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Artificial Intelligence-Based English Vocabulary Test Research on Cognitive Web Services Platforms:
User Retrieval Behavior of English Mobile Learning

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ABSTRACT

Automated interaction between agents necessitates the ability of these agents to discover and select from a set of similar (or identical) services. As a result, trust is used to assess the quality of different cognitive web services. Therefore, this paper proposes artificial intelligence-based English vocabulary test research (AI-EVTR) to overcome the student's requirement. Further, pre-test behavior analysis has been introduced to enhance the apps. Before and after the test period, both groups took a pre-test behavior analysis and post-test log analysis "Vocabulary Test in English." The experimental group used an app-assisted English vocabulary questionnaire to share their points; they were not extremely motivated in the app-assisted approach using machine learning. Statistical approaches comprising independent samples were used to analyze the acquired data. The experimental group greatly improved between the pre-test and post-test in spelling. Language learning on the website can be an option.

KEYWORDS

App-Assisted, App-Memorize, Cognitive Web Services, Data Analytics, Educational Mobile, English Vocabulary, Machine Learning

OVERVIEW OF THE ARTIFICIAL INTELLIGENCE-BASED ENGLISH VOCABULARY TEST RESEARCH

The enhancement in modern society depends on computer technology, which plays an important role in every human area, guaranteeing that knowledge is disseminated worldwide. Telephones, smartphones, and tablets play an important role in digital human lives. Mobile devices are gaining new technical capabilities due to technology breakthroughs. In addition, the speed and reliability of the data transfer in wireless channels have increased (Amudha et al.2021). In addition, the field of linguistics is strongly affected by information technology. In the past, IT was not necessary to teach English; it is important to know it for linguistics and instructors now (Shakeel et al.2020).

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Furthermore, the factors of this study suggest that the artificial intelligence-based English Vocabulary Test Research curriculum may be able to help students of English based on cognitive web services more generally. A better understanding of second language acquisition and teaching processes can begin with this architectural design.

Students and language trainers confront various obstacles in teaching English (Pham et al.2020). These are technological as well as instructional concerns. In particular, it takes time for communication and grammar skills to be developed (Gao et al.2020). Additional electronic education technologies such as mobile applications will be used as one solution (Manogaran et al.2018). Technical aspects of mobile devices: speed, trustworthiness, modernism. Nearly everyone, including small children, has them. This is an excellent tool for Internet access; not everyone exploits this chance (Elgendy et al.2021). However, Smartphone and tablet classes are nowadays extremely widespread (Jan et al.2020). Many English teaching approaches are currently implemented using mobile and interactive technologies (Gunasekaran et al.2018).

In globalization and internationalization, English is becoming more and more vital. With smartphones and wireless networking tests, emerging education approaches can be built (Shakeel et al.2018). The proposed strategy promotes efficient learning while encouraging pupils to research hypotheses and establish their terminology (Ranjan et al.2020). Apps on mobile devices are predicted to lead to lifelong education. The application is short, which signifies a program fora certain task (Gao et al.2020).Learners can work at their own pace with AI-powered language learning platforms, repeating topics and emphasising things they're struggling with, trying to engage them with the tasks they're most proficient at, appealing to their preferences with machine learning, and taking into consideration such variables as cultural influences based on cognitive web services.

Application of mobile devices can download and utilize software devices for a free charge through the wireless network at the mobile app store. Mobile app shops feature proprietary software that provides fast accessibility to the app with a single touch, making it handier than website content and exploring and shopping via web browsers, such as shopping sites (Abdel-Basset et al.2019).

Language labs are used extensively. They offer a high content of information, imagery, the intensity of training, and activity stimulation. For example, the quick, easily accessible, entertaining approach to learning English is learning English with mobile devices (Abd EL-Latif et al.2020), and it is becoming more popular among many people. Such applications usually demand ongoing training. They expand your capacity to speak, read, listen, pronounce grammar, and speech culture in absolute English (Awuson-David et al.2021). In addition, language reproduction tools - electronic dictionaries, audio, and video course - are commonly employed. Applications were first conceived for audio listening, whole language education lessons began, and online chat applications are now widespread, allowing users to communicate (Chi et al.2015). Now, thousands of programs are available to mobile users. Users are interested in that (Hussain et al.2019). Some of the other limitations of AI include implementation times, which can vary widely depending on the project. A lack of knowledge of current systems and integration issues with cognitive web services compatibility with other platforms and systems based on machine learning.

Unlike "paper dictionary," multimedia and hyper textuality is major advantages of mobile applications (Kandlhofer M et al.2016). For instance, mobile software connections might immediately increase learning English. Today's language learning, especially English, is incredibly vital (Lété et al.2004).

The concept of "mobile learning" has become more popular because of laptops' advent and quick advancement. The development of IT and telecommunications in mobile technology provides students with the potential of learning and teaching "anywhere" in the educational process (Littlewort et al.2011). This translates into a more constant, intensive, and technological learning process (Loonen et al.2007). Therefore, the authors designed an application for artificial intelligence and voice recognition in English conversation practice (Black et al.2008).

Currently, artificial intelligence will be used to examine customer behaviors in important to gain knowledge further into customers(McCormick et al.2012). AI may be used in mobile apps to discover what customers have and operate their applications. Mobile artists may utilize this data to make changes to increase user interaction (Cavus et al.2011).

As a result of these considerations, this paper proposes using Artificial Intelligence-based English Vocabulary Test Research (AI-EVTR). Pre-test behaviour analysis has been added to the app to improve its remembering ability. Both groups completed a "Vocabulary Test in English" pre- and post-test behaviour analysis and logged analysis before and after the test period using machine learning. When it came time to present their findings, the test subjects relied on an app-assisted English vocabulary questionnaire.

The Main Contribution of the Paper is

- Designing the AI-EVTR for enhancing the app memorize technique based on machine learning.
- Evaluating student performance based on both groups before and after the test took a pre-test behavior analysis and post-test log data analytics.
- Web-based English learning programs have been linked with artificial intelligence to educate pupils to become active speakers.

The other sections of the research are organized as follows: sections 1 and 2 covered the introduction and traditional models of English learning applications based on machine learning and cognitive web services. AI-EVTR is suggested in section 3. The numerical findings were performed in section 4. Finally, part 5 brings the study paper to a close.

Related Research

Mobile learning may start anytime, anyplace, engage and share in real-time, and cooperate. These innovative and interesting forms of learning make learning entertaining and have huge opportunities; many challenges have to be mastered while enjoying comfort. Teachers need to know the negative technological implications of security, networking, battery, and system software compatibility. This is the problem of researchers encountered in performing studies such as wireless network fluency, the basic label of the online software community, and children's inadequate language. And even in a mobile environment, certain children are less attentive and less technologically proficient, something teachers need to be careful about.

App Research Assisted English Language Teaching

This study suggests using PACARD (Personalized Adaptive CARD-based interface) to improve mobile learning engagement by combining many technologies such as card-based functionality, personalized adaptations, push alerts, and symbols (Cavus et al.2007).They released a learning application through named internet shoppers recruited to participate in the research. PACARD is simple to install and adapt to most of the market: smartphones and digital learning apps. It does, in fact, help educators, mobile app developers, and learners.

Today, digital literacy is very well practised due to its numerous benefits, such as accessing learning content at any time and from any location, tailoring content to student's requirements, and providing rapid feedback (Fok et al.2008).This pilot project demonstrates that using a personalized smartphone app to support foreign language learning improves students' performance (SFLL-ISP) by including smartphone app learning in a continuous evaluation. More research should bring the mobile app to the Apple platform and iOS.

Rain Classroom, a popular mobile website created by Asia's most prestigious institution, is a product of the mobile scientific breakthrough. Few research, however, has developed its adoption model by incorporating the concepts of peer and exceptional influences (Lin et al.2010).The primary focus of this study is the impact of parallel and senior influences on learners' use of Rain Classroom within the framework of the technology acceptance model (TAM).Aside from peer and dominant influences, future research could expand the TAM by including more constructs to give crucial references for Rain Classroom scholars and practitioners.

This article summarises the results of this study that attempted to investigate how to integrate active technology into a Knowledge Management System (LMS) at a Hong Kong college or university. This experiment employed a mobile-enabled learning management system (ME-LMS) to improve students' positively associated academic performance (Lee et al.2012; Chiang et al.2013). The participants who participated were categorized into two parts, one of which was encouraged by the professor to use wireless access the other was discouraged. According to linear regression model studies, permissive variables and achievement expectations were the significant predictors of unprompted and prompted mobile access.

An active study area is providing financial services within a digital structure for sharing resources across traditional borders. Such services often encode the use of storage and compute resources ranging from individual machines to algorithmic clusters conduct an empirical study of data analytics Web Services (Ali et al.2005).

The purpose of this research is to investigate the data demands and knowledge activities on the Intertubes of college-level live music students on mobile platforms. Survey tools were utilized to collect information from visual arts students at the Hong Kong Institute of Theater Program (HKAPA), a major musical theatre educational organization in the metropolitan area (Lee et al.2015).

The examples in the preceding paragraphs show a typical educational app for learning English. The AI-EVTR model has been proposed in this paper based on machine learning to address these issues. In the following section, the proposed system is implemented and compared to the conventional approaches of PACARD, SFLL-ISP, TAM, ME-LMS, and HKAPA. The following section provides a brief overview of the data analytics in our proposed system.

Proposed Artificial Intelligence-Based English Vocabulary Test Research

The capacity for a motivated professional in the current culture is regarded as the norm for communicating in English. If a person speaks English fluently in all aspects, his possibilities for the labor market could be considerably expanded. Several problems support this: The first obstacle is that the time spent acquiring a foreign language is restricted. The second concern is that students of different levels have a different University profile. Third, the lack of student enthusiasm because of a language outside the school is not a priority. AI solutions are continuously attempting to aid marketers in providing an intuitive experience to their users. AI apps are faster and more responsive, allowing users and workers to stay in touch. Artificial Intelligence (AI) has become an inseparable element of all mobile apps, and marketers have embraced it.

According to a study on features of this type of eLearning, many mobile learning features have been described. Mobile learning is connected by interactivity to three aspects:

a) Cognitive learning environments: Even remote learners of languages located in the exact location or points may communicate with the linguistics teacher's online and offline environments.
b) Language students: They are not exclusive to inactive vocabulary learning in the classroom, waiting for the university lecturer to provide the relevant information or facts. They are instead independent and develop their data.
    (c) Skilled: All components relate to using state-of-the-art technology, apps, and tools that enable English learners to interact.

It can be seen that the ownership of mobile devices is growing around the world, and many talks and studies have taken place concerning the benefits of using mobile devices in language learning.

Today's technology has had a tremendous impact on education technology because mobile learning is attracting the attention of many university educators worldwide. Mobile-Assisted Language

Learning (MALL) is the name of this approach to learning a foreign language by data analytics. The teaching world sees its accessibility and universality as a promising tool for teaching linguistics using machine learning.

Over a short amount of time, the appeal of distant learning has proved that different intelligent devices have efficient methods of receiving or assimilating data. Every scientist, therefore, suggested educational devices. Mobile learning uses mobiles for portable mobile devices, such as phones, PDA devices, smartphones, tablets, etc. Specifically, when there have been specific advantages to a portable device, such as device mobility, Internet connectivity, for a short time, instant feedback, etc., some classify this style of training as a language learning mobile technology.

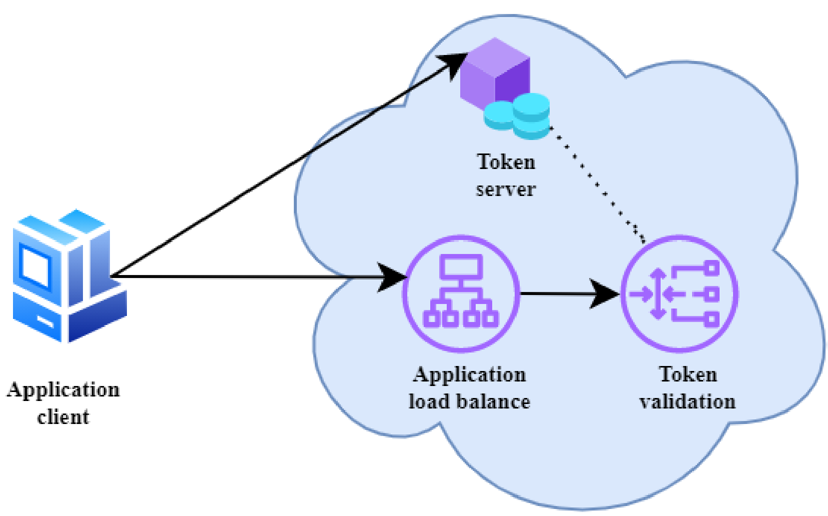
Web-Based Integration Of Artificial Intelligence

Integrating Artificial Intelligence with this application seeks to obtain answers corresponding to the user's audio input and make the discussion more natural. This method may be done by knowing particular codes of the Dialog flow called the Client Access token and a session ID for identifying the dialogue after the artificial intelligence integration. Concepts for mobile apps based on artificial intelligence. Artificial intelligence may be used in the mobile app development industry. App for Android, Make the search procedure more efficient, learn how to put Artificial Intelligence into practice, Create a digital assistant that is both pleasant and clever. The developer creates a customized chatbot for the website. Make use of a chatbot powered by artificial intelligence. These pre-programmed chatbots may be integrated into almost any platform, and many solutions allow customizing the bot.

Figure 1 depicts a service-to-service process on a client access token. It consists of the following steps: Initially token-server pool token endpoint, the application client requests an access token. Then contacting the token validation via the application load balancer, the access token is delivered to the endpoint in the bearer token authorization header. IP Classless Inter-Domain Routing (CIDR) range filtering is enabled on the ALB. The microservice deployed to token validation verifies the access token and enforces the authorization claims using JSON Web Key Sets (JWKS). The technical connections for cognitive web services required in AI-based English vocabulary are,

- Algorithm.
- Chatbots Assemble in a Group

Figure 1. Client Access Token



- The field of cognition
- The process of learning by a computer.
- Extensive training
- The ability to recognise images is known as image processing.
- Computer-Aided Language Understanding (NLP).

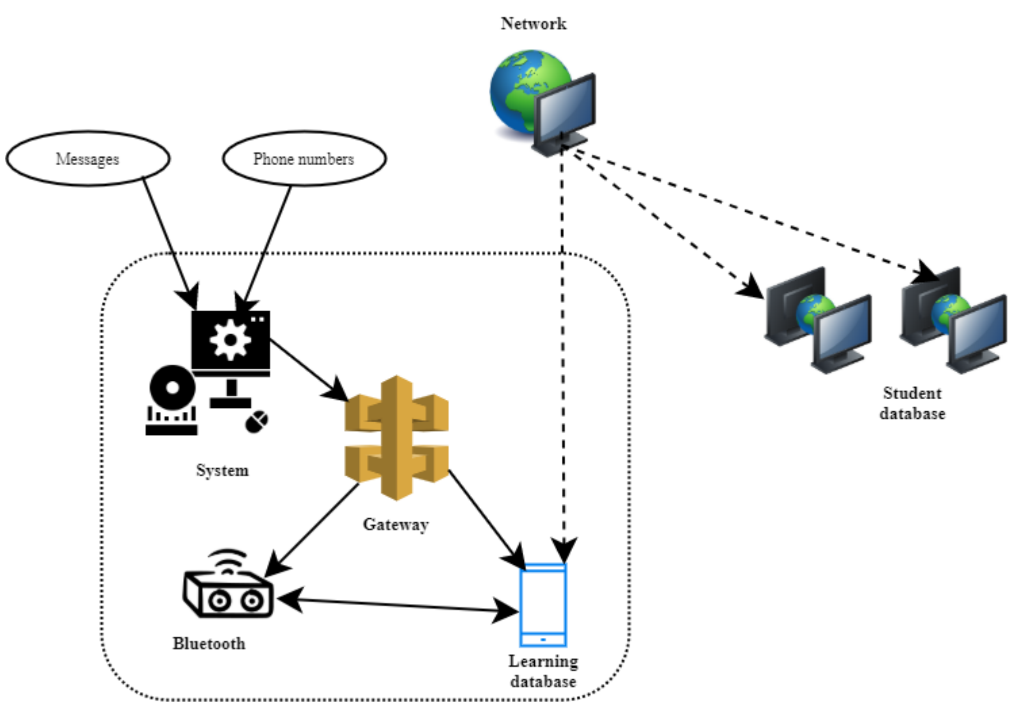
The Client Access Token is a client-specific code that can be accessed and used by those who have it. The previous client access token can be regenerated to no longer access bot programs. Developers can restart the chat, delete the bot, and modify the destination using the Developer Access Token, a specific code for developers.

Test Research Significance

Generally speaking, from the definitions above, various applications on mobile devices contribute to an interactive learning environment in many scenarios. Mobile language education is currently evolving very quickly on this subject is increasing. Several other advantages of MALL training should be considered: Multimedia access: it is a great learning tool to record and play the learner's speech and contrast it with English teachers' voices. Furthermore, it is another advantage when learning a language, capturing and allowing them to search and get details about any subject, and satisfy the students' knowledge requirement within a time.

Social networks: The usage of social networks can efficiently share information, ideas, and thoughts on several subjects. The students can build language skills together through social networks and participate in projects. Instant feedback: Mobile apps provide their consumers with instant responses. Mobile applications offer rapid feedback on work, whether your task has been done by clarifying the error committed and giving the proper alternative response or a recommendation for your work.

Figure 2. Test Research Process



Several studies have indicated that MALL decreases the anxiety of students. In contrast to learners using PCs in an audio lab, mobile devices showed decreased discomfort and excitement in speaking activities, as shown in figure 2. Researchers studied that students have a good culture for using database learning in linguistics acquisition for studying. Although there are numerous advantages of adopting MALL as another learning method using messages and phone numbers, this method has limitations in using MALL as a foreign language teaching method using Bluetooth connections.

The tracking of performance is another problem. Difficulties in monitoring the operation of mobile devices allow pupils to avoid finishing jobs. One of the disadvantages of MALL is that it has a significant variety of mobile applications, which generally target student databases with less than average language abilities. Manuals, interpreters, and mnemonics are applications that help develop the ability to resume, compare, paste and analyze. When learning through mobile devices, large written tasks are inappropriate. There is much research and development on mobile applications to create different language and language abilities. Software for mobiles such as smartphones and Tablet Computers has been built for a mobile application.

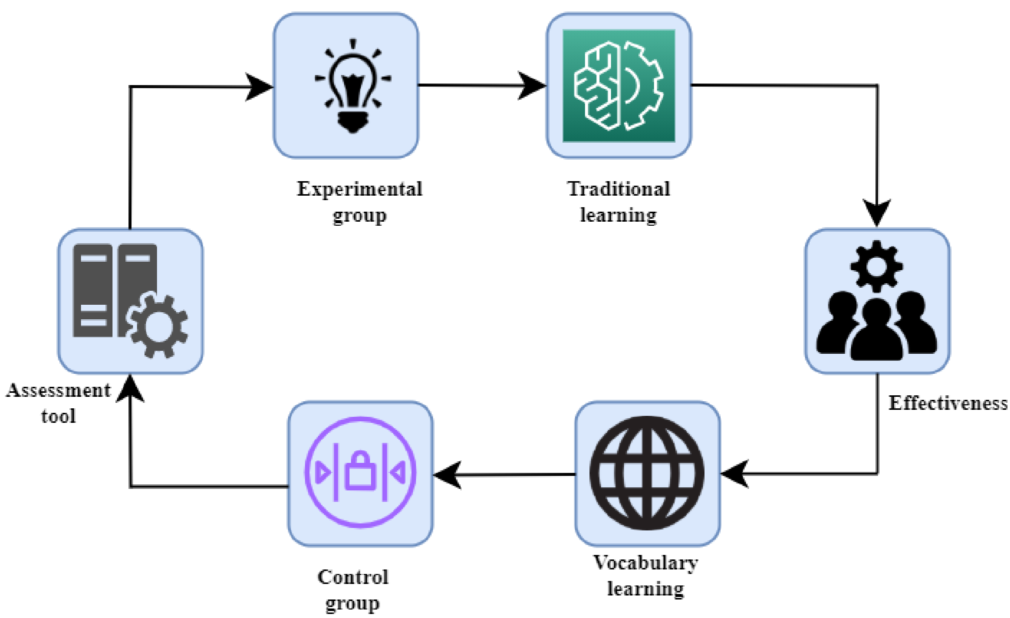
Proposed App Technology

This study examined how effective vocabulary-assisted learning in junior high school pupils was based on a quasi-experimental strategy. The influencing regions of mobile language acquisition are separated into key groups that contribute to lexical and grammatical abilities and different speech activities.

Figure 3 illustrates the random and control groups that allocated the class. The two groups have the same instructors, educational materials, and teaching methodologies. The English vocabulary was tested before the experiment by both groups, and teachers subsequently taught the instructional program in English. 15-20 minutes of App experimental group helped to learn English, the control group learned traditionally. This was 12 weeks of experimentation.

Memory, vocabulary for English performance tests, and an APP-assisted vocabulary questionnaire are all part of the study. Listed here are the options: Memorize, a desktop or mobile phone app, was

Figure 3. Block diagram of research design



used in this study. Users can access and download the website for themselves, the general public, or a specific group of individuals in data analytics.

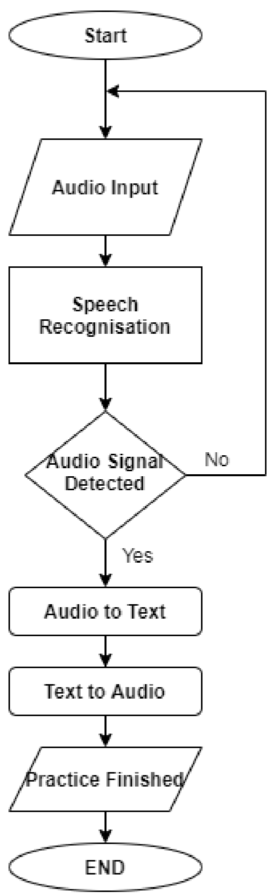
The primary reasons why Memorize is chosen as a tool for research are:

(1) User's textbooks can be made of several learning apps and are arranged or classified according to their vocabulary, for example, 1,000 words or 2000 words. These are not ideal for learners or primary-school junior pupils, where learners advance academically. If such apps are used, the student burden will increase.
(2) Memorize provides different modalities of words, grammar, attention, and revision, among other things, should be practiced. According to the researchers, this can assist students in remembering vocabulary.
(3) Free of charge is most of the functions.

Pupils can learn their accomplishments in real-time to remain competitive psychologists and to inspire students to learn. (4) Mode of ranking: users learning the same resume can view the cumulative scores and rankings. Teachers can use the figures to make awards and understand student use specifics.

Figure 4 shows the application's workflow system begins recording and receiving audio input. During Speech Recognition, the incoming audio will be recognized. When the microphone detects

Figure 4. System design for Learning-App Application



no sound, the sound recording process will pause for a few seconds. Cognitive web services at all levels must be able to use sound information from an assessment system to support learning for all students. Students and teachers can use learning to identify where each student is in mastering learning objectives. Teachers can use differentiation of instruction and specific, actionable feedback to meet data analytics needs. A textbox will receive the user's recorded speech and show it. If the sound is not recognized when the user presses the record button, information will show. The user's voice answer will then be sent to Dialog flow to get the proper response. If it's found, it'll be presented as text and processed by Dialog flow to provide an AI answer. The answer will be g.

The mode of use and the APP features are as follows:

For Teachers

Teachers automatically edit the learning content of this App. Teachers can use the official Memorize website to upload their instructional content. They can upload images and sounds and load the meanings in English and China, causing a range of alterations in keeping with the educational needs of the teacher and the editing process. It is available to students after the upload and application of modules.

For Learners

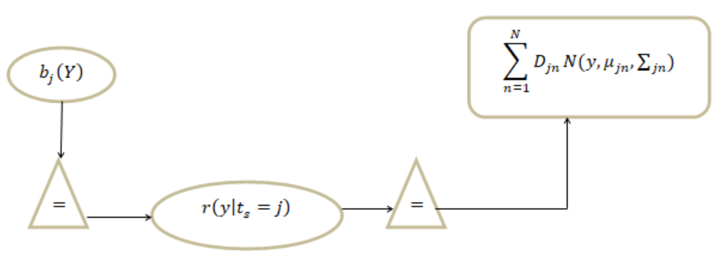
Through repeated answers, kids can memorize their words step by step. If the student does not reply, the app will repeat the same vocabulary until the proper answer is received. This app specifies which words to review and what words pupils can start to forget when the learner learns a certain degree of words. Every day there are usually two review modes. They learn on their own through the app concerning their unique learning circumstances, progress, and time. The fast review mode makes several options in a limited period, whereas the standard review is defined. Incorporate Artificial Intelligence into the development of mobile apps. Mobile app concepts for artificial learning, Improve the search procedure, Take, for example, video or audio recognition, Investigate patterns of behaviour, Learn how to put Artificial Intelligence into practice, Create a digital assistant that is both pleasant and clever.

States are hidden in an AI-EVTR Model and maybe deduced through a sequence of observations in figure 5.

$$b_{ji} = r\left(t_{s+1} = i \middle| t_s = j\right) \tag{1}$$

The change of possibility state has been determined, as indicated in equation (1). While the problem and data collection are generally initiated by a rational number r and subsequently learned using different mathematical analysis approaches, which are addressed later, this is not understood since the conditions are hidden b_{ji}. When the integral values are used as the starting point for the problem and data collection, it is not understood because the conditions under which the problem and data are learned are hidden based on machine learning and cognitive web services. The potential

Figure 5. States of AI-EVTR Model



of state change t_{s+1} and t_s is represented by i, j. It affects the probability of moving from state j to state i as shown in equation (1):

As seen in equation (2), the distribution of observations by the state is as follows:

$$b_j(l) = r(q_s = l | t_s = j) \tag{2}$$

It is difficult to understand the problem and data collection if the integral values are used as the starting point because the conditions under which the problem and data are learned are hidden by machine learning and cognitive web services. The distribution of observations $b_j(l)$ has been mentioned, as specified in equation (2), represents the initial state distribution q_s specified in equation (3) below:

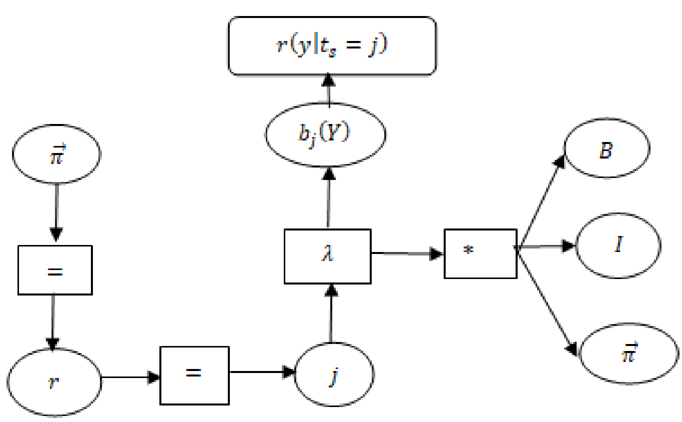
$$\vec{\pi} = r(t_1 = j) \tag{3}$$

As inferred in equation (3), the initial state distribution π has been described. The following are generally referred to as λ explore HMM parameters together in equation (4):

$$\lambda = (B, I, \vec{\pi}) \tag{4}$$

It decided to use HMM, and parameters were expressed in equation (4). Discrete data and the equations from above can fully describe any HMM based on cognitive web services. A combination of forwarding and reversing algorithms is used to estimate the probability of seeing a specific sequence in the future with machine learning. As a result of the lack of time-series labels, the data cannot be linked to states. To approximate HMM parameters I, the Baum-Welch or Expectation-Maximization (EM) technique can be employed. The emission probability distribution should be modified to reflect this transition if continuous measurements (CHMMs) are not discrete.The functions of the probability density $b_j(Y)$ are updated based on the outcomes of continuous observations $(y, \mu_j, \sum_j)$. The data is generally modeled using a Gaussian distribution combination A.

Figure 6. Path diagram HMM



Equation (2) is changed to the following equation (5) if one Gaussian distribution can be used to represent observations for each state:

$$b_j\left(Y\right) = r\left(y \middle| t_s = j\right) = A\left(y, \mu_j, \Sigma_j\right) \tag{5}$$

As defined in equation (5), the Gaussian distribution has been changed. $n = 1toN$ oscillation is the covariance D_{jn} and mean matrices of the Gaussian state j, respectively. If no single distribution can explain the data, observations can be represented using a mixture of Gaussian distributions $\left(y, \mu_{jn}, \Sigma_{jn}\right)$. In this scenario, equation 6 may be used to moderate each state's observations in equation (6):

$$b_j\left(Y\right) = r\left(y \middle| t_s = j\right) = \sum_{n=1}^{N} D_{jn}\left(y, \mu_{jn}, \Sigma_{jn}\right) \tag{6}$$

In equation (6), each state observation has been removed. The mixing coefficient, D jn, determines the weight of each component in the model data. For each mixed variable, jn are the medium and covariance matrix corresponding to the state j. In the equation, there are no state observations (6). The mixing coefficient in cognitive web services determines the weight of each component in the model data. State-specific matrices for each mixed variable are available.

The Viterbi algorithm will decode the optimum state series to give the observations. It takes into account the state sequence that best explains the data in equation (7):

$$T^* = argmax_t R\left(T \middle| q, \lambda\right) \tag{7}$$

As shown in equation (7), the observed data has been computed. The problem of the formula and the HMM prediction method T^* are discussed in this part. The initial forecast is that the students are divided into two groups based on their SP physical education ranking: level 1 students have poor physical education scores $argmax_t$ While level 2 students have high physical education scores R, level 2 pupils get excellent marks on the questions. For each class, the HMM is utilised, and the model's selection methods determine the best restrictions $\left(T \middle| q, \lambda\right)$. Using the Viterbi method, test or decode the observation sequences. There are no state observations in equation (6). The weight of each component in the model data is determined by the mixing coefficient in cognitive web services. The state-specific medium and covariance matrices are available for each mixed variable. The equation represents the result of computing the observed data in equation (7). This section focuses on the issue of formulas and the HMM prediction method. Preliminary estimates suggest grouping students into two subgroups according to their SP physical education scores in data analytics.

The Bayesian Knowledge Criterion (BIC) and Akaike Information Criterion (AIC) models are classification algorithms that employ penalty clauses to prevent overfitting. In equation (8), the following formula will be used to define AIC:

$$AIC = -2InK + 2L \tag{8}$$

The following is how the HMM problem is solved. The Akaike Information Criterion *AIC* has been computed, as indicated in equation (8). AIC and the number of comments M are the same values $InK$and L. In comparison, with equations (8) and (9), BIC appears to have a larger penalizing notion (9). Instead of penalising the AIC, it penalises the hierarchical model. The goal of hidden states, categorised as master's levels of pupils, is to forecast the achievement of their final degree across many levels of physical education. Predicting the (t 1,t 2,...t m) in equation (9) yields the ultimate mastery degree T, which includes all previous mastership levels:Since the last few decades, technological advancements have profoundly impacted nearly every aspect of human life. Until recently, the connection between education and wealth is monetary. Things have changed over time, and the education system worldwide has evolved; as a result, web-based cognitive services. How education is delivered has undergone a radical change. With the introduction of mobile educational apps, this education system has been transformed using machine learning. An entirely new way of learning has been incorporated into it.

Making a decision is a machine learning process that involves deciding between possible mutually exclusive actions from above algorithm 1. To put it another way, there is an option to consider among the possible ones by cognitive web services. It is possible that each of these choices could have one or more uncontrollable consequences that are mutually exclusive.All possible outcomes and their values (positive or negative), as well as the probability of each outcome occurring, should be analysed to arrive at an expected value.

$$BIC = -2InK + LInA \tag{9}$$

The Bayesian Information Criterion BIC has been calculated, as shown in equation 9. The following approaches can be utilized to carry out the forecast InK . 1) Naive: this is the simplest technique L , where the forecast value equals the last time series InA seen in equation (10):

$$\hat{T} = t_m \tag{10}$$

Average of a line $\hat{T}$ indicates that the ultimate anticipated value in equation (11) is the average of all other mastery levels t_m :

Table 1. Making a decision is a machine learning process

Algorithm 1
Aug data $\left(D, x, y\right)$
$Ds_{x+1} = Ds_x$
$ML = option\left(1, x\right)$
$Ds_{x+1} = optionshift\left(k, D\right)$
$ML = option\left(1, y\right)$
$Ds_{x+1} = append\left(R - values\left(ML, Ds_{x+1}\right)\right)$

$$\hat{T} = \frac{\sum_{j=1}^{j=m} T_j}{m} \tag{11}$$

The average mean value m was predicted, as shown in equation (11). The application designer can manually add objects to a design using advanced modelling. An app's advanced modelling allows the developer to include web service features not otherwise available. Acknowledging the implementation views, measurements and approval hierarchy can benefit from machine learning.The average time $j = 1tom$ window is an extension of this method that guarantees T_j that the current values r are taken into account in equation (12):

$$\hat{T} = \frac{\sum_{j=m-r+1}^{j=m} T_j}{r} \tag{12}$$

As shown in equation (12), the average time has been calculated. Another application of this method is exponential smoothing. The goal is to get a linear average by choosing larger weights $j = m$ for the most recent data with lower error rates $j = m - r + 1$ and less weight T_j for remote values. This is explained in equation (13) by the following theorem:

$$\hat{T} = \beta t_m + \beta\left(1 - \beta\right) t_{m-1} + \beta\left(1 - \beta\right)^2 t_{m-2} + \ldots \beta$$

$$\hat{T}_m = \beta t_m + \left(1 - \beta\right) t_{m-1} \tag{13}$$

The linear average value βt_m has been explained as indicated in equation (13). As a result, the last degree of dominance β is the most visible in the series. Equation (14) shows how this may be observed mathematically:

$$\hat{T} = \underset{i}{argmax} \sum_{j=1}^{j=m} 1\left(T_j = i\right) \tag{14}$$

The ultimate degree $\underset{i}{argmax}$ of superiority has been calculated using equation (14) as a guide. Equation (13) is regarded as a smoothing constant, and (14). It's a parameter that's determined depending on how crucial past values $j = 1$ compare to present levels $j = m$ in a given time frame $\left(T_j = i\right)$.

$$b_{ji} = r^{*} r\left(y \middle| t_s = j\right) + A\left(y, \mu_j, \Sigma_j\right) \tag{15}$$

$$t_m = \beta t_m {}^{*} \sum_{n=1}^{N} D_{jn} N(y, \mu_{jn}, \Sigma_{jn} \tag{16}$$

The application designer can manually add objects to a design using advanced modelling. Web service features that would not otherwise be possible can now be included in an app because of its advanced modelling capabilities in equations 15 and 16. Machine learning can help by recognising the implementation views, measurements, and approval hierarchy.

Compared to other current techniques, the suggested HMMCS model improves overall performance, prediction, probability, and student score analysis while lowering the error rate applications based on machine learning and cognitive web services.

Results Discussion

Language students can always access the stored information, even in the language course. If the data is kept on mobile, the learning process is crucial and adaptable because most Internet connectivity problems may be avoided. Table 2 to Table 3 and Figure 6 demonstrate a comparison between conventional learning and English vocabulary tests in experimental and control groups and the outcomes of the English vocabulary test.

From the above table 1, this attribute is based on the pre-test and post-test based on the main aspect, which resulted in mobile learning being widely used and developed by all language learning groups since people with diverse budgets and economic status can provide mobile devices with the average values. Mobile learning cannot be seen as a language choice for learning such as English without mobile technology-based t-value and p-value.

Here in table 2, mobile learning is usually linked to this attribute, same as table 1 with t-value and p-value. Rapid replies are needed for particular questions like definitions, formulas, or equations. This means such files monitor all the information supplied through devices.

Figure 6 depicts the comparison analysis ratio between the proposed and existing applications. This paper addresses the formulation of problems and the AI-EVTR technique. Comparison analysis starts by grouping the Traditional Learning English APP (TLEA), English Vocabulary Test Research (EVTR), and ME-EMS, according to their results in performance. TLEA is the lowest in performance,

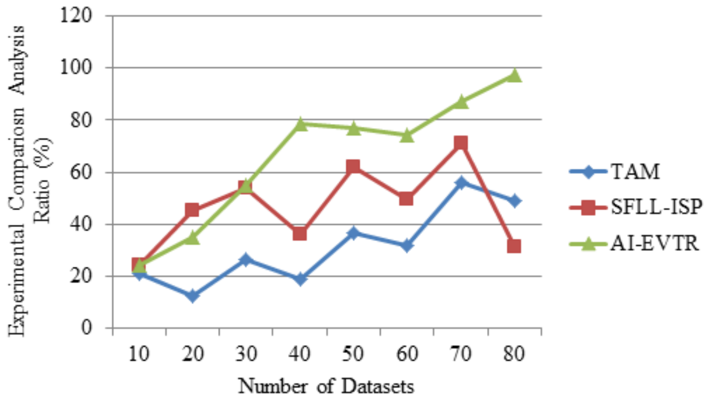
Table 2. Independent-samples Test

Group	Metrics	t –Value	p-Value	Average results
Pre test Experimental group	31	-.455	-.633	59.93
Pre-test Control group	27			64.08
Post test Experimental group	31	-236	.797	73.10
Post-test Control group	27			71.23

Table 3. The written scores and post-written scores of experimental group comparison

Test	t – Value	p-Value	Average Value
Pre test group	-3.901	.001	59.93
Post-test group			73.10
Pre test group	-1.611	.119	64.08
Post-test group			71.23

Figure 7. Experimental comparison analysis



AI-EVTR is the highest. Each performance class will be separately identified, and model selection parameters will be selected. Results suggest that the AI-EVTR can be measured dynamically by evaluating time-series statistics post-test. This can be good for a fast process and efficient feedback technique. Model selection parameters will be selected for each performance class that has been identified separately and is expected to perform well in machine learning. Analyzing time-series statistics after the test yielded results that suggest the AI-EVTR can be evaluated dynamically. This can be useful for quick and efficient feedback using cognitive processes.

Figure 7 illustrates the overall Performance between pre-test and post-test applications. The AI-EVTR shows the highest performance in terms of data accessing post-test. In this graph, post-test performance is highest then. Results indicate that the post-test can be measured dynamically. The AI-EVTR has the best post-test data access performance. Post-test performance peaks at the top of this graph based on machine learning. Using these findings, we can conclude that cognitive web services can dynamically measure the post-test.

Figure 8 depicts the score analysis ratio between the AI-EVTR and TAM, SFLL-ISP existing applications. This AI-EVTR technique analysis starts by grouping the Traditional Learning English APP (TLEA) English Vocabulary Test Research (EVTR) according to their results in performance. TLEA is the least in performance, EVTR is moderate, and AI-EVTR is the highest. Each performance class will be separately identified, and model selection parameters will be selected. Results suggest that the AI-EVTR can be measured dynamically by evaluating time-series statistics post-test. When

Figure 8. Test research performance comparison

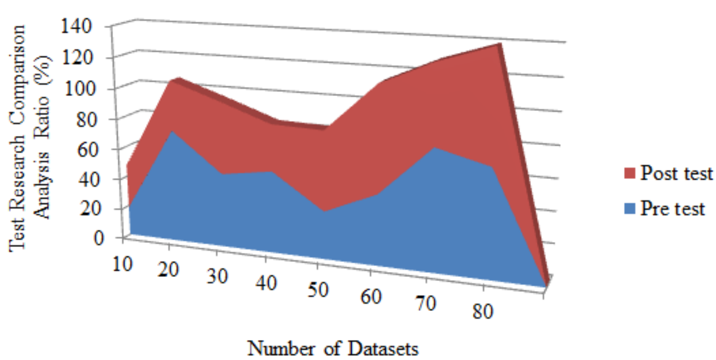


Figure 9. Score Analysis Comparison between other applications

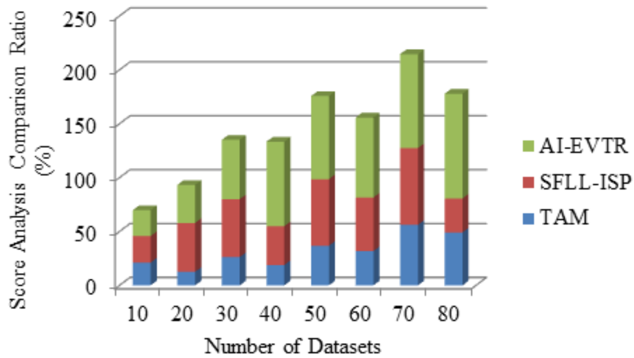
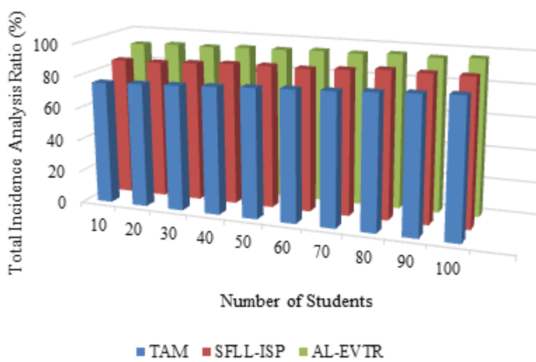


Figure 10. Total incidence of the input



it comes to performance, TLEA is at the bottom of the heap, followed by EVTR and then AI-EVTR. Model selection parameters based on machine learning are selected for each performance class that is identified. This study's findings suggest that the AI-EVTR may be dynamically assessed by examining post-test time-series statistics in data analytics.

Unstructured data can be structured using cognitive analytics, which uses various analytical techniques to analyse large datasets compared in the above figure 10. Cognitive analytics mimics the way humans think to gain insight from data and uncover patterns that might otherwise go unnoticed. Data sources like audio, video, text and images can now be accessed by Analytics processes, which can be used for machine learning and data analytics.

This AI-EVTR technique analysis starts by grouping the Traditional Learning English APP (TLEA) English Vocabulary Test Research (EVTR) according to their overall performance mentioned above results. TLEA is the last one in overall performance, EVTR is moderate, and AI-EVTR has the highest overall performance. Each performance class will be separately identified, and model selection parameters will be selected applications based on machine learning and cognitive web services. Results suggest that the AI-EVTR can be measured dynamically by evaluating time-series statistics post-test.

CONCLUSION

To sum up, the preceding, unique mobile language apps can speed up and enhance the English learning process with our proposed system AI-EVTR. Language characteristics that last, interpersonal abilities grammatical norms are helped. The use by students of various mobile applications in the study of English, both grammatical and non-linguistic, can greatly increase the topic's ability. People who have never done business with each other are often involved in online service transactions. The web service consumer is often unaware of the provider and the products and services in machine learning. On a mobile, the teacher can follow the pupils more easily, at the teacher's convenience. It is evident that technology has come into its way into our education and is here to stay. What remains is the best approach to manage the multitude of benefits and downsides and to find the finest options for your kids and their needs. It has been discovered that learning through mobile has no fixed theory has been formed; nonetheless, this technology is progressing toward the next generation. And all of this portable technology will be harmed as education is the cornerstone of all branches of science that has made our globe a better place to live. The future study shows how the trust factors that create the final trustworthiness for each service depend on applying the framework and machine learning approach. In addition, mobile methods and technology will soon replace all traditional methods and will no longer leave any trace of the old previous techniques in the education field. Using a mathematical tool as an extra benefit has a convergence speed, improved learning efficiency of 97.24%, and somewhat higher performance than TAM. Future improvements to the EVTR performance will be based on mobile education applications.

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