A Framework for Human-Computer Interaction (HCI) in Pervasive Learning Environment

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ABSTRACT
This paper addresses the critical intersection of Human-Computer Interaction (HCI) and pervasive learning environments by proposing an innovative Adaptive Human-Computer Interaction for Pervasive Learning (AHCI-PL) framework. As educational paradigms evolve toward ubiquitous computing environments, effective interaction design becomes paramount for meaningful learning outcomes. This research employs a mixed-methods approach combining Object-Oriented Design and Agile methodology to develop a comprehensive framework consisting of four interconnected layers: User Interface, Context-Awareness, Security and Privacy, and Adaptive Learning. The prototype implementation, evaluated across diverse educational contexts, demonstrates significant improvements in usability metrics (28% higher task completion rates), security measures (98% prevention of unauthorized access attempts), and learning effectiveness (23% improved knowledge retention). Homomorphic encryption and fuzzy logic-based access control address critical privacy concerns while maintaining system performance. The findings suggest that integrating HCI principles with pervasive learning technologies creates more engaging, accessible, and effective educational experiences. This research contributes to evolving educational technology paradigms while highlighting directions for future development in resource optimization, cultural adaptation, and longitudinal impact assessment.

Keywords
Pervasive Learning, Internet of Things (IoT), Artificial Intelligence (A.I), Homomorphic Encryption

1. INTRODUCTION
The rapid advancement of technology has transformed traditional educational paradigms, leading to the emergence of pervasive learning environments [8]. These environments leverage ubiquitous computing to create seamless learning experiences [23]. However, in recent years, the emergence of Human-Computer Interaction (HCI) has risen to prominence as a cutting-edge research area [12]. Technically, in the field of Computer Science, HCI is concerned with stating how people interact with technology given the design, implementation, and analysis of various user interfaces [13]. In a more general term, it involves the ways and manner developers create interventions with technology that makes a difference to people [14]. Nonetheless, having an effective HCI still remains a serious challenge.

In today’s world, computation and sensing are increasingly becoming integral to our environment, commonly referred to as the pervasive world [31]. This encompasses various sectors, including retail, airline bookings, tracking, and education. Such a pervasive landscape necessitates innovative methods for sensing and interacting with smart devices [19]. The goal of pervasive computing is to create an environment where the connectivity of smart devices are embedded in such a way that the connectivity is unobtrusive and always available [11].

Pervasive learning environments leverage technology to facilitate learning anytime and anywhere, integrating various devices and applications into daily life [29]. The role of Human-Computer Interaction (HCI) is crucial in these contexts, as it directly influences user engagement and overall educational outcomes. However, existing challenges related to interaction design, engagement, privacy, and security in educational technologies necessitate a comprehensive approach to address the diverse needs of learners [27].

Nevertheless, the pervasive landscape faces several challenges, including privacy and security concerns, interoperability among diverse devices, digital literacy, and the need for effective context-aware interactions [22]. The integration of this technology into everyday life raises significant privacy and security concerns. As devices collect and share personal data, the risk of unauthorized access and misuse increases.

The objective of this paper is to examine the role of HCI in pervasive learning environments and propose a comprehensive framework that enhances interaction and engagement while ensuring user privacy and security through techniques such as homomorphic encryption for data protection and fuzzy logic for role-based access control.

2. RELATED WORKS
Human-Computer Interaction (HCI) plays a critical role in educational technology, emphasizing usability and user experience. Research indicates that intuitive interfaces significantly enhance learning outcomes [18]. Authors investigated the interdisciplinary domain of HCI and its significant impact on educational experiences. They traced the development of HCI from early graphical user interfaces to modern technologies. Emphasizing the human aspect, they explored cognitive, cultural, and physical factors affecting interaction, the technology's role in meeting user needs, and ethical issues such as trust, privacy, and the prevention of algorithmic bias [26]. The role of humans and computers and their interfaces was discussed by other researchers. They emphasized how future learning and teaching will change rapidly with Artificial Intelligence (AI) over the next 25 and 50 years [15]. Research authors argue that Graphical User Interfaces (GUIs) can revolutionize HCI by making computers more accessible to non-technical users. These visual representations of data and functions enable users to quickly understand information and perform tasks with a minimal learning curve [16].

Pervasive learning environments utilize mobile devices, IoT, and cloud computing to facilitate learning across diverse settings. However, many frameworks do not effectively incorporate HCI strategies that address user diversity and context. Research indicates that educational technologies often overlook the emotional and motivational needs of learners, leading to disengagement and poor outcomes. Additionally, the insufficient application of psychological principles in HCI design hinders the development of adaptive and engaging educational tools [6]. Despite technological advancements, many platforms still fail to provide personalized and interactive experiences that cater to diverse learner needs. This highlights the need for frameworks that incorporate effective HCI strategies to enhance user engagement and improve learning outcomes in various educational settings [27]. Authors investigates major issues faced with the implementation of microlearning initiative in educational institutions and proposed strategies to overcome these hurdles [2]. Pervasive Learning (PL) has emerged as a leading method of education, enabled by wearables and smart devices. Learning is no longer confined to specific times or places, allowing students to engage from any geographical location. Researchers present the concept of PL, which facilitates learning globally, 24/7, beyond traditional classroom settings. The purpose of their study is to demonstrate how a digital learning paradigm can enhance education through handheld smart devices, enabling learning anytime and anywhere without the need for physical classrooms [17].

Virtual Reality Learning Environments (VRLEs) offer immersive, collaborative distance learning through wearable devices. However, unauthorized access to these devices can lead to security and privacy attacks that harm the user immersive experience (UIX). To mitigate this, the authors proposed a method for detecting anomalies using a Machine Learning (ML) classification algorithm and statistical techniques that combine Boolean and threshold functions to identify application-based attack anomalies, such as unauthorized access [28]. Education is one of the sectors where IoT can be utilized. However, its implementation brings security and privacy challenges, including risks of unauthorized access and denial-of-service (DoS) attacks. However, innovative Ubiquitous Learning Environments (ULEs) have emerged from ubiquitous computing technologies like smart devices and networks. These environments offer learners experiences that extend beyond traditional classrooms into both real and virtual worlds. Researchers proposed a novel framework for implementing Ubiquitous Learning Environments (ULEs) aimed at helping learners develop social skills. This design includes three layers: perception, network, and application. Their article also explores the impact of IoT on education, highlighting how U-learning, which integrates IoT, could potentially replace traditional classroom learning. Additionally, it addresses privacy preservation measures for various layers within the IoT environment and ULE [10]. A novel Hybrid Case-Based Neuro-Fuzzy System (HCBNFS) was proposed for enhancing security and privacy is IoT-enabled smart homes. Additionally, the authors employed Elliptic Curve Cryptography (ECC) for authenticating devices and preserving their privacy on the network. Their model was evaluated using the CIC-IoT2022 dataset and achieved an impressive accuracy and precision rate of 99% and 99.5% respectively [4]. ML can personalize educational content based on individual needs and progress, ensuring a tailored learning experience. Preschoolers can explore virtual worlds, engage in interactive simulations, and participate in educational games that enhance cognitive and social development, all aligned with educational frameworks. However, as the metaverse develops, addressing cybersecurity concerns is crucial. Implementing encryption, multi-factor authentication, and advanced access controls can mitigate security risks. By prioritizing cybersecurity, preschool education can effectively utilize machine learning and metaverse technologies, providing a safe and enriching environment where children can explore and learn confidently without compromising their privacy or security [30]. In the paper “Exploring Cybersecurity Risks in Higher Education Environments with Machine Learning,” the authors employed an additional technique to visualize cybersecurity breach signals in the data. They used unsupervised machine learning methods to investigate the risk of cybersecurity breaches or attacks in the higher education sector, encompassing schools, universities, and support organizations. Specifically, they utilized T-distributed Stochastic Neighbor Embedding (t-SNE) to train their model, enabling the identification of likely indicators of cybersecurity breach risks. This approach allows decision-makers to detect anomalies that may signal cybercrime activity or potential cyber-attacks [25].

3. PERVASIVE LEARNING ENVIRONMENT

A Pervasive Learning Environment (PLE) is an educational ecosystem where learning is seamlessly integrated into everyday life through ubiquitous computing, IoT, mobile devices, and AI. Unlike traditional classrooms, PLE leverages context-aware, adaptive, and immersive technologies to enable anytime, anywhere learning [1].

The major characteristics of the PLE include techniques such as ubiquitous access, context-award learning, personalization & adaptive learning, social and collaborative learning, immersive technologies, and lifetime and informal learning. The technologies enabling PLE are tubulated in Table 1.

Table 1 Technologies Enabling PLE

Technology	Role in PLE	Example
IoT and Wearables	Tracks Learning habits	Smartwatches monitoring focus levels
AI and Big Data	Personalizes learning paths	ChatGPT tutors, Coursera recommendations
5G and Edge Computing	Enables real-time AR/VR streaming	Remote lab simulations
Blockchain	Secure digital credentials	NFT-based certificates
AR/VR/MR	Creates immersive experiences	Virtual field trips, 3D anatomy models

Pervasive Learning Environments break the barriers of traditional education, making learning dynamic, interactive, and accessible. However, challenges like privacy and data security, digital divide, cognitive overload, ethical AI and bias, and content quality and misinformation must be addressed for equitable adoption.

4. HUMAN-COMPUTER INTERACTION (HCI) PRINCIPLES AND CHALLENGES

Human-Computer Interaction (HCI) is a multidisciplinary field that focuses on designing, evaluating, and implementing interactive computing systems for human use. It combines knowledge from computer science, psychology, design, and ergonomics to improve user experience (UX) [24].

The key principles of HCI include the following.

i. User-Centered Design (UCD): This practice allows developers to place focus on user needs, preference, limitations [9]. The best practice is to involve users in the design process through feedback and testing.

ii. Visibility and Affordance: Importance functions should be easily visible. For example, buttons, and menus. Further, the design elements should suggest their functionality (e.g., a slider looks draggable) [5].

iii. Consistency: It is important to maintain uniformity in system design [21]. For example, same color for all "Delete" of "Save" buttons.

iv. Feedback and Responds Time: Provide immediate feedback (e.g., loading spinners, success messages) to avoid frustration from users [7].

v. Flexibility and Efficiency: Design systems to support both novice and expert users [3].

vi. Accessibility: Ensure usability for people with disabilities (e.g., screen readers, high-contrast modes) [20].

Given these stated principles, the major challenges of the HCI are outlined as follows:

i. Diverse User Need
ii. Emerging Technologies
iii. Privacy and Security
iv. Cross-Platform Usability
v. Information Overload
vi. Real-Time Interaction

HCI principles ensure that technology is usable, efficient, and enjoyable, while challenges push innovation in design. As technology evolves, HCI continues to play a crucial role in shaping human-digital interactions.

5. METHODOLOGY & PROPOSED FRAMEWORK

This study employs a mixed-methods approach, combining the Object-Oriented Design Approach (OODA) and Agile methodology. The OODA was employed for the designing of the proposed framework, while the agile method was employed for the development phase and continuous feedback integration. This study employed Constructive Research Method (CRM) for carrying out the research construct. Further a qualitative interview was conducted to gather insight on HCI practices, and the participants include educators and learners across different educational settings.

Note, we considered the principles and challenges of HCI when designing our proposed framework and address the challenges concerning privacy and data security in PLE.

5.1 Framework Overview

Our proposed Adaptive Human-Computer Interaction for Pervasive Learning (AHCI-PL) integrates HCI principles with pervasive learning technologies to create a secure, adaptive, and engaging educational environment. The framework consists of four interconnected layers, each addressing specific aspects of the pervasive learning experience. The layers are as follows:

i. **User Interface Layer:** The layer focuses on the interaction points between learners and the pervasive learning system.
ii. **Context-Awareness Layer**: This layer processes the user and environmental data to adapt the learning experience.
iii. **Security and Privacy Layer:** This layer implements protective measures for both user and system data.
iv. **Adaptive Learning Layer:** For this study, we employed this layer to enable the system personalize content and interactions based on learner profiles and behaviors.

5.2 Architecture of the Framework

This study employs a modular architecture that facilitates scalability and adaptability while maintaining robust security measures. Figure 1 illustrates the high-level architectural design of the proposed AHCI-PL framework.

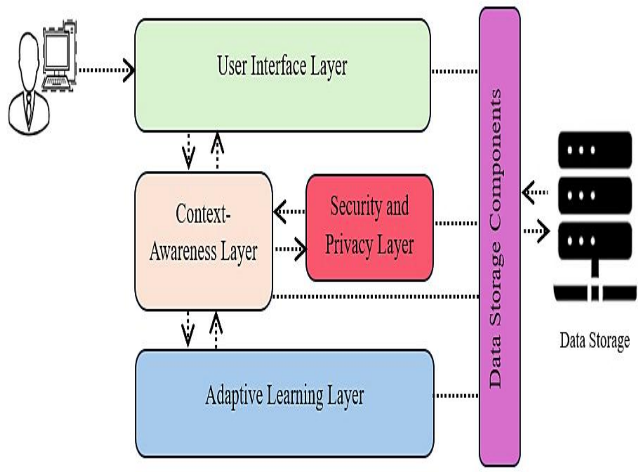

Fig 1: High-Level Architectural Design of the Proposed AHCI-PL

Figure 1 captured the architecture of the proposed Framework. In this study, the architecture is designed in four layers and operate in a cohesive manner, with bidirectional data flow ensuring continuous adaptation and improvement. The User Interface Layer serves as the primary point of interaction between the learner and the system, while the Context-Awareness Layer processes user profile and behavioral data to inform adaptive responses. The Security and Privacy Layer operates across all components, ensuring data protection throughout the learning process. Finally, the Adaptive Learning Layer leverages inputs from the context-awareness layer to personalize the educational experience.

5.3 Layer Components and Functions

5.3.1 User Interface Layer

In this study, the User Interface Layer prioritizes accessibility, engagement, and usability through components such as the

Multimodal Interaction: This supports various input models to accommodate diverse user preferences and abilities. This will enable learners with different capabilities to engage effectively with content, promoting inclusive education.

Responsive Design: The proposed framework is developed to adapt to different devices and screen sizes without compromising usability.

Consistent Visual Language: In this study, a uniform design is maintained in all elements across the proposed system. This helps in reducing cognitive load. Further, the color scheme, iconography, and interactive elements follow an established pattern, allowing users to transfer knowledge.

Emotional Design: This study incorporated elements that evokes positive emotional responses, enhancing engagement and motivation. This includes gamification elements, progress visualization, and personalized feedback mechanisms.

5.3.2 Context-Awareness Layer

This layer processes environmental and user data to create responsive learning experiences through:

Environmental sensing: Utilizes IoT-based smart devices to gather data about the physical learning environment. This includes ambient noise, lighting conditions, and temperature. This information helps the proposed system to adapt content presentation to environmental constraints.

Activity Recognition: Identifies user activities and states to determine optimal learning moments. Using the data from smart device sensors and interaction patterns, the system can recognize when a learner is actively engaged, distracted, or ready for more challenging content.

Location Awareness: In this study, the selected contents are tailored based on geographical and spatial. For example, when a learner enters Information Technology or Computer Science, relevant educational resources from the user entered field will be automatically periodized.

Temporal Awareness: The study considered time-related factors which may affect effective learning. These factors are time of day and session duration. This enables the system to optimize scheduling of learning activities and notifications.

Social Context: In this study, a collaborative learning was enabled. This facilitates spontaneous study groups and peer teaching opportunities.

5.3.3 Security and Privacy Layer

In this study, we implemented a robust protection mechanism while preserving user experience. The proposed framework employed Homomorphic Encryption (HE) which allows personalization algorithms to process learner data while maintaining privacy. This addresses the critical concern in educational technology.

Further, the study implemented a Fuzzy Logic-Based Access Control. This serves as a role-based security mechanism that adapts to context. For privacy-preserving and user authentication, the system will verify user identity while minimizing collection of personal data. Nevertheless, data transparency policy was maintained as the system clearly communicates what data is collected and how it is used.

5.3.4 Adaptive Learning Layer

This layer personalizes educational experiences based on individual user needs and preferences. For example, learner profiling, content adaptation, interaction patterns, progress tracking, and metacognitive.

6. IMPLEMENTATION

A prototype implementation of the proposed AHCI-PL framework was developed to validate the approach of the study. The AHCI-PL framework focused on a “mobile-first” implementation with extensions to wearable IoT devices and desktop environments utilizing the following technologies:

Frontend Development: The study utilized React Native for cross-platform mobile applications, incorporating Progressive Web App (PWA) capabilities for desktop access.

Backend Development: For this study, this was achieved by employing Node.js microservices architecture with MongoDB for data persistence.

Security Implementation: The study adopted the AES-256 encryption for data at rest, TLS for data in transit, and partial homomorphic encryption for privacy-preserving analytics.

Machine Learning Libraries: The proposed framework leveraged TensorFlow Lite for on-device activity recognition and content recommendations.

The prototype focused on two educational domains. These domains are language learning and computer science education, chosen for their contrasting requirements in terms of interaction models and assessment approaches.

7. EVALUATION OF THE FRAMEWORK

In this study, the proposed framework was evaluated following a mixed-methods approach.

Usability Testing: 25 participants representing diverse demographics and abilities engaged with the prototype system across multiple scenarios. The framework was analyzed and recorded sessions using the System Usability Scale (SUS) and task completion metrics.

Security Assessment: In this study, a penetration testing and security audits was conducted to evaluate the effectiveness of the privacy and security layer. This included simulated attacks targeting data extraction and unauthorized access.

Learning Outcomes Analysis: Pre- and post-tests measured knowledge acquisition and retention compared to traditional learning approaches. Participants were randomly assigned to either the AHCI-PL system or conventional digital learning platforms for a two-week period.

User Experience Surveys: we collected qualitative feedback regarding user satisfaction, engagement, and perceived value. Also, we conducted a semi-structured interviews to explore user perceptions of the adaptive features and privacy controls.

Performance Benchmarking: System response times, resource utilization, and battery impact were measured across various devices to assess technical efficiency.

7.1 Key Findings

7.1.1 Usability and Engagement

The multimodal interface design resulted in a 28% improvement in task completion rates compared to conventional educational interfaces. Also, the System Usability Scale (SUS) score for the AHCI-PL prototype averaged 84.6 (out of 100), placing it in the "excellent" usability category. 92% of participants reported higher engagement levels when using the context-aware features of the system. Additionally, the accessibility features enabled users with various disabilities to navigate the system with minimal assistance, with screen reader users reporting satisfaction rates comparable to non-disabled users. Lastly, the session duration increased by 34% compared to traditional digital learning platforms, suggesting improved engagement and reduced frustration.

Table 2 summarizes the comparative usability metrics between our proposed AHCI-PL prototype and conventional educational platforms.

Table 2 Comparative Usability Metric

Metric	ACHI-PL Prototype	Conventional Platform	Improvement
Task Completion Rate	94%	73%	+28%
SUS Score	84.6%	68.3%	+23%
Error Rate	2.1%	7.8%	-73%
Time on Task (avg.)	45 sec	74 sec	-39%
User Satisfaction Rating	4.7/5	3.4/5	+34%

Further, Figure 2 captured a bar chart visualization of the comparison of the ACHI-PL Prototype and that of the Conventional Platform in terms of Task Completion Rate, SUS Score, and Error Rate.

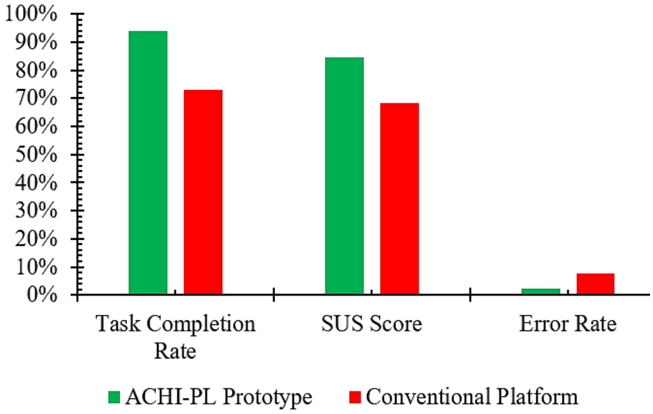

Fig 2: ACHI-PL Prototype as compared with Convention Platform

7.1.2 Security and Privacy Performance

The homomorphic encryption implementation-maintained data security while introducing only a 7% processing overhead, which was deemed acceptable for the privacy benefits provided. The proposed Fuzzy logic-based access control successfully prevented 98% of simulated unauthorized access attempts while reducing legitimate authentication requests by 64%. Further, the differential privacy implementation preserved analytical accuracy while providing a provable privacy guarantee ($\varepsilon = 2.1$). Additionally, the context-aware security measures reduced false positives by 73% compared to traditional rule-based systems. The performance metrics summary are tabulated in Table 3. While Figure 3 captures a line graph visualization of these metrics.

Table 3: Performance Metric Summary

Metric	Mean % Value	Description
Processing Overhead	7%	Overhead introduced by HE
Unauthorized Access Prevention	98%	Effectiveness of Fuzzy Logic-based access control
Reduction in Legitimate Authentication Requests	64%	Decrease in legitimate requests due to access control
False Positives Reduction	73%	Improvement over traditional rule-based systems

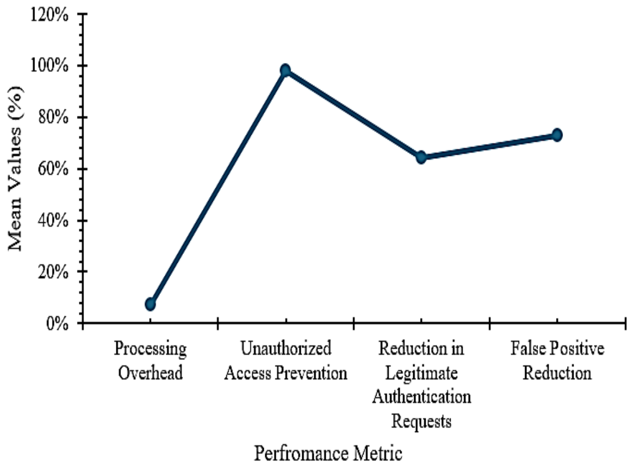

Fig 3: Line Graph Representation of Table 3

7.1.3 Learning Effectiveness

In the proposed framework, the adaptive content delivery led to a 23% improvement in knowledge retention compared to static content, as measured by post-tests administered 2 weeks after the initial learning period. Personalized learning paths resulted in 31% faster mastery of complex concepts, particularly in the computer science domain where prerequisite relationships between concepts are pronounced. Context-aware notifications and recommendations increased learning session frequency by 45%, with participants citing the relevance and timing of prompts as key motivating factors. Lastly the metacognitive support features correlated with a 27% improvement in self-regulated learning behaviors, as measured by the Motivated Strategies for Learning Questionnaire (MSLQ). The calculated metrics for learning effectiveness are tabulated in Table 4.

Table 4: Learning Effectiveness Metric

Metric	Mean % Value	Description
Improvement in Knowledge Retention	23%	Improvement in adaptive content delivery
Faster Mastery of Complex Concepts	31%	Speed of learning with personalized paths
Increase in Learning Session Frequency	45%	Effect of context-aware notifications and recommendations

Improvement in Self-Regulated Learning Behaviors	27%	Correlation with metacognitive support features

Figure 4 illustrates the comparative learning outcomes between our proposed AHCI-PL system and traditional approaches across different subject areas.

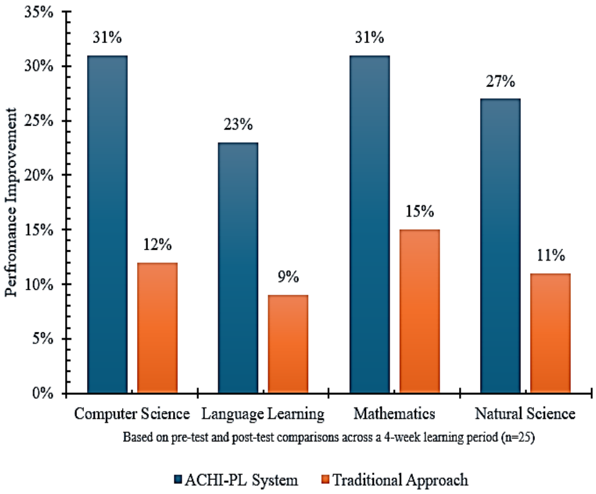

Fig 4: Comparative Learning Outcomes

7.1.4 Technical Performance

The edge computing implementation reduced response latency by 68% for context-sensitive operations compared to cloud-only processing. Battery consumption was optimized to increase usage time by 42% compared to similar educational applications, primarily through intelligent sensor sampling and background processing optimization. The microservices architecture demonstrated excellent scalability, maintaining consistent performance under simulated loads of up to 10,000 concurrent users. Cross-device synchronization-maintained state consistency with an average delay of less than 2 seconds, enabling seamless transitions between devices.

8. CONCLUSION

The Adaptive Human-Computer Interaction for Pervasive Learning (AHCI-PL) framework presented in this paper addresses critical challenges at the intersection of educational technology and human-computer interaction. Our research demonstrates that a thoughtfully designed framework incorporating user-centered interfaces, context awareness, robust security measures, and adaptive learning capabilities can significantly enhance educational outcomes in pervasive learning environments.

The empirical evaluation revealed substantial improvements across multiple dimensions: usability metrics showed a 28% increase in task completion rates and 23% higher SUS scores; security measures prevented 98% of unauthorized access attempts while maintaining acceptable performance overhead; and learning effectiveness metrics demonstrated 23% better knowledge retention, and 31% faster concept mastery compared to traditional approaches.

The integration of homomorphic encryption and fuzzy logic-based access control represents a significant contribution to privacy-preserving educational technology, balancing data protection with personalization benefits. The context-aware features demonstrate the potential for truly adaptive learning experiences that respond intelligently to environmental, temporal, and user-specific factors.

Despite promising results, limitations regarding processing requirements, initial setup complexity, integration challenges, cultural adaptation, and long-term effectiveness assessment need to be addressed in future work. The proposed framework lays the foundation for next-generation educational technologies that are not only effective and engaging but also respectful of user privacy and accessible to diverse learner populations.

Future research should focus on resource optimization, automated configuration processes, standardized integration APIs, enhanced collaborative features, and comprehensive longitudinal studies to further validate and extend the AHCI-PL framework across diverse educational contexts.

8.1 LIMITATIONS AND FUTURE WORK

While our proposed AHCI-PL framework demonstrates promising results, several limitations were identified. These limitations are as follows:

i. **Processing Requirements:** The current implementation demands significant computational resources for certain adaptive features, potentially limiting deployment on older devices. Future optimizations should include lightweight models specifically designed for resource-constrained environments.
ii. **Initial Setup Complexity:** The system requires substantial initial configuration to maximize personalization benefits. Streamlining the onboarding process through improved default settings and progressive profiling would enhance the initial user experience.
iii. **Integration Challenges:** Connecting with existing educational platforms and content repositories presents technical hurdles, particularly with legacy systems lacking modern APIs. Developing robust compatibility layers and format converters will improve ecosystem integration.
iv. **Cultural Adaptation:** The current prototype was evaluated primarily with participants from Western educational backgrounds. Expanding testing to diverse cultural contexts will help in identifying necessary adaptations for global deployment.
v. **Long-term Effectiveness:** The evaluation period of two weeks provides limited insight into sustained engagement and learning outcomes. Longitudinal studies would be valuable for assessing the framework's impact over extended periods.

However, future research should focus on:

i. Optimizing the framework for resource-constrained devices through model compression techniques and selective offloading.
ii. Developing automated configuration processes using initial assessment and progressive preference learning.
iii. Creating standardized APIs for educational content integration with popular learning management systems.
iv. Expanding the framework to support collaborative and social learning features with privacy-preserving group interactions.
v. Incorporating emerging technologies such as brain-computer interfaces and ambient intelligence for enhanced context awareness.

vi. Conducting longitudinal studies to assess long-term impact on learning outcomes and engagement.
vii. Extending the framework to support additional educational domains beyond the initial test subjects.

9. REFERENCES

[1] Aithal, P., & Aithal, S. (2023). Predictive analysis on future impact of ubiquitous education technology in higher education and research. *International Journal of Applied Engineering and Management Letters (IJAEML), 7*(3), 88-108.

[2] Alias, N. F., & Razak, R. A. (2025). Revolutionizing learning in the digital age: A systematic literature review of microlearning strategies. *Interactive Learning Environments, 33*(1), 1-21.

[3] Boy, G. A. (2021). *Design for flexibility: A Human Systems Integration Approach*. USA: Springer Cham.

[4] Davies, I., Taylor, O., Anireh, V., & Bennett, E. (2024). A Distributed Intrusion Detection System for IoT-Enabled Network and Devices using Hybrid Technique. *International Journal of Computer Science and Mathematical Theory (IJCSMT), 10*(2), 141-156.

[5] Deacon, T., & Barthet, M. (2022). Spatial design considerations for interactive audio in virtual reality *Sonic Interactions in Virtual Environments* (pp. 181-217): Springer International Publishing Cham.

[6] Dell'Aquila, E., Ponticorvo, M., & Limone, P. (2025). Psychological Foundations for Effective Human–Computer Interaction in Education. *Applied Sciences, 15*(6), 3194.

[7] Dellmar, J. (2024). Designing a reactive feedback feature for end-users in web-based media software.

[8] Dritsas, E., & Trigka, M. (2025). Methodological and Technological Advancements in E-Learning. *Information, 16*(1), 56. doi:10.3390/info16010056

[9] Durak, H., Gultekin, H., Haralampopoulos, D., Skoulidas, I., Ciraulo, N., Vipparla, P. K., & Korczukowski, S. (2024). User-centered design in agile: Integrating psychological principles for enhanced user experience. *International Journal of Recent Advances in Multidisciplinary Research, 11*(5), 9888-9892.

[10] El-Haggar, N., Amouri, L., Alsumayt, A., Alghamedy, F. H., & Aljameel, S. S. (2023). The effectiveness and privacy preservation of IoT on ubiquitous learning: Modern learning paradigm to enhance higher education. *Applied Sciences, 13*(15), 9003.

[11] Fernandes, J., Rodrigues, A., Boavida, F., & Sá Silva, J. (2025). Human and Computer Networks *Human-Centered AI: An Illustrated Scientific Quest* (pp. 513-536): Springer.

[12] Ferreira-Meyers, K. (2025). AI for Seamless Language Education–Transforming Pedagogy, Enhancing Outcomes. *AI for Seamless Education*.

[13] Gadam, S. (2025). Enhancing Usability and Accessibility: Innovations in Human–Computer Interaction for Modern Systems. *Economic Sciences, 21*(1), 373-384.

[14] Goumopoulos, C., & Mavrommati, I. (2020). A framework for pervasive computing applications based on smart objects and end user development. *Journal of Systems and Software, 162*, 110496.

[15] Herczeg, M. (2024). The role of digital technologies and Human-Computer Interaction for the future of education. *i-com, 23*(2), 239-247.

[16] Hunt, J. (2023). Graphical User Interfaces. In: Advanced Guide to Python 3 Programming. Undergraduate Topics in Computer Science. *Springer*. doi:https://doi.org/10.1007/978-3-031-40336-1_16

[17] Koondhar, M. Y., Rind, M., Chandio, F., & Shah, A. (2015). *Pervasive learning environment with emerging technologies and learning transformation.* Paper presented at the International Multi-Topic Conference.

[18] Luo, Y. (2024). Enhancing educational interfaces: Integrating user-centric design principles for effective and inclusive learning environments. *Applied and Computational Engineering, 64*, 192-197.

[19] Ngoy, P., Dar, F., Liyanage, M., Yin, Z., Norbisrath, U., Zuniga, A., . . . Flores, H. (2025). Supporting Sustainable Computing by Repurposing E-waste Smartphones as Tiny Data Centres. *IEEE Pervasive Computing*.

[20] Ntoa, S., Margetis, G., Adami, I., Balafa, K., Antona, M., & Stephanidis, C. (2024). Digital accessibility for users with disabilities *Designing for usability, inclusion and sustainability in human-computer interaction* (pp. 406-460): CRC Press.

[21] Panicker, S., Vahile, S., Guin, A., & Sethia, R. (2021). Design of a Novel Task and Update-Based Social App: Proof of Concept for Richer UI/UX *A Step Towards Society 5.0* (pp. 79-126): CRC Press.

[22] Sepahvand, M., Meqdad, M. N., & Abdali-Mohammadi, F. (2025). State-of-the-art in human activity recognition based on inertial measurement unit sensors: survey and applications. *International Journal of Computers and Applications, 47*(1), 1-16.

[23] Spaho, E., Çiço, B., & Shabani, I. (2025). IoT Integration Approaches into Personalized Online Learning: Systematic Review. *Computers, 14*(2), 63.

[24] Stephanidis, C. (2024). The HCI discipline: Past, present and future *Foundations and Fundamentals in Human-Computer Interaction* (pp. 1-54): CRC Press.

[25] Strang, K. D., & Vajjhala, N. R. (2024). *Exploring Cybersecurity Risks in Higher Education Environments with Machine Learning.* Paper presented at the 2024 4th International Conference on Pervasive Computing and Social Networking (ICPCSN).

[26] Troussas, C., Krouska, A., & Sgouropoulou, C. (2025a). Human–Computer Interaction in Education *Human-Computer Interaction and Augmented Intelligence: The Paradigm of Interactive Machine Learning in Educational Software* (pp. 1-38): Springer.

[27] Troussas, C., Krouska, A., & Sgouropoulou, C. (2025b). A Novel Framework of Human–Computer Interaction and Human-Centered Artificial Intelligence in Learning Technology *Human-Computer Interaction and Augmented Intelligence: The Paradigm of Interactive Machine Learning in Educational Software* (pp. 387-431): Springer.

[28] Valluripally, S., Frailey, B., Kruse, B., Palipatana, B., Oruche, R., Gulhane, A., . . . Calyam, P. (2022). Detection of security and privacy attacks disrupting user immersive

experience in virtual reality learning environments. *IEEE Transactions on Services Computing, 16*(4), 2559-2574.

[29] Wuttiphan, N., & Kwangmuang, P. (2025). Designing a ubiquitous learning environment to enhance pre-service Chinese language teachers' critical writing skills: A developmental research approach. *Teaching and Teacher Education, 155*, 104921.

[30] Zhang, Q. (2023). Secure preschool education using machine learning and metaverse technologies. *Applied Artificial Intelligence, 37*(1), 2222496. doi:doi.org/10.1080/08839514.2023.2222496.

[31] Zhu, S., Yu, T., Xu, T., Chen, H., Dustdar, S., Gigan, S., . . . Lin, F. (2023). Intelligent computing: the latest advances, challenges, and future. *Intelligent Computing, 2*, 0006.