Omnicomputing: Integrating Mobility, Ubiquity, Learning and Intelligence in the Fourth Industrial Revolution

OLUTAYO BOYINBODE
Department of Information Technology, Federal University of Technology, Akure, Nigeria

Abstract- Omnicomputing is a computing paradigm where intelligent systems are seamlessly embedded into everyday environments, offering pervasive, context-aware, and user-centric services. This paper describes how omnicomputing integrates mobility, ubiquity, learning and real-time intelligence, enabling continuous access to computational resources across devices and locations. Powered by AI and machine learning, omnicomputing adapts to user behaviours and environmental changes, facilitating smart homes, education, healthcare, and industrial automation and revolutionizing how humans engage with technology and fostering seamless, efficient, and intuitive experiences.

I. INTRODUCTION

Omnicomputing refers to a seamless, ubiquitous computing paradigm where devices, systems, and platforms are interconnected and capable of providing context-aware, real-time services across various environments. In other words, omnicomputing refers to a concept of computing where processing power and data are always seamlessly available everywhere, integrating various forms of computing, data storage, and communication technologies into the fabric of everyday life. In this model, computing becomes ubiquitous and invisible, allowing users to access any information or computational resources whenever and wherever the need arises, without being constrained by specific devices or locations. "The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it" (Mark Weiser). In ubiquitous learning, technology fades into the background, enabling a seamless learning experience integrated into daily life (Weiser, 1991). Omnicomputing stands at the forefront of the Fourth Industrial Revolution (4IR), driving significant transformations in learning, mobility, ubiquity, and intelligence. By embedding intelligent computing into every facet of life, it fosters a more connected, efficient, and intelligent world.

II. OMNICOMPUTING

The term "omnicomputing" combines "omni," meaning "all" or "everywhere," with "computing," emphasizing a future where computational power permeates every aspect of human life. Unlike previous paradigms that focused on specific domains such as personal computing or cloud computing, omnicomputing aims to integrate multiple domains into a cohesive, intelligent, and user-centric ecosystem. This paradigm shifts the focus from standalone devices to a holistic network where devices, sensors, and systems work collaboratively, leveraging real-time data and adaptive algorithms to seamlessly enhance user experiences. The concept of omnicomputing builds upon earlier technological paradigms of Mainframe Computing (1950s-70s), Personal Computing (1980s-90s), Ubiquitous Computing (1990s-2000s) and Cloud and Edge Computing (2000s-2020s).

Omnicomputing describes a paradigm of computing characterised by pervasive, integrated, and universally accessible computational resources. It combines elements from ubiquitous computing, edge computing, cloud computing, and artificial intelligence to create a seamless and intelligent computational environment. In the early 1990s, Mark Weiser envisioned a future in which computing would be "invisible" and seamlessly integrated into the environment, enabling users to effortlessly interact with information and technology (Weiser, 1991). Over the past few decades, advancements in the Internet of Things (IoTs), wireless networks, and miniaturised sensors have made this vision increasingly feasible, allowing computing to extend beyond desktops and smartphones to an environment where computing resources are pervasive. The shift from isolated computing to interconnected systems gained momentum with the rise of IoT, which allowed various devices to communicate autonomously and share data. In omnicomputing, IoT serves as a foundational technology by connecting diverse devices and enabling real-time data exchange (Li *et al.,* 2015). Omnicomputing goes beyond traditional IoT by integrating intelligence into these networks, thereby creating an ambient intelligence that can autonomously respond to context and user needs without direct input. Omnicomputing relies on the convergence of several technological domains such as Internet of Things (IoT devices collect and transmit data, forming the backbone of interconnected systems), Artificial Intelligence (Machine learning algorithms analyze data, enabling predictive insights and adaptive behaviour), Quantum Computing (Quantum algorithms provide exponential computational power for complex problem-solving), 5G and Beyond (High-speed, low-latency networks facilitate seamless connectivity), Edge Computing (Processing data closer to the source reduces latency and enhances responsiveness) and Blockchain Technology (Decentralized systems ensure secure data management and transaction integrity).

The transition to omnicomputing introduces enhanced capabilities that reshape how we interact with technology in daily life and across industries. Omnicomputing, with its pervasive and intelligent infrastructure, has broad applications across sectors, enhancing efficiency, personalisation, and interactivity in real-time. Some major applications of omnicomputing include smart cities and urban infrastructure, healthcare and personalized medicine, agriculture and precision farming, environmental monitoring and disaster management.

III. THE FOURTH INDUSTRIAL REVOLUTION (4IR)

The Fourth Industrial Revolution (4IR), also known as Industry 4.0, refers to the ongoing transformation of industries and societies through advanced technologies that blur the boundaries between the physical, digital, and biological realms. It builds on the previous three industrial revolutions, characterised by mechanisation, electrification, and digitisation, respectively. Understanding the historical context of 4IR provides insight into the rapid evolution of technology and the foundational shifts that prepared the way for this era. The journey toward 4IR can be traced back to the First Industrial Revolution in the late 18th century, which introduced mechanized production powered by steam and water. This revolution transformed agrarian societies into industrial powerhouses and laid the groundwork for future innovations. The Second Industrial Revolution emerged in the late 19th and early 20th centuries, driven by electrification, assembly lines, and mass production, which enabled greater productivity and economic expansion. The Third Industrial Revolution, or the Digital Revolution, began in the mid-20th century with the development of electronics, telecommunications, and computing. This period introduced computers and the internet, transforming how information is processed, stored, and shared, and paving the way for globalization and the information age (Castells, 1996). Together, these three revolutions set the stage for the Fourth Industrial Revolution by creating an environment in which technological, social and economic innovations could converge on a global scale. Early manifestations of 4IR began with the increasing integration of digital technologies, such as the IoT, AI, robotics, and big data analytics (Schwab, 2016), into industrial processes and products. This integration created "smart" environments that enabled real-time data processing, automation, and connectivity (Lasi *et al.,* 2014).

The term Fourth Industrial Revolution (4IR) was popularised by Klaus Schwab, founder and executive chairman of the World Economic Forum, who argued that this phase marks a new era distinguished by "a fusion of technologies that is blurring the lines between the physical, digital, and biological spheres" (Schwab, 2016, p. 7). Schwab emphasized that, unlike previous industrial revolutions, which were limited to specific industries, 4IR has a transformative impact across all sectors due to its rapid pace, scope and complexity. This transition led to the emergence of omnicomputing, which provides a ubiquitous computing environment where data, computation, and intelligence are seamlessly distributed across networks of connected devices (Weiser, 1991).

IV. OMNICOMPUTING IN THE FOURTH INDUSTRIAL REVOLUTION

Omnicomputing refers to a seamless, ubiquitous computing paradigm where devices, systems, and platforms are interconnected and capable of providing context-aware, real-time services across various environments. It is an essential component of the 4IR, enabling advanced technologies to function harmoniously and effectively. The roles of omnicomputing in the fourth industrial revolution include, Interconnectivity and IoT Integration where omnicomputing underpins the IoT by connecting billions of devices and sensors; Real-Time Data Exchange which ensures devices communicate efficiently, allowing for real-time data collection and analysis in smart homes, factories, and cities. AI and Machine Learning Enablement, in which omnicomputing facilitates data processing for AI systems, enabling predictive analytics, personalization, and decision-making across industries. Examples of this include autonomous vehicles which rely on omnicomputing for data from GPS, sensors, and traffic systems to make split-second decisions. Omnicomputing also ensures that physical systems like robots or manufacturing tools can operate seamlessly with their digital counterparts, forming the backbone of Industry 4.0's smart factories.

4IR represents a profound transformation in how industries, economies, and societies operate, driven by the fusion of digital, physical, and biological technologies. Omnicomputing is characterised by pervasive, intelligent, and interconnected computing, and emerges as a fundamental enabler of this revolution. It embeds computing capabilities ubiquitously to ensure that the technologies of 4IR function seamlessly, intelligently, and adaptively across various domains. Omnicomputing can be seen as the natural extension of 4IR, taking the interconnectedness of smart technologies further to create a unified, all-encompassing computing paradigm. The main difference lies in the scope and depth of integration. While 4IR focuses on specific industries and applications, omnicomputing aims to permeate every aspect of life, creating an "ambient intelligence" environment (Ducatel *et al.,* 2001). The transition from the 4IR to omnicomputing marks a significant evolution in the technological landscape. Also, 4IR brought about an unprecedented integration of digital technologies in manufacturing, logistics, healthcare, and other sectors, while omnicomputing represents a more comprehensive, interconnected system of computing that supports real-time, ubiquitous access to data and intelligent resources. Omnicomputing, characterised by pervasive, continuous computing across distributed devices and environments, extends the foundations laid by 4IR thereby fostering enhanced connectivity, automation, and the realisation of intelligent ecosystems.

V. OMNICOMPUTING: INTEGRATING MOBILITY, UBIQUITY AND LEARNING

Omnicomputing represents the seamless integration of mobility, ubiquity and learning creating an environment where education is accessible anytime and anywhere. This convergence leverages mobile technologies and pervasive computing to facilitate continuous and context-aware learning experiences. In the context of omnicomputing, learning transcends traditional classroom boundaries, utilizing mobile devices to provide educational content that adapts to the learner's environment and needs. This approach supports personalized learning pathways, enabling individuals to engage with material that aligns with their unique learning styles and paces. Mobility ensures that learners can access educational resources on the go through devices like smartphones and tablets. This flexibility allows for learning opportunities to be interwoven with daily activities, promoting a culture of lifelong learning. For instance, mobile learning (m-learning) facilitates education beyond traditional settings, enabling learners to study in various contexts. Ubiquitous computing embeds technology into everyday objects and environments, creating a pervasive learning atmosphere. This omnipresence allows for context-aware educational experiences, where information is readily available and relevant to the learner's immediate surroundings. The concept of ubiquitous learning (u-learning) reflects this pervasive presence, facilitating learning beyond the classroom in diverse contexts.

A. Mobile Learning

Mobile learning, often referred to as m-learning, is a form of education that leverages mobile devices such as smartphones, tablets, and laptops to facilitate learning anytime and anywhere. M-learning allows for flexibility in educational settings, enabling learners to access resources, communicate, and engage in collaborative activities outside the traditional classroom environment. This approach has gained traction with advancements in mobile technology and the widespread availability of internet connectivity, reshaping the landscape of education. Mobile learning enables learners to access educational content at their convenience, which is particularly beneficial for remote learners or those balancing work and study. This flexibility promotes a learner-centred approach, accommodating diverse schedules and learning preferences (Ally, 2009). Mobile learning allows for customization, where content and activities can be tailored to individual learners' needs and progress. This personalisation helps in enhancing engagement and motivation by addressing the unique learning pace and style of each learner (Traxler, 2007). Through mobile applications and multimedia resources, mobile learning facilitates interactive experiences that can engage learners more deeply. The integration of videos, quizzes, and gamified elements on mobile platforms promotes active learning and enhances knowledge retention (Kukulska-Hulme & Traxler, 2005).

Mobile learning supports collaborative activities, allowing learners to interact with peers and instructors through forums, chats, and shared documents. This collaboration fosters a community of learning, where participants can discuss, share ideas, and provide feedback. Mobile devices are well-suited for delivering bite-sized content, known as microlearning. This approach involves breaking down information into smaller, manageable segments, making it easier for learners to consume content on the go and retain information (Giurgiu, 2017). Mobile learning may currently be most useful as a supplement to ICT, online learning and more traditional learning methods, and can do much to enrich the learning experience. It is widely believed that mobile learning could be a huge factor in getting disaffected young adults to engage in learning, where more traditional methods have failed.

Sharples *et al*. (2005) proposed a theoretical framework defining mobile learning as the intersection of learners, technology, and social contexts. The study conducted case studies involving the use of personal digital assistants (PDAs) in educational settings. The result of the study highlighted the importance of context-aware learning and the need for dynamic adaptation of content and provided a conceptual foundation for understanding how mobile learning differs from traditional e-Learning. However, the study showed that the framework was theoretical and lacked extensive empirical validation.

Ally (2009) examined the potential of mobile learning in distance education through literature review and pilot projects. The study evaluated mobile platforms for delivering course content, enabling communication, and assessing learners. The result of the study demonstrated that mobile learning enhances accessibility for distance learners in remote or underserved areas; and improves engagement and interactivity compared to traditional distance learning methods. However, the study highlighted challenges in limited teacher training on how to effectively integrate mobile learning tools and learners' unfamiliarity with their devices. Research on mobile learning demonstrates its potential to revolutionise education through accessibility, engagement, and personalised learning experiences. However, limitations such as infrastructure requirements, device usability and suitability, and teacher training must be addressed to ensure widespread adoption and success. Boyinbode and Ogundipe (2017) explored the suitability of mobile devices for m-learning. The most important benefit of handheld devices is the fact that they are mobile and can be taken and used anywhere at any place and time. Learning processes must be flexible and robust to be able to withstand lifelong learning. Mobile learning is one of the ways that learning can be extended, and it is easily accepted in our society since mobile devices are readily available. According to our study from evaluation, it was confirmed that students prefer five inches and above screen size for learning. They also prefer devices with very good user interface, preferably screen touch for easy organization and management of information and knowledge, and a very good battery life.

Boyinbode *et al*. (2017) evaluated the media richness of various message delivery methods in a mobile learning (m-learning) environment. Learning occurs from social interactions between students in collaborative learning environments. These social interactions usually involve social media like SMS, WhatsApp, Facebook, Twitter, BBM and so on. Media Richness is described as the ability of information to change understanding within a time interval. Communication is termed to be considered rich if the communication framework can overcome different frames or references, or clarify ambiguous issues in a timely manner. Boyinbode *et al.* (2017) defined media richness in terms of content timeliness, content richness, content accuracy, and content adaptability. This study evaluated media richness in respect to content timeliness, content richness, content accuracy and content adaptability in WhatsApp, Email, SMS, Twitter and BBM. The analysis showed that: (i) SMS has better performance than WhatsApp, Email, Twitter and BBM on content timeliness; this implies that SMS may be more appropriate for delivering real-time information such as notifying or reminding of some time-sensitive matters, (ii) WhatsApp has better performance than Email, SMS, Twitter and BBM on content richness, and so may be applied in information delivery that is rich in images and videos and (iii) WhatsApp has better performance than Email, SMS, Twitter and BBM on content accuracy and content adaptability. WhatsApp, due to its media richness, is more appropriate for supporting learning activities in a mobile learning environment. Boyinbode *et al.* (2017) suggested that developers and designers of an m-learning environment could adopt WhatsApp as a suitable information delivery medium to support corresponding learning activities in a mobile learning environment. From the result of the evaluation, students' preferences for the media that best support mobile learning are as follows: 65% for WhatsApp, 25% for email, 5% for Twitter, and 5% for BBM. Thus, most of the learners agreed that using WhatsApp to learn is much more convenient and also attested to the fact that they chat with friends on WhatsApp using their mobile devices every day, in contrast to the other media.

Boyinbode (2018b) developed a smart platform where instructors or lecturers can upload learning resources to the cloud, and learners can access these resources with their mobile devices. Because of the limitation of traditional mobile learning such as insufficient storage, hence the need to integrate mobile learning with cloud computing. Cloud computing is the delivery of computing services (such as servers, storage, databases, networking, software, and analytics) over the internet ("the cloud") to offer faster innovation, flexible resources, and economies of scale. This cloud-based mobile learning application allows access to learning resources stored in the cloud. In higher education institutions of Africa, some students cannot afford to buy textbooks, thus they can easily have access to learning resources through cloud based mobile learning. Boyinbode and Akintade (2015) also proposed a cloud-based mobile learning interface that allows students to access learning materials stored in the cloud 24/7 to enhance their learning. Boyinbode *et al.* (2020d) developed an ontology-based personalized e-learning system that presents suitable learning contents to learners based on their learning style, preferences, background knowledge, and personal profile. Boyinbode and Akoju (2024) developed a mobile learning system that uses the visual, auditory, and kinesthetics learning model, enabling teachers to tailor curriculum content and exams to match each student's learning style. By also utilising cloud computing, the system provided convenient, anytime access, thereby boosting both teacher and student productivity.

Boyinbode and Akintola (2008a) described the benefits of mobile learning for disseminating crucial information among Nigerian farmers through SMS technology. Boyinbode and Osagiede (2020) also developed "farmcaster" a Mobile Android application which helped in disseminating information to farmers thereby enhancing interaction among farmers and improving farming in Nigeria. Farmers with access to internet or via SMS could get notifications of vital agricultural information through mobile application. The major feature of the system includes timely agricultural information sent to farmers through their android phones. Crucial information was obtained from various government and reliable agricultural website and made available to farmers through the application.

Boyinbode *et al*. (2011) developed an Opencast Mobile Learning System (OMLS), a framework that helped postgraduate students in higher education adapt educational resources from Opencast Matterhorn to their mobile devices which could then be used anytime and anywhere. Opencast is a flexible, reliable, and scalable open-source video management system for academic institutions. Producing e-learning contents with opencast through recording of lectures was relatively easy and flexible than through the conventional Learning Management System (LMS). Recorded lectures serve as supplementary, substitutional or creative materials to the conventional traditional lecture. With the popularity and evolution of powerful mobile devices like mobile phones, iPods and iPads, which are light and portable, it is easy to integrate these devices into the mobile learning system.

Boyinbode *et al.* (2012a, 2012b, 2012c, 2013a) proposed and implemented a Mobile Lecturing model. Mobile lecturing refers to the use of mobile devices to deliver lectures, enabling students to access instructional content anytime and anywhere. Table 1 highlights the advantages of mobile lecturing. This mode of learning supports flexibility and accessibility, making education more adaptable to students' schedules and locations. Mobile lecturing is increasingly popular in higher education and professional development, allowing learners to engage with content on their devices as a supplement to physical classes. This approach leverages mobile technology's multimedia capabilities, facilitating interactive and personalized learning experiences.

Mobile lecturing provides a transformative approach to education, offering flexible, accessible, and personalised learning experiences. By leveraging multimedia, interactive elements, and mobile technology, mobile lecturing supports a learner-centred approach that meets the needs of diverse learners. Although challenges such as device limitations, connectivity issues, and distractions exist, advancements in Artificial Intelligence (AI), Augmented Reality and Virtual Reality (AR/VR), and adaptive learning indicate that mobile lecturing will continue to evolve, shaping the future of education across formal, professional, and distance learning contexts.

Table 1: Advantages of Mobile Lecturing

Advantage	Description
Structured Content Delivery	Provides organized, instructor-led content, beneficial for complex subjects.
Time Efficiency	Delivers key information concisely, ideal for time-constrained learners.
Content Consistency	Ensures uniformity, which is useful for standardized courses.
Reduced Self-Directed Needs	Minimizes the requirement for self-management skills in learners.
Ease of Use	Familiar format resembling traditional lectures, reducing learning curve.
Enhanced Instructor Presence	Strengthens sense of instructor guidance, boosting motivation.
Alignment with Assessments	Matches traditional assessment formats, aiding in test preparation.
Reduced Cognitive Load	Focused on core material, minimizing cognitive strain from multiple options.
Scalability and Accessibility	Easily scalable for large audiences, effective in massive online courses.
Simplified Assessment	Direct assessment of lecture content, allowing clear measurement of comprehension.

Mobile lecturing which emphasizes mobile devices as tools for learning enhance learning among students through high-level engagement. Deep learning will result from high-level engagement of students with lecture vodcasts on their mobile devices. In mobile learning though students learn on the move with their mobile devices at any time and any place, the role of the educator in the m-learning experiences has remained minimal and is in some cases absent; While this is useful, such learning has remained unevaluated, mobile lecturing incorporate educators' involvement. Boyinbode *et al.* (2013) defined mobile learning as "a type of learning that allows students to engage and learn with mobile technologies when they are on the move with minimal or no involvement of the educator". Mobile lecturing is defined as "a form of learning in which students engage in high-level interactions with lecture vodcasts on their mobile devices to enhance their learning, with the educator specifying the learning tasks to trigger students' learning to foster deep learning". Warburton (2003) defines deep learning as a form of learning where students construct meaning and understanding from learning materials and experiences. Boyinbode *et al.* (2013) developed "MOBLEC", an interactive mobile lecturing model and MOBILect (Boyinbode and Ngambi, 2013, Boyinbode and Ngambi, 2015), an interactive mobile lecturing tool that fosters deep learning.

B. Mobile Learning and Gamification

Mobile learning (m-learning) and gamification are transformative educational approaches that leverage technology to enhance learning experiences. Together, they create engaging, flexible, and accessible learning environments that cater to diverse learners' needs. Mobile learning refers to the use of portable devices, such as smartphones, tablets, and laptops, to access educational content and facilitate learning anytime and anywhere. It is characterized by flexibility, interactivity, and personalization, allowing learners to study independently of time and place.

Gamification is the application of game design elements, such as points, badges, levels, and leaderboards, in non-game contexts to enhance engagement, motivation, and productivity. In education, gamification transforms routine learning tasks into more engaging and interactive activities. Deterding *et al.* (2011) introduced the concept of gamification, emphasizing its use in educational contexts. The study conducted a theoretical analysis of game design elements (that is, points, badges and leaderboards) applied to non-game settings, including mobile learning. The results of the study highlighted gamification's potential to improve motivation, engagement, and learning outcomes, and thereafter proposed a framework for integrating game mechanics into educational tools. However, the study lacked empirical studies to validate theoretical claims, and did not focus specifically on mobile learning platforms. Hamari *et al.* (2014) conducted a systematic literature review to examine the effects of gamification in various domains, including mobile learning. The study focused on analysing user engagement metrics such as time spent, participation rates, and retention. The result of the study showed that gamification improves engagement, but its effectiveness depends on the context and user preferences; and identified only intrinsic motivation as a critical factor for success.

Su and Cheng (2015) designed a mobile learning application with gamification elements (badges, progress bars, and leaderboards) for science education. The study conducted an experimental study with high school students. The result of the study highlighted that students using the gamified mobile app showed significantly higher motivation and academic performance compared to those using non-gamified versions and increased collaboration and participation were observed.

Kim *et al.* (2018) developed and tested a gamified mobile language learning app that included quizzes, levels, and virtual rewards. The study conducted a mixed-methods study with college students learning English as a second language. The result of the study showed that the gamified app improved vocabulary acquisition and learner satisfaction, and learners reported feeling more motivated to complete tasks due to gamification. The study relied on self-reported data, which may introduce bias. Chen et al. (2008) developed a mobile application to support English language learning for non-native speakers. The study integrated gamification and multimedia elements such as audio recordings, flashcards, and quizzes. The result of the study highlighted significant improvement in vocabulary retention and pronunciation accuracy, and increased learner motivation and engagement through gamified elements. However, the limitation of the study was a high reliance on user interaction, in which case passive learners may not benefit much from it. Research has shown that vocabulary is the most important element of any language learning, including English language. Motivation is therefore an important factor for learners to learn English vocabulary continuously and effectively (Hasegawa *et al*., 2015). Boyinbode (2018a) adopted the use of gamification-based learning techniques to motivate and encourage learners to continue learning English vocabularies effectively. Hasegawa *et al.* (2015) developed an effective vocabulary learning support system for the learner’s sustainable motivation. The system supported learners’ motivation using gamification techniques, and a new efficient difficulty setting method by calculating the ratio of mastered words to unmastered words. The learning procedure was restricted to classroom learning alone, and the learning materials were obtained from students’ class notes, thereby making it impossible to learn outside the classroom environment. Boyinbode (2018a) significantly enhanced learners’ English vocabulary abilities and promoted learning interests, which facilitated a seamless mobile learning environment for English learning without constraints of time or place imposed by classroom learning. Using extrinsic rewards like levels, points, and badges to improve engagement, while intrinsically motivating towards the achievement, mastery, autonomy, and sense of belonging, Boyinbode and Tiamiyu (2020) implemented a gamification-based English vocabulary system for improving English vocabulary abilities of learners.

C. Ubiquitous Learning

Ubiquitous learning refers to an educational paradigm where learners can access content, interact, and learn in real-world contexts seamlessly, anytime and anywhere, through the integration of digital technologies. It builds on ubiquitous computing to deliver context-aware, adaptive, and personalised learning experiences. Mobile learning and ubiquitous learning (U-learning) offer flexible, technology-enhanced educational experiences, but they differ in approach and scope. Mobile learning focuses on the flexibility of accessing educational resources on the go, while ubiquitous learning integrates technology into the environment to create a seamless, context-aware, and adaptive learning experience.

Ubiquitous learning integrates IoT and context-aware systems to adapt learning content based on real-world environments. Hwang *et al.* (2018) demonstrated how IoT-enabled learning environments enhance knowledge retention by immersing students in relevant scenarios. Ubiquitous learning is a learning style in which the learner can smoothly commence the learning process anytime and anywhere. U-Learning stands on the learning platforms or an environment structured by Ubiquitous computing technology (Weiser, 1991).

With the advent of technological advancement in learning, such as context-awareness, ubiquity and personalisation, various innovations in teaching and learning have led to improved learning. Adewale *et al.* (2018, 2022) developed a system that supports personalised learning through adaptive contents, adaptive learning paths and context awareness to meet individual learner's requirements, and promote the effectiveness and performance of the learning process.

Hwang *et al.* (2008) developed a context-aware ubiquitous learning system that uses Radio Frequency Identification (RFID) and Global Positioning System (GPS) technologies to identify learners' locations and activities. The study focused on outdoor learning activities, particularly in natural science education, such as identifying plants and animals. The results of the study improved learner engagement and retention of information by providing personalized learning experiences based on their physical context; and enhanced students' ability to connect theoretical knowledge with practical experiences. Ogata and Yano (2004) developed the "Classroom Ubiquitous Environment" (CUE) system to support collaborative learning. The study utilised mobile devices and sensors to facilitate communication, and shared task execution among students. The results of the study demonstrated that collaborative learning in ubiquitous environments fosters peer interaction and knowledge sharing, and improved group problem-solving skills through real-time feedback and monitoring. However, the study focused primarily on collaborative settings, with limited insights into individual learning benefits and high dependence on network infrastructure for real-time communication.

Boyinbode and Fatoke (2021) implemented an RFID based context-aware technology and recommender system for adaptive ubiquitous learning to help learners achieve personalized learning goals and greater learning efficiency. Our context-aware recommender suggested courseware to students based on their location, surrounding noise level and time of day. Radio Frequency Identification (RFID) technology was used to acquire context awareness, and fuzzy logic was employed to develop courseware recommendations. Through context awareness, students become conscious of all changes within their learning while performing learning tasks. Thus, it is easier for them to direct their behaviour and to acquire new knowledge (Boyinbode and Fatoke, 2021).

Adaptive Neuro-Fuzzy Inference System (ANFIS) was introduced to rectify the issues of continuous changes in mobile learning environments and to achieve personalization by delivering adaptable learning content to learners with specific disabilities as mentioned in Boyinbode and Amodu (2021). Research on ubiquitous learning demonstrates its ability to provide learning environment using technology that allows students to access information and learning content anywhere and at any time. However, limitations such as access to the internet and digital devices, and the detection and prevention of plagiarism must be addressed in future research.

VI. INTELLIGENCE IN OMNICOMPUTING

Omnicomputing represents an advanced stage in computing, where seamless, ubiquitous access to computational resources is available across devices and environments. Intelligence in omnicomputing refers to the integration of sophisticated technologies like artificial intelligence (AI), machine learning (ML), and advanced data analytics to deliver context-aware, adaptive, and predictive computing capabilities. The concept of Omnicomputing, as it relates to intelligence, addresses the integration of systems and networks that provide a holistic, intelligent response across a variety of data sources. It emphasizes "system intelligence," a concept where diverse sensors or devices cooperate to generate a comprehensive understanding of an environment. Intelligence in omnicomputing, which integrates AI across various computing paradigms like cloud, fog, and edge computing, is a dynamic and evolving field.

A. IoT (Internet of Things)

With billions of devices connected to the internet, the IoT ecosystem is made up of 'things' that have been made smart through embedded systems (sensors, processors, and communication hardware) and can acquire, disseminate and process data gotten from their environment. These 'things' can be humans, animals, plants, structures, or any device. Patel *et al.* (2016) defined IoT as a type of network to connect anything to the Internet based on stipulated protocols through information sensing equipment, to conduct information exchange and communications to achieve smart recognition, positioning, tracking, monitoring, and administration. IoT aims at creating ubiquitous 'things' that can connect anytime, anywhere, with anything or anyone, through any service or network. This accounts for the wide applications of IoTs across different domains. The proliferation of the IoT has significantly contributed to the realization of intelligent omnicomputing environments. IoT involves the interconnection of everyday objects embedded with sensors and communication capabilities, facilitating data exchange and automation without necessarily requiring human-to-machine interaction. Examples include smart factories, smart home devices, medical monitoring devices, wearable fitness trackers, smart city infrastructures, and vehicular telematics. Sophisticated IoT devices can "learn" by recognizing patterns in user preferences and historical use data. An IoT device can become "smarter" as its program adjusts to improve its prediction capability to enhance user experiences or utility. IoT technologies embed computing capabilities into physical environments, enabling continuous data collection and processing, to provide the infrastructure for real-time adaptation in dynamic environments (Gubbi *et al.,* 2013).

B. IoT and Structural Health Monitoring

The lingering cases of building collapse in Nigeria and the attending rate of mortality call for urgent attention. Fortunately, the permeation of the internet and advances in IoT facilities can be leveraged to provide a robust means of monitoring civil infrastructures, especially buildings. With it, users of such infrastructures can be fortified with detailed information about the “state of health” of various parts of the building, so that preventive measures such as retrofitting or demolition, in extreme cases, can be taken to prevent structural failure and collapse with its attendant causalities. Structural Health Monitoring (SHM) is concerned with the continuous monitoring of civil and industrial structures such that public safety is guaranteed. These civil and industrial structures such as buildings, bridges, roads, pipelines, dams, power grids, etc., are indispensable to life and living. Since things left unmonitored and without maintenance tend to deteriorate, these structures can become death traps. Twenty-two school children were killed in July 2024 in Plateau State, Nigeria, after the school building collapsed. Hence the necessity of SHM. SHM has become more robust through IoT, and it now involves the use of sensors (smart objects) for acquiring data (information) about alterations in various parts of the whole structure in a non-invasive manner. Thereafter, suitable mathematical models are applied to the information acquired from the readings from the various parts of the structure which are then used to determine its health status and safety. SHM aims to provide an accurate diagnosis of the state of the structure at any time during its life. This state of the structure includes its different parts (especially those key parts such as foundation, beams, and columns), their constituent materials, and everything that makes the structure whole. Building failures are manifested often through damages to some of its key structures (like pillars, columns, foundations, beams, and roofs) which are seen through cracks. Odeyemi *et al.* (2019) identified the leading cause of the structural collapse (building failure) as structural damage. Cracking is a common failure indicator in buildings, it must thus be detected early to avoid catastrophic failure. Haruna *et al.* (2013) observed that the formation of cracks in buildings and other structural elements is inevitable; however, there is a maximum allowable width of cracks. Thus, the necessity of monitoring, controlling and minimising such cracks. Boyinbode *et al.* (2020) established an IoT framework for structural integrity evaluation and monitoring in buildings. This system can be applied to effectively mitigate the rising cases of building collapse, which is rampant in Nigeria. Statistics say that it has claimed hundreds of lives in the last decade in Nigeria. Traditional means of monitoring civil structures and determining their health seem inadequate, expensive and out of reach to many, hence a simple, effective economical means of SHM which IoT provides was developed (Boyinbode *et al.,* 2022). A system for structural integrity evaluation and monitoring using piezoelectric transducers and microcontrollers was developed. It notifies users about the presence of cracks and their locations in a building to enhance public safety.

C. IoT and Intrusion Detection

Every country in the world relies on agriculture to survive, not just because it is a source of food, but because it is also connected to the production of most basic human needs. In Nigeria, agriculture remains the leading non-oil sector of the country's economy, providing about 70% of the nation's population with jobs. It is a major source of livelihood for those in rural areas as they depend on the proceedings from their farm harvest to cater for their family. However, the sector has suffered a major setback with persistent cases of intruders: humans and animals alike, causing serious damages to crop by stealing, eating, and trampling on crops. In recent times, the destruction of crops has aggravated with the incessant conflicts between herders and farm owners arising from illegal encroachment of cattle into farmlands.

In November 2024, the Nasarawa State Police Command confirmed the death of three persons following a violent clash between farmers and herders in the Dogon Duste community, located between Nasarawa and Toto Local Government Areas. Usually mounting of fences around farmlands, engaging farm guards, use of repellents among other methods are used as means to wade off invaders. Though relatively effective, these methods can be less ideal and are sometimes prohibitively expensive to put in place. Moreover, with herder-farmer conflicts, the existing security measure cannot completely guarantee safety, as several farm guards have been killed. To overcome these challenges, there is need to build a system that will alert farmers of any intruder and also repel animals from the farm. Ibam et al. (2023) implemented an IoT- based intrusion detection model for farmlands using RFID technology and image recognition techniques. Oyelade et al. (2023, 2024) developed an efficient farmland intrusion detection model using IoT and improved Faster R-CNN algorithm to prevent animals and unauthorized persons from intrusion and notify the farm owner about intrusion and a safe defensive mechanism to chase intruders away.

Boyinbode *et al.* (2024) also implemented an IoT-based parking management system. The system uses sensors to determine whether parking spaces are available and gives drivers real-time information, hence improving the parking experience. The usefulness of the system entails speeding up parking time and decreasing the amount of time spent looking for locations to park.

D. IoT and RFID Applications

IoT systems rely on a variety of sensors and data collection methods, and RFID is one of them. RFID is the reading of physical tags on single products, cases, pallets or reusable containers that emit radio signals to be picked up by reader devices. These devices and software must be supported by a sophisticated software architecture that enables the collection and distribution of location-based information in near real time. Boyinbode and Akinyede (2015) developed an RFID based inventory control system in NAO Supermarket Akure, Nigeria. The customer gets to see some beneficial information about the products being purchased which can go a long way in improving the life of a consumer i.e. being able to get a detailed knowledge about the product they are consuming. Olanipekun and Boyinbode (2015) implemented a RFID based automatic attendance system. This system provided an effective and more convenient method of taking attendance when compared to the manual system. Data are more organized, the system is user friendly, data manipulation and retrieval are done via the graphical interface. To eradicate the deficiencies associated with the manual attendance system, an automated approach is implemented through Radio Frequency Identification (RFID) technology. It has become very difficult for libraries to satisfy the increasing demands of the users; hence the need for a better technology that can improve inventory management, and security of library collections. Boyinbode *et al.* (2020b) implemented a radio frequency identification (RFID) based Internet of Things (IoT) model for efficient library information management; this speeds up book borrowing, monitoring and books searching processes, thus enabling staff to do more user-service tasks. While the application of IoT in omnicomputing shows promise in enhancing efficiency and real-time decision-making, the field still faces several challenges related to security, energy efficiency, and system interoperability. Researchers continue to explore methodologies such as federated learning and edge computing to overcome these limitations and unlock the full potential of omnicomputing intelligence.

VII. SOFTWARE INTELLIGENT SYSTEMS

Software intelligent systems are systems designed to simulate human-like intelligence in decision-making, learning, and problem-solving. Software Intelligent Systems, Artificial Intelligence (AI), and Machine Learning (ML) are interconnected, as intelligent systems rely on AI and ML to achieve their goals. AI provides the underlying framework and techniques for intelligent systems to perform tasks that require cognitive functions, such as reasoning, learning, perception, and natural language processing. Intelligent systems often use ML algorithms (e.g., decision trees, neural networks) to extract insights from data (Russell & Norvig, 2020).

A. Academic Performance Predictions

Boyinbode *et al.* (2020a) implemented a soft computing model (Adaptive Neuro Fuzzy Model using Levenberg–Marquardt algorithm) for predicting students' academic performance in tertiary institutions. Students' performance prediction has evolved as a critical factor in attaining high quality education. Educational institutions recognize the importance of student performance and are greatly motivated to predict their student performance to be able to offer good support for their students; this is achieved by locating students with lower performance, and rendering necessary assistance to improve their performance.

Prediction simply means forming an opinion, about what will happen in the future. One of the most potent ways of solving students' performance prediction problems is through the application of Soft Computing (SC) techniques. SC is an approach to computing, which allows the human brain to learn and reason in an environment of uncertainty and imprecision. Soft Computing techniques have their roots in Artificial Intelligence (AI), Fuzzy Logic (FL) and Neural Network (NN). Many SC methods that were applied in the past, had one short coming or the other, therefore, this work embraced Adaptive Neuro Fuzzy Model using Levenberg –Marquardt (LM) algorithm to obtain an effective students performance prediction model. An Adaptive Neuro-Fuzzy Inference System (ANFIS) model for predicting students' academic performance in tertiary institutions using students' cognitive attributes (assimilation ability etc.), personal factors (financial strength and actions, class attendance, rate of solving past questions was developed (Boyinbode *et al.,* 2020a). The ANFIS model has 8 inputs and 1 output. Abdulwahab and Boyinbode (2023) also developed an ANN model to predict the academic performance of distance learning students using the following attributes: Online Class Participation, Assignment Submission, Early Registration, Parent/ Guardian Education, Performance in Secondary School, Online Practical Test, Fast Internet Service, Student Location and Financial Assistance.

B. Disease Predictions

Several diseases are associated with humans; some are associated with females and some to males. Example of a disease associated with the male gender is prostate cancer. Prostate cancer occurs when cells in the prostate gland start to grow uncontrollably. Statistics show that prostate cancer is becoming an epidemic among men. Hence, several research works have tried to solve this problem using various methods to predict and diagnose the occurrence of prostate cancer, unfortunately issues of low prediction, accuracy, inability to implement the model, low sensitivity among others, still linger. Oyewo and Boyinbode (2020) approached these challenges by developing an ensemble model that combines three (3) ML techniques: support vector machine, decision tree, and multilayer perceptron to predict prostate cancer in men. The result showed a prediction accuracy of 99.06%, sensitivity of 98.09% and specificity of 99.54%, which is a relative improvement on the existing systems.

Lassa fever is a deadly viral disease that is prevalent in West Africa. Lassa fever, a haemorrhagic illness transmitted through the Mastomys natalensis rodent, continues to pose a significant public health threat in West Africa. Unlike other viral diseases such as COVID-19 and measles, Lassa fever has no known vaccine for its prevention. Hence, there is need to have a means of predicting its outbreak and to sensitize stakeholders such as governments, health authorities and communities on how to mitigate the disaster risks associated with the Lassa fever outbreak. In Ondo State, Nigeria, Lassa fever remains a dominant infectious disease, accounting for a concerning 35% of reported cases in Nigeria.

Predicting outbreaks and implementing targeted interventions is crucial for curbing its spread. Therefore, Aina et al.,2024 developed a robust model for predicting Lassa fever cases in Ondo State by employing a Bayesian linear regression approach. The model predicted Lassa fever incidence using the Bayesian Ridge Regression model. The model's performance was evaluated using two key metrics: R-squared and Mean Squared Error (MSE). The model achieved a 99% R-squared value which indicated a near-perfect fit between predicted and actual Lassa fever cases. Furthermore, the relatively low MSE score confirmed the model's accuracy in capturing the variability in outbreak patterns. These compelling results showcase the effectiveness of the Bayesian Ridge Regression model in predicting Lassa fever incidence within Ondo State.

Oluwadare *et al*. (2024a, 2024b) investigated the relationship between Lassa fever and the weather. The relationship is combined with Lassa fever incidence cases to design an ensemble Deep Learning (DL) model to predict the outbreak. The Ensemble DL model is good at combining datasets from multiple sources and formats. The stack ensemble model consists of Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU). Performance evaluation was achieved using standard metrics. The result obtained would assist stakeholders in developing appropriate preventive and response mechanisms against the outbreak.

Skin Infection is the most common type of infection. It is caused by multiple reasons, some of which include bacteria, allergies, viruses, etc. The advancement of computer technologies in addition to improvement in the medical field, makes it possible to diagnose skin infections quickly and more accurately. Due to an increase in the cost of diagnosis in hospitals and the time constraints involved, image classification techniques play a major role in skin infection diagnosis. The image classification process makes use of a feature extraction technique to help in the skin infection diagnosis process. Convolutional Neural Network (CNN) has played a major role in the feature extraction process. Kinga and Boyinbode (2024) developed skin infection detection model using CNN and the introduction of first-aid steps depending on what kind of infection is present. Timely disease prediction means a lot to the improvement of the health care services, and this will go a long way to assist communities to avoid unsafe health circumstances before resulting in complex medical situations.

Diabetes Mellitus is one of the deadly diseases that is described by hyperglycemia taking place due to defects in insulin secretion, which allow an irregular increase in glucose level. Diabetes Mellitus can lead to loss of sight, non-traumatic lower extremity amputation, chronic kidney disease, coronary heart disease, stroke, etc. However, prompt diagnosis of the Diabetes Mellitus disease is critical to forestall health complications. Abe *et al*. (2023) developed an ensemble method for early gestational diabetes mellitus prediction. The method acquired information from the Gestational Diabetes Mellitus dataset to enhance the performance of the ensemble methods. The method combines predictions from a set of different supervised classification algorithms: K-Nearest Neighbour (KNN), Random Forest (RF), and Logistic Regression (LR) algorithms to improve prediction accuracy.

C. Natural Language Processing

The trend in language translation systems that support language learners is increasing, particularly for low-resourced languages like Yoruba, which is one of the major languages spoken in Nigeria. Fatoke et al. (2024a, 2024b) developed a ubiquitous bidirectional (Yoruba to English) translation system using neural machine translation (NMT) model – transformer. The results obtained show that ubiquitous bidirectional translation for language learners majorly improved language communication and retention among language learners, making it an effective tool for language education and preservation of the languages.

CONCLUSION

Omnicomputing integrates mobility, ubiquity, learning, and intelligence, laying the foundation for the next era of technological advancement. Its holistic approach ensures that computing resources are seamlessly embedded into our environments, delivering real-time, intelligent, and adaptive solutions across every aspect of life. Mobility and Ubiquity in omnicomputing ensures that computing resources are not bound by location, enabling seamless connectivity and interaction across devices, environments, and platforms. This fosters innovation in areas such as mobile learning, ubiquitous learning and adaptive learning. Learning and Intelligence in omnicomputing also embed AI and machine learning into systems which adapt to user needs and predict occurrences. Omnicomputing has the potential to redefine society in all areas, from healthcare and education to manufacturing and transportation. Its promise of a smarter, more connected world is balanced by the need to address challenges such as data security, ethical AI usage, and equitable access.

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