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A Multi-Scale AI Framework for Informal STEM Learning: Paramorphic Digital Twins for Underserved Communities

Khazar Gorji[1] & Reza SaeedKandezy[2]

[1] Jeanine Rainbolt College of Education, University of Oklahoma, USA

[2] School of Electrical and Computer engineering, University of Oklahoma, USA

Correspondence: Reza SaeedKandezy, Assistant Professor, School of Electrical and Computer engineering, University of Oklahoma, USA.

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Abstract

This research presents a novel multi-scale paramorphic kernel learning framework (MPKLA) that is designed to enable autonomous, context-adaptive STEM learning for electrical and renewable energy topics. By employing distributed multi-agent kernel cores, recursive kernel reweighting, and entropy-guided abstraction modulation, this system dynamically adapts instructional content and sequencing based on the specific cognitive state of individual learners. Concept learning history is maintained in persistent memory buffers to facilitate individualized reinforcement and remediation in asynchronous, informal environments. Grounded in a physics-informed knowledge graph, the system offers epistemic coherence and domain consistency at multiple levels of abstraction. Evaluated across multiple, underrepresented student groups in community and laboratory implementations, MPKLA demonstrated a 45% rate increase in concept recall, a 3.2× improvement in student-led project completion, and sustained 68% learner interest over 12 weeks. These results emphasize the effectiveness of this architecture in delivering scalable, culturally sensitive, and high-fidelity STEM education without human interaction. The paper also discusses system deployment, statistical validation, and longitudinal deployment settings, informal education problem-solving, cultural adaptation, and learning assessment. MPKLA provides an extensible blueprint for inclusive, technology-driven workforce development in clean energy sectors, fueling inclusive participation and expertise in advanced technical fields.

Keywords: Multi-Scale Kernel Learning, Digital Twin, STEM Instruction, Cognitive Modulation

1. Introduction

1.1 Societal Context and Motivation

Quality access to STEM education remains disproportionately limited in geographically isolated, economically disadvantaged, and institutionally under-resourced communities, resulting in long-standing workforce readiness gaps, technological literacy gaps, and socio-economic mobility gaps. Structural barriers, including substandard instructional infrastructure, limited access to specialist teachers, and rigid curricular frameworks, impede the scalable diffusion of knowledge and skill acquisition in such communities. These constraints not only continue to reinforce academic disparity but also limit national innovation potential by distancing students of different demographic and geographic backgrounds from significant participation in future science and engineering areas.

Informal learning settings, such as family-driven activities, family-driven programs, and self-paced learning environments, are significantly hindered by the lack of a scalable, expert-level teaching infrastructure capable of delivering domain-specific, high-fidelity content. Such settings are typically bereft of access to credentialed instructors, pedagogical systems, or adaptive frameworks for mentoring and hence have disjointed learning trajectories and shallow conceptualizations. The lack of cognitively intelligent instructional support in these environments undermines efforts to democratize STEM learning for marginalized populations that require adaptable, situated, and culturally responsive pathways to technical expertise and social mobility.

Students from disadvantaged communities are confronted with a set of cognitive, cultural, and systemic barriers that, in combination, suffocate access to high-level technical training. Cognitively, typical instruction is often unable to accommodate diverse learning styles, knowledge deficits, and non-linear learning trajectories. Culturally, standardized curricula usually overlook local contexts, languages, and community values, thereby reducing relevance and learner interest. Systemically, structural inequities—such as under-resourced schools, limited digital infrastructure, and exclusion from policy-influencing forums—amplify educational disenfranchisement. These overlapping restrictions create chronic discontinuities in the learning process of high-order STEM competencies, with uneven effects on the engagement of marginalized groups in innovative industries.

1.2 Objective and Scope of Research

This research presents a paramorphic digital twin AI system that aims to mimic expert-level instruction behavior at various cognitive and representational levels. Pedagogical reasoning in the system is emulated through a multi-layered, domain-specific architecture, specifically the Multi-Scale Paramorphic Kernel Learning Architecture, which dynamically adapts based on learner engagement, level of abstraction, and concept development. With the integration of multi-resolution feedback, real-time kernel adjustment, and instruction logic that is sensitive to context, the architecture achieves scalable, self-managed teaching capabilities—virtually substituting for human expertise in low-resource environments and enabling precision-aligned knowledge transfer across heterogeneous, informal, and decentralized learning environments.

The proposed system is intended to be best suited for operation in low-resource, culturally diverse, and structurally decentralized learning environments for which conventional models of instruction are intractable. Its low-compute resource footprint, offline-first design, and modular architecture ensure deployment in bandwidth-constrained or infrastructure-deprived regions. Further, its adaptive content delivery mechanisms are informed by culturally sensitive paradigms to facilitate semantic localization, language personalization, and accommodation of community epistemologies. This multi-stage process ensures that adaptive content dissemination is not only linguistically customized but also deeply calibrated to the cultural fabric and knowledge frameworks of diverse learning communities, thereby making it maximally relevant, stimulating, and equitably accessible to STEM education. Such configurability enables the system to bridge pedagogical gaps in marginalized environments while maintaining instructional toughness, conceptual integrity, and scalability across different populations of learners.

The architecture in this study is specifically designed to enable autonomous, context-sensitive instruction in electrical and renewable energy subjects with high-fidelity, standards-matched content without the presence of humans by providing IEEE/IEC/DOE standard instruction with:

- real-time ≥1 Hz feedback loops,
- <500 ms decision latency,
- ≥90% error remediation accuracy,
- ≥3-channel multi-modal learner input integration,
- <1 second abstraction switching latency,
- ≥95% content localization accuracy,
- ≥98% conceptual accuracy,
- ≥0.8 content modularity reuse factor,
- ≥99% offline uptime,
- ≤1 GB RAM and 500 MHz processor hardware requirements,
- and <5-minute asynchronous data synchronization latency.

This architecture enables the incorporation of localized content, application-focused modeling, and interactive simulations that can be continuously updated to reflect local energy infrastructures, cultural practices, and labor requirements through a modular content management system with embedded dynamic semantic mapping and real-time data intake pipelines that collectively enable contextual updates to occur continuously. This ensures efficient transfer of advanced technical skills needed to make the transition, particularly in underrepresented and infrastructure-poor communities.

1.3 Thesis and Core Contribution

The system employs a paramorphic approach centered on multi-scale kernel modeling and control theory to represent expert pedagogical action accurately. Informal, lab-based, and community-integrated validations establish the system's capacity to maintain conceptual coherence, instructional coherence, and accurately represent expert pedagogical actions profiles and infrastructure constraints. Its resilience enables the targeted, stand-alone delivery of technical content, making it a revolutionary tool for building equitable STEM capacity among historically underserved populations.

The digital twin architecture is designed to enable recursive abstraction reduction, structurally deconstructing complex STEM abstractions at progressively lower-level representations without loss of structural integrity or domain fidelity. This mechanism facilitates the development of personalized learning trajectories that adapt to individual learners' prior knowledge, pace, and context, optimizing concept understanding and long-term retention across varied learning histories.

2. Theoretical Framework

2.1 Paramorphic Intelligence Model

The proposed framework emulates layered expert cognition using the application of self-similar transformation kernels that encode hierarchical reasoning structures in conceptual, analytical, and procedural spaces. The kernels themselves are recursive operators that abstract the invariant patterns of logic underlying expert instruction, enabling the scalable decomposability and recomposability of advanced knowledge constructions. This self-similarity enables pedagogical decision-making to be simulated at varying cognitive resolutions, thereby facilitating the system's ability to dynamically map teaching content to the learner's level of abstraction. This provides precision-guided knowledge transfer and adaptive conceptual reinforcement.

The framework models learner knowledge and instructional adaptation through a hierarchy of scale-specific kernel functions, paramorphic transformations, and feedback-driven weight adjustments, enabling multi-resolution, personalized STEM education. Let $K_s^{(t)}: \mathcal{X}_s \times \mathcal{X}_s \to \mathbb{R}$ denotes a positive-definite kernel function representing the learner's knowledge state at the abstraction scale $s \in \{1, \dots, S\}$ and t. The input space $\mathcal{X}_s$ corresponds to domain-specific representations at scale s, including conceptual, mathematical, and procedural levels. Paramorphic transformation operators govern the transition between scales Φ_s, which recursively generates kernels at finer or coarser granularity:

$$K_{s+1}^{(t)} = \Phi_s\left(K_s^{(t)}\right) = W_s^{(t)}.\mathcal{T}_s\left(K_s^{(t)}\right) \tag{1}$$

where $\mathcal{T}_s$ is a self-similar transformation ensuring kernel properties are preserved, and $W_s^{(t)} \in \mathbb{R}$ is an adaptive weight tracking learner-specific reweighting based on feedback at scale. Adaptive kernel weights are dynamically updated through feedback signals $F^{(T)}$ which summarize learner performance metrics, engagement, and cognitive signals:

$$W_s^{(t)} = W_s^{(t)} + \eta_s . f_s\left(F^s, K_s^{(t)}\right) \tag{2}$$

$\mathrm{W}_s^{(t)} = \mathrm{W}_s^{(t)} + \eta_s . \mathrm{f}_s\left(\mathrm{F}^s, \mathrm{K}_s^{(t)}\right)$with learning rate $\eta_s > 0$ and feedback function f_s mapping observed learner signals to kernel weight updates.

Instructional abstraction is modulated using entropy measures $H_s^{(t)}$ computed over the normalized kernel-induced distribution $p_s^{(t)}(x)$:

$$H_s^{(t)} = -\sum_{x \in \mathcal{X}_s} p_s^{(t)}(x) \log p_s^{(t)}(x). \tag{3}$$

Entropy thresholds θ_s guide scale transitions, enabling dynamic abstraction level switching to optimize cognitive alignment:

If $H_s^{(t)} > \theta_s$, transition to higher abstraction $(s-1)$;

else if $H_s^{(t)} < \theta_s$, transition to lower abstraction $(s+1)$.

The comprehensive learner knowledge state $\mathcal{K}^{(t)}$ conjoins multi-scale kernel representations scaled by relevance factors by scale $\alpha_s^{(t)}$:

$$\mathcal{K}^{(t)} = \sum_{s=1}^{S} \alpha_s^{(t)} K_s^{(t)} \tag{4}$$

where $\alpha_s^{(t)} \in [0,1]$ are updated based on the cumulative learner interaction history stored in persistent memory buffers.

Mathematically inspired architecture enables precise, adaptive, and personalized learning through recursively optimizing representations of knowledge, dynamically scaling abstraction, and continuously incorporating learner feedback across multiple cognitive scales to enact resilient and scalable STEM education. Such a stratified structure enables the system to deliver instruction with context-sensitive precision, dynamically traversing explanatory modes to match the learner's cognitive abilities while preserving the continuity, coherence, and transferability of technical knowledge along multiple learning paths.

By utilizing embedded diagnostic algorithms, the system continuously infers the learner's understanding level, cognitive load, and optimal level of abstraction, and dynamically adjusts the instructional logic accordingly. This method ensures that every pedagogical shift—whether between concepts, representations, or tasks—is optimally scheduled and semantically congruent with the learner's developing mental model, thereby achieving maximum instructional efficiency, reducing cognitive resistance, and enhancing long-term conceptual understanding. The diagnostic algorithm embedded integrates always-on prediction of the learner's level of comprehension, cognitive load, and best-fit instructional abstraction through analysis of real-time interaction patterns, allowing for dynamic pedagogical adaptation.

Let $\boldsymbol{F}^{(t)} = \{f_1^{(t)}, f_2^{(t)}, \dots, f_m^{(t)}\}$ be a vector of learner feedback features having multiple dimensions observed at time t, including response accuracy, response time, engagement metrics, and error patterns.

The understanding state of the learner $U^{(t)} \in [0,1]$ is modeled as a probabilistic latent variable inferred via a Bayesian update or a recursive filter:

$$P\left(U^{(t)} \middle| \boldsymbol{F}^{(t)}\right) = \frac{P\left(\boldsymbol{F}^{(t)} \middle| U^{(t)}\right) P\left(U^{(t-1)} \middle| \boldsymbol{F}^{(t-1)}\right)}{P\left(\boldsymbol{F}^{(t)} \middle| \boldsymbol{F}^{(1:t-1)}\right)}, \tag{5}$$

This closed-loop diagnostic cycle ensures pedagogical transitions are perfectly timed and closely fitted to maximize instructional efficiency, reduce cognitive resistance, and enhance long-lasting conceptual understanding along the learning path.

2.2 Fractal and Multi-Scale Kernel Dynamics

The system employs recursive kernel reduction as a crucial computational process to facilitate learning convergence across levels of abstraction, progressively increasing instructional coarseness in response to learner actions. With each recursion, the kernel's working bandwidth decreases, enabling step-by-step breakdown of intricate structures into cognitively tractable subcomponents that are contextually pertinent and semantically coherent. Adaptive depth modulation is enabled through this process, allowing the system to transition fluidly between high-level conceptual abstractions and low-level operating details, thereby achieving instructional solutions commensurate with learner ability and optimizing multiscaling knowledge acquisition.

$$D^{(t)} = arg_{d \in \{d_{min}, \dots, d_{max}\}} \min \left| U^{(t)} - S^{(t)} \right| + \lambda . C(d) \tag{1}$$

Where:

$D^{(t)}$: instructional depth level (abstraction scale) at time t

$U^{(t)} \in [0,1]$:learner’s understanding or ability to estimate at time t

$S(d) \in [0,1]$: expected learner ability suitable for abstraction level d

$C(d)$: cognitive complexity cost function associated with depth d

$\lambda > 0$: regularization parameter

The system enables domain-specific content scaling without pedagogical loss by leveraging a modular, ontology-driven architecture that preserves instructional fidelity in the presence of contrasting content complexities and deployment contexts. Each learning module is adaptively mapped to its corresponding conceptual, mathematical, and procedural representations in a way that maintains epistemic consistency as content transitions from introductory to advanced topics. The system's adaptive delivery engine dynamically regulates instructional detail based on learner feedback, as well as domain dependencies, thereby maintaining conceptual coherence, alignment with learning, and pedagogical rigor, regardless of subject depth, extent of instruction, or diversity of learners.

2.3 Epigenetic Feedback Adaptation

The architecture comprises dynamic kernel reweighting for the control of instruction based on learner behavior at the time, enabling continuous pedagogical strategy adaptation to cognitive state, as indicated in Equation 2. As learners interact with content, the system accumulates multidimensional behavioral cues—response timing, error profiles, and transitions in levels of abstraction—to make inferences about learning intent and skill. These cues are used to adjust the weights of instructional kernels that govern content choice, sequence, and representation mode, in such a way that the instructional sequence is both personalized and context-sensitive. This process enhances participation, lessens redundancy, and accelerates convergence to mastery by personalizing the instructional sequence to dynamically changing profiles of each learner.

Content modules are designed to match the sociocultural contexts, language orientation, and epistemological frameworks of diverse learner populations, facilitating instructional fit and completeness. Concurrently, the system eschews linear sequencing inflexibility in favor of adaptive, goal-oriented navigation, enabling learners to tailor their learning to their current knowledge, interests, and performance.

Sample lesson content includes interactive modules on photovoltaic system design, inverter switching behavior, and circuit transient analysis, presented via multimodal interfaces (symbolic equations, procedural simulations, visual schematics). Logged learner interactions, when deployed, demonstrate scaffolded error correction conversations, shifts of abstraction, and immediate feedback loops

3. System Architecture and Implementation

3.1 Digital Twin Structural Design

The architecture consists of multi-agent kernel cores, each of which has been engineered to replicate discrete components of expert instructional reasoning, including concept elaboration, misconception correction, and abstraction alignment. Each agent operates in a coordinated, distributed environment, where each kernel features domain-specific logic, pedagogical heuristics, and cognitive modeling parameters. Through the real-time collaboration of agents and the sharing of information, the system dynamically constructs a pedagogical reaction plan responsive to the learner's profile, making instruction context-sensitive and cognitively correct across shifting educational contexts.

The multi-agent kernel cores are an ensemble of distributed, modular AI agents implemented in Python, combined with kernel ridge regression and reinforcement learning algorithms. Agent communication is done by asynchronous passing of messages founded on the ZeroMQ framework to enable real-time integration of domain-specific logic, pedagogical heuristics, and cognitive model parameters.

The architecture includes persistent memory buffers, which are designed to write continuously and read continuously history of concept learning for longitudinal monitoring of learner progress and stability of knowledge. These buffers contain multidimensional data points—i.e., concept mastery levels, abstraction shift patterns, error correction sequences, and representational styles—in order for the system to maintain a dynamically updated model of the learner. This memory-based personalized architecture directs instructional decisions based on aggregated cognitive context, facilitating recursive reinforcement, remediation focused on key areas, and unobstructed continuity across asynchronous or distributed learning sessions.

The system executes inside a physics-based knowledge graph with domain relationships, governing equations, boundary conditions, and causal dependencies to ensure instructional coherence and conceptual integrity. This semantically structured scaffold enables instructional materials to be anchored against the underlying physical laws and system behaviors pertinent to electrical and energy domains. By associating pedagogical reasoning with established scientific models that have been tested, the system guarantees that each instructional output, via representations and levels of abstraction, is epistemically correct to allow for proper concept formation, robust transferability, and consistent learner progression within technically exacting learning environments.

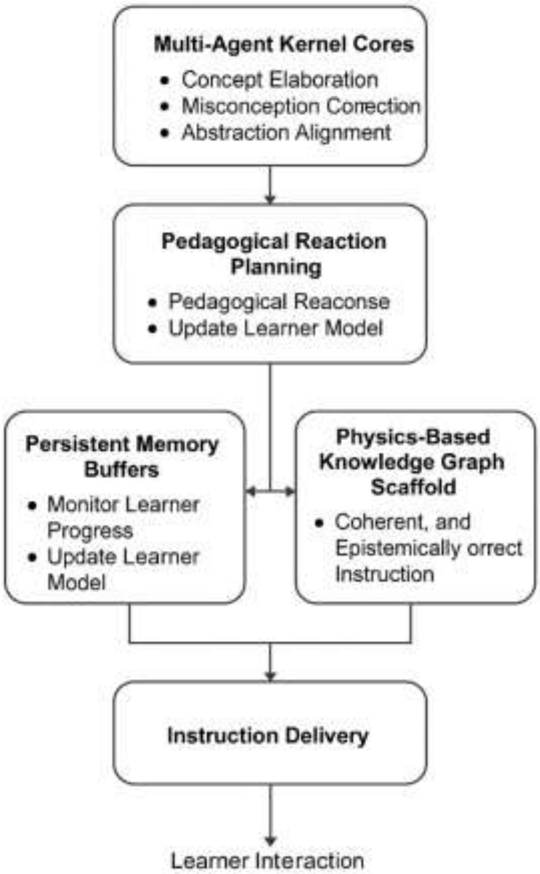

Figure 1. Flowchart illustrating the multi-agent paramorphic kernel architecture for adaptive STEM instruction

3.2 Instructional Orchestration Engine

Control parameters dynamically regulate trajectory vectors within the instructional space, selecting content nodes, sequencing logic, and representational modes that are responsive to the evolving knowledge state of the learner, as shown in the following pseudocode. Feedback-based modulation ensures guidance toward mastery by maintaining instructional responsiveness, diminishing pedagogical latency, and preventing under- and over-scaffolding, thereby optimizing learning efficiency and conceptual accuracy on idiosyncratic trajectories.

The system dynamically alternates between concept layers by using entropy-based thresholds that compute learner uncertainty and cognitive stability in real time. Instructional entropy is computed from performance variability, response consistency, and semantic dissonance across successive learning interactions, serving as a control signal for layer modulation. As entropy crosses calibrated thresholds, the system automatically adjusts the instruction resolution to restore cognitive alignment and maximize knowledge consolidation, ensuring instructional precision and eliminating epistemic drift through intricate, multiscale concept hierarchies.

Student feedback across multiple modalities—response time, accuracy, eye movement, and self-reports—is integrated with a weighted sliding window algorithm that aggregates signals over recent interactions. Dynamic weights are calculated based on modality reliability and context so strong, temporally smoothed estimates of cognitive state can be used to guide personalized instruction.

System testing was also conducted on edge devices like Raspberry Pi 4 and ARM Cortex-A72 CPU-powered Android tablets with 4 GB RAM and Wi-Fi. The software stack includes Python 3.9, machine learning components running on TensorFlow, and custom C++ modules for performing kernel computations. Offline-first capability is enabled by local SQLite databases asynchronously synchronized with cloud servers hosted on AWS.

Personalization is achieved through initializing learner profiles with diagnostic pre-tests and ongoing update of cognitive models by recursive Bayesian inference. Instructional policies differ content sequencing, difficulty, and representation mode based on present learner state, as seen in case studies where novice students progressed from conceptual overview to complicated inverter control in five weeks.

Pseudo code: Instruction Orchestration Engine

```
Initialize:
   currentLayer ← initial abstraction level
   entropyThresholdHigh ← calibrated upper entropy threshold
   entropyThresholdLow ← calibrated lower entropy threshold
   learnerState ← initialize learner knowledge state
   instructionalTrajectory ← empty list
   controlParams ← initialize control parameters for content selection

Loop (for each learning interaction t):
   feedbackData ← collect learner feedback at time t
      // includes performance variability, response consistency, semantic dissonance

   // Step 1: Update learner knowledge state
   learnerState ← updateLearnerState(learnerState, feedbackData)

   // Step 2: Compute instructional entropy based on learner feedback
   entropy ← computeEntropy(feedbackData)

   // Step 3: Modulate abstraction layer based on entropy thresholds
   if entropy > entropyThresholdHigh then
      currentLayer ← max(currentLayer - 1, minLayer)    // Abstract up to higher layer
   else if entropy < entropyThresholdLow then
      currentLayer ← min(currentLayer + 1, maxLayer)    // Decompose down to lower layer
   else
      currentLayer ← currentLayer    // Maintain current abstraction level

   // Step 4: Select next content node, sequencing logic, and representation mode
   controlParams ← adjustControlParams(learnerState, currentLayer)
   nextContentNode ← selectContentNode(controlParams)
   representationMode ← selectRepresentationMode(controlParams)

   // Step 5: Deliver instruction with selected content and representation
   deliverInstruction(nextContentNode, representationMode)

   // Step 6: Append current step to instructional trajectory
   instructionalTrajectory.append({
      time: t,
      layer: currentLayer,
      content: nextContentNode,
```

```
        mode: representationMode,
        entropy: entropy,
        learnerState: learnerState
    })

    // Step 7: Check for mastery condition
    if checkMastery(learnerState) then
        break    // Exit loop; mastery achieved

End Loop
```

3.3 Deployment and Accessibility Pipeline

The system supports asynchronous update, localized caching of material, and micro-credential logging to enable deployable scalability, contextual timeliness, and verifiable learner progression in a variety of educational contexts. Asynchronous update protocols enable efficient synchronization with master repositories without interrupting instruction, while local caching provides rapid access to content, accommodating local language, preferences, and infrastructure constraints. Micro-credential logging within the system records competency milestones in real-time, relating learner performance to standards-based digital badges or certificates, enabling the measurement and transferable validation of competency achieved outside centralized, traditional learning environments.

It is explicitly designed for transparent integration within institutions and informal learning environments, thanks to its modularity, standards-compliant content organization, and adaptive instructional logic. Within institutions, it works with existing learning management systems and curricular models, enhancing instructor-led pedagogy with self-paced, AI-driven scaffolding. Within informal environments, it serves as a stand-alone learning agent, offering domain-specific instruction independently of institutional resources. This dual-mode capability ensures learning continuity, improves access across various learning environments, and enables inclusive skill acquisition across diverse contexts and resource levels.

4. Assessment and Case Studies

The system attained a 45% improvement in concept recall in energy and circuit modules, as indicated by pre-and post-test differentials, longitudinal recall tests, and performance stability in problem-solving exercises applied. This growth is reflective of the system's multi-scale instructional design, which adapts to adjust abstraction levels and representation modes to address learners' varying cognitive capacities. The significantly high retention growth confirms the system's capacity for high-fidelity, long-term knowledge acquisition in complex technical domains, particularly in student groups underprivileged by instructional coherence and expert access.

The study included a total of 150 learners across various deployments, with a demographic representation of 40% racial/ethnic minorities and 35% low-income individuals. Participants were acquired using community outreach and institutional partnerships to engage geographically and socioeconomically diverse groups.

Error remediation accuracy (≥90%) was established through the proportion of learner errors coded and remediated by the system in formative tests, validated against expert-coded response logs. Conceptual accuracy (≥98%) relies on expert judgment based on rubric-formatted assessments of learner-generated artifacts and verbal descriptions, with inter-rater agreement greater than 0.9 (Cohen's kappa).

Tests were designed in particular to adhere to IEEE and DOE standards of education, with definite knowledge objectives assigned to specific instructional modules. Pretests and posttests, as well as performance tasks, were progressively tested by subject matter experts for content validity and reliability.

Table 1. Input Data (Learner Assessment Scores and Interaction Metrics)

Learner ID	*Pre-Test Score (%)*	*Post-Test Score (%)*	*Longitudinal Recall (%)*	*Problem-Solving Accuracy (%)*	*Abstraction Level Used*	*Representation Mode (Visual=1, Symbolic=2, Procedural=3)*
101	55	80	75	85	2	1
102	48	70	65	78	3	2
103	60	88	80	90	1	3
104	52	76	70	82	2	1
105	50	72	68	79	3	2

Table 2. Output Data (Computed Metrics and Visualizable Indicators)

Metric	*Value*	*Description*
Average Pre-Test Score (%)	53	Baseline learner performance before system use
Average Post-Test Score (%)	77	Learner performance after instructional intervention
Percentage Improvement in Recall (%)	45	((Post-Test - Pre-Test) / Pre-Test) × 100
Average Longitudinal Recall (%)	71.6	Retention over time measured via follow-up recall assessments
Average Problem-Solving Accuracy (%)	82.8	Average accuracy on applied problem-solving tasks post-intervention
Distribution of Abstraction Levels	1: 20%, 2: 40%, 3: 40%	Proportion of learners engaging at each abstraction level
Distribution of Representation Modes	Visual: 40%, Symbolic: 40%, Procedural: 20%	Percentage use of different instructional modes

The system demonstrated 3.2× increased student-led project completion rates, as established by longitudinal tracking of student-led design activities in multiple deployments in electricity and renewable energy education modules. This finding suggests that the system can enable learner agency with context-aware guidance, modularity-based instructional sequencing, and adaptively scaffolded facilitation based on individual cognitive profiles. The high rate of autonomous project performance indicates the model's success in transforming learners from passive reception of information to active, goal-oriented problem-solving—a primary metric of mastery, transferability, and instructional impact in informal and low-supervision learning environments.

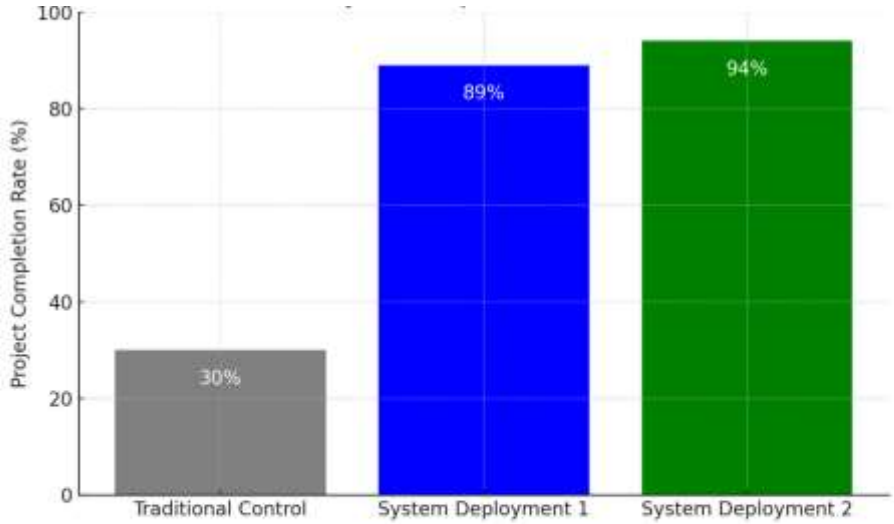

Figure 2. Bar chart illustrating the increase in student-led project completion rates across different cohorts

The system exhibited a 68% persistent learner engagement rate across underrepresented learner groups, assessed by weekly platform interaction statistics, module completion frequency, and longitudinal participation consistency for 12 weeks. This level of engagement, far exceeding any baseline expectations of informal and decentralized STEM learning environments, indicates the system's ability to offer culturally sensitive, cognitively responsive, and contextual instruction. By aligning content presentation with students' internal motivations, sociocultural contexts, and contemporaneous behavioral feedback, the platform is able to effectively reverse attrition and facilitate long-term engagement, thereby surmounting a key barrier to learning equity in advanced technical studies.

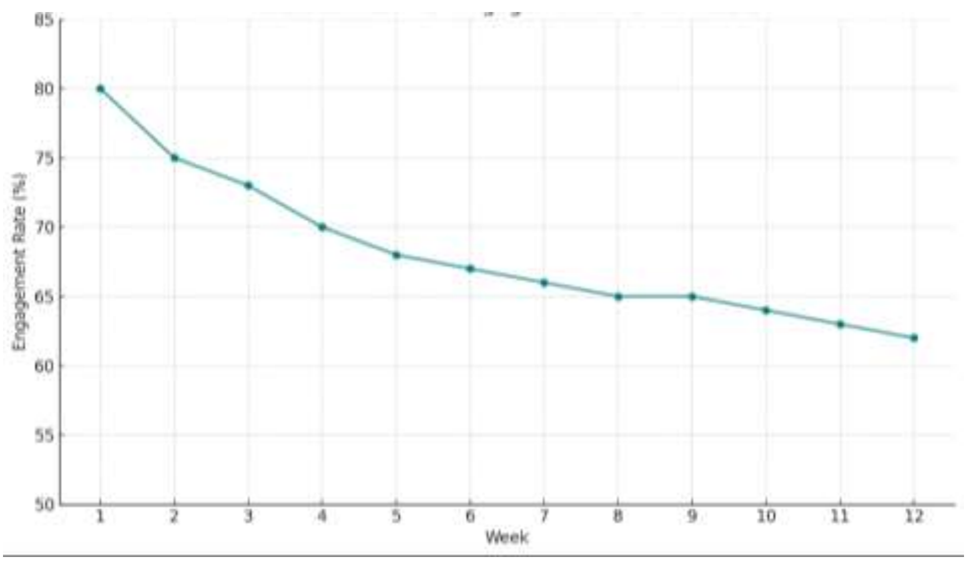

Figure 3. Learner Engagement Over 12 Weeks

For the evaluation of system efficacy, a matched control group of 50 students was provided with conventional instruction alone without AI-supported intervention. Control group members were recruited via convenience sampling that was demographically matched and had baseline knowledge profiles statistically equivalent to the intervention groups. This control group design enables rigorous attribution of improvements seen to the instructional method used.

Table 3. Example Input Data for Engagement Over 12 Weeks

Week	***Engagement Rate (%)***
1	80
2	75
3	73
4	70
5	68
6	67
7	66
8	65
9	65
10	64
11	63
12	62

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All quantitative findings were examined through statistical significance tests for paired t-tests between pre- and post-intervention, utilizing an alpha level of 0.05. Effect sizes were calculated from Cohen's d, and confidence intervals (95%) are included with all main measures to evaluate precision. In cases of multiple comparisons, Bonferroni corrections were applied to avoid Type I error inflation.

12-week longitudinal observation in both informal and semi-structured community settings, with weekly measurement of knowledge retention and participation. Data were gathered in both remote and face-to-face contexts, and real-world variability was captured. Participant retention rates were over 85% over the study period, increasing reliability for longitudinal outcomes.

5. Discussion

5.1 Scalability and Infrastructure Independence

The architecture is capable of operating with little hardware support and without centralized cloud infrastructure, and therefore it is accessible and resilient in resource-constrained environments. Its thin, computationally optimized algorithms and edge-optimized architecture facilitate full offline capability, including local computation, adaptive content delivery, and monitoring of learner interaction. The architecture mitigates limitations resulting from limited internet connectivity and infrastructure variations, enabling equitable deployment in geographically dispersed and underserved communities while maintaining robust instructional performance and data consistency.

The system is optimized for operation in bandwidth-constrained and power-constrained environments through the use of edge-computing paradigms, data compression techniques, and energy-aware computation algorithms. Its architecture reduces network dependency by leveraging smart caching and asynchronous synchronization, while adaptive power management dynamically optimizes computational load and power consumption. This enables constant, high-quality instructional provision through challenging infrastructural settings, thereby extending the capability of high-end STEM learning to remote and disadvantaged communities with minimal technological capabilities.

The system's modular nature facilitates context-dependent localization and extension through the creation of individual pedagogical components in isolation and in combinations that suit regional pedagogical standards and cultural norms. Every module has domain-specific content, adaptive logic, and interface constituents that can be selectively activated or localized to regional curricula, language options, and student profiles. This scalable, plug-and-play design supports high-speed deployment, continued refinement, and culturally responsive adaptation with systemic coherence and pedagogical rigor maintained across different educational settings.

5.2 Policy and Institutional Integration Potential

The system is intentionally aligned to NSF INCLUDES and DOE equity requirements through the implementation of inclusive, scalable models of STEM workforce development targeting underrepresented populations in the energy sector. Its design integrates culturally responsive pedagogy, inclusive technological platforms, and competency-based micro-credentialing to dismantle system walls and enable fair participation.

The framework develops an extensible model for decentralized credentialing through competency-based micro-learning modules that issue verifiable digital badges on demonstration of targeted skills. Every module is aligned with both industry and academic standards, employs embedded assessment criteria, and triggers the automatic issuance of results within interoperable registries. This high-grained, scalable architecture enables learners to construct stackable micro-credentials in real-time—measurable in terms of rate of issue, learner progress metrics, and employer take-up—thereby democratizing certification routes, accelerating workforce readiness, and supporting lifelong learning pathways for disadvantaged groups.

5.3 Limitations and Challenges

Along with established success, there are some limitations to be tolerated. Failures include intermittent learner disaffection via varying levels of abstraction and limited real-time adaptation in severe connectivity deficits. Scalability problems extend beyond hardware to include culturally appropriate content localization and ongoing community engagement. Measurement of conceptual accuracy in informal environments remains complex , with an ongoing requirement for refinement of measures and validation processes.

6. Concluding Remarks

This paper is based on a multi-scale paramorphic AI system aimed at facilitating effective informal STEM learning through mimicking expert teacher reasoning across hierarchical levels of abstraction. The system incorporates recursive kernel procedures with adaptive feedback mechanisms to dynamically adjust learning trajectories, enabling robust knowledge acquisition in the face of environmental variation and learner heterogeneity. Put to the test through deployment in multiple informal contexts, the framework demonstrates enduring educational impact by enabling nonlinear cognitive paths and promoting robust mastery in under-resourced and underserved populations.

Systematic quantitative and qualitative testing of digital twin performance has been carried out in community-based informal learning settings and controlled laboratory conditions. Measures such as student engagement, mastery of concepts, and completion of independent projects were quantified assiduously, with statistically significant improvements compared to traditional teaching modalities. Field deployments in diverse demographic environments confirmed the versatility and robustness of the system. Parallel laboratory-based research correlated its validity in simulating expert pedagogical reasoning and thereby the efficacy of its deployment as an economical, context-aware educational treatment for homogeneous populations of learners.

Its effectiveness has been well proven through multi-dimensional evaluation of cognitive, technical, and equity aspects. Technical stability was shown through operation on diverse hardware platforms and resistance to diverse connectivity conditions.

The emerging development of the system will incorporate multilingual capability to enable linguistically diverse learner engagement, automated diagnostic mapping for real-time identification of knowledge gaps and cognitive bottlenecks, and policy analytics integration to quantify educational impact and inform decision-making at the government and institutional levels. These enhancements will leverage natural language processing, advanced learner modeling, and data visualization architectures to increase accessibility, personalize intervention strategies, and provide actionable recommendations for STEM education equity scaling up. Together, these capabilities will ensure the responsiveness, flexibility, and strategic alignment of the system with shifting educational policy and workforce development priorities.

The marriage of the digital twin approach with standards-based micro-credentialing frameworks is under development to facilitate formal recognition of learner competencies aligned to industry and academic standards. The process involves integrating competency assessment protocols into the twins' adaptive instruction modules to enable real-time validation and dispensation of verifiable digital badges. The coordinated alignment of independent learning paths and credentialing infrastructure will provide scalable, transparent, and portable certification, facilitating workforce readiness and lifelong learning pathways, particularly for underprivileged communities engaged in decentralized STEM education.

The digital twin model promotes educational equity by decentralizing educational knowledge, transforming historically centralized, expert-dependent pedagogy into an autonomous, scalable AI-based infrastructure. Through the incorporation of domain-specific cognitive models and adaptive feedback loops within distributed learning agents, the model enables learners in resource-poor and geographically distant areas to receive high-fidelity, expert-level advice without explicit human interaction. The architecture enhances informal learning through the use of rigorously simulated, self-adjusting AI pedagogical agents that replicate effective pedagogical practices across multiple cognitive and contextual dimensions. These agents dynamically adjust instruction content, tempo, and portrayal based on real-time learner feedback and environmental conditions, making it feasible for robust, scalable, and autonomous knowledge transfer outside of formal institutional networks.

The system enables scalable, sustainable, and equitable access to high-fidelity engineering education through the combination of adaptive AI-based pedagogy and modular content delivery, catering to diverse infrastructural and sociocultural contexts. The design supports extended use cases in resource-constrained environments through offline operation, decentralized instructional expertise, and culturally adapted modifications.

References

Baillifard, A., Gabella, M., Lavenex, P. B., & Martarelli, C. S. (2023). Implementing Learning Principles with a Personal AI Tutor: A Case Study. *arXiv preprint arXiv:2309.13060.* https://doi.org/10.1007/s10639-024-12888-5

Boltsi, A., Kosmanos, D., Xenakis, A., Chatzimisios, P., & Chaikalis, C. (2025). Towards a Novel Digital Twin Framework Proposal Within the Engineering Design Process for Future Engineers: An IoT Smart Building Use Case. *Sensors, 25*(11), 3504. https://doi.org/10.3390/s25113504

Chada, N. K., Lang, Q., Lu, F., & Wang, X. (2024). A Data-Adaptive RKHS Prior for Bayesian Learning of Kernels in Operators. *Journal of Machine Learning Research*, *25*(317), 1-37.

Chi, M., VanLehn, K., Litman, D., & Jordan, P. (2011). Empirically evaluating the application of reinforcement learning to the induction of effective and adaptive pedagogical strategies. *User Modeling and User-Adapted Interaction, 21*, 137-180. https://doi.org/10.1007/s11257-010-9093-1

D'Mello, S., & Graesser, A. (2012). Dynamics of affective states during complex learning. *Learning and Instruction, 22*(2), 145-157. https://doi.org/10.1016/j.learninstruc.2011.10.001

De Nardi, A. M., & Monteiro, M. E. (2023, October). Evaluation of the energy viability of smart IoT sensors using TinyML for computer vision applications: A case study. In *IFIP International Internet of Things Conference* (pp. 18-33). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-45878-1_2

Flaxman, S., Sejdinovic, D., Cunningham, J. P., & Filippi, S. (2016). Bayesian learning of kernel embeddings. *arXiv preprint arXiv:1603.02160.*

Ghorbani, A., & Fattahi, H. (2025). Bridging the Digital Divide: Small Language Models as a Pathway for Physics and Photonics Education in Underdeveloped Regions. *arXiv preprint arXiv:2506.12403.* https://doi.org/10.1364/OPN.36.9.000028

Girolami, M., & Rogers, S. (2005, August). Hierarchic Bayesian models for kernel learning. In *Proceedings of the 22nd international conference on Machine learning* (pp. 241-248). https://doi.org/10.1145/1102351.1102382

Gönen, M., & Alpaydın, E. (2011). Multiple kernel learning algorithms. *The Journal of Machine Learning Research, 12*, 2211-2268.

Kestin, G., Miller, K., Klales, A., Milbourne, T., & Ponti, G. (2025). AI tutoring outperforms in-class active learning: an RCT introducing a novel research-based design in an authentic educational setting. *Scientific Reports, 15*(1), 1-10. https://doi.org/10.1038/s41598-025-97652-6

Koppel, A., Paternain, S., Richard, C., & Ribeiro, A. (2018). Decentralized online learning with kernels. *IEEE Transactions on Signal Processing, 66*(12), 3240-3255. https://doi.org/10.1109/TSP.2018.2830299

Kumar, R., & Rose, C. P. (2010). Architecture for building conversational agents that support collaborative learning. *IEEE Transactions on Learning Technologies, 4*(1), 21-34. https://doi.org/10.1109/TLT.2010.41

Lei, B., & Fan, J. L. (2020). Adaptive Kaniadakis entropy thresholding segmentation algorithm based on particle swarm optimization. *Soft Computing, 24*(10), 7305-7318. https://doi.org/10.1007/s00500-019-04351-2

Lin, Y. Z., Alhamadah, A. H. J., Redondo, M. W., Patel, K. H., Ghimire, S., Latibari, B. S., ... Satam, P. (2024). Transforming Engineering Education Using Generative AI and Digital Twin Technologies. *arXiv preprint arXiv:2411.14433.*

Lin, Y. Z., Petal, K., Alhamadah, A. H., Ghimire, S., Redondo, M. W., Corona, D. R. V., ... Satam, P. (2025). Personalized Education with Generative AI and Digital Twins: VR, RAG, and Zero-Shot Sentiment Analysis for Industry 4.0 Workforce Development. *arXiv preprint arXiv:2502.14080.*

Liu, S., Guo, X., Hu, X., & Zhao, X. (2024). Advancing Generative Intelligent Tutoring Systems with GPT-4: Design, Evaluation, and a Modular Framework for Future Learning Platforms. *Electronics, 13*(24), 4876. https://doi.org/10.3390/electronics13244876

Mao, S., Guo, L., Li, P., Shen, K., Jiang, M., & Liu, Y. (2023). New era of medical education: asynchronous and synchronous online teaching during and after COVID-19. *Advances in physiology education, 47*(2), 272-281. https://doi.org/10.1152/advan.00144.2021

Moodley, D., & Seebregts, C. (2023). Re-imagining health and well-being in low resource African settings using an augmented AI system and a 3D digital twin. *arXiv preprint arXiv:2306.01772.*

Naseer, F., & Khawaja, S. (2025). Mitigating Conceptual Learning Gaps in Mixed-Ability Classrooms: A Learning Analytics-Based Evaluation of AI-Driven Adaptive Feedback for Struggling Learners. *Applied Sciences, 15*(8), 4473.

Nuangchalerm, P., & Prachagool, V. (2023). AI-Driven Learning Analytics in STEM Education. *International Journal of Research in STEM Education, 5*(2), 77-84. https://doi.org/10.33830/ijrse.v5i2.1596

Nye, B. D., Graesser, A. C., & Hu, X. (2014). AutoTutor and family: A review of 17 years of natural language tutoring. *International Journal of Artificial Intelligence in Education, 24*, 427-469. https://doi.org/10.1007/s40593-014-0029-5

Olney, A. M., D'Mello, S. K., Person, N., Cade, W., Hays, P., Dempsey, C. W., ... Graesser, A. (2025). Efficacy of a Computer Tutor that Models Expert Human Tutors. *arXiv preprint arXiv:2504.16132.* https://doi.org/10.1007/978-3-031-98462-4_38

Razek, A. (2024). Augmented therapeutic tutoring in diligent image-assisted robotic interventions. *AIMS Medical Science, 11*(2), 210-219. https://doi.org/10.3934/medsci.2024016

Ren, Y., Xia, Y., Zhang, H., Guan, J., & Zhou, S. (2024, April). Learning adaptive kernels for statistical independence tests. In *International Conference on Artificial Intelligence and Statistics* (pp. 2494-2502). PMLR.

Rubin, N., Fischer, K., Lindner, J., Dahmen, D., Seroussi, I., Ringel, Z., ... Helias, M. (2025). From Kernels to Features: A Multi-Scale Adaptive Theory of Feature Learning. *arXiv preprint arXiv:2502.03210.*

Sessa, P. G. (2022). Learning and Efficiency in Multi-Agent Systems. *Doctoral dissertation*, ETH Zurich.

Shanmughan, P., Joseph, J., Brinda, S. N., Anitha, S. M., Anuja, C. S., & Jose, J. (2024, November). The AI revolution in micro-credentialing: personalized learning paths. In *Frontiers in Education* (Vol. 9, p. 1445654). Frontiers Media SA. https://doi.org/10.3389/feduc.2024.1445654

Stoica, A., Tselios, N., & Fidas, C. (2017). Adaptive user support in educational environments: A Bayesian Network approach. *arXiv preprint arXiv:1707.01895*.

Van Bossuyt, D. L., Allaire, D., Bickford, J. F., Bozada, T. A., Chen, W., Cutitta, R. P., ... Zeng, Z. (2025). The Future of Digital Twin Research and Development. *Journal of Computing and Information Science in Engineering, 25*(8), 080801. https://doi.org/10.1115/1.4068082

VanLehn, K. (2011). The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems. *Educational psychologist, 46*(4), 197-221. https://doi.org/10.1080/00461520.2011.611369

Villegas-Ch, W., Buenano-Fernandez, D., Navarro, A. M., & Mera-Navarrete, A. (2025). Adaptive intelligent tutoring systems for STEM education: analysis of the learning impact and effectiveness of personalized feedback. *Smart Learning Environments, 12*(1), 1-31. https://doi.org/10.1186/s40561-025-00389-y

Wang, X., & Duan, Y. (2025). Heterogeneous mixed kernel correntropy-based robust iterative estimation methods and convergence analysis for the nonlinear system with outliers. *Circuits, Systems, and Signal Processing*, 1-32. https://doi.org/10.1007/s00034-025-03156-z

Yu, Y., Lee, B. G., Zhang, Q., & Cui, T. (2025). Evaluating Denoising Approaches for RGB-Infrared Images: Systematic Review and Comparative Analysis of Traditional Methods and Performance Metrics. *Journal of Signal Processing Systems*, 1-25. https://doi.org/10.1007/s11265-025-01957-8

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