of simulated AI-for-cybersecurity scenarios (Otoum et al., 2025).

Delimitations elucidate the envisioned scope and related boundaries of a study (Behlert, 2026). In conceptual work on AI laboratories, such delimitations characteristically include the assumption of a certain type of ELE ecosystem and a limited set of implementation roles, which restricts how widely the resulting insights can be generalized. ELE ecosystems with diverse levels of digital maturity, AI capacity, and instructional support are poised to develop in divergent paths when implemented in a given laboratory model (Dwivedi & Joshi, 2021). Moreover, dissimilarity in ELE ecosystem mission, curricular configurations (i.e., such as which courses are required or elective and the sequence in which they are taken), and pedagogical and andragogical approaches is anticipated to influence how an AI conceptual laboratory is situated within programs and what changes are essential for it to operate effectively. The focus of this article is on ELE ecosystems offering cybersecurity programs. The discussion excludes specialized research labs dedicated solely to advanced threat analysis or government-sponsored facilities because such facilities frequently comprise security clearances, export controls, and policy-driven agendas that diverge from environments that emphasize learner choice, flexible structures, and collaboration with learning professionals.

### **4. Research Gaps**

Despite the mounting interest in AI intelligence education, considerable gaps persist in how AI conceptual laboratories are conceived, structured, and sustained within ELE ecosystems. Prevailing efforts regularly accentuate computational capacity, model training workflows, or isolated tool exposure, but offer limited guidance on the manner to design laboratories

that purposely nurture conceptual understanding of AI principles, ethical awareness, and human–AI teaming together with technical skill growth (Bradley, 2021). This disproportion limits the ability of ELE ecosystems to use AI labs as engines for deep reasoning, reflective practice, and transfer of learning across domains, as opposed to generic compute spaces or demonstration venues.

A fundamental deficiency centers on the weak alignment between AI laboratory experiences and lucidly articulated conceptual learning outcomes. According to Garzón et al. (2025), numerous initiatives prioritize model performance metrics, dataset size, or infrastructure benchmarks, yet merely minimally confront foundational concepts (i.e., abstraction in model design, bias and fairness, interpretability, and risk-aware deployment) in operational settings.

Consequently, learners may conclude AI laboratory tasks without completely understanding three key points: (1) why specific design choices matter, (2) how AI systems behave under uncertainty, or (3) how AI-enabled decisions intersect with organizational policy, cybersecurity posture, and societal expectations (UNESCO, 2025). This misalignment of the three points is significant in cybersecurity-relevant contexts. Misinterpretation of AI capabilities or limitations can lead to undue dependence on automated defenses, insufficient threat modeling, or deficient incident-response planning (Jones, 2024; Tang et al., 2024).

A second gap involves the limited integration of AI conceptual laboratories into coherent curricular pathways that span multiple courses, levels, and stakeholder groups (Mills et al., 2024). Also, the literature and practice base tend to document individual exercises, narrow pilot projects, or single-course implementations rather than systematic sequences of conceptual lab experiences that progressively build AI literacy, critical reflection, and applied judgment over time. Further, a few models explicitly show how AI conceptual labs should evolve from introductory exploration of core ideas (e.g., supervised versus unsupervised learning, training and validation cycles) toward advanced, scenario-based work that connects AI reasoning to cyber defense, digital forensics, or resilience planning (Mills et al., 2024). This lack of vertical integration makes it difficult for ELE ecosystems to ensure that graduates emerge with a durable, scaffolded comprehension of AI concepts that can be adapted to fast-changing tools and threat environments.

Third, as given by Kim (2025), there is a visible lack of frameworks that describe how AI conceptual laboratories should concentrate on issues spanning *multiple areas* as opposed to one domain (i.e., ethics, governance, and human-centered design in tandem with cybersecurity concerns). Although policy documents and workforce studies distinguish the significance of responsible AI, secure AI pipelines, and transparency in AI-assisted decision making, a small number of laboratory models implement these urgencies in specific learning exercises, assessment strategies, or design requirements (Kim, 2025). Further, for instance, according to the U. S. Department of Education (2023), there is narrow empirical guidance on how to design conceptual lab experiences that necessitate learners to think through data origins, model exploitation, security controls regarding training environments, or the work and process impacts and ramifications of AI-driven automation. This gap confuses the manner that AI conceptual labs can be utilized to practice and work through technical workflows, as well as the judgment, risk–benefit evaluation, comparative assessment, and decision-making discourse that encircle AI adoption in cyber-aware ELE ecosystems.

A fourth, connected gap is substantiation on the effectiveness of AI conceptual laboratories in yielding measurable, long-range outcomes and gains in learner competence and workforce readiness (Galeano et al., 2025; Tatipamula & Madni, 2025). Studies often report immediate performance improvements within a single course or workshop, yet few examine how conceptual AI lab experiences influence subsequent learning, cross-course

integration, or professional practice after learners leave the lab setting. In particular, there is insufficient longitudinal research on whether AI conceptual labs improve learners' ability to interpret model outputs in security operations, collaborate with AI specialists and cybersecurity teams, or adapt conceptual knowledge to new tools and platforms without extensive retraining (Galeano et al., 2025; Tatipamula & Madni, 2025). The deficiency of such proof restricts the capacity of ELE ecosystems to make well-versed decisions regarding resource allocation, lab governance, and strategic scaling of AI-focused initiatives.

Together, these shortcomings create an interconnected research gap for AI conceptual laboratories. ELE ecosystems lack adaptable, holistic models that (a) align AI conceptual outcomes with laboratory design, (b) entrench AI conceptual labs within a structure where learning is purposely organized across levels, courses, or phases, instead of as isolated lessons, (c) mix ethics, governance, and cybersecurity viewpoints into laboratory activities, and (d) are supported by empirical proof of impact on learner performance and workforce competences. Addressing this gap requires a framework that treats AI conceptual labs as both technical infrastructures and purposefully designed learning environments. Such a framework must combine theory, practice, and the ELE ecosystems framework to allow replication, evaluation, and continual improvement across diverse ELE ecosystems.

## 5. Conceptual Approach

This study adopts a conceptual approach to framework development (Garzón et al., 2025; World Economic Forum, 2023). It draws upon interdisciplinary literature, established theories in artificial intelligence education, and principles from adult learning and sociotechnical systems (Alaku & Drake, 2025). The purpose is to synthesize existing knowledge and provide a structured model. This model supports conceptual understanding, reasoning, and engagement within AI-enabled environments. Instead of relying on formal empirical data collection or statistical analysis, the framework is based on theoretical integration. It also uses practice-aligned insights from scenario-based instructional contexts. These contexts serve as illustrative references. They show how learners may interact with AI systems, interpret outputs, and engage in decision-making processes within dynamic environments. In this study, the term *illustrative* refers to scenario-based or practice-aligned examples. These examples demonstrate conceptual application without formal empirical data collection or statistical analysis. The development of the AI Conceptual Learning Framework (AICLF) emphasizes interconnected conceptual dimensions. Together, these dimensions support learner progression from foundational understanding to applied reasoning. The approach aligns with constructivist and experiential learning perspectives. Knowledge is developed through interaction, reflection, and contextual engagement. This conceptual orientation helps the framework stay adaptable across diverse educational and professional settings. It also provides a foundation for future empirical investigation and validation.

### 5.1 Illustrative Application Context

To support the conceptual development of the proposed framework, illustrative, practice-informed observations were drawn from pilot-aligned instructional environments and scenario-based learning activities. These contexts incorporated elements such as pre- and post-engagement reflections, observational insights into learner interaction with AI-enabled tools, and informal feedback mechanisms resembling interview-style inputs. These observations were not intended to produce generalizable findings but to offer contextually grounded insights that inform the conceptual structure and practical relevance of the proposed framework (Herr & Anderson, 2024).

These elements were not employed as part of a formal empirical research design, but rather as contextual lenses to examine how learners engage with conceptual AI constructs, reasoning processes, and sociotechnical considerations within simulated environments. The purpose of incorporating these illustrative inputs is to provide grounded insight into how the framework may function in applied settings, without asserting generalizable or statistically validated outcomes. These inputs contribute to conceptual refinement while remaining distinct from formal empirical validation and hypothesis testing (Herr & Anderson, 2024).

### ***5.2 Research Design***

This study advances an applied AI conceptual approach that uses a mixed-methods, multi-stage case study orientation, informed by action research (Herr & Anderson, 2024). The multistage, mixed methods case study operates as a structured vehicle for AI conceptual framework development. Action research cycles of planning, intervention, observation, reflection, and revision are treated as generative mechanisms for identifying key elements and relationships within the AI conceptual framework. Empirically, case study designs are widely recognized as the gold standard for educational innovation research where the phenomenon under study is intertwined with context; also, where the aim is to develop or refine practical frameworks rather than test isolated hypotheses (Creswell & Plano Clark, 2018; Kemmis et al., 2014; Yin, 2018).

### ***5.3 Data Sources***

The AI conceptual approach draws on (a) semi-structured interviews with facilitators and learners; (b) direct participant observation during lab sessions; (c) structured document analysis of training and session logs; and (d) administration and statistical analysis of standardized pre- and post-training assessments (Herr and Anderson, 2022).

First, experiential data from semi-structured interviews with facilitators and learners should capture lived experiences, perceived value, challenges, and suggestions for enhancement in AI-enabled laboratories. These narratives provide the raw material for defining framework elements such as learner experience, instructional roles, and organizational readiness (Saldaña, 2021). To establish a foundation for comprehending learner and facilitator perspectives, experiential data from semi-structured interviews should be examined.

Second, behavioral and interactional data should be gathered through direct participant observation in live lab sessions. Observation notes document patterns of engagement, collaboration, problem-solving strategies, and facilitator interventions, informing framework constructs related to pedagogical and androgogical practice, AI tool integration, and the dynamics of hands-on competence building (Herr & Anderson, 2024). To complement these experiential insights, behavioral and interactional data should be examined through direct participant observation in live laboratory settings.

Third, structural and organizational data should be obtained through structured analysis of curriculum materials, laboratory documentation, resource deployments, and session logs. This information clarifies how AI labs are positioned within programs, how resources and infrastructure are configured, and how policies and procedures shape practice, grounding framework dimensions such as governance, infrastructure, and curricular alignment (Bradley, 2021). To further contextualize these observed practices, structural and organizational data should be analyzed to comprehend how AI laboratories are positioned and supported within broader program environments.

Fourth, outcome-oriented data should come from standardized pre- and post-training assessments and basic performance metrics (e.g., test scores, completion rates, error patterns). These data should be used to examine how specific configurations of curriculum,

infrastructure, pedagogy, and andragogy relate to observable changes in learner competence and performance over time, sharpening the framework's depiction of the link between design choices and learning impact.

#### ***5.4 Data Analysis***

Participant activity should be monitored using a structured observation protocol capturing engagement with AI tools, collaboration patterns, problem-solving approaches, and facilitator responsiveness.

Thematic coding of qualitative data and descriptive statistical analysis of learning assessments were triangulated to reveal both subtle and overt influences on laboratory effectiveness, improving the depth and reliability of findings (Creswell & Plano Clark, 2018; Saldaña, 2021). Textual data, including structured observation records, would be examined inductively to allow coding categories to emerge from the ways stakeholders describe AI laboratory teaching and learning. Over successive rounds of coding, the scheme would be refined to highlight themes such as instructional strategies specific to AI tools, the adaptability of the lab environment, perceived value of AI activities, and recurring constraints within ELE ecosystems. To strengthen the credibility of this interpretive process, portions of the dataset would be independently coded by multiple analysts, who would reconcile divergent readings through formal adjudication discussions. Learners would then be invited to review and comment on provisional interpretations so that their perspectives help shape the evolving understanding of AI laboratory practice.

To construct the AI conceptual framework, this conceptual research draws on four primary data streams that together illuminate how AI education and laboratories function within ELE Ecosystems (Herr & Anderson, 2024). Action research cycles (i.e., planning, intervention, observation, reflection, and revision) organize and connect these data streams (Herr & Anderson, 2024). Each cycle yields updated experiential, behavioral, structural, and outcome data, which are interpreted to identify recurring elements, relationships, and contextual conditions. As these cycles repeat, the framework progressively evolves while data are collected, interpreted, and fed back into design decisions. Across repeated cycles, these emergent patterns are synthesized into a multidimensional, context-aware AI conceptual framework that guides the design, implementation, and continuous improvement of AI education and laboratories across diverse ELE ecosystems.

#### ***5.5 Conceptual Framing Approach***

In this study, the methodological combination is applied conceptually, using mixed-methods case material to illuminate how AI laboratories operate in context rather than to test isolated hypotheses (Yin, 2018). The empirical elements are treated as illustrative and framework-informing, allowing lived experiences, institutional dynamics, and observed practices to inform the development of a multidimensional, context-aware AI conceptual framework. In this way, empirical materials function as sources of conceptual insight that guide the design, implementation, and continuous improvement of AI education and laboratories across diverse ELE ecosystems.

In a proposed series of AI-enabled laboratory sessions, participant activity would be monitored through a structured observation protocol rather than informal note-taking. The observation tool would be constructed to foreground indicators such as depth of learner engagement with AI tools, the character of peer collaboration on AI-related tasks, preferred problem-solving approaches, and the responsiveness of facilitators to technical or conceptual breakdowns. Observers would log salient behavioral markers (i.e., how often learners initiate interaction with AI systems or successfully navigate AI-mediated tasks) alongside brief analytic memos capturing perceived shifts in learner confidence,

adaptability, and persistence (Saldaña, 2021). Complementary descriptive data would be assembled from session records, inventory summaries of AI resources, and selected training artifacts to situate these observations within the broader laboratory configuration. Planned interviews and focus groups with facilitators and learners would be recorded and prepared for qualitative analysis (Saldaña, 2021).

Within this conceptual study, the inquiry itself would be structured as a sequence of action research cycles (Herr & Anderson, 2024). Following each hypothetical or pilot iteration of the AI laboratory, synthesized insights from observations, interviews, focus groups, and artifacts would be fed into facilitated reflection sessions with key stakeholders and any external partners. These deliberations would be used to propose adjustments to lab layout and infrastructure, re-sequence or redesign AI learning activities, recalibrate facilitation practices, and reconsider assessment strategies. Over time, this recurrent pattern of planning, implementing, examining, and re-designing AI laboratory experiences would be expected to generate increasingly stable patterns and relationships, which could be abstracted into a multidimensional AI conceptual framework for guiding future AI education and laboratory development in diverse ELE ecosystems.

### ***5.6 Proposed Pilot Design Under Realistic Educational and Workforce Conditions***

A future-oriented pilot laboratory initiative is proposed across multiple six-week sessions to evaluate the feasibility of the AI conceptual laboratory design and its instructional effectiveness in ELE ecosystems. The envisioned pilot would enroll cohorts of 10 to 30 adult learners (Ying et al., 2025) with prior technical or operational experience, drawing from diverse professional and vocational backgrounds, to test the model under realistic educational (i.e., courses, programs, academic governance) and workforce (i.e., production realities, operational constraints, and job-embedded use of AI tools) conditions. The pilot trials are meant to be small. These pilots represent a structured refinement cycle and are meant to be small. The focus is on feasibility. Successive revisions are guided by systematic evidence, evaluative data, and clearly defined criteria for enhancement (Ying et al., 2025). To ensure that the AI conceptual laboratory model is tested in contexts that reflect the manner in which people actually learn and work, the pilot should be crafted to operate under educational and realistic workforce conditions.

#### *5.6.1 Realistic Educational Conditions*

These activities mirror how learning actually happens in courses and programs. Specifically, program developers should review semester schedules, credit/contact hours, assessment practices, supervision norms, academic policies, and student roles to safeguard that AI laboratory experiences are embedded in authentic instructional structures rather than treated as isolated add-ons. This action should occur even when labs are high fidelity or industry-linked, with the purpose of pilot implementations generating evidence that is meaningful for long-term curricular integration and scaling decisions. Curricular integration references the careful harmonization of content, skills, and learning experiences across courses, modules, or disciplines so that learners come across ideas in a connected, mutually reinforcing way. Also, Curricular integration encompasses planning instruction so that concepts are entwined together to support deeper comprehension, coherence, and transfer of learning across contexts, not given in isolation (Bradley, 2021).

#### *5.6.2 Realistic Workforce Conditions*

These activities mirror the manner in which work is organized and performed in operational settings. These settings include team-based problem solving, deadlines driven by production or mission needs, organizational constraints, customer or stakeholder demands, and consequences for performance (World Economic Forum, 2023). For a conceptual AI

laboratory model or framework, this account is meaningful because it specifies the types of authentic workplace pressures that AI-enabled labs should simulate if they are to prepare learners for real decision-making and teamwork in organizations. Also, it identifies design requirements for scenarios (e.g., time-bounded tasks, interdependent team roles, feedback from clients or systems) that connect conceptual AI work to operational risk, accountability, and service quality.

### 5.6.3 *The In-person Pilot*

The in-person pilot would deliver full-day laboratory sessions over a six-week period, integrating structured formative and summative assessments (Gottlieb & Honigsfeld, 2026) into hands-on AI-enabled cybersecurity scenarios. These scenarios could include system simulation, vulnerability exploration in AI-supported environments, guided software use, facilitated classroom dialogue, and procedural walkthroughs that surface how learners reason about AI tools in operational contexts. Assessment mechanisms should encompass quizzes, demonstrations, and applied system-interaction tasks designed to capture real-world ability attainment and generate numerical evidence of conceptual and practical learning (Scully, 2017; Sotiriadou et al., 2020). Data from these scenarios and assessments should be systematically analyzed and mapped back to the AI conceptual laboratory dimensions (e.g., governance, infrastructure, pedagogy, and assessment), so that observed strengths and gaps in learner performance directly inform iterative adjustments (i.e., a process of making repeated, incremental refinements based on feedback, evaluation, or emerging conditions) to the framework and its implementation across ELE ecosystems. A parallel series of virtual pilots should also be conducted to examine how the AI conceptual laboratory performs when delivered through online and hybrid environments to complement the in-person implementation and test the scalability and flexibility of the model.

### 5.6.4 *The Virtual Pilot*

In addition to in-person pilots, AI conceptual laboratories can be piloted through virtual pilots that utilize online or hybrid techniques to test core design assumptions (Tate et al., 2023). Virtual pilots allow ELE ecosystems and organizations to reach geographically distributed learners, vary technical configurations rapidly, and collect rich usage data from digital learning platforms. Generally, virtual pilot testing can be completed at a lower cost and with greater flexibility. Pilot testing is fundamental to safeguard validity and reliability, lessen bias, and psychologically prepare researchers for data collection (Tate et al., 2023).

This mode is specifically practical for stress-testing the scalability, accessibility and support requirements of the AI conceptual lab model before committing to large, facility-based implementations (Beets et al., 2021). Another option is to apply synchronous virtual pilots that deliver live instructor-facilitated AI laboratory sessions through networked platforms to operationalize this approach in real time.

#### 5.6.4.1 *Synchronous Virtual Pilots*

Synchronous virtual pilots are delivered in various modalities: live, instructor-led laboratory sessions through audio and videoconferencing (Coletta et al., 2025), remote desktops (Dubbledam et al., 2022), and cloud-hosted AI environments (Skypilot, 2024). This modality type enables real-time interaction, troubleshooting, and collaboration. As given by Petersen et al. (2021), learners connected simultaneously to shared AI tools or simulated environments, finish guided activities, and receive instant feedback, resembling the social and temporal dynamics of an in-person lab. For the AI conceptual framework, synchronous virtual pilots are significant because they reveal how facilitation practices, communication norms, and real-time coordination must adapt when AI-enabled labs are mediated entirely through networked platforms. Asynchronous or blended virtual pilots can be used to

investigate the manner in which AI conceptual laboratory functions when learners engage with activities on flexible schedules and with differing levels of live instructor presence.

#### *5.6.4.2 Asynchronous or Blended Virtual Pilots*

Asynchronous or blended virtual pilots combine self-paced online modules, virtual sandboxes, and discussion tools with periodic live touchpoints, allowing learners to engage with AI scenarios at times and locations that match their academic or workplace schedules (de Jong et al., 2022). In this format, learners complete scenario-based tasks, submit artifacts or logs, and receive delayed but structured feedback, while analytics from platforms and sandboxes provide detailed traces of interaction with AI systems. Designing and developing asynchronous learning experiences are more diverse challenges than preparing instructor-led or live online learning. There is necessity for the learner to go through real-life scenarios, work through tasks, and attain feedback as the work continues (O’keeffe, 2022). This overall approach is significant for the AI conceptual lab model because it tests how well the framework supports continuity of learning across time, varying levels of instructor presence, and diverse contexts, and it surfaces design requirements for dashboards, scaffolds, and assessment strategies that can function effectively without constant real-time oversight.

### **5.7 Summary**

Conceptual evaluation approaches may include reflective assessments, scenario-based analysis, and structured feedback mechanisms that support understanding of learner engagement and reasoning processes (Szczeny, 2023). These approaches may provide illustrative insight into how learning environments support conceptual development and adaptability (Leon, 2011). Integrated evaluation strategies may combine qualitative interpretation with structured analysis to support a comprehensive understanding of learning effectiveness (Khojasteh et al., 2025).

Quantitative results (i.e., targeted percentage gains in assessment scores or completion rates), establishing the “what” would be triangulated with qualitative, establishing the “why” insights from observations and reflections to ascertain which design features, instructional strategies, and AI tool configurations most effectively foster learner engagement and capability. The combination of quantitative and qualitative methods would combine numerical data with descriptive insights to offer a holistic view of learning efficacy (Khojasteh et al., 2025). Action research cycles would be used to adjust lab activities, reconfigure infrastructure, or recalibrate assessment approaches, with succeeding pilot iterations testing these revisions when outcomes fall short of expectations. The cycle initially determined by Walter A. Shewhart and later refined after World War II by W. Edwards Deming, Plan, Do, Check, Act, could be implemented to offer the organization an orderly, repeatable manner to enhance systems, processes, and outcomes over time (Lovitt, 1997). Over time, this cyclical use of pilot findings would help stabilize and validate a transferable AI conceptual laboratory model that ELE ecosystems can adapt to their specific missions and resource profiles. As pilot results amass, they would increasingly strengthen and substantiate a scalable AI laboratory framework that ELE ecosystems could adapt to their distinctive goals and capacities.

### **5.8 Structured Taxonomy of Instructional Materials**

This taxonomy offers a structured framework for categorizing instructional materials used within AI-enhanced or digital learning environments. Its purpose is to ensure alignment between learning objectives, content type, and assessment strategy while responding to the evolving demands of data-driven education (Bradley, 2021). Structured learning resources

for usage could include core learning content, demonstration and modeling resources, interactive practice environments, performance support tools, assessment and feedback mechanisms, collaborative & reflective learning supports, and supplemental enrichment resources.

#### *5.8.1 Core Learning Content*

Core learning content is foundational materials that present concepts and offer central knowledge. Such materials help learners build an effective conceptual framework before employing knowledge through practice or assessment (Bradley, 2021). These materials serve as indispensable references that learners can revisit throughout the course to strengthen comprehension and support mastery of skills. Examples of core learning content include:

- Manuals and scenario-based guides
- Readings and reference texts
- Infographics, diagrams, and concept maps
- Micro-learning modules

After foundational comprehension is established, learners benefit from resources that demonstrate how concepts are applied in realistic contexts.

#### *5.8.2 Demonstration & Modeling Resources*

Demonstration and modeling resources are used to show learners how to accomplish tasks or decipher processes. These resources offer learners guided revelation to professional reasoning and skilled task execution. They close the divide between speculative knowledge and practical application, thereby enabling learners to envision best practices and recurring real-time challenges (Hormazd, 2023). Examples of demonstration and modeling resources include:

- Video lectures and procedural demonstrations
- Annotated examples and worked solutions
- Expert walkthroughs or narrated screen recordings

Building on modeled examples, the next stage emphasizes interactive environments that facilitate experiential learning and applied engagement.

#### *5.8.3 Interactive Practice Environments*

Interactive practice environments are guided spaces where learners apply skills, experiment, or explore AI systems (Hormazd, 2023; Straight, 2024). Interactive practice environments embolden active experimentation, reflection, and problem-solving within controlled, feedback-rich contexts. These spaces foster more in-depth learning by permitting learners to test approaches, analyze outcomes, and rehearse toward mastery without real-world risk. Examples of demonstration and modeling resources include:

- Software simulations
- Virtual sandboxes and exploratory environments
- Branching scenarios or decision-tree activities
- Data dashboards or AI model-interaction tools

As learners transition from practice to application, performance support tools facilitate continued accuracy, efficiency, and decision-making in real-time environments.

#### *5.8.4 Performance Support Tools*

Performance support tools are job-embedded aids that support learners in completing tasks correctly. Performance support tools expand learning past formal instruction by serving as just-in-time resources that strengthen accuracy and consistency in daily tasks. These tools encourage learners to learn with confidence and reduce errors in dynamic or high-stakes environments. Well-crafted tools integrate effortlessly into workflows, stimulating

continuous learning and performance improvement without interrupting productivity (Bradley, 2021). Examples of performance support tools include:

- Checklists and workflow guides
- Job aids and quick-reference cards
- Templates and operator task sheets

As learners apply skills in practice, assessment and feedback mechanisms play a critical role in identifying strengths, addressing gaps, and guiding ongoing development.

#### *5.8.5 Assessment & Feedback Mechanisms*

Assessment & feedback mechanisms are tools that measure comprehension and offer feedback loops (Gašević et al., 2023). Assessment & feedback mechanisms safeguard that learners can assess their progress and identify areas for directed development. Effective feedback systems reinforce the learning cycle by presenting timely, actionable discernments that foster growth and retention (Ifenthaler & Yau, 2023). When affiliated with clear learning objectives, these mechanisms support learners' and instructors' track achievements and inform the next stages of skill development. Examples of assessment & feedback mechanisms include:

- Knowledge checks and quizzes
- Skills assessments or performance tasks
- Rubrics and evaluation criteria
- Automated or AI-generated feedback

As learners interpret feedback and refine their skills, collaborative and reflective supports foster deeper comprehension through discourse, perspective sharing, and reflective practice.

#### *5.8.6 Collaborative & Reflective Learning Supports*

Collaborative and reflective learning supports materials that promote communication, reflection, and shared meaning-making (Burton, 2014). Also, Collaborative and reflective learning supports nurturing dialogue, community building, and critical thinking among learners. These tools urge learners to connect theory to practice through shared experiences and distinct perspectives (Ryan et al., 2021). By incorporating structured reflection and guided interaction, these supports encourage more in-depth insight, comprehending, and sustained engagement in the learning process (Burton, 2014). Examples of collaborative and reflective learning supports include:

- Discussion prompts and forum activities
- Peer-review tasks
- Reflective journals or learning logs
- Facilitator debrief guides

As learners engage in shared reflection, supplemental enrichment resources offer opportunities for individualized exploration and deeper content engagement.

#### *5.8.7 Supplemental Enrichment Resources*

Supplemental enrichment resources are non-compulsory materials that broaden or intensify learning. Supplemental enrichment resources provide learners with opportunities to investigate topics beyond core requirements, championing curiosity and intellectual flexibility. These resources help learners make interdisciplinary connections and relate concepts in innovative or real-world contexts. Supplemental enrichment materials address diverse interests and learning preferences, augmenting motivation and intellectual self-sufficiency when thoughtfully selected (Ryan et al., 2021). Collectively, these structured materials initiate a cohesive learning ecosystem that supports adaptive instruction, measurable skill development, and continuous performance improvement in AI-driven educational settings. Examples of supplemental enrichment resources include:

- Case studies and narrative problem sets
- Curated external links or resource libraries
- Podcasts or audio briefings
- Guest expert videos or interviews

Together, these instructional categories offer the foundational structure for implementing the conceptual AI Learning Lab framework, where experiential learning and assessment are integrated within adaptive, data-rich environments.

The AI Learning Lab should function as an adaptive virtual sandbox engineered to support controlled experimentation within authentic, data-rich environments (Hormazd, 2023). It should be designed to cultivate advanced competencies in algorithmic reasoning, model interpretability, and ethical decision-making. The environment provided a secure framework for iterative learning and performance evaluation. Building on the established use of sandbox simulations in cybersecurity education, this implementation expands the paradigm toward interdisciplinary AI proficiency, encompassing machine learning operations, bias mitigation, and governance analysis. The distinguishing feature of such contemporary environments lies not in their technical infrastructure, but in their pedagogical intent (i.e., to operationalize experiential learning through cycles of observation, feedback, and refinement consistent), with andragogical principles (i.e., self-directed learning, practical problem orientation, and immediate application of knowledge) as articulated by the father of adult learning Malcolm Knowles (1970; 1975; 1980).

This approach also aligns with constructivist and experiential learning theories (Kolb, 1984), which emphasize knowledge construction through active engagement, reflection, and iterative application within authentic problem contexts. In Kolb's 4 steps experiential learning theory (1984), learning progresses through a cyclical process of (a) concrete experience, (b) reflective observation, (c) abstract conceptualization - organizing the experience into a comprehension of the world, and (d) active experimentation - endeavoring to apply these experiences in life, thereby offering a structured lens for designing iterative AI lab activities (Svinicki & Dixon, 1987). System logs should be designed to systematically record engagement behaviors, task performance, and instructional variations, while AI-driven analytics aggregate these data to assess learning efficacy and inform continuous instructional optimization.

### ***5.9 Implementation Integrity and Contextual Challenges***

The data shows that consistency across the learning offers learners a coherent point of contact (Carlos et al., 2023). Implementation fidelity may be supported through adherence checks, responsive adjustments, and clear documentation of instructional deviations. Effective implementation of the AI Learning Lab requires proactive planning for operational mishaps, including spatial disruptions, technology failures, and scheduling conflicts (Myeka, 2025). Anticipatory strategies (i.e., identifying contingency spaces, instituting redundant access to core systems, and preparing low-tech or discussion-based contingency activities) to help preserve instructional continuity and learning quality when disruptions occur (Denton & Simmons, 2021). Openly articulated contingency protocols, communicated in advance to facilitators and support staff, additionally diminish cognitive load during incidents and enable rapid, coordinated responses that protect implementation fidelity and learner engagement (Waters & Johnstone, 2022).

#### ***5.9.1 Constraint One: Spatial Reallocation***

In AI Learning Lab implementations, facility scheduling conflicts could necessitate rapid spatial reallocation. Facilitators should identify other spaces with analogous technological infrastructure in advance and develop procedures for transitioning learners with minimal

interruption. Even when relocation proceeds smoothly, planning should account for the potential impact of reallocation disruptions on learner focus, logistical flow, and group cohesion (Waters & Johnstone, 2022).

### *5.9.2 Constraint Two: Sandbox Instability*

Periodic sandbox downtime due to software updates, interface revisions, or system maintenance is similarly foreseeable (Dautov et al., 2025). During such intervals, facilitators can preserve instructional continuity by shifting to theoretically oriented discussion, concept-based assessment, and peer-led analysis that reinforce core learning objectives. These adaptations highlight the need for resilient and flexible learning environments. The continued integrity of AI Learning Lab implementation depends upon the careful alignment of instructional reliability, infrastructural constancy, and adaptive facilitation strategies. Proactive contingency planning and distinctly articulated operational protocols support instructional fidelity and sustained learner engagement under conditions of variability. Together, these practices introduce the AI Learning Lab as a model of adaptive stability, demonstrating applicable integration of technological innovation within complex educational environments.

## **6. Literature Review**

### ***6.1 Evolution of Artificial Intelligence Education***

Digital security education changed from teacher-centered instruction to hands-on environments that engage learners in real sociotechnical systems (Kasneji et al., 2023) over the past twenty years. Early courses often relied on static (lecture-centric education) and abstract discussions of risks, threats, and controls, which were deemed insufficient for preparing students to handle data-driven, AI-enabled attack surfaces and fast-changing adversarial tactics (Burrell, 2019; National Security Commission on Artificial Intelligence, 2021). Also, Mukherjee et al. (20204) posited that, notwithstanding technological improvements such as virtual classrooms and remote labs, many higher-education cybersecurity programs failed to address the root causes of the skills gap, due to relying on established, theory-centric models that lack holistic, context-aware, and applied learning components. As AI, automation, and large-scale analytics become entrenched in offensive and defensive cyber operations, there is a mounting acknowledgment that forthcoming curricula must center experiential encounters with AI tools, models, and decision workflows rather than simply treat AI as a nonconcrete append to prevailing content. Offensive cyber operations (OCO) actions, proactive, public-facing, and often classified, are designed to disrupt, degrade, deny, manipulate, or destroy an adversary's information systems or digital infrastructure (U.S. Government Accountability Office [GAO] - Cyberspace Operations Report, 2025, p.5). Defensive cyber operations (DCO), protective and inward-facing, are actions focused on protecting, detecting, and responding to threats targeting one's own systems (U.S. Government Accountability Office [GAO] - Cyberspace Operations Report, 2025, p.5).

As given by the National Security Commission on Artificial Intelligence (2021) and Mukherjee et al. (2024), traditional instruction has exposed constraints in preparing learners for AI-intensive threat landscapes. This AI conceptual study positions AI-enabled laboratory environments as a primary vehicle for future learning, supporting conceptual understanding, reasoning, and adaptive engagement (Dwivedi & Joshi, 2021). In this proposed model, AI security labs would not just copy conventional attack-and-defense scenarios (ISC2, 2024), but rather position learners in replicated ecosystems where AI systems participate in detection, decision-making, and response. Inside such environments, learners would cross-examine, interrogate, and configure AI models, investigate

vulnerabilities in data pipelines and model behavior, and iteratively test mitigation strategies in a controlled, nonetheless genuinely convincing context (Fong et al., 2022). Such AI-focused laboratories are conceived to modify learning from passive reception of AI concepts toward active engagement with AI as a vigorous, dynamic, fallible, and configurable actor in socio-technical security systems.

### ***6.2 Best Practices in AI Laboratory Design***

In this AI conceptual study, operative and applicable AI laboratory environments are intended as purposely designed socio-technical spaces that order modularity, scalability, and continuous adaptation to rapidly evolving AI tools and practices. The labs should serve as settings in which learners are able to participate in challenging analytical inquiry and complex reasoning actions. At the start, organizers must establish well-defined objectives (Langas, 2022), an inclusive strategic vision (Simard & Aubry, 2025), a well-defined operational model (Siwach et al., 2025), demarcated governance and accountability structures (Pospieszna & Hoffmann, 2026), means planning (Dubey et al., 2024), and cultural and organizational norms, risk and contingency planning (Şahin, 2026), cross-stakeholder agreement (Mitteer et al., 2020), in addition to assessment and augmentation mechanisms (Xie et al., 2026) for the AI labs. As opposed to treating AI labs as fixed installations, this concept proposes labs as configurable platforms that can support altering instructional goals, levels of AI literacy, in addition to institutional and organizational constraints over time. These actions will set the direction for technological advancements, drive the development process, and safeguard alignment with educational goals, along with nurturing a culture of innovation. An AI lab should be more than a technological hub.

### ***6.3 AI Conceptual Curriculum Integration and Instructional Alignment***

Useful AI conceptual laboratories do not function as isolated and out-of-the-way instructional components; more exactly, they function as multidisciplinary systems and frameworks, deep-seated curricula, organizational learning systems, and workforce development corridors. The value of these AI conceptual laboratories emerges through premeditated alignment with intangible learning outcomes that extend past technical proficiency to involve engaging in model analysis, data, ethics, and decision-making in AI-enabled environments. As given by Luckin et al. (2016) and Holmes et al. (2022), AI in education must be situated within learner-centered instructional frameworks that encourage comprehension of how AI systems operate, beyond merely the manner in which they are used. Instructional positioning likewise necessitates thoughtful coordination amongst facilitators, instructional designers, and organizational stakeholders to safeguard that AI lab undertakings strengthen conceptual comprehensions while revealing real-world sociotechnical settings. As stated by Miao et al (2021), AI education's obligation is to integrate ethical reasoning, governance awareness, and human-centered design principles together with technical capabilities. Thus, AI conceptual laboratories should entrench interdisciplinary scenarios that not simply pull from diverse domains but correspondingly assimilate AI reasoning with organizational policy, cybersecurity considerations, and societal impact, permitting learners to steer and evaluate complex sociotechnical systems.

Additionally, alignment with workforce frameworks has to exist past task-based competencies toward adaptive know-how. The World Economic Forum (2023) offers that future-focused learners necessitate not just technical skills but evaluative and reflective thinking, systems analysis, and the proficiency to evaluate AI yields in undefined conditions. AI conceptual laboratories, therefore, serve as springboards for nurturing these capabilities through iterative, reflective, and scenario-based learning events that bond curriculum, practice, and sprouting professional expectancies.

#### ***6.4 AI Conceptual Challenges and Critiques***

Notwithstanding the mounting prominence of AI in education, momentous confronts persevere in the design, implementation, and sustainability of AI conceptual laboratories. One of the primary encounters comprises the jagged dispersal of resources, involving access to computational infrastructure, high-quality datasets, and a workforce with know-how in AI systems and instructional design. As given by Zawacki-Richter et al. (2019), differences in institutional capacity can restrict the adeptness to implement consequential AI learning experiences, predominantly in under-resourced environments.

Apart from infrastructure, a calamitous limitation exists in the tendency to blur interaction with AI tools with conceptual comprehension. A mounting body of prevailing work accentuates tool usage (Holmes et al., 2022) or model deployment without satisfactorily taking into account preliminary concepts such as uncertainty, bias, interpretability, and system limitations (Ng et al., 2021). No specific number is given; however, Zawacki-Richter (2019) referred to the number as a substantial portion of existing research. On the whole, this difference risks yielding learners who can operate AI systems but have a void of the analytical capacity to evaluate their outputs or propositions in real-world contexts.

Facilitator readiness signifies another significant constraint. Operational AI conceptual laboratories necessitate educators who can effectively bridge technical knowledge with pedagogical and andragogical strategies, guiding learners through multifaceted reasoning processes as opposed to just procedural tasks. Nevertheless, research suggests that numerous instructors are void of formal training in AI or lack experience facilitating experiential, concept-driven learning environments (Miao et al., 2021). Prolonged investment in facilitator advancement is fundamental for fruitful implementation.

Ethical and governance concerns further obfuscate AI lab design. AI systems fundamentally raise concerns related to fairness, transparency, accountability, and data privacy. Incorporating these aspects into laboratory experiences entails deliberate instructional design and institutional commitment. As documented by Floridi et al. (2018), responsible AI education must shift past technical training and education to embrace ethical reflection and governance literacy, safeguarding that learners can analytically engage with the societal ramifications of AI technologies.

Last, the fast evolution of AI technologies offers a challenge for curricular stability and long-term planning. AI conceptual laboratories must be devised as malleable systems capable of developing together with budding tools, methodologies, and regulatory prospects. This requirement strengthens the significance of modular, iterative frameworks that support incessant refinement and responsiveness within ELE ecosystems.

#### ***6.5 Synthesis***

The literature increasingly frames AI laboratories as transformative components of contemporary educational ecosystems, extending beyond technical environments to function as sociotechnical platforms that foster conceptual understanding, reasoning, and adaptive learning. Within this given framework, AI conceptual laboratories range beyond the application of tools to nurture a deeper encounter with data, models, and decision-making processes in complicated environments.

Their efficiency is contingent on the purposeful integration of organized operational models that delineate roles, workflows, and communication pathways, together with explicitly expressed governance and accountability mechanisms that safeguard ethical, transparent, and responsible utilization of AI systems.

Continued functionality additionally necessitates thorough resource planning, comprising staffing, infrastructure, and technological capacity, along with the cultivation of

organizational norms that accentuate collaboration, ethical awareness, and continuous learning. Moreover, AI laboratories are required to include risk and contingency planning for the purpose of addressing reservations connected with progressing technologies, data integrity, and system limitations. Alignment amongst institutional stakeholders, including leadership, facilitators, and external partners, is vital to preserving coherence between strategic objectives and instructional practice. Finally, the insertion of continuing evaluation and improvement mechanisms, sustained by feedback loops and performance metrics, safeguards that AI conceptual laboratories remain adaptive, responsive, and aligned with evolving educational and technological demands.

### 7. Conceptual Frameworks for Reframing

This study proposes the AI Conceptual Learning Framework, a socio-technical model that explains how AI-enabled learning environments support the development of conceptual understanding, ethical reasoning, and adaptive decision-making within ELE ecosystems. The framework integrates the AI literacy framework (Long & Magerko, 2020) with six complementary theoretical perspectives, including sociotechnical systems theory, actor-network theory, socio-materiality, institutional theory, social constructionism, and situated learning. Together, these perspectives conceptualize AI learning environments as integrated socio-technical systems in which human, technological, and organizational elements interact to shape learning outcomes. Within this context, AI-enabled laboratories are reframed as environments that cultivate analytical reasoning, ethical awareness, and system-level understanding of AI technologies. As illustrated in Figure 1, the AICLF conceptualizes AI learning as a dynamic, iterative system in which core dimensions interact within broader sociotechnical contexts to support learner development.



Figure 1. The AI Conceptual Learning Framework

Note. The AI Conceptual Learning Framework (AICLF) is developed by the author, Dr. S. L. Burton, as a Sociotechnical Learning Ecosystem. The AICLF conceptualizes AI learning as a dynamic, iterative process in which learners develop conceptual understanding, ethical reasoning, and adaptive decision-making through the interaction of five interconnected conceptual dimensions: conceptual foundations, sociotechnical integration, scenario-based learning, adaptive learning environments, and feedback and iteration. These dimensions operate within broader educational, technological, and sustainability contexts, forming an integrated sociotechnical learning ecosystem.

The AI literacy framework is appropriate for this study because it was developed specifically for AI education. It emphasizes learners’ ability to understand models, data, limitations, and societal implications of AI systems (Long & Magerko, 2020). This aligns directly with the goals of the AICLF, which prioritizes conceptual comprehension, interpretability, bias awareness, and informed decision-making. Accordingly, this study adopts the AI literacy framework to position AI laboratories as environments in which learners develop the capacity to critically evaluate and reason about AI systems.

Sociotechnical systems theory was developed by Trist and Emery in the 1950s. It offers a foundational way to understand AI laboratories as more than technical systems. These environments also include organizational structures, governance processes, and human interactions (Baxter & Sommerville, 2011). This perspective underscores that effective AI learning environments must account for the interdependence of technological, social, and institutional factors. Intrinsically, the framework supports considerations of governance, stakeholder engagement, and real-world integration, reinforcing the role of AI laboratories as complex, adaptive systems embedded within broader educational and societal contexts. The framework, developed by Dr. S. L. Burton, integrates modular design principles, virtualized learning environments, and continuous feedback mechanisms to support responsiveness to evolving technological contexts and learning needs. Each component of the framework is aligned with Kolb’s experiential learning cycle, reinforcing iterative knowledge construction and reflective practice (see Table 1).

Table 1. Alignment of AICLF Dimensions with Kolb’s Experiential Learning Cycle

<b>AI Conceptual Learning Framework (AICLF)</b>	<b>AI Conceptual Learning Dimension</b>
Conceptual Foundations (AI literacy, models, limitations)	Development of foundational AI understanding, including model behavior, data dependencies, and epistemic limitations
Sociotechnical Integration (ethics, governance, cybersecurity)	Integration of AI within broader sociotechnical systems, emphasizing ethical reasoning, governance awareness, and risk-informed decision-making.”
Scenario-Based Learning (real-world problems)	Application of interdisciplinary reasoning through scenario-based problem spaces that simulate real-world complexity, uncertainty, and trade-offs
Adaptive Infrastructure	Adaptive learning environments that dynamically support learner interaction, exploration, and iterative knowledge construction across diverse contexts.
Feedback and Iteration (continuous assessment, reflective practice, and adaptive learning refinement)	Continuous feedback loops that support metacognition, reflective learning, and iterative refinement of learner understanding and system design

Note. The AICLF dimensions are conceptually aligned with AI learning dimensions to support the development of higher-order cognitive, ethical, and adaptive competencies within AI-enabled environments. This structure prioritizes conceptual understanding, sociotechnical integration, and iterative learning, positioning AI education as a process of reasoning and reflection rather than task-based or tool-centric proficiency.

The AI Conceptual Learning Framework (AICLF) is well-matched for AI-enabled learning environments because it balances structural coherence with the flexibility required to accommodate evolving AI knowledge domains and diverse educational contexts. As opposed to stressing procedural or tool-based proficiency, the framework prioritizes the development of conceptual comprehension, analytical reasoning, and the capacity to

evaluate AI systems within complex sociotechnical settings. This orientation enables institutions to align AI learning environments with their specific instructional goals while maintaining consistency with emerging standards in AI education.

The framework further recognizes that its effectiveness is shaped by contextual factors, including institutional capacity, strategic priorities, and learner diversity. Accordingly, AICLF is designed to be adaptive, allowing institutions to tailor its dimensions to varying levels of AI literacy, facilitator expertise, and resource availability.

From a conceptual perspective, implementation considerations extend past technical infrastructure to include instructional design, organizational structures, human expertise, and data-informed feedback systems. These elements, jointly, support the creation of integrated learning environments in which learners engage with AI systems, interpret outputs, and refine their understanding through iterative and reflective processes. Rather than prescribing specific technologies or platforms, the framework emphasizes alignment between learning objectives, sociotechnical context, and adaptive feedback mechanisms to support meaningful and sustainable AI learning experiences.

## **8. AI Conceptual Framework Challenges and Critiques**

Despite the increasing emphasis on artificial intelligence within educational environments, several conceptual and structural challenges continue to influence the design and sustainability of AI conceptual laboratories. A central concern involves the dependence on facilitator expertise capable of integrating technical AI knowledge with pedagogical and andragogical practices (Burton, 2014). AI conceptual laboratories require facilitators who can guide learners beyond procedural interaction with tools toward deeper reasoning about models, data behavior, uncertainty, and system limitations. Without sustained investment in facilitator development, the effectiveness of concept-driven AI learning environments may be constrained (Miao et al., 2021; Holmes et al., 2022).

Another critical challenge relates to disparities in institutional capacity. Differences in access to computational resources, quality datasets, and specialized expertise are important factors. Variations in technology, data, and human infrastructure can strongly affect AI conceptual learning depth and quality (Zawacki-Richter et al., 2019). These disparities emphasize the need for adaptable frameworks that support equitable implementation across different educational contexts.

A further limitation emerges in the tendency to equate exposure to AI tools with conceptual understanding. A substantial portion of existing initiatives emphasizes model deployment or tool interaction while insufficiently addressing foundational concepts such as bias, interpretability, uncertainty, and ethical implications (Ng et al., 2021; UNESCO, 2025). This misalignment may result in learners who can operate AI systems but lack the analytical capacity to critically evaluate outputs or apply reasoning in complex, real-world scenarios.

Ethical and governance considerations introduce additional complexity. AI systems consistently raise concerns related to fairness, transparency, accountability, and data privacy. Embedding these dimensions within laboratory design requires intentional integration of sociotechnical perspectives, ensuring that learners critically examine not only how AI systems function, but also their broader organizational and societal consequences (Floridi et al., 2018).

Finally, the rapid evolution of AI technologies presents ongoing challenges for curricular stability and long-term planning. AI conceptual laboratories must be designed as adaptive, modular environments capable of evolving alongside emerging tools, regulatory expectations, and workforce demands. This reinforces the importance of flexible frameworks that support continuous refinement, interdisciplinary integration, and sustained alignment with the dynamic nature of AI-enabled ecosystems.

## 9. Originality and Contribution of the Text

This text's strongest originality claim is not that it recommends "best practices" for AI labs, but that it theorizes how an AI-focused laboratory becomes a durable learning infrastructure that links conceptual AI understanding to situated performance in cyber-relevant environments. Recent syntheses of AI in higher education show rapid growth in "AI applications" work, alongside a recurring weakness: pedagogical rationales and educator-facing design logics are often under-specified relative to technical capability narratives (Zawacki-Richter et al., 2019). This text addresses this gap by treating the lab as an integrated system for learning, assessment, governance, and iteration, anchored in an explicit competency frame for "AI literacy" rather than ad hoc tool exposure (Long & Magerko, 2020). It also aligns that competency orientation with experiential learning logics, where learning is conceptualized as a cycle of action and reflection that can be intentionally designed into lab activities (Kolb, 1984).

A second, more novel conceptual move is the text's implicit shift in unit of analysis from "training intervention" to "socio-technical learning system." Socio-technical design scholarship has long argued that system performance and human practice co-evolve, and that design work must bridge organizational change and technical development, yet this stance is often invoked rhetorically rather than operationalized in implementable frameworks (Baxter & Sommerville, 2011). The proposed modular, adaptive laboratory framework advances this literature in an education and workforce-readiness setting by specifying interacting dimensions (conceptual foundations, sociotechnical integration, scenario-based reasoning, adaptive infrastructure, feedback and iteration, as described in the text) and by treating iteration as constitutive rather than a post-hoc evaluation step. This is a theoretical contribution insofar as it proposes a mechanism-based account: modular technical infrastructure plus structured learning design plus governance and assessment loops jointly produce adaptability, transfer, and resilience under evolving threats (interpretive suggestion, since the exact mechanism tests depend on how the text's empirical materials are ultimately presented).

Third, the text contributes by foregrounding adult learning and heterogeneous learner populations as design constraints that reshape what "effective AI lab learning" means. In adult learning theory, learners' self-direction and problem orientation motivate designs that privilege authentic tasks, immediate applicability, and shared responsibility for learning (Knowles, 1970). In this text, this emphasis strengthens novelty because it reframes AI lab design as a problem of enabling competence trajectories across academic and professional contexts, not merely optimizing course delivery. Put differently, the contribution is a portable conceptual architecture for building AI capability ecosystems that can endure tool and threat volatility, since it treats technical change as expected and designs the lab to absorb that change through modularity and feedback (interpretive suggestion).

## 10. Conceptual Insights

Observations from illustrative and pilot-informed environments suggest that learners may demonstrate increased engagement and improved conceptual reasoning when interacting with AI-enabled scenarios. These observations reflect patterns in which learners engage more actively when presented with dynamic, scenario-based challenges that require interpretation and evaluation of AI-generated outputs. Such interactions align with experiential learning perspectives, where knowledge develops through active engagement and reflection (Kolb, 1984).

Engagement patterns indicate that learners may sustain participation when instructional environments incorporate interactive elements, real-world contexts, and opportunities for exploration. These environments appear to support curiosity, persistence,

and deeper involvement in the learning process. This perspective aligns with sociotechnical contexts where human interaction with AI systems shapes understanding and decision-making (Floridi et al., 2018).

Conceptual reasoning development may be supported through exposure to AI-enabled tools that require learners to interpret outputs, assess implications, and make informed decisions. These interactions encourage movement beyond procedural knowledge toward structured understanding and knowledge application. This approach reflects principles of knowledge management that emphasize interpretation and contextualization of information (Dodla & Jones, 2023).

Adaptive learning behaviors may also emerge within scenario-based environments, where learners refine their thinking, revisit assumptions, and adjust their approaches in response to evolving conditions. These patterns highlight the importance of human judgment, decision-making, and behavioral factors in AI-supported environments. This reinforces the role of human-centered considerations in reducing risk and improving outcomes (Jones, 2024).

Collectively, these insights suggest that structured, interactive learning environments may support the development of flexible, context-aware reasoning skills. These environments may help learners engage with complex AI systems and evolving technological demands. This aligns with broader workforce readiness needs in artificial intelligence and cybersecurity domains (National Security Commission on Artificial Intelligence, 2021; Burrell, 2019).

## 11. Discussion

The conceptual insights presented in this study highlight the potential of structured, AI-enabled learning environments to support deeper engagement and the development of applied reasoning skills. These environments emphasize interaction, reflection, and contextual understanding, aligning with experiential learning theory and constructivist perspectives (Kolb, 1984). Learners may benefit from engaging with scenarios that require interpretation, evaluation, and decision-making within dynamic contexts.

These observations, while not derived from formal empirical testing, provide directional insight into how conceptual laboratory environments may support applied understanding and adaptive reasoning. Such environments reflect sociotechnical systems in which human interaction with AI technologies shapes learning processes and decision-making outcomes (Floridi et al., 2018). This perspective reinforces the importance of integrating technical and human-centered considerations within AI education.

The patterns identified in this study can be interpreted through the AICLF, where interconnected conceptual dimensions such as foundational understanding, sociotechnical contextualization, and adaptive learning processes collectively support learner development. These dimensions encourage movement beyond procedural knowledge toward deeper conceptual comprehension and applied reasoning. This aligns with knowledge management principles that emphasize interpretation, contextualization, and the practical use of information (Dodla & Jones, 2023). From a broader perspective, the framework contributes to ongoing discussions regarding artificial intelligence literacy and workforce readiness by emphasizing conceptual understanding in addition to technical proficiency. Human factors, including judgment, decision-making, and behavioral influences, remain critical in AI-supported environments and influence how systems are interpreted and applied (Jones, 2024). Instructional models that incorporate these elements may better prepare learners to engage with complex and evolving technological systems.

The implications of this framework extend to educational design and professional training, where structured and adaptive learning environments may support the development of flexible and context-aware reasoning skills. These environments may help

bridge gaps between theoretical knowledge and applied practice within artificial intelligence and cybersecurity domains. This aligns with broader workforce development needs identified in national and academic discussions on emerging technologies (National Security Commission on Artificial Intelligence, 2021; Burrell, 2019).

## 12. Practical Implications

The AI Conceptual Learning Framework (AICLF) offers guidance for the design of instructional environments that emphasize conceptual understanding, reasoning, and engagement with AI-enabled systems. Educational programs may incorporate scenario-based learning, interactive tools, and reflective activities to support deeper comprehension and application of AI concepts. These approaches align with experiential learning principles that emphasize active engagement and contextualized knowledge development (Kolb, 1984).

The framework also has implications for workforce development, where organizations may adopt structured learning environments that integrate technical knowledge with sociotechnical awareness. Training initiatives that emphasize interpretation, decision-making, and contextual understanding may better prepare individuals to operate within complex AI-driven systems. This perspective aligns with broader workforce readiness efforts that emphasize the need for adaptable and conceptually grounded skill development (National Security Commission on Artificial Intelligence, 2021; Burrell, 2019).

From a design perspective, the AICLF supports the development of flexible and scalable learning environments that can be adapted across educational and professional contexts. These environments may incorporate feedback mechanisms, iterative learning processes, and opportunities for continuous improvement. Such approaches reflect knowledge management principles that emphasize the interpretation and application of information within evolving contexts (Dodla & Jones, 2023).

## 13. Conclusions

This study presents the AI Conceptual Learning Framework (AICLF) as a conceptual contribution to artificial intelligence education, emphasizing structured reasoning, sociotechnical awareness, and adaptive learning processes. The framework addresses limitations in traditional instructional approaches by prioritizing conceptual understanding and applied reasoning within AI-enabled environments. This orientation supports the development of learners who can interpret, evaluate, and engage with complex AI systems.

The AICLF provides a flexible and scalable model that may inform instructional design, workforce development strategies, and artificial intelligence literacy initiatives across diverse contexts. By organizing learning around interconnected conceptual dimensions, the framework supports engagement, reflection, and context-aware decision-making. These elements align with sociotechnical perspectives that recognize the interaction between human behavior and technological systems (Floridi et al., 2018).

While this study is conceptual in nature, it establishes a foundation for future research that may explore the application and evaluation of the framework in practice. Further investigation may examine how structured learning environments influence conceptual reasoning, engagement, and adaptability across different domains. Such efforts may contribute to ongoing discussions regarding the development of effective and sustainable approaches to artificial intelligence education (Jones, 2024).

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