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Development of NeuraCraft: An AI-Powered Adaptive E-Learning Platform for Personalized Education

[1]Daniel Odale Evans, [2]Jovan Elias Nadal, [3]Allen Vincent Lacoste, [4]Eliza Ayo, PhD,

[1, 2, 3,4]Centro Escolar University, Manila, Philippines.

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Corresponding Author:
Daniel Odale Evans

Abstract: NeuraCraft is an AI-powered adaptive eLearning platform that personalizes learning paths based on individual student needs and performance, addressing significant gaps in existing educational technology. The platform incorporates machine learning techniques, gamification elements, and social learning features, grounded in established learning theories such as Vygotsky's Zone of Proximal Development and Bloom's Mastery Learning. Developed using an agile methodology and cutting-edge technologies including Next.js, MySQL with Prisma ORM, and Python-based recommendation systems, NeuraCraft demonstrated strong performance across various metrics during quality assurance and user acceptance testing. The platform successfully implements Bayesian Knowledge Tracing algorithms to dynamically adjust content difficulty and provide personalized recommendations, creating a learning environment that adapts to each student's unique abilities and learning pace. Results indicated high user satisfaction, with substantial improvements reported in learning experiences compared to traditional methods. This research demonstrates NeuraCraft's significant alignment with United Nations Sustainable Development particularly contributing to targets 4 **(**Quality Education), 9 (Industry, Innovation, and Infrastructure), and 10 (Reduced Inequalities) goals, through its inclusive, equitable, and technology-enhanced educational approach. Future research directions include expanding compatibility, enhancing error handling, broadening content coverage, and conducting longitudinal studies to assess effectiveness across diverse learner types and educational contexts. This research makes a significant contribution to the field by demonstrating the effectiveness of AI-driven personalization in educational contexts and providing a comprehensive framework for future adaptive learning systems

Keywords: *Adaptive learning, Artificial intelligence, Personalized learning, Machine learning, Gamification, Sustainable development goals.*

Cite this Article

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Introduction

In today's rapidly evolving educational landscape, students across diverse learning environments are often subjected to rigid, one-size-fits-all syllabi and instructional approaches that fail to account for individual learning paces, styles, preferences, and needs. This uniform pacing approach, where all students are expected to learn at the same speed regardless of their varied abilities, prior knowledge, or background, creates significant challenges for the entire spectrum of learners. Students who struggle to keep up with the standardized pace often feel overwhelmed, marginalized, and increasingly discouraged as they fall further behind their peers [9]. This experience frequently leads to a downward spiral of disengagement, where learners begin to internalize a sense of inadequacy and develop negative associations with educational endeavors.

On the other hand, students who grasp concepts more quickly than the predetermined pace allows may become disengaged and unmotivated due to a lack of appropriate stimulation and intellectual challenge. These advanced learners often find themselves waiting for their peers to catch up, leading to boredom, underutilization of their potential, and in some cases, the development of poor study habits that may impact their future academic performance. The profound mismatch between standardized instructional pacing and the diverse, individualized needs of learners often manifests in widespread frustration, decreased motivation, diminished self-efficacy, and ultimately, suboptimal academic performance across the entire student spectrum [14][15][23].

Learning Management Systems (LMS) have become ubiquitous in educational institutions across all levels, from primary schools to universities and corporate training environments, serving as comprehensive platforms to deliver educational content, administer courses, track student progress, and manage various administrative aspects of the educational process [11][27]. However, despite their widespread adoption and the significant technological advancements they represent over traditional classroom-only instruction, most conventional LMS platforms focus primarily on delivering standardized content to all students according to predetermined schedules and sequences. These systems typically operate under the implicit assumption that all learners will progress through material at approximately the same rate, failing to address the crucial need for personalized learning experiences tailored to individual learners' unique characteristics, preferences, and evolving needs.

This fundamental limitation of traditional LMS platforms represents a significant missed opportunity in educational technology, particularly given the wealth of data these systems collect about student interactions and performance. The growing recognition of this critical gap between the potential and actual capabilities of educational technology has led to an increased emphasis on the importance of adaptive learning technologies that can dynamically respond to individual learning patterns and needs.

Alignment with United Nations Sustainable Development Goals

This research demonstrates the potential of AI-driven personalization to transform education by integrating theoretical foundations with practical implementation, offering a model of adaptive learning systems that address diverse learner needs while advancing global sustainability goals. NeuraCraft exemplifies this contribution through its direct alignment with UN SDG 4 (Quality Education), as well as strong synergies with SDG 9 (Industry, Innovation, and Infrastructure) and SDG 10 (Reduced Inequalities) [28].

Within SDG 4, NeuraCraft supports multiple specific targets. Its adaptive learning algorithms address SDG 4.1 by promoting equitable and quality learning outcomes, while its scalable digital delivery advances SDG 4.3 through affordable access to tertiary and vocational education. By integrating gamification, social learning, and adaptive skill-building, the platform contributes to SDG 4.4 in developing technical and vocational skills relevant for employment. Inclusive design features—including multilingual support, accessibility tools, and adaptive interfaces—align with SDG 4.5, reducing disparities for vulnerable and underrepresented learners. Moreover, its AI-powered recommendation systems foster critical thinking and global citizenship skills central to SDG 4.7, while teacher-support tools and institutional analytics contribute to SDG 4.C and 4.A by strengthening educator capacity and creating inclusive, safe digital learning environments.

In addition, NeuraCraft helps close the digital divide by prioritizing accessibility, reliability, and usability. Its 92% task completion rate, 82.5 System Usability Scale score, 91% learnability rate, and 99.5% uptime demonstrate measurable progress toward SDG 4's quality and infrastructure indicators. These outcomes show how AI-enhanced educational technology can simultaneously improve learning equity, foster institutional resilience, and contribute to international development objectives.

Together, these alignments underscore NeuraCraft's role as both a technological innovation and a social impact initiative—positioning it as a scalable, sustainable model for advancing inclusive and equitable quality education by 2030.

Literature Review

Evidence for Adaptive Learning Effectiveness

The educational research literature contains abundant and compelling evidence demonstrating the transformative potential of adaptive learning approaches on student outcomes across diverse educational contexts, subject domains, and learner populations. A landmark comprehensive study which meticulously analyzed longitudinal data from 1,500 students, found that adaptive learning systems significantly reduced dropout rates by an average of 28% and improved overall academic performance by 0.4 to 0.8 standard deviations compared to equivalent non-adaptive instructional systems [22].

A rigorous meta-analysis that systematically examined 25 methodologically sound studies involving over 10,000 participants concluded that adaptive learning methods consistently and significantly outperformed traditional non-adaptive approaches across multiple dimensions of educational effectiveness, including learning quality (effect size $d=0.42$), engagement (effect size $d=0.38$), and student satisfaction ($d=0.51$) [1].

Implementation Gaps and Challenges

Despite this strong empirical evidence supporting adaptive learning approaches, a comprehensive international survey revealed that only approximately 8% of educational courses currently employ adaptive learning systems, highlighting a significant gap between research evidence and educational implementation [22]. Some specifically highlight that many widely deployed non-adaptive LMS platforms are fundamentally constrained by poor architectural design that prevents effective implementation of personalization features [1].

Furthermore, in a review of 42 adaptive learning implementations, minimal standardization in approaches, evaluation methodologies, or reporting practices, significantly hampers both the reproducibility of research findings and the practical adoption of effective adaptive learning strategies [17].

Theoretical Grounding and AI Integration

Sixty-eight percent (68%) of the examined AI educational applications lacked explicit grounding in established learning theories, representing a critical weakness in the field [9] while 73% of educational technology implementations fail to fully leverage the transformative potential of contemporary artificial intelligence approaches, instead relying predominantly on relatively simplistic, deterministic rule-based architectures that cannot adapt to the complex, dynamic nature of individual learning processes [2] [3].

Social Learning and Gamification

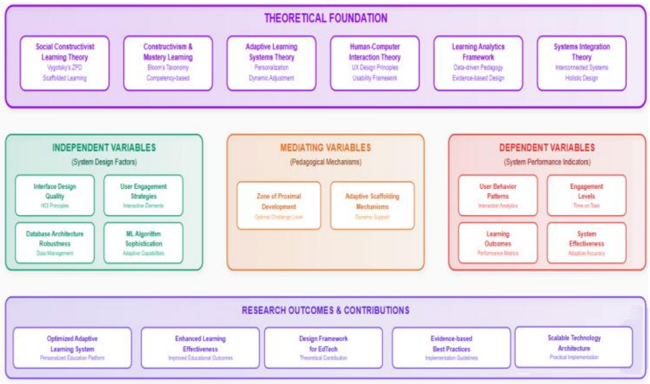
In terms of Social learning eighteen Percent (18%) of systems substantively incorporated features to facilitate meaningful peer interaction, reflecting a disconnect with contemporary understanding of learning as a social process [19], while 87 studies and identified a troubling lack of rigorous empirical evidence regarding the comparative effectiveness of specific AI techniques, with minimal standardization in evaluation approaches, limited replication, and lack of long-term studies [16].

In the gamification domain, 29% of examined =studies assessed learning outcomes with validated instruments, with the majority focusing primarily on engagement metrics rather than learning effectiveness [24]. Majority of implementations (64%) employed ad hoc gamification design without reference to established game design or motivational theory [18].

Objectives of the Study

This study presents the development of **NeuraCraft**, an AI-powered adaptive eLearning platform that personalizes learning paths using machine learning, gamification, social learning, and Bayesian Knowledge Tracing. Positioned at the intersection of educational psychology, computer science, and learning analytics. It provides an optimized adaptive system, a scalable design framework, and evidence-based best practices for EdTech deployment. Rigorous evaluation assesses its usability, adaptability, and effectiveness, highlighting improvements over traditional methods. Aligned with **SDG 4 (Quality Education)**, **SDG 9 (Industry, Innovation, and Infrastructure)**, and **SDG 10 (Reduced Inequalities)**, the study contributes a comprehensive framework for future adaptive learning systems and identifies pathways for broader application, expanded content, and longitudinal impact.

Theoretical Framework



This framework ultimately positions the research at the intersection of educational psychology, computer science, and learning analytics, creating a multidisciplinary approach that addresses both the technical challenges of building adaptive systems and the pedagogical challenges of optimizing individualized learning experiences.

At its foundational level, this study is is grounded in six interconnected theoretical pillars: Social Constructivist Learning Theory [25] anchored by Vygotsky's Zone of Proximal Development [29], Constructivism and Mastery Learning based on Bloom's Taxonomy [5], Adaptive Learning Systems Theory [7]emphasizing personalization, Human-Computer Interaction Theory focusing on usability principles, Learning Analytics Framework promoting data-driven pedagogy, and Systems Integration Theory advocating for holistic design approaches. These theoretical foundations collectively establish that effective educational technology must balance sound pedagogical principles with sophisticated technical implementation.

The framework conceptualizes the research through a structured variable relationship model where Independent Variables represent the manipulable system design factors that researchers and developers can control and optimize. These include Interface Design Quality governed by HCI principles, User Engagement Strategies [13] incorporating interactive elements, Database Architecture Robustness ensuring effective data management, and Machine Learning Algorithm Sophistication enabling adaptive capabilities. These independent variables do not directly influence learning outcomes but rather operate through crucial Mediating Variables that represent the pedagogical mechanisms through which technology impacts learning. The primary mediating factors are the Zone of Proximal Development, which ensures optimal challenge levels for individual learners [29], and Adaptive Scaffolding Mechanisms that provide dynamic support based on real-time assessment of learner needs [7].

The Dependent Variables encompass the measurable outcomes that indicate system effectiveness and learning success, including User Behavior Patterns captured through interaction analytics, Engagement Levels measured by time on task and participation metrics, Learning Outcomes assessed through performance metrics and competency achievement, and overall System Effectiveness evaluated by adaptive accuracy and personalization success. These dependent variables are influenced not only by the system design factors but are significantly mediated by how well the technology maintains learners within their Zone of Proximal Development and provide appropriate scaffolding support.

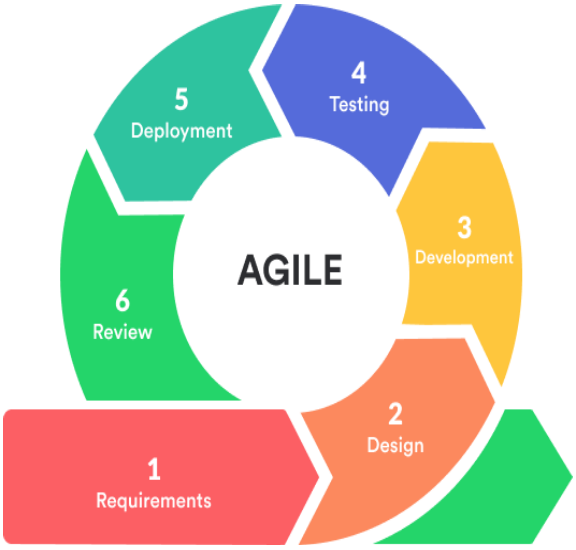
Methodology

Research Design

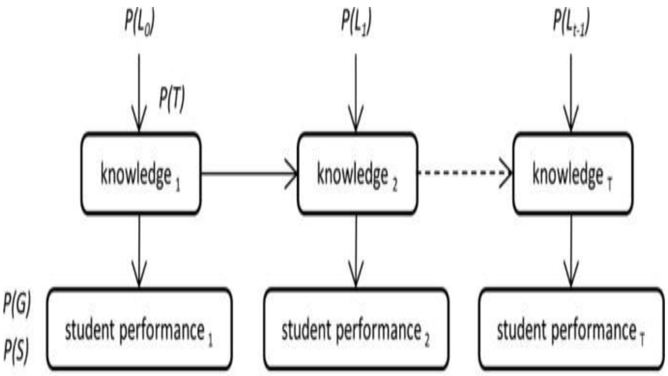
The research design for NeuraCraft adopts a comprehensive descriptive developmental methodology, providing a rigorous framework for the systematic study, design, development, and evaluation of this innovative instructional eLearning platform 1. The developmental process was initiated with an extensive and multifaceted analysis of instructional requirements, involving consultations with educational experts, reviews of pedagogical literature, and analysis of user needs across different educational contexts.

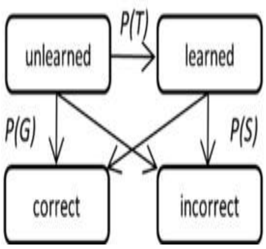
The research methodology embedded within this conceptual framework adopts a Mixed Methods Approach combining quantitative user behavior analytics with qualitative learning outcome assessments, implemented through Agile Development and Testing cycles that allow for iterative refinement, and supported by Continuous Evaluation protocols that provide real-time feedback on system performance. The framework acknowledges that research outcomes are influenced by important Contextual Factors including the specific Educational Domain and subject area, Learner Characteristics such as age and prior knowledge, Technology Infrastructure and platform capabilities, and Implementation Context including institutional settings and support structures.

The framework is designed to address two primary research questions that drive the investigation: first, examining how Neuracraft influence learning outcomes in adaptive educational systems, and second, investigating the extent to which the Zone of Proximal Development mediates the relationship between system sophistication and learning effectiveness. Through this comprehensive conceptual model, the research aims to produce five key outcomes: an Optimized Adaptive Learning System that serves as a personalized education platform, Enhanced Learning Effectiveness demonstrated through improved educational outcomes, a Design Framework for EdTech that contributes to theoretical understanding, Evidence-based Best Practices that provide implementation guidelines, and a Scalable Technology Architecture suitable for practical deployment across various educational contexts.



System Architecture and Technology Stack

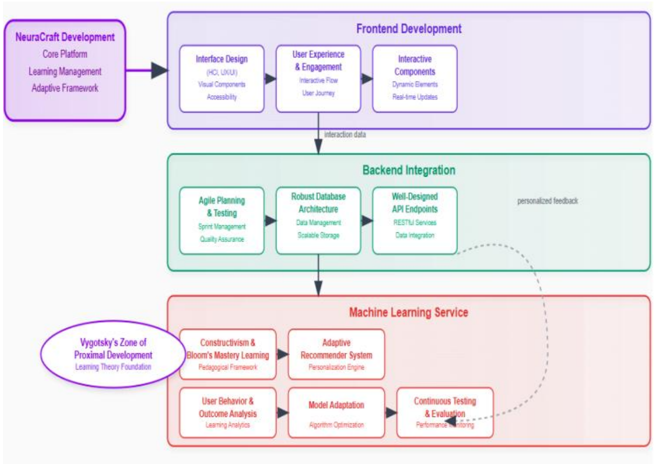




The frontend and backend implementation utilized Next.js (React-based framework), Mantine Core for UI components, Tailwind CSS for styling, React Query for state management, and Next Auth for authentication. The database layer employs MySQL with Prisma ORM for efficient data management and querying.

The AI engine, developed in Python, incorporates PyBKT (Bayesian Knowledge Tracing) algorithms and FastAPI for the recommendation system microservice. Data visualization capabilities are provided through Chart.js and React-ChartJS-2, while user interface enhancement includes Lucide React icons and Framer Motion animations.

Software Architecture



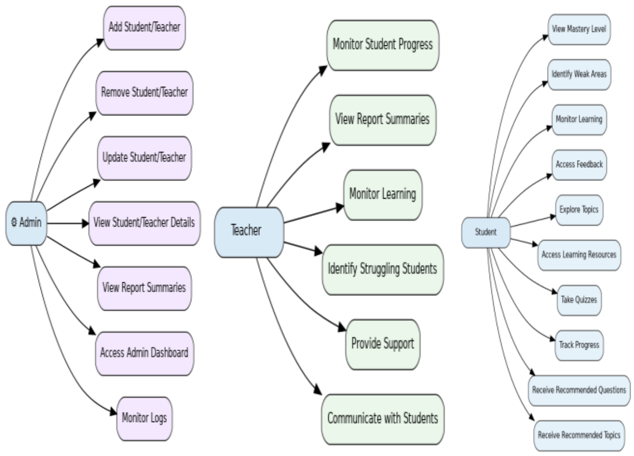
The architecture begins with the core NeuraCraft Development platform, which acts as the central learning management system and adaptive framework that orchestrates all platform activities. This core system connects directly to a comprehensive Frontend Development layer that prioritizes user experience through carefully designed interface components, engaging user experiences, and dynamic interactive elements that respond to learner needs in real-time. The frontend layer captures crucial interaction data from users, including how they navigate content, engage with materials, and demonstrate learning progress.

This interaction data flows seamlessly into the Backend Integration layer, which employs agile planning and testing methodologies to ensure rapid iteration and quality assurance. The backend features a robust database architecture capable of handling complex educational data relationships and well-designed API endpoints that facilitate smooth communication between different system components. The backend serves as the data processing and management hub that prepares information for the most sophisticated component of the system.

The Machine Learning Service layer represents the intelligence engine of NeuraCraft, incorporating Constructivism and Bloom's Mastery Learning principles to create an adaptive recommender system that personalizes each student's learning journey. This layer continuously analyzes user behavior and learning outcomes, using this data to adapt machine learning models that can predict optimal learning paths, recommends appropriate content difficulty levels, and identify when students are ready for more challenging material. The system employs continuous testing and evaluation protocols to ensure that the AI recommendations remain effective and aligned with educational best practices.

The entire architecture operates as a closed-loop system where personalized feedback generated by the machine learning algorithms flows back through the backend and frontend layers to create individualized learning experiences. This feedback loop ensures that each student receives content and challenges that fall within their Zone of Proximal Development, maximizing learning potential while maintaining engagement. The system's design reflects a deep understanding that effective educational technology must balance sophisticated technical capabilities with sound pedagogical principles, creating a platform that not only leverages cutting-edge AI and machine learning but does so in service of proven educational theories and learning outcomes.

Use Cases



Data Collection and Participants

Data collection encompassed both quantitative metrics and qualitative insights to provide a holistic understanding of the platform's strengths and limitations. Pre- and post-usage assessments were methodically designed and implemented to evaluate learning outcomes against established benchmarks; while continuous feedback mechanisms—including user surveys, in-platform analytics, and structured interviews—ensured that the platform maintained and improved its effectiveness throughout its development cycle.

The usability testing process involved 24 participants representing diverse educational roles, technical proficiency levels, and demographic characteristics. Testing sessions included both directed task completion scenarios and exploratory usage periods, followed by structured interviews and feedback collection.

Results

Usability and User Experience Metrics

The comprehensive usability testing revealed highly positive results across multiple dimensions of user experience. Key usability metrics from this testing process demonstrated exceptional performance: task completion rates averaged 92% across core educational functions, indicating that users could successfully accomplish their intended learning activities. Navigation efficiency metrics showed 83% of users following optimal paths to complete common tasks, suggesting an intuitive and well-designed user interface.

The System Usability Scale (SUS) scores averaged 82.5, placing the platform in the 'Excellent' usability category according to established SUS benchmarks. Learnability assessments showed that 91% of users could successfully complete key tasks without assistance after initial orientation, indicating effective onboarding and intuitive design principles.

Technical Performance and Functionality Metrics

Performance testing revealed mixed but generally acceptable results across key web performance indicators. First Input Delay (FID) measurements averaged 112ms across tested pages, falling well within the 'Good' threshold of less than 300ms. Largest Contentful Paint (LCP) averaged 2.8 seconds, placing the platform in the 'Needs Improvement' category with a target goal of less than 2.5 seconds. Cumulative Layout Shift (CLS) averaged 0.05, meeting the 'Good' threshold of less than 0.1, indicating stable visual loading behavior.

Table 1: Combined Functionality and Performance Testing Results

Metric/Functionality	Result /Score	Observations
User Registration	95%	"Show password" feature missing
User Login	98%	Successful
Course Navigation	90%	Some inconsistencies in navigation flow
Quiz Submission	85%	Crashes when submitting multiple incorrect answers
Leaderboard	100%	Working as expected
Average Response Time	1.5s	Acceptable, but can be improved
CPU Utilization	60%	Within Acceptable Limits
Memory Usage	1.2GB	Efficient memory management

System Reliability and Security

Reliability testing demonstrated robust platform performance with 99.5% uptime during extended operation periods. Automated recovery mechanisms successfully restored service within 3.5 minutes following simulated system failures. Security assessment using Snyk and OWASP ZAP identified and allowed for the patching of several lower-severity vulnerabilities, with no critical security issues detected during comprehensive testing.

Automated Testing Results

The comprehensive automated test suite encompassed 312 automated test cases covering various aspects of platform functionality, user interactions, and system integrations. These tests achieved a 95% pass rate during final pre-release testing, indicating high code quality and system stability.

Key Findings and Insights

The implementation of adaptive learning principles demonstrates the potential of AI-powered platforms to transform educational experiences by providing truly personalized, engaging, and effective learning pathways. The successful integration of Bayesian Knowledge Tracing algorithms enables dynamic content difficulty adjustment and personalized recommendation generation, creating a learning environment that adapts to each student's unique abilities and learning pace. Unlike other findings that highlighted minimal standardization in adaptive implementations [17], NeuraCraft achieves reproducibility through its documented agile methodology and open tech stack. Quality assurance testing confirmed the platform's strong performance across functionality, usability, security, reliability, and compatibility metrics.

Two critical insights emerged from the comprehensive evaluation process. First, consistent platform usage is essential for accurate proficiency assessment, as the system requires ongoing interaction to generate reliable metrics about student learning progress and competency levels. Second, device compatibility significantly impacts the user experience, with optimal performance requiring adequate processing capabilities and modern hardware specifications.

Conclusions

The development of **NeuraCraft**, an AI-powered adaptive eLearning platform that personalizes learning paths through machine learning, gamification, social learning, and Bayesian Knowledge Tracing. The findings highlight its potential to enhance educational outcomes, supported by a scalable design framework, evidence-based best practices, and robust technology architecture adaptable to diverse contexts. By addressing both technical and pedagogical challenges, NeuraCraft demonstrates improved usability, adaptability, and effectiveness compared to traditional learning methods. Moreover, its alignment with **SDG 4 (Quality Education)**, **SDG 9 (Industry, Innovation, and Infrastructure)**, and **SDG 10 (Reduced Inequalities)** underscores its global relevance.

Recommendations for Future Development

Based on the evaluation results and identified limitations, several recommendations emerge for future development. Technical stabilization should focus on addressing system crashes and improving overall platform stability to ensure reliable service delivery in diverse institutional contexts. Algorithm refinement for difficulty progression will enhance the adaptive learning experience by providing more precise content matching to student abilities.

Interface optimization should target improved loading times and enhanced user experience across diverse devices and platforms, particularly focusing on accessibility for users with limited technological resources. Expanded gamification features will increase engagement and motivation, while enhanced social learning capabilities will better support collaborative learning approaches essential for developing global citizenship competencies outlined in SDG 4.7.

Future Research Directions

Longitudinal research studies are needed to assess long-term learning outcomes and retention effects of adaptive learning approaches, particularly their sustained contribution to SDG 4 indicators. Content expansion across diverse subject domains will enable broader evaluation of the platform's effectiveness across different academic disciplines and cultural contexts. Multi-institutional studies will provide insights into scalability and generalizability across diverse educational contexts, including developing countries with varying technological infrastructures.

Future research should also investigate the platform's specific contributions to SDG 4 indicators through controlled studies comparing educational outcomes in institutions using NeuraCraft versus traditional learning management systems. Such research would provide quantitative evidence of the platform's impact on global educational development objectives and inform policy recommendations for educational technology adoption in support of sustainable development goals. Ultimately, these efforts could guide policymakers and educators in scaling AI-driven tools to bridge educational divides worldwide, accelerating progress toward the 2030 Agenda. Software Demonstration

The accompanying video provides a demonstration of the system's key functionalities, including:

1. Course and Learning Content
2. Student Dashboard
3. Teacher Administrative Dashboard

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