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Application of Mobile Learning in Higher English Education Systems Using Cognitive Web Services

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ABSTRACT

Students choose from various learning pathways and resources while using mobile learning, which creates a universal learning environment. Machine learning techniques developed to handle AI-related challenges are known as cognitive web services. Adaptive education methods and good knowledge path design can help achieve the goal of studying whenever. In addition, mobile learning devices' display capabilities are becoming a critical determinant of students' attention and time to proficiency. Getting the necessary mobile learning components is now a hot issue. Current mobile learning environments do not include cognitive learning services to be self-adaptive to improvise the standard of the intended service. Student Performance ratio 92.11%, Students' efficiency ratio 89.9, Professional teaching ratio 95.23%, Error rate 43.86%, English learning ratio 93.32%, Interactive ratio 92.5% and Learning flexibility ratio 94.86% are obtained as the experimental results for the suggested method, which proves that the system is more efficient.

KEYWORDS

Classroom Activities, Cognitive Web Services, Data Analytics, English Education, Machine Learning, Mobile, Mobile Learning, Wireless Network

INTRODUCTION

Overview Of Mobile Learning In The Intelligent Higher English Education System

In today's hypercompetitive culture, the ability to communicate in English is highly prized. English is widely spoken worldwide and is the principal language of communication in various disciplines. However, there is still much room for improvement in English language proficiency among graduates, particularly those from rural areas who are still struggling with the basics. In addition, many students worldwide have begun to acquire and use English as a second language in place of their native speech (Gao et al.2020). The importance of the English language in education has been acknowledged by most countries, which have addressed deficits by making English language instruction a priority in

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their planning and strategy. Because the English language is essential in non-native English-speaking nations, using current methods to help learners learn English (Chandrasekaran et al.2021)

In addition, English is required in many academic fields, including publishing research papers and book chapters. English is the main center of instruction and other academic disciplines; therefore, most research papers are produced and translated into English. This is how one learns a foreign language like English. Teachers must use technology to help students achieve better. The most recent technological advancements in English language instruction are mobile applications (Amudha et al.2021). Purity smartphone application refers to software applications solely compatible with mobile devices, not computers or e-learning platforms. Game techniques, gaming programs for learning, non-games that employ other apps, and utilities are all examples of pure mobile applications. A blended mobile application is a computer program that combines mobile and other technology (Balaanand et al.2019).

Because mobile learning equipment is widely utilized and wireless connection has improved recently, students have employed mobile learning techniques to choose suitable learning materials. Enhance meets their educational requirements, enabling them to study whenever and wherever they choose. In an m-learning setting, students study using mobile phones and a wireless connection (Awuson-David et al.2021). Despite the government's best efforts, the standard of English among undergraduates continues to deteriorate. In the face of this problem, comprehensive educational initiatives are urgently needed to ensure that future generations of individuals can master the English language and remain competitive in the employment market (Liu et al.2020). Because grammar is still one of the most challenging topics for most students, it is worth improving their English proficiency due to its importance in speech and writing in academic endeavors. As a result, students must speak effectively in English and use and comprehend English language forms and functions appropriately (Lakshmanan et al.2016). Students today were not the same as students a few decades ago. Today's pupils are tech-savvy, with rapid access to many information and services. They are looking for motivation, inspiration, and guidance. They use technology to express themselves and increase their understanding by utilizing their creativity. They are technology's creators, not users. Due to these internet characteristics, English language education has seen rapid changes in teaching methods, material production, and evaluation (Abdel-Basset et al.2019).

No studies have been done on mobile English learning despite its growing popularity. For this reason, it is the first research to do a complete study and assessment of current papers on mobile English learning languages to identify the research classification, advantages, and problems and suggest alternatives to users, developers, and learners. Mobile aided learning technologies are important in English-language education since studying English is popular. Numerous researches have examined the effectiveness of mobile and anywhere learning (Shahriar et al.2018). When it comes to solving common challenges like reading text for emotional content or looking at photographs to identify specific objects or faces, cognitive web services' for machine learning capabilities are invaluable. These exams addressed various topics, including mobile learning applications, games, ubiquitous learning, and emerging m-learning research trends. Increased the popularity of mobile English learners, no studies have been conducted on the topic too far. Teaching and learning have been changed by online technology and will continue to be revolutionized.

The proliferation of mobile devices and mobile internet increased the possibilities for mobile learning and pushed it into institutions (Gao et al.2020). New mobile learning solutions are being promised by new technologies such as cloud information technology, learning analytics, and augmented reality. According to technological advancements, the concept of open learning is constantly shifting its meaning to things; it has become synonymous with educational technology. The idea of an informal educational tool has become an essential part of formal education due to conceptual and semantic changes (Amudha et al.2021). This trend has accelerated due to the widespread adoption of the blended learning model. The notion of internet-assisted education or e-enabled education has been used extensively rather than the concept of online higher education, owing to the expansion and strengthening of internet infrastructure. Its applications have become prevalent in higher learning.

According to technological advancements, the concept of open learning is constantly shifting its meaning to things; it has become synonymous with educational technology (MeenaakshiSundhari et al.2021). Creating an automated IT system that can solve problems and provide solutions without human intervention is the primary goal of cognitive web services. The idea of an informal educational tool has become an essential part of formal education due to conceptual and semantic changes. This trend has accelerated due to the widespread adoption of the blended learning model.

The notion of internet-assisted or e-enabled education has been used extensively rather than the concept of online higher education, owing to the expansion and strengthening of internet infrastructure. Its applications have become prevalent in higher learning (Revathi et al.2015). However, as the use of mobile platforms has risen over time, the concept of mobile learning has grown in popularity, and e-learning has begun to transform into m-learning rather than network education or e-enabled education. They can say that mobile devices are technological advancements, especially now, because they give users greater flexibility in terms of time and location and a lower cost than desktop computers (Manimuthu et al.2021) Floor Substation and cable, Shore station, High Power Moorings, Coastal Mooring, Cascade Zone, Potential sites, Internet Hub and ONC substation, are the components of Cabled Ocean observatory

It is incomprehensible that this ability is not being utilized in education. Aside from the advantages of mobile learning, there are several issues and constrictions to consider, including what design considerations should be used in mobile learning environments. What needs to be changed, what significant differences in curriculum strategies for mobile environments, what characteristics should be included in a mobile learning system, and which framework will be used (Khan et al.2020).M-learning includes a lot of educational planning or the creation of learning paths. Good curricula help students remain on track during the whole learning system. Personalized adaptive learning necessitates a strong focus on curricula. Many modern individualized learning environments take into account the learner's preferences, hobbies, and browsing activities in addition to course scheduling. On the other hand, these systems disregard the learner's talents (Wang et al.2020).

The debate over whether mobile learning for studying makes sense has already passed; technology-based learning forms permit didactic-methodical designs that cater to a wide range of learning demands, learning biographies, and media interests. Learning with mobile devices and apps provides substantially more variety and variation in teaching and learning styles than before. Teaching and learning apps provide various multi-media engagement and communication options (Elhoseny et al.2018). There are numerous ways to employ emerging technology, such as mobile online for learning. Mobile learning can achieve several types of tasks: Mobile learning as a stand-alone learning solution; replacing earlier learning solutions, enhancing the standard offering with additional features; having the same or less essential data as the classic scenario (Elaish et al.2017). Despite the rapid rise of M-learning technology, research on the elements that promote M-learning adoption is lacking. Before implementing M-learning, the learner's perspective and acceptability of the technology must be assessed. As a result, researching to identify the characteristics that drive M-learning adoption is critical. The variables for M-learning adoption can be determined using a variety of ways. Acceptance of M-learning by users is crucial for developing successful M-learning software (Bai et al.2019). As a result, it is necessary to investigate the elements considered when creating an application. In the early stages of M-learning development, mobility is the most crucial issue to consider. It allows users to communicate even outside of traditional communication zones. The concept of integrating M-learning in the influential educational technology industries has significantly advanced over the last decade(Sarrab et al.2016). With the expanding use of mobile devices, it is more important than ever to create appropriate learning and educational techniques that mobile devices can be used to their full potential for greater understanding. M-learning is defined as learning delivered through social media (e.g., connections via portable and mobile platforms such as smartphones and tablets, cellphones, or other mobile platforms) in various settings (Zhu et al.2020).

Instructional designers and educators have lately questioned Mobile technology's usefulness in education. It is little wonder that research on m-scope learning and its implications for education has gotten little attention. According to the existing body of knowledge, the results of previous research are contradictory. There were many useful syntheses of previous m-learning studies; then further research is needed in certain areas (Wang et al.2009). The use of mobile devices to support learning is an exciting prospect, especially given their multi-media capabilities, portability, connectivity, and flexibility. Despite these advantages, there is little proof that mobile technology improves student learning, especially English language learners. This is especially true for English language learners (Wang et al.2012).In higher education, machine learning and data analytics offer the ability to free learning from the rote method of acquiring knowledge and take benefit of cognitive analytics to more purposefully involve learners. M-learning is still outside of classroom instruction when it comes to language learning. There have been no studies on mobile learning the English language despite its increasing popularity. For this reason, this is the first research to do a thorough examination and evaluation of previous papers on smartphone English learning languages to identify the research taxonomy, advantages, and problems and offer suggestions to users, developers, and learners [24].

The paper's essential contribution is the intelligent higher English education system, and mobile learning covers various topics. Nonetheless, the expertise of the authors is divided into four categories:

- Classify and organize studies on m-learning English teaching and its applications;
- Analyze the cognitive web services for machine learning and data analytics higher english education system.
- Identify the advantages and challenges of mobile learning the English language, and some assist it to be utilized more effectively.
- The optimum learning pathways and objects are found using carrier selection fuzzy interpolation calculation methods.
- This study aims to show that research on mobile learning in the intelligent higher English education system is based on experiences and theoretical studies to enhance the advantages of foreign education.

An upcoming section is organized: The second discusses similar work and its corresponding discussion. Section 3 discusses mobile learning in the intelligent higher English education system (ML-IHEES). Section 4 results and forum have been compared with an existing method. Section 5 concludes the study by discussing the following research scope based on the preceding section analysis.

BACKGROUND STUDY

M-learning and cognitive web services for machine learning are gaining popularity worldwide as a mobile teaching strategy. It was a learning method given via wireless mobile handheld devices, allowing learning to occur at any time and in any location. Individuals, groups, and counties that were previously too remote, socially or physically, for other sorts of educational initiatives can now learn through m - learning. In this sense, it was more beneficial and convenient than m-learning, which requires constant computer and internet connectivity. This section discusses supporting them in finding relevant concepts, methodologies, and future studies. This section contains an evaluation of scholarly articles on a particular topic

(Komalawardhana, N et al.2021) presented the integrated learning diagnosis and mastery learning mechanism for programs that improve gaming stages based on an individual student's conceptual levels in a pre-test and monitoring learning throughout the gaming process. To test a mobile game-based learning system (MG-LS), some students from four Thai elementary schools took part in a general science course. The pupils grasped the concepts of force and motion used the recommended method,

according to the results of the experiments. The data link the suggested game and the traditional activity regarding accomplishment areas, efficiency, and impression.

(Qashou A. et al.2021) provided the hypothesized model of Technology Acceptance Model-based m-learning (ML-TAM) at higher education institutions. Using the technology acceptance model (TAM) and other irrelevant variables, researchers looked at what factors influenced Palestinian university students' willingness to utilize M-learning systems in the classroom and their coursework. According to the results, perceived usefulness and attitude significantly affect M-learning adoption intention. In contrast, attitudes toward M-learning adoption are strongly influenced by perceptions of efficacy, ease of use, and self-efficacy.

(France D. et al.2021) discussed the study lays out a strategy for teachers to handle pedagogical and technological concerns while bringing mobile learning into the classroom. In all cases, the teachers' reflective responses to the eight pathway issues imply a well-structured activity with engaged students that consider equal access, experience, and contingency preparation. This path outlines a strategy for instructors to determine whether a mobile learning intervention was appropriate and adds value to their classes. External review of the pathway with new teaching examples will improve the methodology's effectiveness.

(Luan H et al.2021) examined the 40 empirical research on machine-learning-based precision teaching in this paper (ML-PT). The findings revealed that the bulk of studies focused on predicting academic achievement among university students majoring in computer science or STEM and that the data sources were varied. The most commonly used machine learning algorithms, evaluation methods, and validation techniques are discussed. Issues can happen, and future directions are discussed appropriately.

(Al Mansoori S. et al.2021)discussed the impact of artificial intelligence (AI) and information technology (IT) concepts and methodologies on knowledge management efficiency in modern businesses (AI-IT-KM-MB). This study examines and highlights contemporary knowledge management strategies that rely on IT and AI technologies and the challenges and constraints to modern enterprises. The current research seeks to thoroughly explore 15 research papers published in high-quality journals and conference proceedings between 2009 and 2019. This research study was significant for academics since it fills in some gaps in performance management, particularly in IT and AI-related studies.

(Nikolopoulou K et al.2021) explored the readiness of instructors in K-12 classrooms to embrace mobile learning. Teachers' opinions of mobile learning benefits and preferences were favorably modified by ICT training and attendance at ICT conferences. An increased likelihood of using mobile devices in the classroom was linked to stronger perceptions of the benefits of mobile learning, preferences, and external factors. Teachers' preparedness perceptions can be investigated from various angles, and they can be linked to classroom use of mobile devices. The implications for teacher education, methodology, and pedagogy are examined.

(Ageed Z. S. et al.2021) investigated the big data mining approaches in cloud systems (BDM-CS) and cloud-compatible challenges and computational methodologies to promote Big Data Mining in Cloud Systems. The data analytical viewpoint was frequently examined when exploring various techniques for data storage in big data. Methodological development and problem statements have been addressed using this vocabulary and aspects. This will aid in examining computational capacity and discovering new information in this field.

(Wang Z et al.2019) proposed massive open online courses (MO-IOC) beyond standard classroom instruction and space to share educational resources. The impact of this new teaching approach has yet to be evaluated. This report presents the results of an intensive data analysis to assess the quality of teaching MOOCs. As a result, the author developed a system for evaluating instruction quality. In addition, using the Bayesian Network model, the costs of learning were computed, and the assessment findings were thoroughly examined. The research findings provide a realistic new perspective on evaluating the quality of MO-IOCs.

(Beheshti A et al.2020) presented the cognitive recommender systems (CRS) as the new smart Decision Support systems would be able to grasp the user interests, recognize differences in consumer choices over time, forecast the user's unknown favorites, and study adaptive mechanisms to allow intelligent activities inside the complex and evolving surroundings. Recommender Systems in contemporary organizations are heavily data- and awareness and can rely on user cognitive factors, including individuality, behavior, and mindset, and assistance data capture and predictive analysis around customers' mental skills and use it to provide smart and moment suggestions.

The above analysis proves that mobile learning environments must be more interactive and provide more flexible analytical services to the end-user with diverse technologies. Hence, here presents a new strategy for successfully enhancing the learning approach that mobile learning in the intelligent higher English education system (ML-IHEES) uses cognitive web services for data analytics. The study explored new techniques to develop training models to help with the aforementioned challenges.

METHODOLOGY

This section explains how mobile learning fits into the intelligent higher English education system (ML-IHEES) as social information technology advances. The selected papers' study subjects were first examined, and similar issues were consolidated and summarized during the review process rather than written separately. They are generally described in the structure and organization of the technique structure below.

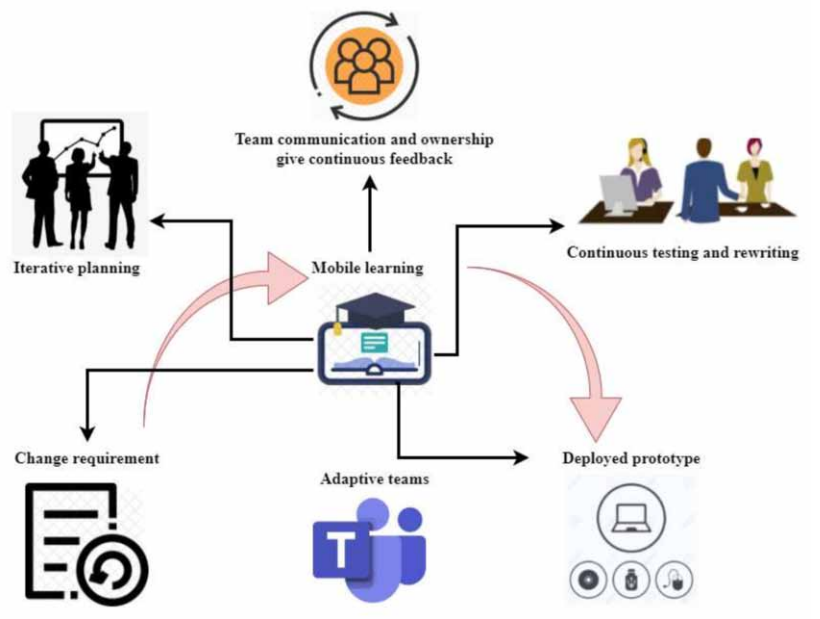
Mobile Learning Fits Into The Intelligent Higher English Education System (ML-IHEES)

This research integrates mobile learning into the ML-IHEES intelligent higher English education system. The model is presented as an alternate on-the-hand method to English Education system teaching and learning. The term 'ML-IHEES' was coined to describe the mobile aspect of English learning. The ability of the suggested approach to build a customized grammar learning environment for the learners is what makes it "intelligent. In this application, customization refers to the supply of curriculum materials matched to each learner's educational experience.

In this regard, the suggested approach includes modeling learners' teaching methods simultaneously and afterward tailoring language learning content to each aspect. The ML-IHEES model will create a mobile learning system that will allow for a smooth, ubiquitous learning environment for English. Notes, alerts, queries, and a forum will be among the system's mobile-based English learning apps. Researchers proposed mobile learning in the intelligent higher English education system to create users with the most suitable educational routes. According to the number of incorrect answers students gave in a pre-test, this technology creates personalized learning pathways. It is important to note that pre-test results are estimates of future course difficulty, and the results serve as a starting point for planning future learning strategies. Greater than free surfing teaching techniques is a customized M-learning system that utilizes an optimization approach to provide students with higher quality learning and more efficient and productive learning pathways.

Figure 1 shows the ML-IHEES method. Mobile learners in the intelligence higher English higher education (ML-IHEES) learning method The expansion of education did not occur consistently across all levels. Primary schools suffered as a result of a lack of resources. The personnel attention to women's education or the promotion of higher education in science and technology. The team's ability to quickly assess the findings and develop solutions is critical. The testing process helps to ensure that the deployable prototype is continuously improving. Students can interact and share ideas using the discussions component. Cognitive web services for machine learning can offer solutions to problems. Their participation in the learning system is possible. They submit question after question to the professor for addition to the questionnaire and afterward add four alternative responses for examinations. As a result, their problem-solving, teamwork, and communication skills have improved,

Figure 1. Mobile learning in the intelligent higher English education system



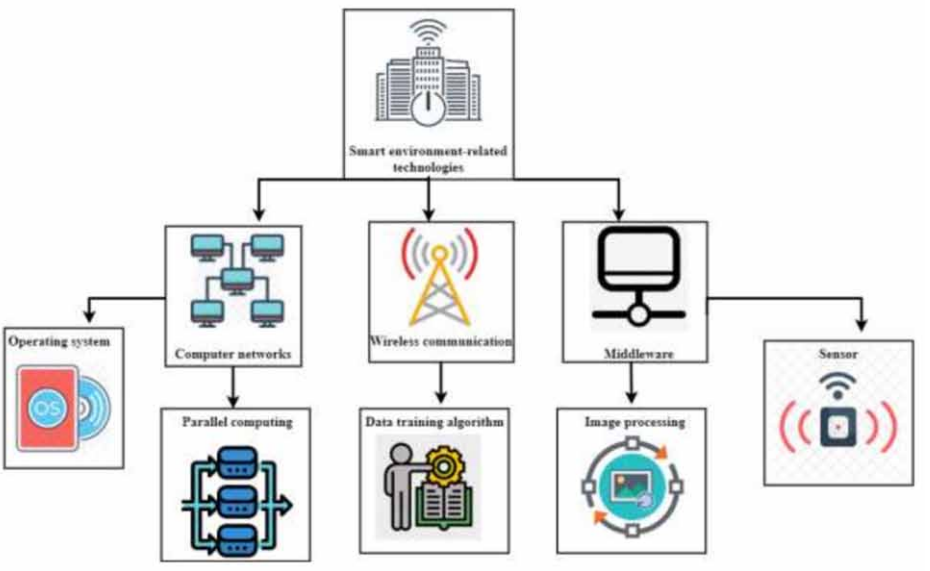
as has their analytical thinking. . The system efficiently analyses the context to select the phrase of similar type and one is marked. This helps find the same type of resources, and learner performance is analyzed for similar types. The requirements were not precise and were subject to frequent revision. Every meeting with the students at the institution generated a flood of demands and suggestions. Versions are the foundation of agile development, and each iteration involves prototype construction and testing. Numerous studies show that fixing a problem in later manufacturing stages is more expensive than catching it early.

On the other hand, Agile techniques aim to deal with issues as soon as they arise. As a result, as students go from one level of difficulty to another, the system adjusts to their understanding. The approach is an Iterative framework widely used as an agile method. Sprint enables members of the team to deliver software to consumers more rapidly. Accountability, attention, and effort will improve the system's strategy and execution.

This idea began to take shape with the rise of non-universal computers. As defined by Wikipedia, an innovative environment is a suitable environment made up of interactive sensing, mathematical units, displays, and computer units that link everyday items in our life through the internet to one other. It offers a wide range of processes industrial automation to its customers. Pervasive computers, cognitive technologies, environmental sensing, and device communication are some of the technological knowledge areas that make up the intelligent environment.

Ecosystem intelligence relies on people's capacity to successfully monitor their surroundings, as illustrated in Figure 2. Installations, user to connect, and drive elements are examples of implementations. The elegant surroundings are primarily in charge of manually creating sensors in the scene. For example, machine learning and data analytics can be used to help students discover what works best for them in the classroom, then in a way that takes into account all of their differences. Additionally, machine learning can be utilized to review a difficult subject. The nodes work together to detect and collect contextual information and measure the scene's items of interest using dual sensors. Nodes share information via using communication. The collecting node analyses the incoming

Figure 2. Monitor the environment is critical to ecosystem intelligence

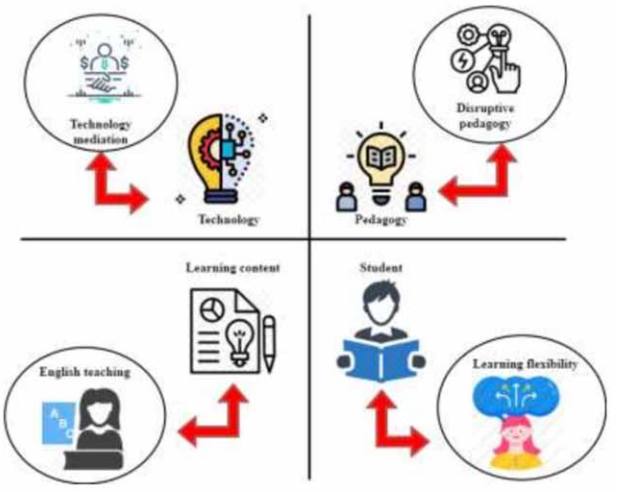


data before sending the findings to PCs, mobile phones, and other terminals through the network, observatory, wireless Local area network, and other effective evaluation methods.

Figure 3 depicts the four main themes connected to English teaching in higher education using mobile technology. Technology mediation is a term that refers to the use of hardware, software, and mobile devices to intervene in the educational system. Infrastructure, servers, and Wi-Fi connectors are examples of physical components. The intangible elements embedded in the hardware, such as the communication system, learning management system, and application, are referred to as software.

Any mobile device linked to mobile learning, such as a laptop, tablet, or smartphone, is considered portable. Most participants believed that digital education plays an essential role in higher education,

Figure 3. Four main stages connected to English teaching in higher education using mobile technology



then many were sceptical about combining digital education with current technical abilities. Teachers were concerned that they lacked skills in terms of technology-assisted instruction. As a result, mobile learning environments have transformed educational behavior, moving toward virtual online course transmission beyond social and geographical boundaries. Teachers have been compelled to develop pedagogies due to digital education employing mobile technology, which has disrupted traditional teaching approaches.

Figure 4 depicts the architecture for the smart M-learning competence-based platform. The system comprises an efficient learning interface and a personalized learner. Learners' skills are assessed, and learning items are selected and sent through the intelligent learning interface. The display device used here helps in displaying the relevant information. The learner's activities are fed to the Reader of the M-Learning Device to collect the data for intelligent learning and decision making. The system dynamically updates the activities, and the intelligence added helps in decision making. The personalized learner uses a termites approach to build learning paths tailored to the learners' ability. For each future objective, the effective learning interface uses a pre-test to determine the skills learners need. It uses extrapolation to choose relevant learning elements. A depiction of a competency-based course diagram and a sample of a before examination before the effective instructional functionality turns questionnaire from of the comment assessment into questions for the which was before evaluation to analyze a person's learning measurement. Education substances $X_{learning-objects}$ that are appropriate for learners' career plans are chosen depending on the competencies that they lack:

$$X_{learning-objects} = X_{Career} \times X_{pretest} \tag{1}$$

Equation 1 expresses the career-oriented educational substances. X_{Career} **and** $X_{pretest}$ represent the learner's subjective skill variable towards the career and pretest performance. Accordingly, the learner driver experience, abilities gaps, and the flexible approximation. The learner's career goals and objectives are reflected in the random numbers of the learner career analysis:

Figure 4. Intelligent M-learning system built on competence

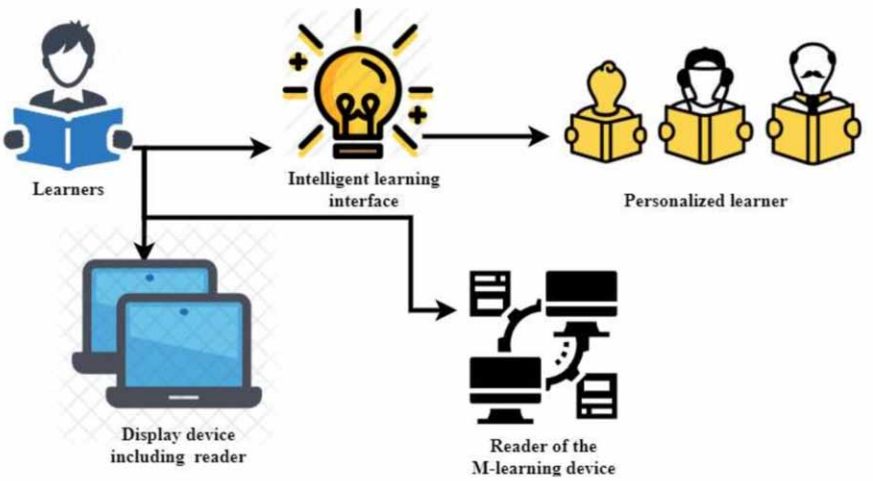
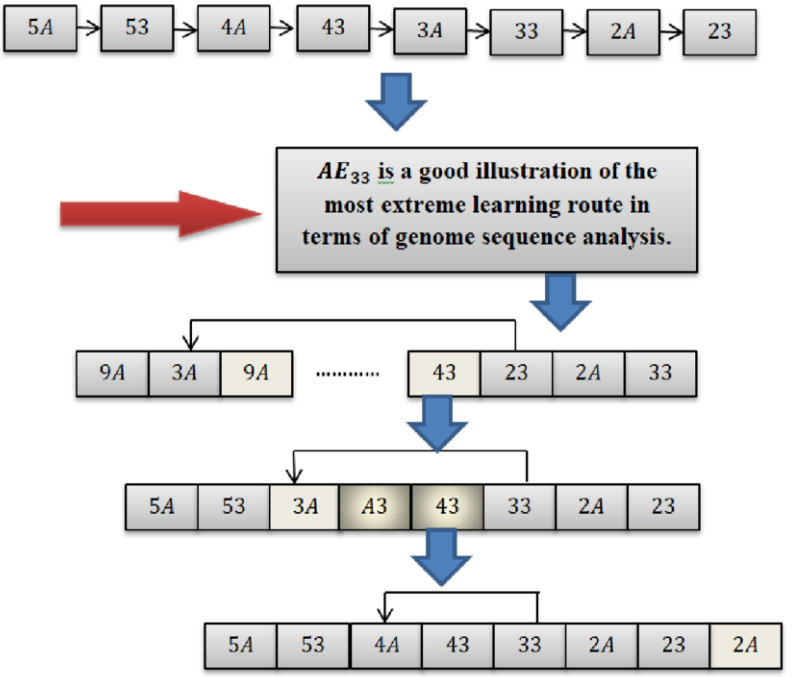


Figure 5. Learning benefits



$$X_{Career} = \prod_{m=1}^{k} X_h\left(A_n\right), X_{pretest} = \prod_{m=1}^{k} X_g\left(Y_i^{wrong}\right) \tag{2}$$

Equation 2 shows the imprecise essential learning elements for the learner's professional goals and future career. k denotes the number of experience X_h learners professional goal oriented skill and A learners level of skills. where n , X_g $refers to$ the number of incorrect questionnaire forms in the fuzz variables associated with pre-test learning content correlate to article solutions and Y_i^{wrong} represent the incorrectly responded questionnaires as in the pre-test, n is the identification variable for the learner. m is the iteration variable, h refers to the number of skills in the list. The learner's deficiencies in knowledge and skills reveal what the learner lacks as a learning object. It tracks incorrectly completed a questionnaire as well as connections between learning items.

The fitness functions use maximum learning benefits to find appropriate educational experiences:

$$A' = \max imum\left(\sum_{i=1}^{n}\beta\left(AE_i\right) + \sum_{m=1}^{k-1}\left(\frac{Q_{AE_{i+1}}^{pass}}{100} - \frac{Q_{AE_{i+1}}^{pass}}{100}\right)\right) \tag{3}$$

Equation 3 calculates the learners level of a skill $A'W$ ith the help of fitness function. Here n is the identification variable for the learner, β skill deficient fraction, i and m are the iteration variable, k denotes the number of experience $Q_{AE_{i+1}}^{pass}$ is the fitness performance of the skill. Finding the shortest learning path between any two learning items is a good starting point because their distance from inherent chromosomal needs determines the benefits of learning things. Figure 5 illustrates the learning benefits of learning things. This helps find the benefit obtained by the learner

using the proposed platform. Another consideration is how well the students have previously performed on the material they have studied. All appropriate educational objects, the advantages of every learning object, the number of instructional technology students have previously served on, and the student's prior performance on those educational technologies are considered.

As often as possible, the fitness functions bring unlearned or skill deficient fraction of the learners to the front of the learning path that learners re-learn them:

$$\beta = \begin{vmatrix} +o,1\ Basic\ learning\ goals\ occur\ before\ other\ than\ five\ learning\ goals \\ +o,33\ and\ 4\ teaching\ items\ that\ are\ prerequisites\ are\ listed\ first \\ +0.53\ and\ 1\ to\ 2\ teaching\ items\ that\ are\ prerequisites\ are\ listed\ first \end{vmatrix} \tag{4}$$

Equation 4 shows the decide each student's future route; the quantity of signals collected on their learning journey is crucial. Learners create evidence portfolios based on their self-reflection on the level of proficiency they believe they have demonstrated. They use technology to record their performances; Learners are evaluated by their peers on the strength of evidence they provide concerning the agreed-upon indicators of skill or capability. Feature Dissimilarity assesses the differences in a set of variables between the different contexts of use. Except for numerical wobbling, all methods of boundary delineation call for them. Polygon wombling, category wombling, and spatially constrained clustering all rely on them. Here, the measure of dissimilarity refers to poor performance of learner compared to other learning goals.

$$XY_{offspring} = XY\left(\max imum\tau_{i,j}^{parantA}, \tau_{i,j}^{parantB}\right) \tag{5}$$

Equation 5 indications as follows: whereby the learning pathways are denoted by the letter $\tau_{i,j}^{parantA}$, the letter $\tau_{i,j}^{parantB}$, the scent levels of paternal generations X from I to j, and the XY pheromone values of paternal generation B from I to j, correspondingly.

$$\left.\begin{aligned} \tau_{\max} &= \frac{1}{XY_{best}^{\lim it} \times \beta}\ ,\beta = 0,1 \\ \tau_{\min} &= \frac{\tau_{\max}}{m} \end{aligned}\right\} \tag{6}$$

This method utilizes the max-min ant system to restrict the range of possible pheromone quantities to be between a specified τ_{max} maximum and τ_{min} minimum. Equation 6 manipulates the learners maximum and minimum duration spend in achieving the goal to find efficiency. Pheromone values higher than the maximum value are chosen; those more minor than the minimum are selected throughout the computation.

Equation 6 shows which indicate the efficiency characteristics of the optimum initial achieve shared in the termite's method, and time to full saturation of the pulse β and whole integer m of knowledge things retrieved by $XY_{best}^{\lim it}$. In general, the value of pheromone decay falls between $0 < \beta \leq 1$, with a higher number indicating a quicker decay rate. To avoid too rapid decomposition and arrive at an optimum solution, this system chooses a decay value of 0.1.

All learning pathways are started with a pheromone value of $\tau_{\max}$ Nevertheless, the pheromone value must be raised if the learning route seems to be the best option at this time. since it is the most

that the termite's system can handle, the pheromones value is updated when each decade's optimum solution is produced via the learning path of the solution. If the learning route is not shown in the optimum solution, a lower pheromone value should be used.

$$\left.\begin{array}{l}\tau_{i,j} = \left(1-\beta\right)\tau_{i,j} + \Delta\tau_{i,j} \\ \Delta\tau_{i,j} = \left\{\begin{array}{c}\dfrac{1}{XY_{best}^{\lim it}} if the path from AE_i and AE_j is optimal path \\ 0 otherwise\end{array}\right\}\end{array}\right. \tag{7}$$

Equation 7 denotes the pheromones levels $\tau_{i,j}, \Delta\tau_{i,j}$ to raise the pheromones levels and AE_i, AE_j is the learning advantages of the optimization technique of these generations are denoted by $XY_{best}^{\lim it}$. Equation 7 calculates the time stamp required to achieve the goal. Suppose there is variation in the expected timestamp. In that case, the differences are calculated, and the reason is being analyzed in different aspects to bring the modification by automatic learning in the system.

A student's time spent using the application in class and different learning tasks will determine the proportion of time accessible to them depending on their teacher's recommendations and the amount of time spent studying autonomously on their smartphones in this research.

$$\left.\begin{array}{l}\varphi_{classroom} = A_{facetoface} : A_{learning} \\ A_{learning} = A_{practice} + A_{\text{int}eractive} \\ A_{facetoface} 40 - A_{learning}\end{array}\right\} \tag{8}$$

Equation 8 analyses the learning efficiency of the student v=based on time spent over the learner in the Smartphone. To calculate this, it uses the parameters $A_{practice}$ referring Practicing ability of the learner, $A_{interactive}$ denoting interaction ability, $\varphi_{classroom}$ specifying time spent in the classroom, $A_{facetoface}$ showing the ability of direct presence of the learner to reach the goal

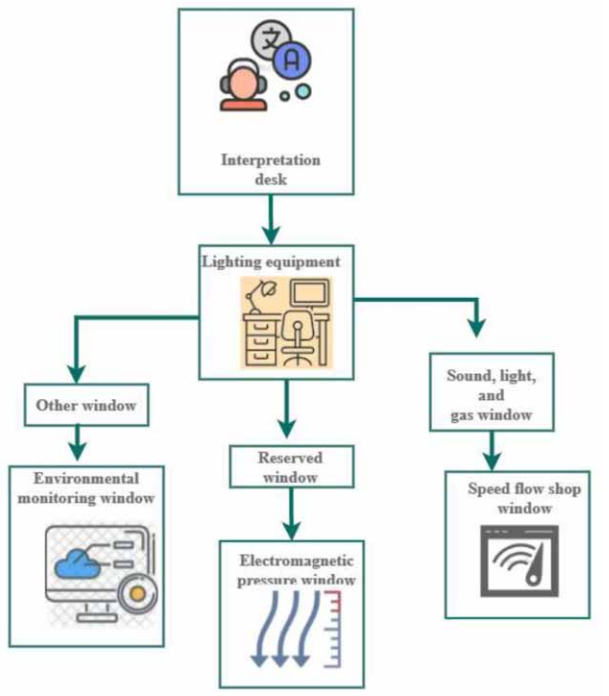
The following formula is used to estimate how much classroom instruction should be allocated:

$$\varphi_{classroom} = \frac{40 - A_{learning} - A_{\text{int}eractive}}{A_{practice} + A_{\text{int}eractive}} \tag{9}$$

It is possible to accurately assess students' learning effects and their timeliness and dependability by analyzing learning data in this manner. Teachers can then use this information to understand student learning situations better and teach students in conformance with strengths.

Figures 6 demonstrate the Learning system with sensor display. The teaching table has an infrared sensor that connects to the computer and assists students in oral instruction, to the instructors in drawing lines and promoting energy conservation. With the help of a sensor screen window and desk, the system serves as a sensor teaching demonstration model. The sensors are monitoring the environmental parameters. The open window senses the wind flow, temperature, lighting level from the daylight and the values are forwarded. The speedn flow shop window measures the wind speed. The electromagnetic pressure sensor observes the air pressure in the room. Teaching desks include computers, audio equipment, wireless transmission modules, and information recognition devices linked to the spoken language trainer on the desk. The laptop on the desk has a connection to the

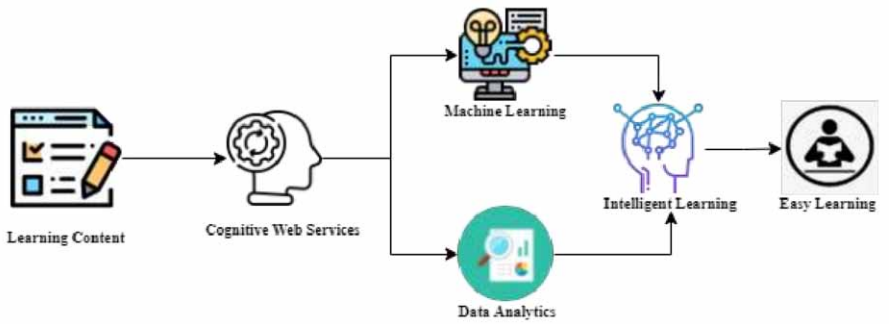
Figure 6. Learning system with sensor display



spoken language trainer. A recorder has been installed on the surface. Using physical displays and multi-media presentations of different sensors, the auxiliary model teaches trainers about sensor technology and products, laying the groundwork for more advanced sensor application development. English teaching systems using human infrared sensors benefit from this technology, as can the technical area of English teaching equipment as a whole. There is a shell included in the said language training program. The writer is linked to the shell's CPU. Personal information and English learning materials are stored in a memory connected to the CPU. The fingerprint collector on the information identification device is linked to the CPU.

Crowd-sourced tutoring has been improved through the use of machine learning technology. The purpose of crowd-sourced tutoring is to aid students in finding excellent teachers and classmates who can augment what they learn in school. Cognitive web services help students get their study contents

Figure 7. Cognitive web services for machine learning and data analytics



and easy learning techniques through various ways. Figure 7 illustrates the working of cognitive web services for machine learning and data analytics in intelligent learning of the English language.

$$Q_v\left(s_i\right) = \log Y_v\left(s_i\right) / \log \sum_j Y_v\left(s_i\right)' \tag{10}$$

$$P_v = -\sum_{i=1}^{n} Y_v\left(s_i\right) * \log Y_v\left(s_i\right) * \log Q_v\left(s_i\right) \tag{11}$$

$$C_i = P_v \prod_{i=1}^{n} \alpha_i + Q_v\left(s_i\right) \prod_{i=1}^{n} \beta_i / \gamma_i \tag{12}$$

As per equations 10,11and 12, the interval's influence on the likelihood of a person's actions $Q_v\left(s_i\right)$ is the log function of incidence consistency about the period $Y_v\left(s_i\right)$ following the calculation of the unpredictability of the behavior v. Interpretation prediction ratio P_v is multiplying the log function of intervals influence on the likelihood of a person's actions $Q_v\left(s_i\right)$ and incidence consistency about the period $Y_v\left(s_i\right)$. Display their expertise in front of a large audience $\boldsymbol{C_i}$ is summing up the assessment based on marks assigned $\pm_{i}$, an indicator's value that corresponds to $^{2}{}_{i}$, the ability of young entrepreneurship to operate on an equal footing $^{3}{}_{i}$, interval's influence on the likelihood of a person's actions $\boldsymbol{Q_v}\left(\boldsymbol{s_i}\right)$ and Interpretation prediction ratio $\boldsymbol{P_v}$.

Advantages And Disadvantages Of English Teaching

English Is taught with rich, real-time, accessible, and contextual materials that have never been easier thanks to mobile pedagogy. Even in the development of language skills, almost everything English abilities are appropriate for mobile pedagogical with contextual innovation education. Although most participants felt that employing technology to enhance language abilities had many advantages, several participants pointed out some drawbacks. Table 1 represents the benefits and drawbacks of English Teaching in digital settings. The benefits of connecting with a worldwide network of specialists, such as native English speakers and professionals in the field, through multimodal communication are apparent. Online materials are naturally native language; thus, speaking is entirely relevant (n=26). Students use internet videos to study as much as they want.

In virtual learning settings made possible by mobile technology, it is essential to pay attention to inflection, consonants, and syllables. However, despite the benefits of m - learning, the drawbacks are mostly related to the entertaining features of cellphones, especially the disruptions produced by alerts (N=29). P19 expressed dissatisfaction with the reading experience on mobile devices. The tiny screens of cellphones made it challenging to conduct in-depth and lengthy reading activities. Using a mobile device is practical for receiving urgent information, such as important news. It is challenging to practice reading skills or take exams like the Reading in International Teaching English Testing on a smartphone because of the small screen size. Even with a larger screen, a laptop still has the

Table 1. Benefits and drawbacks of English Teaching in digital settings

Languages skills	**Advantages**	**Disadvantages**
	Descriptions	**Descriptions**
Listening Speaking Reading Writing overall	Listening There are many resources available right away for learning. Disruption with notifications Engagement with video and social networking sites is easy. Quick information for news, stories, events Access to media n general Positioned and genuine English	Visualize themself being addicted to music Lack of accuracy There is a slight amount of space on the screen Problems with typing Envisioned having to learn compulsion

same issue with page-turning: it is inconvenient. Finally, writing makes it easy to get information and look up terms in a dictionary on a smartphone. However, writing on mobile devices, particularly smartphones, is difficult. For typing, the keyboard is inadequate due to its tiny size and poor usability. Larger instruments, like laptops, are better for writing on. Students' poor handwriting and excessive cellphones and computers were issues that participants raised during the focus group. To summarize, digital teaching has more benefits than drawbacks. Mobile devices aside, digital education provides immediate and omnipresent Teaching English materials via open distance learning via social media. The online information that is authentic and interactive provides chances for the immersion programs, which contributes to the development of an efficient system for learning a foreign language.

Finally, the student performance ratio, students' efficiency ratio, professional teaching ratio, error rate, improved English learning ratio, interactive ratio, and learning flexibility analysis ratio were all considered. According to this study, a mobile app for English language instruction uses the ML-IHEES and intelligent cognitive web services compares survey findings with other studies.

RESULT AND DISCUSSIONS

Earning approach that mobile learning in the intelligent higher English education system -addressed research, problems are diversified significantly, directed to many fields, based on various learning methods, and primarily in the creation and usefulness of a natural place. Apart from that, there are a wide range of topics in mobile learning, such as the academic achievements of students and the impact on their attitudes and perceptions, attitudes or conceptions of teaching staff members in modern applications, and the adaptive and collaborative context of shared, self-regulated m - learning, machine learning, data analytics and mobile platforms for taking notes. In addition, a categorization of the study's aim has been used to identify the study's architectural orientations. Innovative mobile applications are incorporated into English classroom instruction to pique students' interest in learning the language. The following premise is advanced: Incorporating mobile apps into English classroom instruction can increase student engagement and enhance the teacher's effectiveness. Smartphones and tablets have excellent wireless connections.

The real-time interaction adds a significant amount of value to cognitive web services. To communicate with instructors or teaching companions in real-time, students utilize the speech function and software for a specific place, which is very useful in transmitting the information. According to the data analysis, this class engages in a smartphone-assisted teaching experiment. Finally, learners must learn as much as they can about all aspects of students' needs and address the learning approach that mobile learning in the intelligent higher English education system. The significant elements where the research is concentrated include student performance ratio, students' efficiency ratio, professional teaching ratio, error rate, improved English learning ratio, interactive ratio, and learning flexibility analysis ratio. Moreover, understanding the approach that mobile learning in the intelligent higher English education system (ML-IHEES) with the advancement of social information technology' research and information capacities according to this research.

Table 2 shows the comparisons of performance metrics. It should take from all data that measures essential data within a range, allowing a foundation to support the concern's overall aims. Metrics are needed to determine how employees perform and whether or not goals are accomplished. Metrics inform us if a procedure is adequate to satisfy the user's needs or if it needs to be improved. As a result, metrics are critical for converting customer requirements and operational success into data compared. Financial measurements are used to assess a company's ability to translate operating outcomes into financial targets, and comparable measures are included in this indicator. Finally, understanding both types of measurements and what they suggest is necessary for making informed judgments regarding the process. As a result, metrics are critical since they convert consumer and operational needs into data compared.

Student Performance Ratio (%) And Professional Teaching Ratio (%)

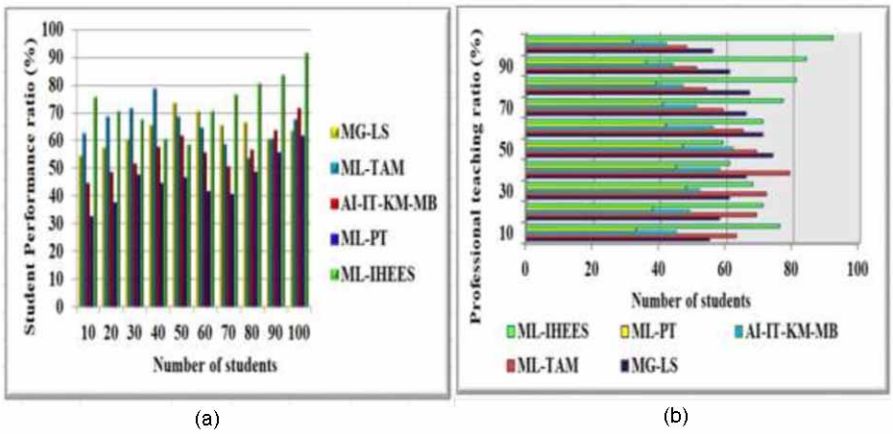
Figure 8(a) depicts the student performance ratio for the given number of students under assessment. The results showed that students in the intervention group outperformed those in the control group

Table 2. Comparisons of Performance metrics

Parameters	MG-LS	ML-TAM	AI-IT-KM-MB	ML-PT	ML-IHEES
Student Performance ratio (%)	45.7	55.67	65.6	47.7	92.11
Students' efficiency ratio (%)	55.6	50.5	65.4	67.8	89.9
Professional teaching ratio (%)	62.3	52.3	42.3	64.3	95.23
Error rate (%)	23.5	43.5	53.5	25.5	43.86
English learning ratio (%)	58.2	68.2	38.2	59.2	93.32
Interactive ratio (%)	58.5	38.5	68.5	57.5	92.5
Learning flexibility analysis ratio (%)	58.5	38.5	68.5	57.5	94.86

on a post-test. The rise in the average score of 12 points, the decrease in the number of grades in the single digits, and the increase in the number of high grades of 13 points suggest an improvement in student performance. Students will be less likely to waste time on unproductive pursuits while also more likely to pay attention to what is being taught. There were more significant differences in pre-experiment scores differences in English competence between various subgroups of students were almost similar, as shown in figure 8 (a). The mobile academic programs are improved, and mobile applications technologies are brought into the classroom. Mobile learning was an excellent tool for improving one's English. English is conducted with the use of smartphone learning. It can enhance educational outcomes and pique students' curiosity in the subject matter.MG-LS had a 38.76% interest rate and performance of students while increasing the interest rate resulted in a 90%, according to the experiential learning method for 100 students. Figure 8(b) represents the comparison of the Professional teaching Ratio for the proposed method. A wide range of functions can be performed on a smartphone, from voice calls to online chats to amusement games to student engagement. This is due to technological advancements. Fortunately, as network information systems advance at breakneck speed, the intelligent capabilities of mobile phones are realized. Students' learning styles and English language proficiency differ. It is impossible to meet the needs of today's students with a single conventional teaching method. They must create a customized database for various English components and merge it with an individual-tailored curriculum resource library to share resources across the system and encourage students to engage in m-learning below the connected

Figure 8. Student Performance ratio (%) and Professional teaching ratio (%)



device of communication networks to meet the various English needs of students, in the long run, The professional teaching ratio shows that proposed achieves the efficient value up to 95.91%.

Students' Efficiency Ratio (%) And Error Rate (%)

Figure 9(a) shows how adequately people can use smartphones and tablets as learning aids and phone apps to create a fair and efficient learning model in the form of student Efficiency ratio and Error rate. The primary reason why most college students purchase cellphones or tablets is to stay in touch with their peers. Mobile phones were designed primarily for communication purposes. According to the study results, 52% of students purchased smartphones or tablets to help with schoolwork. In the case of computers, this implies that students are still aware of mobile phones such as phones to study. 21% of mobile devices like smartphones are used by students who study online alone, while 44%are used for gaming. According to this study, most high school students prefer to play video games on their smartphones and tablets rather than use them for educational purposes. Because of this, kids in lower grades are more likely to wander from their studies and risk their health and quality of life if instructors and research do not intervene promptly. According to this idea, when the government is appropriately suspended, there is a corresponding loss of authority. The error faced by students, on the other hand, range from possible losses to additional hazards. Term limits are increasingly hampering English learning's success. The error rate has been reduced with the application of the proposed methodology. This part spoke about the additional difficulties and their consequences. Mobile learning predicts that the outcomes will differ in the intelligent higher English education system. Due to the organization's restricted gaining architecture, the murdered representative return to the student level despite the substantial loss in resources, which significantly incentivizes the student to act in whatever manner imaginable. Figure 8(b) shows the error in English higher education. They conducted interviews with students before and after the experiment to see how well they recognized different tidbits of knowledge. It was found in the teaching of ideological and political courses by comparison at the same time. Make use of various intelligence sources to assess the function's importance and utility

English Learning Ratio (%)

Learning challenges like these have been significantly reduced due to using mobile teaching. Studies indicate that foreign language study is becoming more popular among students, shown in Figure 10. After one semester, the paper conducts a survey questionnaires on Teaching English based on utilizing a variety of the class's 61 students to successfully implement and comprehend the present condition of students' English learning. They created, disseminated, and gathered data from 61 different surveys. To summarize, here are some stats: According to the statistics, 24% of students often took the opportunity to speak before mobile teaching was implemented; this number rose to

Figure 9. Students' efficiency ratio (%) and Error rate (%)

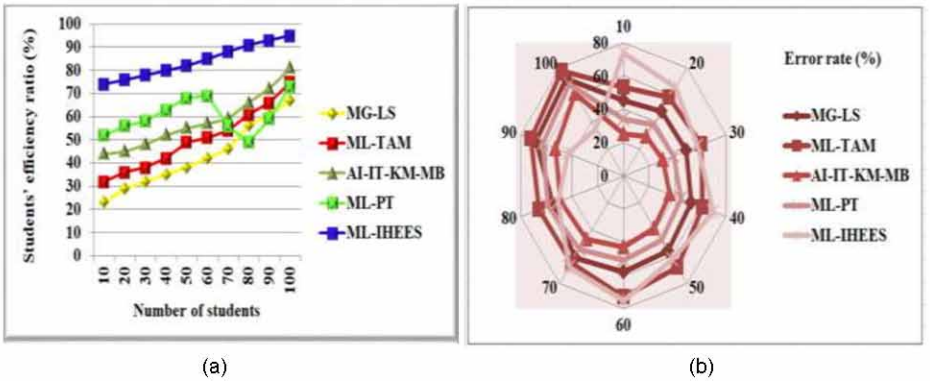
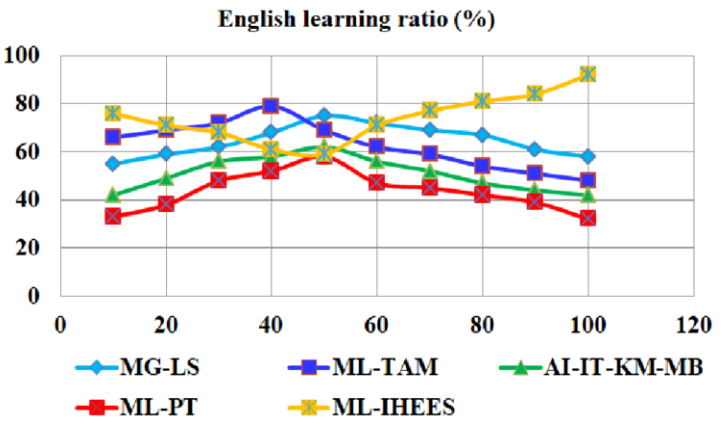


Figure 10. English learning ratio (%)

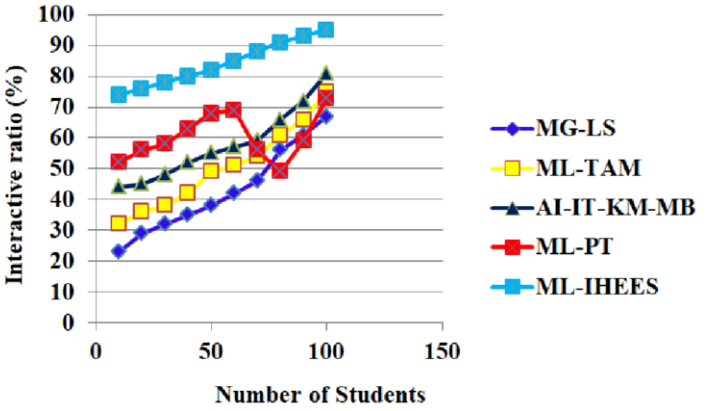


76% after a semester. As a result, it represents the fact that pupils seldom speak up in class and do when the instructor asks a question. When speaking in English, a fair 21% of pupils feel fearful. Twenty-six percent had pronunciation difficulties, while 19 percent had a restriction on the number of words they could use. Native English speakers are now more likely to be students who can talk and communicate well in the language. Alternative approaches are required to meet the demands of younger digital students to reach possible pedagogical results. According to the available studies, teachers who use mobile technology to educate suffer psychological distress, expanded educational responsibilities, and more cognitive adaptability in digital settings. Institutions should offer instructors in online learning long-term technical assistance to address these issues.

Interactive Ratio (%)

Figure 11 shows the student classroom interactive ratio. This research looked at the pedagogical issues that arise while teaching English as a second language online. This study's conclusions will be used to address the following three major topics: technological disagreements, digital era education, and an examination of student classroom interactive ratio. A mobile learning model with various delivery methods is developed, and the mobile platform is fully used. The English language serves as a vital

Figure 11. Interactive ratio(%)



means of communication. According to the present system, students' learning outcomes are not outstanding when taught English. As a result of the restrictions on teaching place and time, pupils' learning initiative is stifled. Suppose a school's academic affairs department wants to enhance the quality of English classroom instruction. In that case, it should use a varied mobile learning model that makes full use of various learning components and makes appropriate use of smartphone advantages. The study's working groups are primarily drawn from higher education institutions. Many projects are being done at the elementary and high school levels. Meanwhile, high school students have a limited range of options for academic pursuits. According to studies in higher education have been done, none have been conducted in elementary or secondary schools. Similar outcomes have been obtained in the past. All relevant topics not be covered by the keywords chosen in the study. Because of this, future research should utilize a more extensive set of keywords to find additional research on m-learning and its related features. Teachers and researchers benefit from the systematic review's findings by getting a clearer picture of current research trends in mobile learning's application to ML-IHEES teaching and learning.

Interpretation Prediction Ratio (%)

A significant consideration in higher education and machine learning is the ability to predict students' success. Predicting a student's future performance allows students to choose classes and plan their future studies. There are many attempts to enhance the chances of a student's academic achievement, and early prediction of their interpretation can be a useful tool for decision-makers. Research using data mining approaches to forecast academic achievement in students has been reported in several articles. A student's academic performance is defined as their academic achievements in various subjects. Beginners and experienced administrators commonly use classroom performance, academic achievement, and outcomes from standardized examinations to gauge student progress. Parents and teachers must keep an eye on their children's social and behavioral development in the early grades, as these skills are major determinants of students' academic achievement. Motivated students are more enthusiastic about participating in-class activities, and as soon as they feel a sense of purpose in completing the duties, they will put in their all. Figure 12 shows that this technique's interpretation prediction ratio is much greater than prior approaches based on Equation 11.

The study of learning flexibility is shown in table 3. A teacher-centered approach governs learning in formal contexts. For this reason, conventional schooling-style criteria for learning skills apply. In informal contexts, however, greater degrees of thinking are required for learning skills to process information autonomously. Essential consideration and customized learning are critical to the

Figure 12. Interpretation prediction analysis

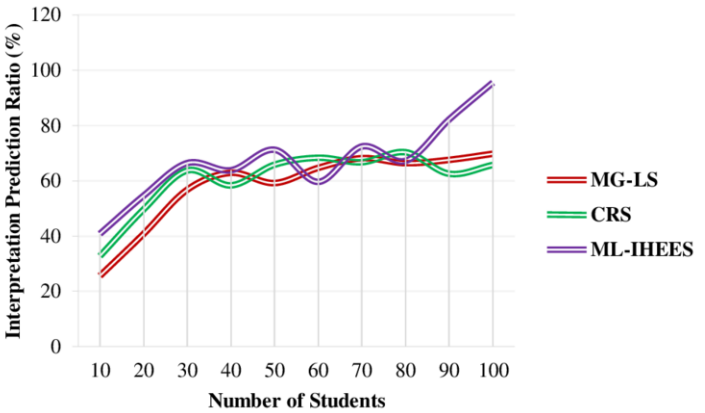


Table 3. Learning flexibility analysis ratio (%)

Number of Students	Learning flexibility analysis ratio (%)				
	MG-LS	ML-TAM	AI-IT-KM-MB	ML-PT	ML-IHEES
10	31.36	65.37	77.52	91.22	87.62
20	30.01	66.65	77.27	92.11	88.71
30	39.94	64.57	77.94	92.15	89.15
40	38.24	64.22	78.51	93.18	89.31
50	38.82	66.42	78.79	94.24	90.72
60	47.52	72.12	79.34	94.48	90.64
70	47.27	74.54	80.45	95.27	91.72
80	45.94	63.04	81.65	96.9	92.92
90	55.57	66.14	82.87	97.32	93.32
100	55.128	64.124	83.111	95.76	94.86

foundation of information scaffolding. Reactive and synchronous learning creates mobile pedagogy, allowing students to study when and where they choose. Digitalization enhances and changes students' learning styles. Because of the feeling of a learning community in virtual settings, learners perform activities relevant to autonomous learning in mobile learning environments. Students' conduct in the larger context helps to accomplish the learning objective. A more cognitive learning process is needed in digital education because of this. In terms of increased stages of cognition, our results support demonstrating the need to enhance higher thinking skills in digital settings.

To summarize, the proposed design suggests that digital education's ability to create, evaluate, and analyze improves. Innovative pedagogies examine the impact of digital education on students studying flexibility in digital settings. Various instructional environments and skills such as personality and rational reasoning are considered. Researchers found that mobile technologies improved both teaching and learning in various settings. An experimental examination on ML-IHEES and intelligent cognitive web services for machine learning and data analytics demonstrates that the proposed approach is highly competitive in predicting high accuracy compared to existing systems.

CONCLUSION

The mobile industry is still in its infancy, was the use of mobile devices. Instructional designers and teachers have significant difficulty in using this technology for learning. As information technology and network connections continue to grow at breakneck speed, there are many advantages to be had using powerful mobile learning technologies. Social communication and learning capacity will be more critical in mobile learning in the future. This research looked at the challenges of utilizing mobile technologies to teach English in higher education. Despite this, teachers are beginning to realize how machine learning technologies can simplify and accomplish duties with the help of cognitive web services. In both the classroom and non-classroom tasks, teachers' time has been greatly reduced due to developments in machine learning adoption in education. It sought to provide suggestions on making portable English language learning more successful. Qualitative interview findings touched on technology, methodology, curriculum, and student demographics. The difficulties in intersecting areas were determined based on how these problems were perceived. According to the results, mobile technology improves teaching and learning in various settings. Future educational outcomes need innovative approaches to satisfy the expectations of online students.

To test whether using a mobile app to support English teaching affects student English proficiency, researchers conducted an experiment in which they observed an increase in students' motivation to learn English while simultaneously increasing student English proficiency. Understanding mobile learning helps teachers refocus classroom activities and rewrites the guide to reflect mobile learning. The experimental shows that the following parameters are achieved with the proposed model. Student Performance ratio 92.11%, Students' efficiency ratio 89.9, Professional teaching ratio 95.23%, Error rate 43.86%, English learning ratio 93.32%, Interactive ratio 92.5% and Learning flexibility ratio 94.86%. It is concluded that a mobile app developed using the suggested method predicts all aspects of relative progress in a class's English ability. The results indicate that it is effective and accurate. The limitation of the study refers to the non-concentration of security and scalability. Future research may concentrate on the effectiveness of resources with the secured automated system teaching the benefits of Bigdata Analytics.

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