THE FEDERAL UNIVERSITY OF TECHNOLOGY, AKURE

DEEP KNOWLEDGE COMMUNITY: TRIAD OF ANATOMY, DYNAMICS AND PATTERN OF LEARNING PRINCIPLES

INAUGURAL LECTURE SERIES 207



Delivered by

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PROFESSOR OF INTELLIGENT SYSTEMS AND E-LEARNING

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My Lords Spiritual and Temporal,
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Great FUTARIANS

PREAMBLE

With profound gratitude and deep humility, I give honour and glory to Almighty God, the King of kings and Lord of lords, the Creator of heaven and earth, who, in His providence, guided my academic journey and graciously sustained me through every stage of my career. It is by His divine orchestration that I stand before this distinguished audience today as a Professor of Intelligent Systems and E-Learning in the School of Computing, to deliver the 207th Inaugural Lecture of this great institution. This inaugural lecture presents the intellectual trajectory of my research contributions in Learning Sciences and Educational Technology. The central thesis of this lecture is both

fundamental and far-reaching: technology alone does not produce learning; rather, transformative learning occurs when sound learning principles are intelligently embedded within technological systems.

Madam Vice Chancellor, today's lecture is the seventh to be delivered within the School of Computing, the third by a female in the School, and the second by a female in the Department of Information Systems. The title of this inaugural lecture, "***Deep Knowledge Community: Triad of Anatomy, Dynamics and Pattern of Learning Principles***," reflects its central proposition: that transformative learning emerges from the effective integration of **Anatomy, Dynamics and Pattern of Learning Principles**, while intelligent technologies function as enablers rather than drivers of the learning process. The lecture draws inspiration from both philosophical thought and the biblical worldview, each affirming that enduring outcomes are governed by foundational principles rather than chance. Scripture records that creation unfolded through divine order and the creative power of God's Word (*Genesis 1:3*), illustrating that purposeful outcomes emerge from established principles rather than random events. Furthermore, this lecture represents not merely an academic proposition, but a philosophical commitment to rethinking how knowledge is structured, transmitted, experienced, and transformed in the digital age.

Permit me to say that the lecture also draws an analogy from computer science. Computer scientists do not solve complex computational problems by randomly selecting algorithms or programming languages. Rather, they analyse the structure of the problem before choosing the algorithm, data structure, and computational architecture that best fit the task. The effectiveness of any computational solution depends not merely on computational power but on the alignment between problem structure and solution architecture. Similarly, instructional

designers and curriculum developers must not merely deploy technology; they must carefully align learning principles with technological architectures to reduce cognitive load, optimise engagement, enhance retention and support knowledge transfer. The fundamental problem in digital education today is not lack of technology. It is a misalignment between learning principles and technological architecture. My research contributions respond directly to this misalignment.

1.0 INTRODUCTION

1.1 My Career Journey

Indeed, my career journey has been divinely ordered. Like many children at an early stage of life, learning often seemed difficult and complex, largely due to limited understanding of life's purpose and direction. In my formative years, I was greatly influenced by my late father, a peasant farmer and tailor, who, despite lacking formal education himself, possessed a deep passion for ensuring that all his children attained university education.

My educational journey took a significant turn during my secondary school years under the care and guidance of the late Professor Olusola Akinyele and Dr. (Mrs.) Elizabeth Taiwo Akinyele. My late father entrusted my academic upbringing to them to ensure that I received a sound and disciplined education. Notably, Dr. (Mrs.) Elizabeth Taiwo Akinyele, who is my elder sister and the first child of my late parents, has remained a steadfast maternal figure in my life to this day.

The choice of Computer Science as my field of study was also divinely orchestrated. My initial attempt at the University Matriculation Examination (UME) did not meet the cut-off mark for Chemistry, a course I had reluctantly chosen, as my true aspiration was to study Medicine, an option my guardian,

whom I fondly called “Daddy,” discouraged me from. However, through God’s help, my second UME attempt led me to choose Computer Science, a field I knew nothing about at first. This decision culminated in my admission in 1990 into the Department of Computer Science, University of Ibadan, Ibadan, Nigeria. My passion for the field was ignited through exposure to diverse computing courses and the dedication of my amiable lecturers, many of whom made great sacrifices by remaining in the department despite many opportunities abroad. Thus began my professional journey in computing, and I graduated in 1995 with a Second Class (Upper Division).

In March 1997, I was appointed as a Systems Programmer II at the Federal University of Technology, Akure, and rose to the position of Senior Systems Programmer in October 2004. By divine favour, I transitioned into academia in May 2006 with my appointment as an Assistant Lecturer in the Department of Computer Science. With the creation of the School of Computing in 2018, I was deployed to the Department of Information Systems. I rose through the ranks and was promoted to the rank of Professor in October 2021.

Since 2006, a major strand of my academic research has been driven by a sustained interest in understanding how technology can be used to improve learning experiences. Beginning with my Master's research on collaborative and distance learning systems and extending through my doctoral research on Neuro-Fuzzy models for active and collaborative learning, my scholarship has consistently focused on designing technology-mediated environments that foster deep, purposeful, and effective learning. Over the years, this research trajectory has expanded to include adaptive learning systems, digital game-based learning, virtual reality, educational data mining, and learning analytics. Across these domains, a recurring question has guided my work: How can technology be designed to

support the way people learn rather than merely delivering information?

1.2 The Paradox of Technological Abundance and Learning Principles Misalignment

The twenty-first century has witnessed an unprecedented expansion of educational technologies. E-learning platforms, artificial intelligence, adaptive learning systems, and immersive digital environments have transformed how, when, and where learning occurs, extending education beyond the traditional classroom (**Agbonifo**, 2014; UNESCO, 2023). Yet, despite this technological abundance, meaningful learning remains dependent on fundamentally human processes that are cognitive, social, emotional, and motivational in nature.

A major reason for this paradox is the continued emphasis on technological functionality and content delivery over evidence-based learning design. Poorly designed digital environments often produce cognitive overload, fragmented learning, superficial engagement, weak retention and limited accessibility (Kirschner *et al*., 2006; CAST, 2024). The central challenge is therefore not technological scarcity but the misalignment between technology and established principles of learning. This challenge provides the rationale for the **Triad of Anatomy, Dynamics and Pattern of Learning Principles** (ADP), which forms the conceptual foundation of the **Deep Knowledge Community** (DKC).

1.3 The Imperative for a Deep Knowledge Community in Digital Learning Ecologies

The paradox of technological abundance necessitates a new way of conceptualising digital learning. Although technology has dramatically expanded access to educational resources, meaningful learning depends not on access alone but on

environments that promote conceptual understanding, reflection, collaboration, and the application of knowledge. The challenge confronting contemporary education is therefore not simply the provision of information, but the creation of learning ecosystems capable of transforming information into deep, enduring knowledge. Deep learning extends beyond memorisation and short-term recall to foster conceptual understanding, integration of ideas, critical thinking, and knowledge transfer (Biggs and Tang, 2011).

This challenge raises fundamental questions: How can digital learning environments move learners from information acquisition to knowledge transformation? How can technology be aligned with learning principles to support deep engagement rather than superficial interaction? Addressing these questions requires a framework that places learning principles, rather than technology, at the centre of educational design.

In response, this inaugural lecture proposes the Deep Knowledge Community as a technology-enabled learning ecosystem designed to foster deep, collaborative, and transformative learning. Its foundation is the Triad of Anatomy, Dynamics and Pattern of Learning Principles, where Anatomy represents the structural elements of learning, Dynamics signifies the processes that drive learning, and Pattern denotes the developmental progression of learning. Within the DKC, technology functions as a cognitive amplifier rather than the driver of learning, aligning intelligent technologies with enduring learning principles to achieve accessible, equitable, and transformative learning outcomes.

2.0 CONCEPTUAL FOUNDATION OF LEARNING AND LEARNING PRINCIPLES

2.1 What is Learning?

Learning is the foundation of human development and educational practice (Illeris, 2018; Schunk, 2020; OECD, 2023). It is the process through which individuals acquire, organise, apply, and transform knowledge, skills, attitudes, and competencies through experience, instruction, and interaction. Across history, learning has consistently exhibited three characteristics: there is content to be learned, processes through which learning occurs, and observable patterns through which learning develops.

As education becomes increasingly technology-mediated, it is important to distinguish between human learning and machine learning. Human learning is conscious, contextual, cognitive, social, and transformative, whereas machine learning enables computational systems to learn from data, identify patterns and improve performance (Russell and Norvig, 2021; Goodfellow *et al*., 2016). Their convergence produces **Hybrid Intelligence**, where human and artificial intelligence complement one another in personalised learning, adaptive instruction, intelligent tutoring and learning analytics (Dellermann *et al.*, 2019; Akata *et al*., 2020). Nevertheless, technology remains an enabler of learning, not its centre. Effective learning continues to depend on sound pedagogical principles and thoughtful instructional design.

2.2 What are Learning Principles?

Learning principles are evidence-based guidelines derived from learning theories, cognitive science, educational psychology and instructional design (Mayer, 2021; Ambrose *et al*., 2019). They guide the design of instruction, learning environments and

educational technologies to: minimise cognitive overload; promote engagement; support collaboration; accommodate learner diversity; and improve learning effectiveness.

However, learner diversity and the increasing complexity of digital education require these principles to be reinterpreted within technology-enabled environments. These principles are grounded in established theories of learning, whose understanding provides the conceptual basis for this inaugural lecture.

3.0 THEORETICAL FOUNDATIONS OF LEARNING

Understanding how people learn has long been a central concern of educational psychology, cognitive science and instructional design. Learning theories and styles provide the theoretical foundation for designing effective instructional strategies, adaptive learning environments and educational technologies.

3.1 Learning Theories

Learning theories explain how learning occurs and provide the foundation for instructional design and learner support. Behaviourism emphasises observable behaviour (Schunk, 2020; Woolfolk, 2021); Cognitivism focuses on internal mental processes (Mayer, 2021); Constructivism views learning as active knowledge construction (Fosnot, 1996); Connectivism explains learning in networked environments (Siemens, 2005; Downes, 2019); and Collaborativism highlights knowledge co-construction through interaction (Harasim, 2017; Dillenbourg, 2019). Collectively, these theories provide complementary perspectives that inform the learning principles synthesised in the Triad of Anatomy, Dynamics and Pattern of Learning Principles**.**

3.2 Learning Styles

Learning style frameworks seek to account for learner diversity and inform flexible instructional design. Models such as Visual, Auditory, Reading/Writing, and Kinesthetic (VARK) (Fleming, 2001), Kolb's Experiential Learning Theory (Kolb and Kolb, 2012), Honey and Mumford's Learning Styles (Honey and Mumford, 2000), Felder–Silverman Learning Style Model (FSLSM) (Felder and Silverman, 1988), Gregorc Style Delineator (Gregorc, 1984), and Myers–Briggs Type Indicator (MBTI) (Myers *et al.*, 2018) illustrate different perspectives on how individuals perceive information, make decisions, and interact with learning environments. Although contemporary research discourages rigid categorisation of learners, these frameworks provide useful insights for designing flexible and learner-centred environments that recognise differences among learners. This recognition of learner diversity is synthesised within the Triad of Anatomy, Dynamics and Pattern of Learning Principles.

4.0 LEARNING THEORIES AND LEARNING STYLES THROUGH THE LENS OF ANATOMY, DYNAMICS AND PATTERN OF LEARNING PRINCIPLES

Although learning theories and learning style frameworks differ in emphasis, they converge on fundamental principles of how learning occurs. Viewed through the lens of the Triad of Anatomy, Dynamics and Pattern of Learning Principles, they reveal three interconnected dimensions that underpin effective learning.

A. **Anatomy** comprises the foundational structural elements of learning, including cognition, memory, prior knowledge, motivation, learner characteristics,

instructional resources, and the learning environment. Within the ADP Framework, motivation is regarded as a core learner attribute because it influences learners' readiness to invest cognitive resources in learning, while its activation and sustenance are addressed within the Dynamics.

B. **Dynamics** encompasses the cognitive, social, emotional, and instructional processes through which learning occurs, including interaction, collaboration, feedback, reflection, metacognition, and knowledge construction.

C. **Pattern** describes the sequencing, adaptation, and developmental progression through which learning advances from initial understanding to deeper knowledge acquisition and transfer.

Together, these dimensions constitute the Triad of Anatomy, Dynamics and Pattern of Learning Principles, which serves as the conceptual foundation of the Deep Knowledge Community. The ADP provides a unifying lens for integrating learning theories, learning style frameworks, cognitive science, and educational technologies into a coherent framework for designing intelligent, responsive, collaborative, and transformative learning environments.

5.0 MY CONTRIBUTIONS TO KNOWLEDGE IN THE FIELDS OF LEARNING SCIENCES AND EDUCATIONAL TECHNOLOGY

Madam Vice Chancellor, my research contributions have therefore focused on integrating educational technologies with the three pillars of learning principles to create adaptive, learner-centred, and evidence-based learning environments. These contributions collectively demonstrate how technology can support the development of deep knowledge community by

strengthening the anatomy, enriching the dynamics and optimising the patterns of learning. My major contributions to knowledge are highlighted under the following five headings:

A. Cognitive Load, Cognitive Tasks, Motivational Factors, and Curriculum Sequencing in E-Learning Systems.
B. Identification of Individual Learning Preferences and Affective-Adaptive Activities in Personalised E-Learning Systems.
C. Digital Game-Based Learning Systems.
D. Virtual Reality as a Tool for Students' Adaptive Learning.
E. Artificial Intelligence for Learning Analytics in Educational Data Mining.

5.1 Cognitive Load, Cognitive Tasks, Motivational Factors and Curriculum Sequencing in E-Learning Systems

Madam Vice Chancellor, one of my major contributions to knowledge is the application of cognitive learning principles to the design of intelligent and adaptive e-learning systems. This work addresses a fundamental challenge in digital education: aligning instructional design with human cognitive architecture to reduce cognitive overload, enhance learner engagement, improve knowledge retention, and promote effective learning.

A foundational contribution was the presentation of a human cognitive processing model (**Agbonifo**, 2014), illustrated in Figure 1, which examined how information is received, processed, stored, and retrieved within the human memory system. The model demonstrated learning as a progression from sensory memory through working memory to long-term memory, where knowledge is organised into cognitive schemas. It established that effective instructional systems must

accommodate the capacity limitations of working memory while supporting efficient schema construction and knowledge transfer. The model therefore provided a theoretical foundation for designing educational technologies that respect the principles of human cognition. It also strengthened the **Anatomy of Learning Principles** within the Deep Knowledge Community framework.

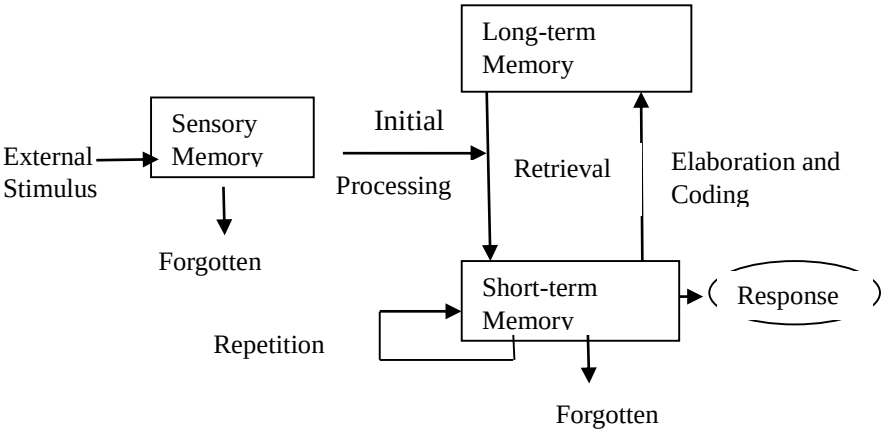


Figure 1. *The Architecture of Human Memory Processing Model*

Building upon the principles of human cognitive architecture, my research explored the application of cognitive load theory to instructional design in technology-mediated learning environments. **Agbonifo** and Ibam (2014) developed a cognitive load theory-based e-learning framework that organised instructional materials into manageable interactive elements and adapted content to learners' abilities and skill levels, thereby reducing unnecessary complexity and supporting effective learning. The study demonstrated that instructional designers must deliberately manage intrinsic cognitive load,

minimise extraneous load, and promote germane load to optimise learning outcomes. This contribution advanced the Dynamics of Learning Principles by demonstrating how cognitive processes can be supported through intelligent instructional design.

Extending this work from instructional content to the organisation of learning materials, **Agbonifo** and Adewale (2009**)** developed a cognitive learning model for adaptive course sequencing. The model presented learning concepts dynamically according to learners' characteristics and instructional objectives, promoting a meaningful progression through learning materials. It established that curriculum sequencing should not be static but responsive to learner needs and cognitive readiness.

This line of enquiry culminated in the development of a genetic algorithm-based curriculum sequencing model by **Agbonifo** and Obolo (2018a). As shown in Figure 2, the model introduced an intelligent mechanism for generating personalised learning pathways based on two critical variables: concept difficulty and concept relationship degree. The course concept database contains *n* concepts, while the relationships among these concepts are represented through a course concept relation matrix, denoted by *R*, as expressed in Equation 1. The matrix captures the relational strength between every pair of course concepts within the system.

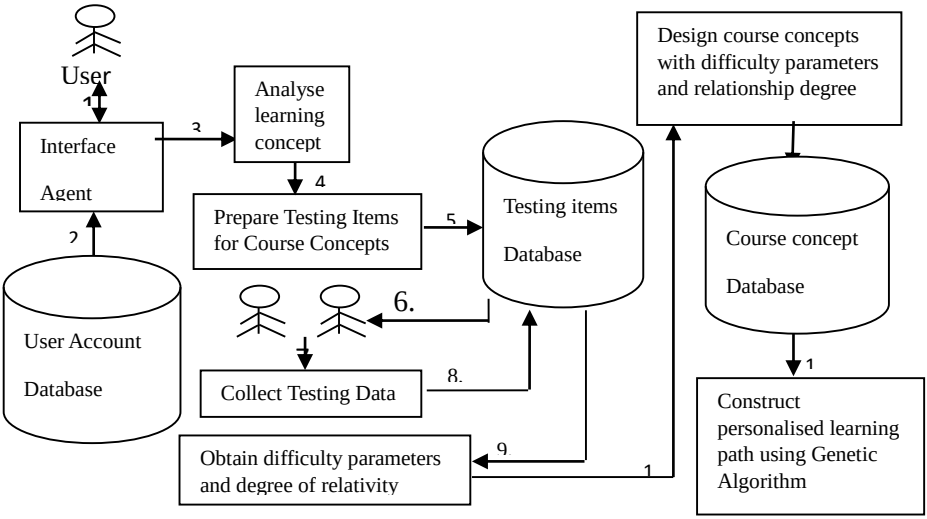


Figure 2. System Architecture of the Genetic-Based Curriculum Sequencing

$$R = \begin{matrix} C_1 \\ C_2 \\ \vdots \\ C_n \end{matrix} \begin{bmatrix} C_1 & C_2 & \cdots & C_n \\ r_{1,1} & r_{1,2} & \cdots & r_{1,n} \\ r_{2,1} & r_{2,2} & \cdots & r_{2,n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{n,1} & r_{n,2} & \cdots & r_{n,n} \end{bmatrix} \quad (1)$$

Term Frequency-Inverse Document Frequency (TF-IDF) weighting was used to determine the significance of each term within a concept, as shown in Equation 2.

$$w_{i,k} = tf_{i,k} \times log \frac{N}{df_k} = tf_{i,k} \times IDF \quad (2)$$

where $w_{i,k}$ represents the weight of the k^{th} term associated with the i^{th} concept. It is calculated as the product of the term frequency of the term within the concept and its inverse document frequency across the concept database. Thus, terms

that occur frequently within a concept but less frequently across other concepts receive greater weights in representing that concept.

The degree of relationship between any two course concepts, i^{th} and j^{th}, was computed using cosine similarity, as defined in Equation 3.

$$r_{i,j} = \frac{\sum_{h=1}^{m} (w_{i,h})(w_{j,h})}{\sqrt{\sum_{h=1}^{m} (w_{i,h}^2)\ (w_{j,h}^2)}} \quad (3)$$

The resulting similarity values represented the semantic relationships among learning concepts, while concept difficulty levels were established through collaborative evaluations involving experts and learners. These two parameters, concept difficulty and conceptual relationship were subsequently used by a genetic algorithm to generate personalised learning pathways.

The optimisation process began with the initialisation of a population of candidate learning sequences. Each chromosome represented a possible ordering of course concepts. A fitness function evaluated each sequence according to its ability to minimise cognitive overload and maximise conceptual continuity. Through successive evolutionary cycles involving selection, crossover, and mutation, the algorithm progressively improved the candidate learning paths.

The study was conducted using the Computer Networks course, comprising five core concepts: Introduction to Computer Networks (C_1), Networks Physical Topology (C_2), Transmission Media (C_3), OSI Reference model (C_4) and Switching (C_5). The results presented in Tables 1–3 demonstrated the effectiveness

of integrating concept difficulty and conceptual relationships to generate an adaptive learning sequence.

Table 1 revealed variations in concept difficulty based on collaborative assessments by experts and learners. C_1 and C_3 were identified as the most demanding concepts, whereas C_2 and C_5 were perceived as relatively less difficult. Table 2 presents the conceptual relationship matrix, highlighting the semantic dependencies among concepts. The highest relationship value (0.4118) occurred between C_1 and C_3, indicating a strong conceptual relationship, while lower values suggested weaker prerequisite connections among other concepts.

Using the concept difficulty indices and conceptual relationship matrix, the genetic algorithm generated the optimal learning sequence: $C_1 \rightarrow C_3 \rightarrow C_2 \rightarrow C_4 \rightarrow C_5$, as presented in Table 3.

Table 1. The difficulty level Computed for the Course Concepts

	Learners	Experts	Initial	Response	Initial + Response
C_1	1.73	1.88	0.0376	1.6954	1.7330
C_2	1.13	1.46	0.0292	1.1074	1.1366
C_3	1.63	1.66	0.0332	1.5974	1.6306
C_4	1.33	1.66	0.0332	1.3034	1.3366
C_5	1.19	1.46	0.0292	1.1662	1.1954

Note. C_1 = Introduction to Computer Networks; C_2 = Network Physical Topology; C_3 = Transmission Media; C_4 = OSI Reference Model; C_5 = Switching.

Table 2. The Degree of Relationship between Course Cncepts

	C_1	C_2	C_{31}	C_{41}	C_5
C_1	1	0.3866	0.4118	0.2000	0.1034
C_2	0.3866	1	0.2488	0.0134	0.0974
C_3	0.4118	0.2488	1	0.0459	0.0009
C_4	0.2000	0.0134	0.0459	1	0.0601
C_5	0.1034	0.0975	0.0009	0.0601	1

Note. C_1–C_5 are as defined in Table 1.

Table 3. Optimal Learning Path Generated

Learning Path		Difficulty Level	Concept relationship degree between two successive concepts
C_1	Introduction to computer networks	1.7	-
C_3	Transmission media	1.6	0.4118
C_2	Networks physical topology	1.1	0.2488
C_4	OSI Reference model	1.3	0.0134
C_5	Switching	1.2	0.0601

Note. C_1–C_5 are as defined in Table 1.

These findings demonstrated that effective curriculum organisation should consider not only content difficulty but also the logical interdependence among concepts, enabling learners to construct knowledge in an appropriate sequence while reducing cognitive overload and facilitating meaningful learning.

Further extending this work, **Agbonifo** and Akinsete (2020) developed an ontology-based personalised recommender system to reduce information overload through semantic

technologies and collaborative filtering. The system classified learners according to their prior knowledge levels and employed ontology structures, adjusted cosine similarity measures, and collaborative filtering techniques to recommend appropriate learning resources. The model was evaluated using 150 learning materials and 100 learners. Learners were classified as beginner, intermediate, advanced, or expert based on their pre-test performance, and learning content was recommended according to their respective knowledge levels. Learners evaluated the recommended contents using a five-point scale ranging from 1 (very irrelevant) to 5 (very relevant). Collaborative filtering was subsequently employed to refine recommendations based on collective user preferences.

Evaluation of the top 20 recommended learning contents demonstrated strong recommendation accuracy across all learner levels. The system achieved precision, recall, and F1-measure scores of 0.88, 0.84, and 0.85 for beginners; 0.80, 0.77, and 0.78 for intermediate learners; 0.74, 0.71, and 0.75 for advanced learners; and 0.68, 0.76, and 0.66 for expert learners, respectively. These results demonstrated that intelligent recommendation systems can reduce learners' search effort, minimise exposure to irrelevant content, and improve learning efficiency by matching instructional resources with learners' existing knowledge structures.

Beyond cognitive architecture and curriculum sequencing, my research also explored cognitive tasks and motivational factors as complementary mechanisms for improving learning efficiency. **Agbonifo** and Adewale (2014) developed a goal-oriented instructional framework that organised learning content around clearly defined learning objectives and

structured knowledge networks. The framework reduced extraneous cognitive load by directing learners' attention towards relevant information while supporting retention and recall through problem-solving activities embedded within instructional content.

A particularly significant contribution was the integration of visual attention mechanisms into e-learning design. The framework proposed that learners' gaze behaviour could serve as an indicator of ongoing cognitive processing and that instructional interfaces should strategically direct attention towards relevant learning elements. This line of research was further extended by **Agbonifo** and Kolawole (2026) through the use of eye-tracking and accelerometer technologies to monitor learners' attention and engagement during instructional activities. The findings demonstrated that attention-aware learning environments can enhance cognitive engagement and learning efficiency while providing valuable information for the development of intelligent instructional systems.

Complementing the cognitive dimension, **Agbonifo** (2014) integrated motivational theories into the e-learning system by combining Keller's ARCS Model with Wlodkowski's Time-Continuum Model. The framework incorporated goal statements, discussion forums, multimedia presentation strategies, communication mechanisms, and emoticon-based feedback systems to sustain learner engagement and motivation. The study established that motivation is not merely an affective variable but an important determinant of cognitive resource allocation and learning effectiveness. Through collaborative interaction, timely feedback, and multimodal content

presentation, the framework enhanced learner confidence, satisfaction, participation, and persistence.

Collectively, these studies demonstrate the progressive development of intelligent learning environments from cognitive load management and curriculum sequencing to personalised resource recommendation, attention-aware instruction, and motivational support. The central contribution lies in demonstrating that effective educational technology depends not simply on the delivery of digital content, but on the deliberate alignment of cognitive processes, learner characteristics, motivational factors, and instructional structures. Within the Deep Knowledge Community framework, these contributions strengthen the anatomy of learning through cognitive architecture, enrich the dynamics of learning through attention, engagement, and motivation, and optimise the patterns of learning through intelligent sequencing and personalisation. Together, they provide a foundation for adaptive and cognitively informed learning environments capable of supporting deep, meaningful, and sustained knowledge construction.

5.2 Identification of Individual Learning Preferences and the Activity Sequencing in Personalised E-Learning Systems

Madam Vice Chancellor, one of my major contributions to knowledge lies in advancing personalised e-learning systems through the identification of individual learning preferences, adaptive activity sequencing, learner modelling, ubiquitous learning, and affect-aware instructional environments. This work emerged from the recognition that conventional e-learning systems often adopt a uniform instructional approach, exposing

learners to identical materials, instructional sequences, and learning experiences despite differences in cognitive abilities, prior knowledge, preferences, motivations, learning behaviours, and emotional states. My research has therefore focused on developing learning environments that recognise such differences and adapt instructional experiences accordingly.

A contribution in this area was presented in Agbonifo (2013), where the traditional notion of fixed learner categorisation was challenged through the application of the Fuzzy C-Means (FCM) clustering algorithm to learning preference identification based on the Honey and Mumford Learning Styles Model. Unlike conventional classification approaches that assign learners rigidly to a single category, the model recognised that learners may exhibit characteristics associated with multiple learning dimensions simultaneously. Using responses from an 80-item Learning Styles Questionnaire (LSQ) measured on a four-point Likert scale, the FCM algorithm iteratively identified learner groupings based on membership values and Euclidean distance. Learners were subsequently assigned to the category corresponding to their highest membership value: Reflector, Pragmatist, Theorist, or Activist.

The experiment involved 50 second- and third-year Computer Science students of the Federal University of Technology, Akure (FUTA), Nigeria. The results showed that the FCM algorithm successfully identified the dominant learning preferences of 48 learners, representing 96% of the participants, while 4% remained unclassified because of inconsistent response patterns. As shown in Table 4, the distribution comprised 18 Reflectors, 23 Pragmatists, 5 Theorists, 2 Activists, and 2 unclassified learners. The significance of this contribution demonstrated that learner preferences can be

represented more realistically through fuzzy membership values than through rigid categorical assignments. The work provided a foundation for adaptive learning environments capable of responding to learner variability and thereby strengthened learner-centred and constructivist approaches to instructional design.

Table 4. The distribution of learners across the identified learning style dimensions

Learning Style Dimension	Frequency
Reflector	18
Pragmatist	23
Theorist	5
Activist	2
Null	2
Total	**50**

Building upon this foundation, our e-learning research group, supported by a TETFund research grant in 2015, extended personalisation beyond learning style identification to encompass adaptive activity sequencing, ubiquitous learning, collaborative learning, and location-aware educational environments. One of the outcomes of this effort was reported by Adewale *et al*.(2018), where a model was developed for sequencing learning activities based on both learner preferences and physical location.

The study was implemented within the FUTA wireless local area network environment and employed trilateration and fingerprinting techniques to determine learners' locations from wireless access point signals. Integrating location awareness into the learning process enabled learners to access personalised

learning experiences irrespective of where they were within the university environment. The model also employed a Fuzzy Cognitive Map (FCM) based on the Felder–Silverman Learning Style Model to identify dominant learner preferences from online behavioural activities.

The experimental study involved 129 100-level FUTA students during the 2016/2017 academic session. The system captured each learner's activities in relation to their learning preferences and location within the university. Simulation results demonstrated that the model supported adaptive learning, location-aware interaction, and collaborative group activities. The findings further indicated that group work had a significant positive effect on students' learning performance.

The detected learning preferences and their distribution across locations are summarised in Table 5. Sensory learners constituted the largest group, with 28 students distributed across classrooms, lecture halls, hostels, laboratories, and workshops. Active learners accounted for 19 students, while Intuitive and Global learners each recorded 16 students. Other identified preferences included Inductive, Sequential, Reflective, Verbal, Visual, and Deductive. The results confirmed that learners accessed the system across the different locations.

Similarly, Table 6 presents the heterogeneous group formations generated using the FSLSM and FCM techniques. A total of 38 heterogeneous groups were formed from the 129 learners. The Female Hostel (Obanla) recorded the highest participation, with 32 learners forming five groups, while the laboratory and library environments each produced six groups.

Table 5. Learners' Styles and Locations Detected

Learning Styles	Locations							Total
	Class rooms	Lecture halls	Hostels	Library	Laboratory	Workshop	School Compound	
Sensory	8	5	7	-	6	2	-	**28**
Visual	-	-	8	-	-	-	2	**10**
Inductive	-	-	8	5	-	-	-	**13**
Active	-	-	11	6	-	-	2	**19**
Sequential	-	-	-	-	6	2	-	**8**
Intuitive	10	6	-	-	-	-	-	**16**
Verbal	-	-	8	-	-	-	-	**8**
Deductive	-	-	-	-	-	-	2	**2**
Reflective	-	-	-	-	8	1	-	**9**
Global	-	-	9	7	-	-	-	**16**

Table 6. Group Heterogeneous Formation using FSLSM and FCM

Locations	No of Learners	Number of Group formed
Class rooms	18	8
Lecture Halls	11	4
Library	18	6
Laboratory	20	6
Workshop	5	2
Male Hostel (Obanla)	12	2
Female Hostel (Obanla)	32	5
Male Hostel (Obakekere)	7	1
School compound	6	2
TOTAL	129	38

The findings demonstrated that integrating learner preferences, fuzzy intelligence, and location awareness can support more responsive collaborative learning environments. This represents an important advancement in adaptive learning design by connecting learner characteristics, context, and social interaction within a unified learning environment.

Another significant contribution of our collaborative research was published in the high-impact Q1 Taylor and Francis journal *Interactive Learning Environments* (Adewale *et al.*, 2022). The study developed an intelligent personalised e-learning system based on Bayesian Networks to model uncertainty in learners' preferences. Moving beyond traditional questionnaire-based approaches, the system continuously analysed learners' interactions with text, graphics, videos, quizzes, discussion forums, chats, and animations to update learner profiles and deliver more precise instructional experiences.

The model was evaluated during a five-week *Introduction to Computing* course involving 127 first-year students from the 2018/2019 academic session in the Department of Computer Science. As presented in Table 7, Bayesian inference successfully modelled learner preferences across the FSLSM dimensions, with the Visual learning style recording the highest posterior probability among the learners (98 learners). While the Active/Reflective, Sensing/Intuitive, and Visual/Verbal dimensions exhibited stronger preference distributions, the Sequential/Global dimension showed a more balanced pattern.

This study established Bayesian Networks as a robust framework for modelling uncertainty and variability in learners' preferences. It advanced personalised e-learning from relatively static learner profiles towards evidence-driven models that continuously respond to observed behaviour. The study further demonstrated that effective personalisation emerges from the

interaction among learners, instructional content, learning environments, and feedback. This finding strengthens the development of intelligent and adaptive e-learning systems.

Table 7. Learning Style based on ILS Questionnaire Result

FSLSM Dimension	**G1-G3 (Mild Preference)**		**G5-G7 (Moderate Preference)**		**G9-G11 (Strong Preference)**		**TOTAL**
	∑	⁒	∑	⁒	∑	⁒	
Active	5	7.143	29	41.429	36	51.429	70
Reflective	2	3.509	16	28.07	39	68.421	57
Sensing	22	25	21	23.864	45	51.136	88
Intuitive	16	41.026	12	30.769	11	28.205	39
Visual	19	19.388	41	41.837	38	38.776	98
Verbal	3	10.345	7	24.138	19	65.517	29
Sequential	5	7.463	28	41.791	34	50.746	67
Global	1	1.667	21	35	38	63.333	60

Recognising that learning is influenced not only by cognitive preferences but also by affective factors, our research extended personalisation into the affective domain. Adewale *et al.* (2018) developed an affect-adaptive ubiquitous learning environment that examined how emotional states such as confidence, effort, independence, and confusion influence learner engagement and performance.

Using received signal strength techniques for location detection and the Ant Colony Clustering Algorithm for behavioural analysis, the system monitored learners' interactions with instructional resources, discussion forums, assignments, and self-assessment activities. The model was evaluated with 129 learners across two five-week online courses: Course A, which

incorporated affective adaptation, and Course B, which did not. As presented in Tables 8 and 9, Course A recorded substantially higher levels of learner interaction, collaboration, confidence, effort, independence, and overall academic performance than Course B, with statistically significant improvements across all affective dimensions ($p < 0.05$).

The findings established that affect-aware adaptation can enhance the effectiveness of personalised learning by incorporating learners' emotional states into instructional decision-making. This contribution extended intelligent learning environments beyond cognitive and behavioural adaptation to include the affective dimension of learning, thereby strengthening the development of responsive and learner-centred educational systems.

Table 8. Number of responses posted by learners of course A and course B

Number of responses posted	**Course A Discussion 1**		**Course B Discussion 1**		**Course B Discussion 2**		**Course A Discussion 2**	
	No.	%	No.	%	No.	%	No.	%
0	6	5%	29	22	32	25	1	1%
1	110	85%	90	70	93	72	92	71%
2	10	8%	10	8	3	2	31	24%
3	3	2%	0	0	1	1	5	4%

Table 9. Statistical details of learners' Affect-Adaptive states

Affect states	**Course A**		**Course B**		**t TE**		
	Mean	SD	Mean	SD	T Stat	p	d
Confidence	330.33	302.25	237.33	223.36	2.858	0.021	8
Effort	273	214.09	206.57	188.26	3.857	0.008	7
Independence	241.83	266.85	170.75	201.11	3.039	0.011	11
Confusion	259.78	305.89	187.67	229.31	2.342	0.047	8
AVERAGE VALUE	**276.23**	**272.27**	**200.58**	**210.51**			

In addition to these major contributions, our collaborative research further strengthened the theoretical and methodological foundations of personalised learning. Adewale *et al.* (2019) demonstrated the application of the Myers–Briggs Type Indicator for learner modelling in adaptive e-learning environments. Although structurally different from the Felder–Silverman Learning Style Model, the study reinforced the broader principle that individual cognitive and behavioural differences can be computationally represented to inform instructional adaptation.

Similarly, Fakoya *et al.* (2020) extended the Felder–Silverman Learning Style Model by introducing continuous updating of learner profiles based on interaction data rather than relying solely on initial questionnaire responses. This contribution reflected the dynamic nature of learning and strengthened the methodological basis for systems capable of responding to changes in learner behaviour over time.

Furthermore, **Agbonifo** and Adeleke (2019) developed a fuzzy logic-based personalised mobile learning system that addressed

uncertainty and variability in learner behaviour. By allowing learners to possess varying degrees of membership across multiple FSLSM dimensions, the system moved beyond rigid classification schemes towards a more flexible representation of learner characteristics for instructional adaptation.

Collectively, these studies strengthened the theoretical and computational basis for personalised learning by demonstrating that learner characteristics can be represented dynamically and adapted to changing patterns of interaction. Their significance lies in moving beyond static learner categorisation towards intelligent systems capable of incorporating cognitive, behavioural, contextual, and affective information in instructional decision-making. Within the DKC framework, these contributions demonstrate how technology operationalises the **Dynamics and Pattern of Learning Principles**, enabling learning environments to respond intelligently to individual differences and changes in the learning process.

5.3 Digital Game-Based Learning Systems

Madam Vice Chancellor, another significant contribution of my research is the development and application of Digital Game-Based Learning (DGBL) systems as innovative educational technologies that promote critical thinking, problem-solving, collaboration, active participation, sustained engagement, deep conceptual understanding, and meaningful knowledge construction. This research was motivated by the persistent perception of mathematics as abstract, difficult, and disconnected from everyday experiences, leading to low motivation and poor learning outcomes.

To address this challenge, a research concept christened "*Mathematics Created by You"* was initiated which seeks to

transform mathematics learning into an engaging, interactive, and learner-centred experience. This research has produced substantial scholarly outputs published in reputable national and international journals, including Scopus-indexed publications, and aligns with the concerns raised in the 188th Inaugural Lecture, *Mathematics: Myths, Mysteries and Life*, by challenging misconceptions surrounding the teaching and learning of mathematics.

This research concept has resulted in the development of several DGBL systems, including a LEGO-based game for fractional ordering (**Agbonifo** and Ogunmoronti, 2015); a chess-based strategy for solving simultaneous equations (**Agbonifo** and Onu, 2017); a Tic-Tac-Toe game-theoretic model for quadratic factorisation (**Agbonifo** and Ofueu, 2018); a Snakes and Ladders model for matrix operations (**Agbonifo** *et al*., 2021a); a Snakes and Ladders approach for fraction algebra (**Agbonifo** *et al*., 2021b); and a Battleship game model for solving quadratic equations by the completing-the-square method (**Agbonifo** *et a*l., 2021c). Collectively, these innovations demonstrate the potential of Digital Game-Based Learning to transform mathematics education through engaging, interactive, and experiential learning. The design and implementation of these DGBL systems are discussed in the following subsections.

5.3.1 Learning Fractional Ordering through a Digital Lego-Based Game Environment

Agbonifo and Ogunmoronti (2015) developed a digital LEGO-based learning environment that transformed fraction learning into an interactive, learner-centred experience by integrating game mechanics with mathematical reasoning and cognitive engagement. The narrative-driven game required learners to arrange fraction cubes in ascending order progressively, ensuring that learning objectives remained central to gameplay.

The system promoted constructivist learning through active reasoning, immediate feedback, reward mechanisms, and time-based challenges, thereby enhancing conceptual understanding, motivation, and persistence. The game was developed using Construct 2 and incorporated interactive features such as player avatars, LEGO obstacles, fraction cubes, fruit rewards, and a Heads-Up Display (HUD), as illustrated in Figures 3 and 4.

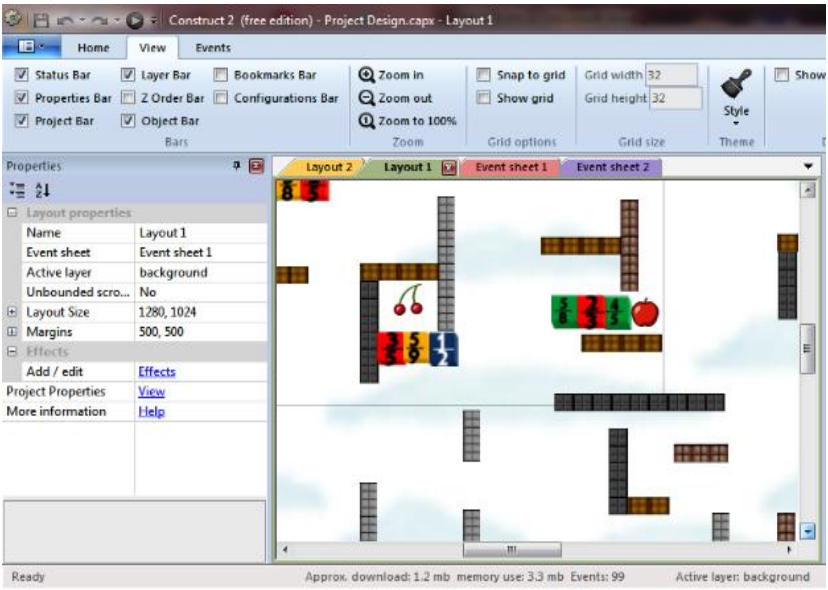


Figure 3*. Design Process for Constructing Digital Lego-Based Learning Environment*

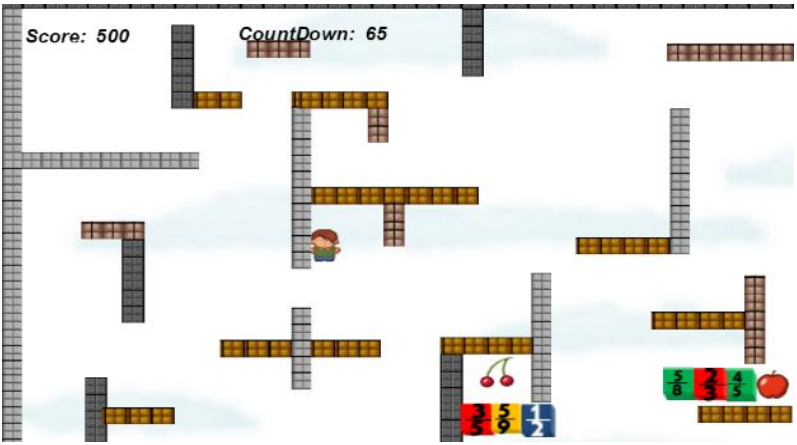


Figure 4. *Digital Lego-Based Learning Environment*

The model was evaluated with ten Primary four pupils from a private primary school near the Federal University of Technology, Akure, Nigeria. As presented in Figure 5, the results demonstrated improved fraction-ordering skills, conceptual understanding, learner enthusiasm, concentration, persistence, and active participation. The study provided empirical evidence that Digital Game-Based Learning is an effective approach for promoting conceptual understanding, active knowledge construction, and sustained engagement in mathematics education.



***Figure 5**. Game Output*

5.3.2 Design and Pedagogical Framing of a Digital Game-Based Algebraic Learning System

Agbonifo and Onu (2017**)** introduced a DGBL system for learning simultaneous equations by integrating mathematical reasoning with game-based instructional strategies. The adventure-based game cast learners as a knight on a rescue mission, embedding the elimination method for solving simultaneous equations into gameplay, with algebraic variables functioning as symbolic keys to unlock successive levels. This transformed procedural practice into an interactive learning experience that promoted strategic thinking, exploration, and conceptual understanding.

Within a timed, chessboard-inspired environment, learners applied elimination, substitution, and verification techniques to progress through the game. Immediate feedback, context-sensitive hints, progress indicators, reward mechanisms, and solution expanders provided instructional support and

reinforced conceptual mastery. The gameplay interface and instructional features are illustrated in Figures 6 and 7.



Figure 6. *Chess Mediated Environment for Solving Two Simultaneous Linear Equations*

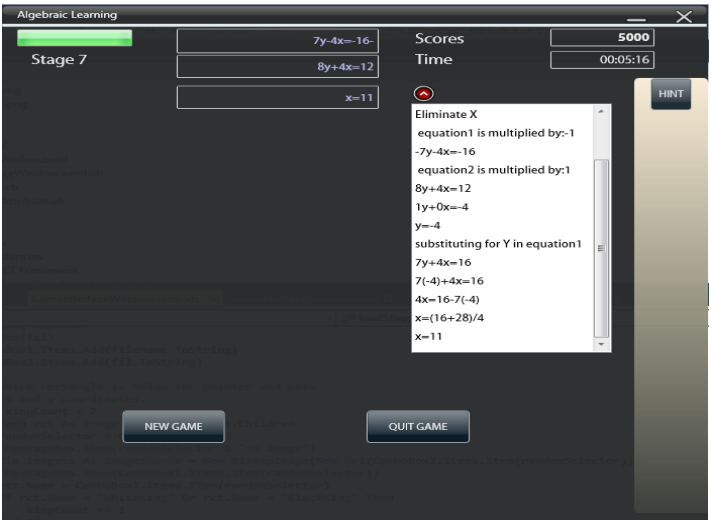
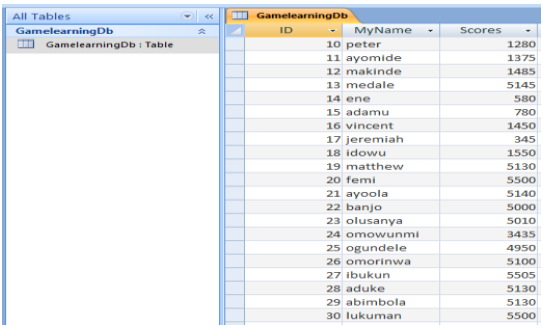


Figure 7*. A Player's Task Progress with Step-Wise Solution*

The system was evaluated with 20 pre-degree students of the Federal University of Technology, Akure, during the 2014/2015 academic session. Performance outcomes presented in Figure 8 demonstrated strong engagement and progressive mastery of simultaneous equations. Learners' perceptions were further assessed using a 23-item, five-point Likert-scale questionnaire covering Capability, Intended Learning Outcomes and Game Attributes, Learning Activity, Reflection, and Game Achievement. The aggregated weighted scores are presented in Table 10.


All Tables
GamelearningDb
GamelearningDb : Table

GamelearningDb

ID	MyName	Scores
10	peter	1280
11	ayomide	1375
12	makinde	1485
13	medale	5145
14	ene	580
15	adamu	780
16	vincent	1450
17	jeremiah	345
18	idowu	1550
19	matthew	5130
20	femi	5500
21	ayoola	5140
22	banjo	5000
23	olusanya	5010
24	omowunmi	3435
25	ogundele	4950
26	omorinwa	5100
27	ibukun	5505
28	aduke	5130
29	abimbola	5130
30	lukuman	5500

Figure 8. Scores of Twenty Students' Generated

Table 10.Variables combination with respect to Framework variables

Conceptual Framework Variables	**Points**		**Percentage Points**
	Obtained	**Obtainable**	
Capability	623	700	89%
Intended Learning Outcomes and Game Attribute	712	900	79%
Learning Activity	275	300	91%
Reflection	92	100	92%
Game Achievement	253	300	84%

The five dimensions recorded positive ratings ranging from 79% to 92%, with Reflection achieving the highest score (92%), followed by Learning Activity (91%), Capability (89%), and Game Achievement (84%). Intended Learning Outcomes and Game Attributes recorded 79%, which nevertheless indicated a favourable evaluation of the system's instructional design and usability.

The study demonstrated that DGBL can embed algebraic reasoning within engaging gameplay without compromising conceptual rigour. Through progressive challenges, immediate feedback, and strategic decision-making, the system supported motivation, confidence, persistence, problem-solving, and conceptual understanding while helping to reduce anxiety towards algebra. The findings established the game-based environment as an effective technology-enhanced strategy for promoting active knowledge construction in mathematics education.

5.3.3 Learning Quadratic Factorisation through the Game-Theoretic Structure of Tic-Tac-Toe

Agbonifo and Ofueu (2018b) developed an innovative DGBL environment that adapted the game-theoretic principles of Tic-Tac-Toe to teach quadratic factorisation. The system transformed factorisation from a procedural exercise into an interactive, learner-centred experience by integrating game theory, mathematical reasoning, and narrative-based learning.

The game immersed learners in a storyline that required them to escape from a mysterious island by solving Tic-Tac-Toe challenges involving quadratic equations. As illustrated in Figure 9, the game employed a 3 x 3 Tic-Tac-Toe grid, while Figure 10 presents a worked example of factorising the quadratic equation $r^2 + 10r + 16 = 0$. Learners identified appropriate factor pairs and strategically positioned them within

the game environment to complete the factorisation process, thereby promoting conceptual understanding rather than rote memorisation.
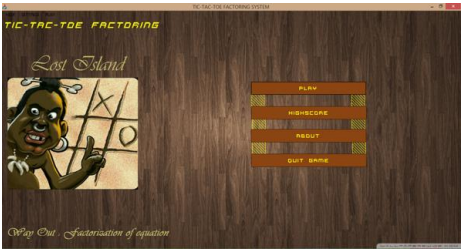


Figure 9*. Game Interface of the Game when Launched*

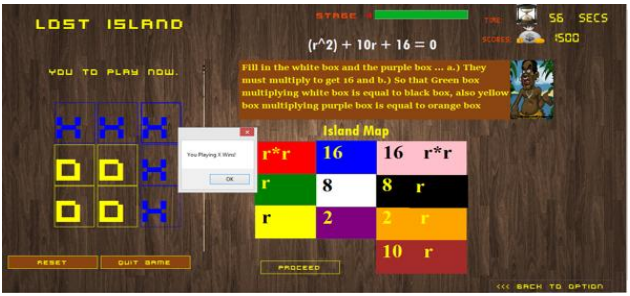


Figure 10. *Showing the Factors of the Equation to be 8 and 2*

The system also generated worksheets with step-by-step solution pathways for attempted problems (Figure 11). These pathways enabled learners to review their solutions, identify errors, and strengthen procedural and conceptual understanding through reflection.

The study demonstrated that the game-theoretic DGBL environment effectively aligned game mechanics with sound instructional principles, enhancing conceptual understanding, critical thinking, motivation, and sustained knowledge construction in mathematics education.

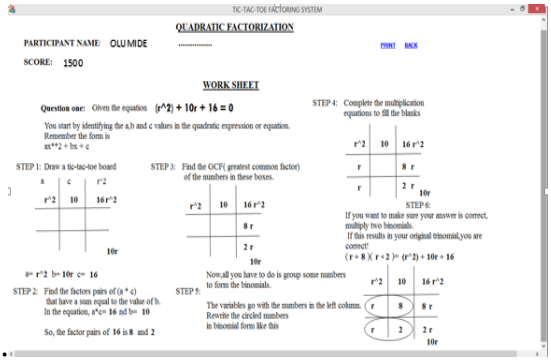


Figure 11. *The Worksheet for Step-Wise Solution*

5.3.4 Understanding Matrix Operations Using Snakes and Ladder Game Structure

Agbonifo *et al.* (2021a) developed a Digital Game-Based Learning system based on *Snakes and Ladders* to teach the computation of determinants of a 3 x 3 matrix using the cofactor expansion method. The system integrated mathematical reasoning, strategic gameplay, and instructional scaffolding, with learners progressing through three compulsory checkpoints covering minors, cofactors, and the final determinant, as illustrated in Figures 12 and 13.

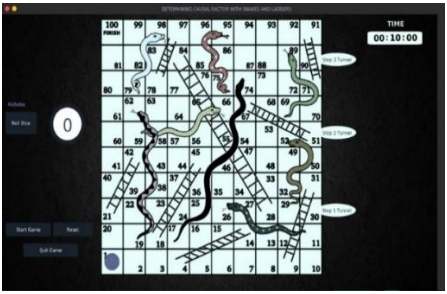


Figure 12. *Main Game Page*

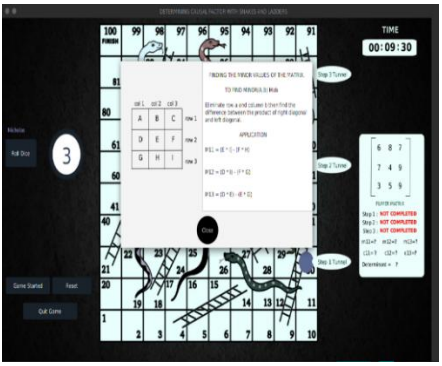
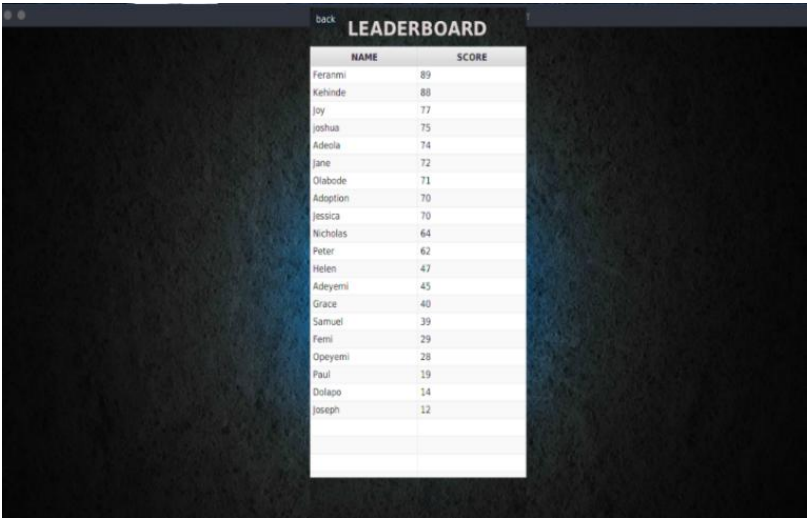


Figure 13. *Game Stage Showing Minor Hints*

The system was evaluated with 20 Senior Secondary School III students from the Federal University of Technology, Akure Staff Secondary School. Learners' achievement was assessed using the system-generated leaderboard and stepwise solution worksheet (Figures 14 and 15).



NAME	SCORE
Feranmi	89
Kehinde	88
Joy	77
joshua	75
Adeola	74
Jane	72
Olabode	71
Adoption	70
Jessica	70
Nicholas	64
Peter	62
Helen	47
Adeyemi	45
Grace	40
Samuel	39
Femi	29
Opeyemi	28
Paul	19
Dolapo	14
Joseph	12

Figure 14*. Leaderboard Stage*

```
STEPWISE DOCUMENTATION OF THE GAMEPLAY FOR PLAYER NICHOLAS

        | 6 8 7 |
        | 7 4 9 |
        | 3 5 9 |

STEP 1: Computing the Minors

Minor(m11)= (4 * 9) - (9 * 5)  = -9
Minor(m12)= (7 * 9) - (9 * 3)  = 36
Minor(m13)= (7 * 5) - (4 * 3)  = 23

STEP 2: Computing the Cofactors

Cofactor(c11)= ((-1)^(1+1)) * m11= ((-1)^(1+1)) * -9 = -9
Cofactor(c12)= ((-1)^(1+2)) * m11= ((-1)^(1+2)) * 23 = -36
Cofactor(c13)= ((-1)^(1+3)) * m11= ((-1)^(1+3)) * 23 = 23

STEP 3: Computing the Determinant

Determinant= (x11*c11) + (x12*c12) + (x13*c13) = (6*-9) - (8
*-36) - (7*23) = -181
```

Figure 15. *Game Stage Showing the Worksheet of the First Player*

The learners' perceptions were measured using a 20-item five-point Likert-scale questionnaire covering five dimensions and summarised in Table 11. The results were highly positive, with Learning Outcome (91.3%) recording the highest rating, followed by Game Objective (90%), Ease of Use (89.8%), Critical Thinking and Motivation (89%), and Usefulness of Game Features (88%). The study demonstrated that well-designed game mechanics combined with instructional scaffolding can enhance conceptual understanding, motivation, engagement, logical reasoning, and mathematics learning outcomes.

Table 11. Result of Total Response Points and Percentage Point Value for the Survey Variables

VARIABLES	POINTS		PERCENTAGE POINT	PERCENTAGE POINT VALUE
	OBTAINED	OBTAINABLE		
Game Objective	270	300	90%	High
Critical Thinking and Motivation	356	400	89%	High
Usefulness of Game Features in Solving the Problem	352	400	88%	High
Ease of Use	539	600	89.8 %	High
Learning Outcome	274	300	91.3 %	High

5.3.5 Learning Fraction Algebra using Snake and Ladder Game Model

Agbonifo *et al.* (2021b) developed a Digital Game-Based Learning system based on *Snakes and Ladders* to learn fraction algebra through cognitive problem-solving rather than chance-based gameplay. The system integrated mathematical tasks, game mechanics, and instructional scaffolding. Its five modules comprise of Game Interface, Game Input, Game Logic, Database, and Game Output which are presented in Figure 16. The instructional process followed four sequential stages: generating the Lowest Common Multiple (LCM), entering numerators and denominators, substituting the LCM, and computing the final solution with embedded hints, confidence indicators, and animated feedback providing continuous scaffolding throughout the learning process (Figure 17).



Figure 16. *Game Interface at Runtime*

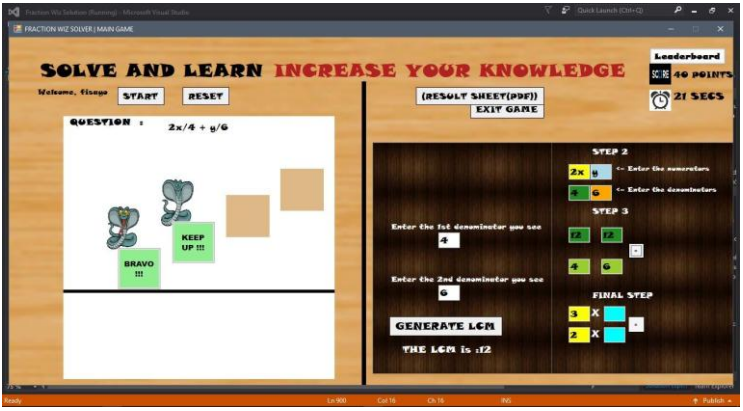


Figure 17. *Solving Fraction Algebraic Question with the Game Logic Panel at the Right Side*

The system was evaluated with 64 Primary 4–6 pupils from FUTA Staff School. Learners' perceptions were assessed using a 37-item four-point Likert-scale questionnaire measuring five dimensions: Ease of Use, Intuitive User Interface, Optimisation, Improvement of Calculation Skills, and Correctness of Results. Descriptive statistics (Table 12) revealed positive ratings across

all dimensions, with Improvement of Calculation Skills (Mean = 26.13) and Optimisation (Mean = 26.11) recording the highest scores, followed by Intuitive User Interface (Mean = 24.72), Ease of Use (Mean = 24.25), and Correctness of Results (Mean = 15.98).

Table 12. Results of Analysis of System Performance Evaluation

	N	Minimum	Maximum	Sum	Mean	Std. Deviation
Ease of use	64	16.00	32.00	1552.00	24.2500	4.57391
Intuitive User Interface	64	15.00	32.00	1582.00	24.7188	4.62385
Optimsation	64	12.00	34.00	1671.00	26.1094	4.48673
Improvement of Calculating Skills	64	13.00	32.00	1672.00	26.1250	4.59986
Correctness of Results	64	8.00	20.00	1023.00	15.9844	3.11928
Valid N (listwise)	64					

Overall, the findings indicate that the DGBL system significantly enhanced learners' understanding of fraction algebra, calculation skills, confidence, and engagement. The study demonstrates that integrating mathematical instruction with well-designed game mechanics and instructional scaffolding can effectively improve conceptual understanding and promote meaningful knowledge construction in mathematics education.

5.3.6 Solving Quadratic Equations using the Completing-the-Square Method through a Battleship Game Framework

Agbonifo *et al.* (2021c) developed a Digital Game-Based Learning environment that integrated the *Battleship* game with the learning of quadratic equations using the completing-the-square method. The learning environment transformed a traditionally procedural topic into an interactive, learner-centred problem-solving experience by embedding mathematical tasks within strategic gameplay. Learners assumed the role of a Navy Captain defending a coastal kingdom by locating enemy ships on a 10×10 battlefield grid, where each successful strike on the battlefield generated a quadratic equation that had to be solved before gameplay could continue. The environment incorporated instructional scaffolding, including visual feedback, countdown timers, hints, and downloadable step-by-step solution worksheets to support learning and reflection (Figures 18–20).

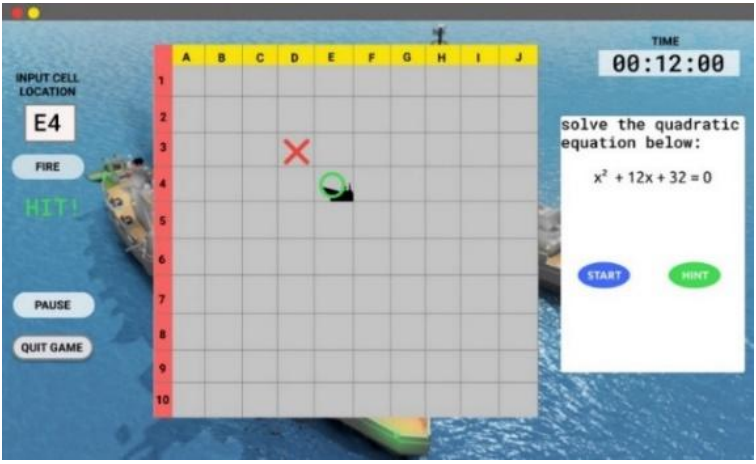


Figure 18. *Game Page with Quadratic Equation Generated*

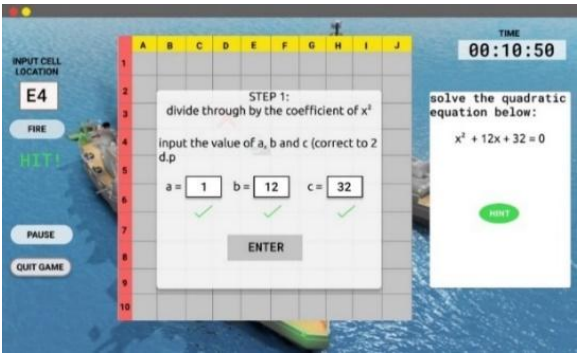


Figure 19*. Green Check Marks for Correct Answers Provided by the Play*

Stepwise worksheet of the gameplay

EQUATION: $x^2 + 12X + 32 = 0$

STEP 1: Divide through by the coefficient of x^2

$x^2/1 + 12x/1 + 32 = 0$

STEP 2: move c to the other side and add half the square of x to both sides

$x^2 + 12x = -32$
$x^2 + 12x + 36 = -32 + 36$
$x^2 + 12x + 36 = 4$

STEP 3: complete the square of the equation and take square root

$(x + 6)(x + 6) = 4$
$(x + 6)^2 = 4$
$\sqrt{(x + 6)^2} = \sqrt{4}$
$(x + 6) = +2$ or -2

STEP 4: solve for x

$x = 2 - 6$ or $x = -2 - 6$
$x = -4$ or $x = -8$

Figure 20. *Stepwise Worksheet of the Gameplay by a Player.*

The system was evaluated with 40 first-year students of the Federal University of Technology, Akure, during 2018/2019 academic session, using a 21-item five-point Likert-scale questionnaire that assessed five dimensions: Capability, Intended Learning Outcomes and Game Attributes, Learning Activity, Reflection, and Game Achievement. The results (Table 13) showed consistently high ratings across all dimensions, with Game Achievement recording the highest score (93%), followed by Intended Learning Outcomes and Game Attributes (91%), Learning Activity (88%), Capability (86%), and Reflection (78%).

Table 13. Percentage Points of the Respondents

VARIABLES	POINTS		PERCENTAGE POINTS
	OBTAINED	OBTAINABLE	
Capability	430	500	86%
Intended Learning outcome and Game attribute	546	600	91%
Learning Activity	264	300	88%
Reflection	234	300	78%
Game Achievement	279	300	93%

The findings demonstrate that the Battleship-based DGBL environment effectively enhanced learners' engagement, conceptual understanding, procedural fluency, and critical thinking in solving quadratic equations. The study provides empirical evidence that integrating game mechanics with structured instructional support creates meaningful, learner-centred experiences that improve mathematics learning outcomes.

5.3.7 Summary: Advancing Mathematical Learning through Digital Game-Based Learning Environments

These digital game-based learning environments demonstrated how the Dynamics and Pattern dimensions of the Deep Knowledge Community framework were operationalised across diverse mathematical topics. Rather than emphasising memorisation, the environments promote conceptual understanding, strategic reasoning, learner engagement, procedural fluency, and sustained knowledge construction. The collective evidence illustrated that well-designed digital game-based learning environments transformed abstract mathematical concepts into engaging learning experiences while fostering deeper cognitive development and long-term mathematical competence.

5.4 Virtual Reality as a tool for Students' Adaptive Learning

Madam Vice Chancellor, Virtual Reality (VR) offers an interactive approach to enhancing learning experiences and practical engagement (Akinola *et al.*, 2020). **Agbonifo** *et al.* (2020) developed a Virtual Chemistry Laboratory (VCL) to support adaptive learning and address limited access to physical laboratories by providing safe, repeatable, and immersive practical experiences. The web-based system simulated acid–base titration and enabled learners represented by avatars to interact with virtual laboratory equipment through an immersive environment, as illustrated in Figures 21 and 22.

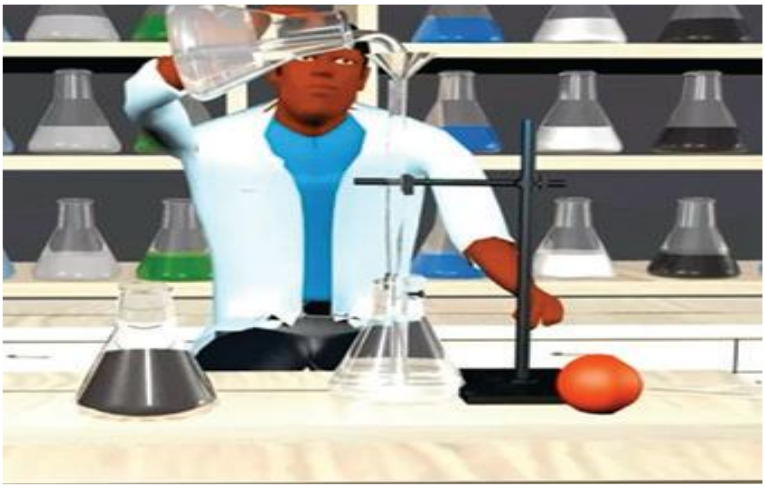


Figure 21. *Student as Avatar and Performing Titration*

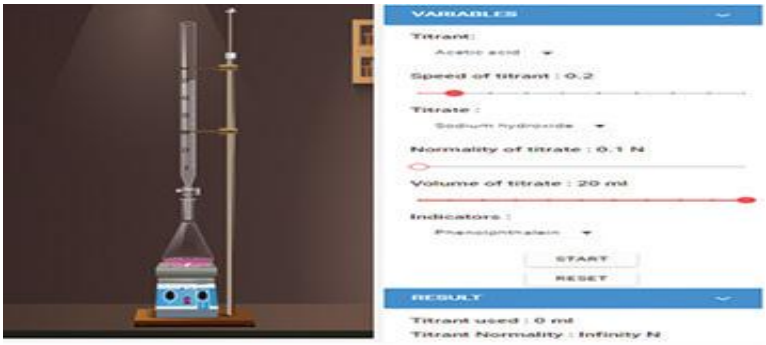


Figure 22. *Titration Experiment Setup.*

The system was evaluated with 50 participants comprising 25 secondary school students and 25 first-year undergraduate students from the Federal University of Technology, Akure. The responses presented in Figure 23 revealed overwhelmingly positive perceptions of the virtual laboratory, particularly its usefulness, accessibility, realism, enjoyment, and contribution to learning outcomes.

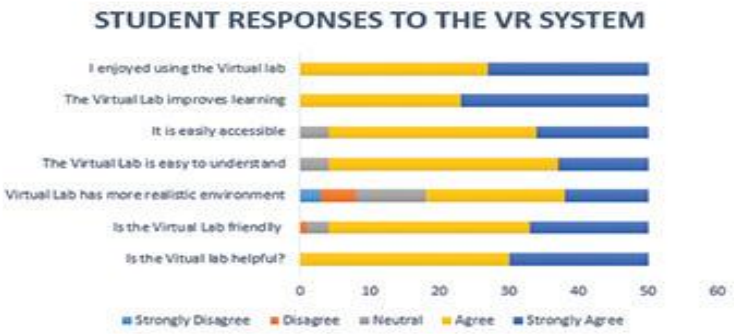


***Figure 23**. Analysis of the Student Responses to the VCL System*

Within the DKC framework, the VCL strengthened the **Dynamics** dimension through immersion, interaction, motivation, confidence, and experiential learning, while supporting the **Pattern** dimension through the structured sequencing of laboratory procedures. The study demonstrated that virtual laboratories can complement, and, in resource-constrained settings provide alternatives to, conventional laboratory instruction by enhancing learner engagement, practical competence, and personalised learning.

5.5 Artificial Intelligence for Learning Analytics in Educational Data Mining

Artificial Intelligence (AI) strengthens Learning Analytics and Educational Data Mining (EDM) by transforming educational data into actionable insights for personalised learning, adaptive instruction, and evidence-based decision-making. Through machine learning, AI identifies patterns in learner behaviour, predict outcomes, model learner characteristics, and support personalised learning pathways.

A significant contribution by **Agbonifo** and Femi-Falade (2025) applied Support Vector Machines (SVM) to predict learners' styles using gameplay data from the *Jo Wilder* educational game competition on the Kaggle platform and the Gregorc Learning Style Model. Three kernel functions, namely Linear, Polynomial, and Radial Basis Function (RBF), were evaluated. The RBF kernel achieved the highest classification accuracy of 93% (Tables 14 and 15), demonstrating the potential of AI-driven learning analytics to predict learners' cognitive styles and support personalised learning.

Table 14. Classification Results

Cluster	Precision	Recall	F1-Score	Support
0	0.90	0.88	0.89	41
1	0.90	0.97	0.94	77
2	0.97	0.88	0.92	41
3	0.98	0.95	0.96	41
Accuracy	**0.93**			**200**
Macro Avg	0.94	0.92	0.93	200
Weighted Avg	0.93	0.93	0.93	200

Table 15. Comparison of the Kernel functions Accuracy

Kernel	Accuracy
Linear	0.88
Polynomial	0.89
Radial Basis Function	0.93

Building on this work, Femi-Falade and **Agbonifo** (2025) developed a hybrid machime learning model which emloyed K-Means Clustering and Decision Tree model to classify learners into the four Gregorc learning style categories: Concrete Sequential, Abstract Sequential, Concrete Random, and Abstract Random. Using interaction data from the *Jo Wilder* and *Capitol Case* educational games, the model achieved an overall classification accuracy of approximately 89%, with consistently high precision, recall, and F1-scores across all learner categories, as presented in Table 16.

Table 16. Performance by Learning Style Cluster

Style	Precision	Recall	F1-score	Support
Concrete Sequential	0.88	0.86	0.87	50
Abstract Sequential	0.90	0.92	0.91	50
Concrete Random	0.85	0.83	0.84	50
Abstract Random	0.92	0.93	0.92	50
Accuracy			0.89	200

Further extending this research, **Agbonifo** and Faremi (2026) integrated K-Means Clustering and Decision Tree Classification to classify learners according to the Felder–Silverman Learning Style Model using interaction data extracted from the Moodle Learning Management System. The model attained an overall classification accuracy of 95%, with strong precision, recall, and F1-measure values across the Active–Reflective, Sequential–Global, Sensing–Intuitive, and Visual–Verbal dimensions of learning style, as shown in Table 17.

Table 17. Summary of Performance Evaluation Precision, Recall, F1-measure, Accuracy

LSD	Precision (%)	Recall (%)	F1 (%)	Accuracy (%)
Active (ACT)	98.87	95.96	97.39	95.96
Reflective (REF)	99.82	96.48	98.12	96.48
Sequential (SEQ)	96.49	97.32	96.90	97.32
Global (GLO)	92.47	96.02	94.21	96.02
Sensing (SEN)	81.30	96.20	88.12	96.20
Intuitive (INT)	75.14	95.83	84.23	95.83
Visual (VIS)	87.84	95.97	91.72	95.97
Verbal (VER)	78.95	91.88	84.93	91.88

Viewed through the Deep Knowledge Community framework, these studies strengthened the Anatomy dimension through AI-driven learner profiling, the Dynamics dimension through continuous monitoring and analysis of learner behaviour, and the Pattern dimension through identifying learning trajectories and adaptive pathways. Collectively, they demonstrate that AI-powered Learning Analytics can model learner characteristics, personalise instruction, and enhance engagement, retention, and learning outcomes.

6.0 APPLICATIONS AND PRACTICAL CONTRIBUTIONS OF THE RESEARCH

Madam Vice Chancellor, this body of research demonstrates that advances in cognitive science can be translated into intelligent educational technologies that improve learning quality, engagement and institutional effectiveness. These innovations support deeper understanding, retention, learner motivation, early identification of at-risk learners, performance prediction, curriculum evaluation and evidence-based decision-making.

These contributions culminate in the Deep Knowledge Community Framework, a comprehensive socio-technical architecture that integrates cognitive science, instructional design, artificial intelligence, adaptive learning, immersive technologies, learning analytics, and collaborative knowledge construction. The framework demonstrates that sustainable educational transformation depends on aligning technology with sound principles of learning rather than technological sophistication alone. Its applications extend beyond universities to schools, professional training, healthcare, industry, government, military training, technical education, and lifelong learning, contributing to national development and workforce preparedness.

7.0 CONCLUSION

Madam Vice Chancellor, distinguished ladies and gentlemen, this inaugural lecture has taken us on a journey from the paradox of technology abundance to a deeper understanding of how technology can be deliberately aligned with the science of human learning. It demonstrates that technology becomes educationally transformative when it responds to the cognitive, affective, behavioural, social, and contextual dimensions of learning.

My research, grounded in the Deep Knowledge Community framework and its anatomy, dynamics and pattern of learning, has translated principles of human learning into innovations spanning cognitive architecture, adaptive sequencing, personalised and affect-aware learning, learner modelling, AI, educational data mining, virtual reality, and digital game-based learning.

Collectively, these contributions affirm that the future of educational technology does not lie merely in developing more sophisticated technologies, but in developing more intelligent

relationships between technology and human cognition. The way forward is a shift from technology-centred education to learning-centred technology; from information delivery to knowledge construction; from uniform instruction to adaptive personalisation; and from passive consumption to active participation.

8.0 RECOMMENDATIONS

Based on the findings and contributions of this research trajectory, the following recommendations are proposed:

A, Governments and public policymakers must establish national educational technology frameworks that mandate alignment between digital learning platforms and evidence-based instructional design principles. Public investment should prioritise broadband infrastructure, equitable digital access, power stability, assistive technologies, and inclusive design standards to ensure that all learners regardless of location, socio-economic background, or disability can participate meaningfully in digital education. Ministries of Education should develop robust regulatory standards for usability, accessibility, adaptive learning, and cognitive load optimisation in all public educational technologies.

B. Universities and tertiary institutions should redesign curricula to embed personalised, adaptive, and learner-centred digital pedagogies. Faculty training programmes should equip educators not merely as content providers but as architects of transformative learning experiences grounded in cognitive psychology, instructional design, learning analytics, and technological fluency. Institutional policies should support interdisciplinary collaboration among computer scientists, educational

technologists, psychologists, curriculum developers, and policymakers to ensure coherent implementation of learning technologies.

C. Educational stakeholders including software developers, instructional designers, private sector innovators, accreditation agencies, and international organisations should adopt the Triad Framework as a foundational model for designing, evaluating, and deploying educational technologies. Learning systems should integrate adaptive personalisation, emotional responsiveness, collaborative engagement tools, and analytics-driven interventions that support diverse learner trajectories. Ethical frameworks must also govern the use of artificial intelligence, learner data, and predictive analytics to protect privacy, equity, and human agency.

D. Community and societal engagement must be strengthened. Families, civil society organisations, local communities, and cultural institutions should be integrated into lifelong digital learning ecosystems. Educational technologies must support not only formal university systems but also informal, vocational, community-based, and workforce development learning. This broadens educational transformation beyond classrooms into society-wide knowledge development.

E. For Africa specifically, continental collaboration through regional educational policies, shared digital infrastructures, and indigenous innovation ecosystems is critical. African governments and institutions should prioritise locally relevant educational technologies that address contextual realities while participating

competitively in global knowledge economies. Investment in research, indigenous software development, educational entrepreneurship, and cross-border academic collaboration will be essential in establishing Africa as a leader, not merely a consumer in global educational transformation.

9.0 FUTURE DIRECTIONS

Future research should expand the Deep Knowledge Community Framework through advanced AI, emotionally intelligent adaptive systems, neuroeducational analytics, mixed/extended reality, predictive personalised learning and blockchain-based credentialing. This should be supported by governance structures, centres of excellence, public-private partnerships and international collaboration. The overarching direction is to harmonise technological innovation with the enduring principles of human learning, creating equitable, culturally responsive, intelligent and sustainable learning ecosystems.

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