# Impact of Read Theory in Mobile-Assisted Language Learning on Engineering Freshmen's Reading Comprehension Using BI-LSTM

E. Pearlin[1], Dr. S. Mercy Gnana Gandhi[2]
Research Scholar, Department of English, Sathyabama Institute of Science and Technology, Tamil Nadu, India[1]
Professor, Department of English, Sathyabama Institute of Science and Technology, Tamil Nadu, India[2]

***Abstract*—The effect of Read Theory in Mobile-Assisted Language Learning (MALL) on reading comprehension is critical, especially for engineering freshmen who require excellent language abilities to navigate their complicated academic courses. Read Theory is a customized reading platform that offers adaptive reading activities based on the user's ability level, which is especially useful in MALL settings where accessibility and flexibility are essential. However, traditional methods of MALL have frequently faced with constraints, such as the inability to completely adapt to students' different and dynamic learning demands. This deficiency usually results in poor improvement in reading skills because the conventional paradigms do not capture the intricate and diverse learning processes that are necessary for the effective learning of languages. To fix these issues, a Deep Learning approach that involves the implementation of BI-LSTM networks for enhancing the completion's reading outcomes is offered. BI-LSTM is more suitable for this task because it has forward and backward reading capabilities to better understand and predict the dynamics of language acquisition. The research established improvement and an astonishing accuracy of 99.3%. The implementation was done using Python. This high value of accuracy disproves the common weakness of the strategy and provides convincing evidence that the proposed approach can significantly enhance MALL projects' outcomes. The specified technique, which improves on the flaws of previous approaches, does not only improve the process of reading but has the potential to revolutionize language acquisition for engineering students, making it more effective and conforming to ability.**

***Keywords*—Read theory; language learning; Bi-LSTM; mobile-assisted; deep learning***

## I. Introduction

Reading skills in a person's native language usually develop during early childhood. Acquiring reading skills in a second language can be tough and demands an alternative approach to thinking. This is why reading in English as a Foreign Language (EFL) is still being studied. In most contexts, reading and listening are understood as processes for taking in information while speaking and writing are recognized as methods for expressing information. However, newer studies have looked at how reading links to other skills, especially how it relates to writing [1]. Reading is important in people's lives because it helps them learn and stay informed about all the information around them. It becomes a regular part of the free time, school tasks, or job responsibilities. Students in universities need to pay close attention to this because they will be required to read a lot of material for their coursework. Print or digital are the two alternatives available to them. The primary goal of authors is to pique readers' interest and aid in the retention of the content. Typically, the text is enhanced and remembered by adding images or movies. Since practically everyone may now publish and distribute their work, viewers have a wide variety of texts and forms to choose from. [2]. Developing reading skills is very important because reading is a complicated and interactive task that depends on how a person understands a text. It moves back and forth between basic steps, like recognizing words and decoding them, and higher-level thinking. Reading in a foreign language is harder because everyone experiences and understands a text differently based on their own background and thinking skills. Studies show that it's helpful to use a broad approach when working with text [3].

The educational activities implemented within the framework of the initial academic year for the students who have chosen engineering, Read Theory, an online tool aimed at improving the reading comprehension abilities, explore a very effective direction to develop the language competencies with focus on the specific area of interest [4]. Read Theory is computer algorithm-based application that offers reading tests and quizzes at the appropriate level of difficulty for each student making it very effective program for enhancing the students' reading skills. Science students, especially engineering students, may spend most of their time reading technical materials and thus may not be as proficient in reading as they ought to be especially in contexts that demand deep understanding of technical and academic texts as well as industry literature [5]. Incorporation of Read Theory into MALL is proposed because with the help of Mobile-Assisted Language Learning students can practice reading exercises or take reading assessments at any time and at any place they wish by using their mobile devices. MALL is an outreach of the conventional classroom setting and refers to the use of mobile learning as a flexible means of learning a language on one's own time and pace [6].

The relevance of Read Theory in MALL is made prominent by the kind of data-focused learning that it embodies. Since students engage with the application, their reading behaviours, achievements, and challenges are identified and logged. This information can be collected to have an understanding of the dynamics in understanding and areas that need improvement regarding the comprehension of what is taught to ensure that changes that could be made to effectively teach can be made by educators [7]. In addition, extending Read Theory in MALL can promote more learner-centred context that means learners are likely to have more control of how they learn. The learners can be informed promptly of their performance, get many reading materials, and build their skills in a very systematic yet somewhat freeway. It can be inferred from the above findings that for engineering freshmen particularly, who rely on their capacity to rapidly put into effect and decode technical content for class performance, advantages of applying Read Theory in MALL are vast. Students should also learn to improve their general performance in class, comprehension of class content and improve their skills in interpreting texts. This can help them in the future employment in the engineering field where the clarity of understanding as well as the ability of conveying that understanding becomes crucial [8]. Most engineering students go through a tight outline of subjects that are technical that do not let them practice reading a lot or even do so with much effort [9]. Apparently, the given competence of understanding rather complex texts is important for their further academic and work experience. Several programs have been named earlier: Read Theory with the built-in option of adaptive learning that allows the learner to focus on reading exercises with the relevant difficulty level and a great choice of texts. When it is used through mobile environment, it becomes more convenient since the students can be involved with the reading exercises at any spare time as they wait for their classes, during transport among other times hence making reading part and parcel of their everyday lives [10].

Thus, the efficiency of Read Theory in a mobile frame can be defined by the regular interest of students; steadily increased level of comprehension of the texts read; and flexibility to the time limitations of students. Mobile devices can prove beneficial when learning is being done at a variety of locations including the college, homes or while on the move. This goes hand in hand with increased chances of going through the material, which is beneficial in check and balance learning session and to reinforce what has been learnt. In addition, the mentioned environment is highly flexible and it provides students with a number of opportunities regarding feedback; it is possible to provide immediate feedback in the context of a mobile environment so that students could see the results of their efforts and alter their approach in case of it is necessary [11]. The post Sherpa use of Read theory desired outcome is also measurable by comparing pre and post-test where, if the scores were to rise significantly after the inclusion of the mobile assisted use of Read theory, then the desired outcome would have been achieved. Also, questionnaire or survey with the students in terms of their experience with the particular developed platform can afford prose description of its usefulness as well as its effectiveness in enhancing student learning. To the engineering students the deployment of Read Theory in the mobile context means that those overloaded with multiple difficult subjects can use it as the supplement to the standard approaches. It is not only a method of developing the skills in reading comprehension but also a current method of constant learning. Making use of this instrument, students have the chance to foster gradually their independent reading-skills, respectively instrumental reading-skills which are important for the engagement with more advanced academic texts [12]. The key contribution of the work.

- Utilizes BI-LSTM models to increase the accuracy of reading comprehension prediction, delivering enhanced insights into the usefulness of mobile-assisted learning technologies.
- Implements Read Theory inside a mobile-assisted learning framework to assess its influence on engineering freshmen's reading comprehension, adding to the practical use of technology in education.
- Assesses improvements in reading comprehension scores before and after the intervention, providing measurable proof of the efficacy of mobile educational platforms.
- Provides empirical data on the benefits and problems of using Read Theory in a mobile learning environment, contributing to the corpus of knowledge in educational technology.
- Improves the design and effectiveness of mobile-assisted learning tools by combining user input and performance data, resulting in more effective instructional tactics and resources.

The study is structured as Section I provides an introduction of the research, and Section II has Related Work which reviews the existing literature. Problem statement is given in Section III. Section IV details the data collection methods, preprocessing steps, and analytical approaches, including the use of BI-LSTM models and Section V presents the Result and Discussion and ends with Conclusion and future works in Section VI.

## II. Related Work

Many adults learning a second language or a foreign language don’t have enough chances to practice. However, learning a new language well is important for many reasons. It helps them fit in quickly in a new country and adjust easily to new jobs or schools. This means they need more help to learn their second language successfully thinking that advancements in learning analytics, self-directed language learning, and mobile language learning will enhance this support. MALLAS, which stands for mobile-assisted language learning through learning analytics for self-regulated learning, is a novel concept that is presented in this study. It is intended to assist individuals who plan educational initiatives in assisting folks acquiring a second language. This is accomplished by utilizing learning data to assist students in better managing their own learning. Here, the MALLAS framework is demonstrated as a tool to aid with the application of mobile-assisted language learning in a particular scenario. Researchers who wish to learn more about and support language learners who utilize mobile devices for self-study may also find it helpful. A possible problem with the MALLAS framework is that it depends a lot on how good the learning analytics tools are. These tools can have problems if the data is not high quality or if it’s not understood correctly. Also, it may not consider the different ways people learn and what motivates them, which could make it less effective for various groups of learners [13].

In this study, Mortazavi et al. [14] looked at various factors that affect how MALL can help improve speaking and listening skills. 100 research papers were chosen from the best journals about how MALL affects language learning in higher education. A selection of eight papers was made according to particular criteria to consolidate findings related to language abilities and technology concepts. So, after carefully looking at the suggested methods and comparing them, explaining the basic beliefs about this issue and provide complete and lasting solutions to deal with it. This analysis showed that people in developing countries use mobile devices a lot for learning. The main area where technology helps is vocabulary, and it is giving good results. According to this survey, university students prefer to use WhatsApp for chatting and writing, and LINE for listening and reading comprehension. Teachers should consider using the TAM to modify their present and future lesson plans. This means they can improve students' learning by using more than just in-person classes [14].

Mobile technologies and the reasons that affect EFL learners' desire to use them in their studies are important. This study looks at how factors like support, ease of use, and usefulness affect Iranian EFL learners' views on MALL. Data were gathered from 223 Iranian students learning English as a foreign language, who took their classes in two main places: public schools and private institutes. In the first part of the study, a meaningful connection between three important factors and what learners think about MALL is found. Also, the support available was linked to how easy learners felt using it. In the second part of the study, the results showed that how useful people think MALL is really affects their views about it. This study also shows that having good support makes it easier for learners to use tools. The results are talked about based on other studies, and ideas for more research are given [15].

In this study, university students learning EFL used mobile devices to help them learn. The research focused on understanding how students feel about using mobile phones for language learning, how they use these tools, and how helpful they are for their studies. The findings demonstrated that students utilize different MALL software for distinct objectives. Five important criteria that influenced students' adoption of MALL software were identified from a study conducted among 581 students from Indian colleges and universities. These factors are individual desires and reasons, how easy the software is to use, technology features, social influence, and how useful the students think the software is. These factors impacted students' readiness to use the software, their motivation, and ultimately their performance. The study showed how prepared and motivated students are affected by the way they use MALL and the results they see from it. The importance of good language learning results, the ideas added to the theory, and practical uses for managers from the study are talked about. Some language abilities, such as speaking and listening, require more practice due to hardware restrictions, especially for mobile activities that may be improved [16].

This study looked at how using mobile apps for language learning can help university students who are learning English improve their skills and support their ability to learn on their own. It also aimed to help them become more skilled with technology. The global epidemic and spread of COVID-19 have accelerated the usage of technology in schools because to the urgent necessity to keep education going. As digital technology has advanced, many smart mobile apps are now used for learning and teaching English. Using these technologies can help language learners practice learning on their own outside of the classroom. This is important for staying motivated and becoming independent learners. Mobile phone apps can be very helpful for teaching because they are easy to use, available to many people, and have various features. There hasn't been much research on using mobile phones to help people learn languages on their own outside of school. In this research, university students studying English utilized their smartphones to facilitate independent learning outside the classroom. This made their learning more lasting and independent. The findings of this study showed that students had a positive attitude towards using mobile devices to help them learn English. The results show that using mobile apps for learning languages can increase students' motivation and make their learning more enjoyable and lasting compared to traditional teaching methods. People in this study said that the biggest advantages of using mobile learning for studying English were easy access to learning materials, the ability to carry their tools anywhere, the freedom to learn on their own, better interaction with others, and feeling more confident in their English skills. The study talks about how to teach better and suggests ways to create a learning environment that fits with the changes brought by technology. Learners plan to use mobile phone apps to learn English in the future. This shows that these apps can be useful for helping them learn on their own and make their learning more effective over time [17].

Mobile-assisted language learning (MALL) has had a significant impact on language learning by encouraging self-directed learning and providing practice opportunities outside of traditional classroom settings MALL has shown have proved particularly effective for vocabulary acquisition and are widely used in developing countries, where mobile technology facilitates language learning [18]. Key factors affecting acceptance of MALL tools are personal motivation, ease of use, and perceived usefulness, which directly affect learning outcomes and motivation Students' perceptions of MALL are also influenced by the support and usefulness of technology a they get it and it shows [19]. The COVID-19 pandemic reaffirmed the value of MALL, as it increased student motivation and enabled a more flexible and consistent learning experience compared to traditional methods but the potential of MALL was well realized, challenges such as ensuring data quality in academic research and retrieving a variety of materials must meet student preferences.

## III. Problem Statement

The study aims to fill the identified knowledge gap in the analysed literature, especially when it comes to adapting learning analytics practices to broaden the topical area of MALL and foster self-regulated learning strategy among adult second language learners. In the prior research, the effects of introducing the use of mobile technologies to support second language acquisition have been researched but there is a lack of research in the best ways of using learning analytics to facilitate support and feedback in a mobile learning environment [20]. Besides, there is lack of research evidence on how frameworks such as MALLAS can be used to address the needs of the learners given the different learning styles, motivation, and quality of data collected.

## IV. PROPSOED METHODOLOGY FOR IMPACT OF READ THEORY IN MOBILE-ASSISTED LANGUAGE LEARNING ON ENGINEERING FRESHMEN'S READING COMPREHENSION USING BI-LSTM

Read Theory in MALL provides an interactive environment that improves reading comprehension through tailored practice. Adapting content to learners' competence levels, Read Theory promotes focused skill development and engagement. The study makes use of Bi-LSTM networks to evaluate the impact of Read Theory on engineering freshman's studying comprehension. Bi-LSTM networks are well-acceptable for capturing contextual relationships in sequential data due to their ability to process information in each forward and backward directions. This bidirectional method complements the model's functionality to apprehend the nuances of language and context, making it effective for analyzing comprehension. Bi-LSTM on data collected from Read Theory's platform, focusing on studying comprehension tasks and assessments. The model can be evaluated based on its capacity to assume enhancements in comprehension ranges and usual common performance. Leveraging Bi-LSTM networks, the research offer insights into the efficacy of Read Theory in enhancing reading skills and making a contribution to the optimization of MALL programs for students as shown in the Fig. 1.

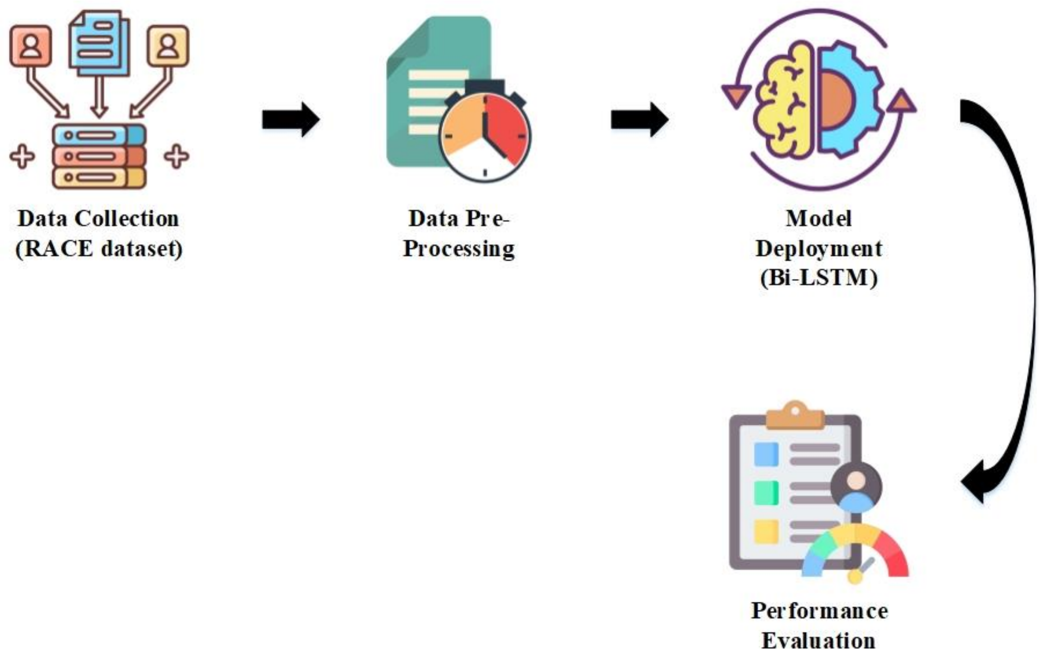


Fig. 1. Block diagram of the proposed study.

The study examines the potential of the mobile learning tool known as Read Theory to contribute to development of freshmen's engineering reading skills. To examine the impact of Read Theory on students' ability to understand the difficult texts, the study employs deep learning technique referred to as the Bi-LSTM networks. The study procedure consists of three critical stages: data acquisition which captures students' details and their reading literacy levels, and data pre-cleaning which sequentially purges the data that it harvested from the internet. Subsequently, an enhanced model in the form of Bi-LSTM is developed and applied in order to estimate students' reading comprehension according to their progress in Read Theory. Lastly, the ability of the Bi-LSTM model to predict reading comprehension results is assessed. Through such extensive research, the study aims at providing useful information on the effectiveness of Read Theory for enhancing comprehension of freshmen in the engineering field hence help in the development of better language learning techniques.

### A. Data Collection

The RACE [21] dataset which is an analyzing dataset comprising of more than 28000 passages and nearly 100000 questions extracted from the English examination conducted in China is used. The forms are designed especially for center and high school students and, therefore, will make the dataset rather useful for measuring reading comprehension. It offers a vast amount of textual information and related questions that can be used as schooling and test sets for the system comprehension models. Using this dataset, analyze the degree to which the Read Theory platform impacts the studying comprehension of engineering newbies within a MALL environment. The collection of passages and questions in the RACE dataset will create a strong basis for the assessment of students' analyzing skills, and the results will offer an understanding of how the adaptive learning can benefit language education and understanding potential for students in academic context.

### B. Data Pre-Processing

Data preprocessing is an initial step in data analysis and ML that emphasizes preparing the raw data for cleaning, transformation, and proper formatting. This process includes numerous key activities: It includes steps like cleaning data by dealing with missing values, errors and inconsistencies; normalize or standardize the information to get certain degree of uniformity and code the categorical data in number form, compatible to the models. It is also equipped with characteristic extraction and selection to determine the maximum eligible variables for the analysis. Data preprocessing increases the purity of data and performance of device by correcting that the record of data is accurate, complete and arranged in the proper format. By performing feature preprocessing, more accurate results are obtained and, therefore, more likely to define the desired version, and is a non-trivial process for any works based on data analysis.

*1) Text normalization:* Text cleaning is one of the key steps in the preparation of data in the field of NLP that brings raw text data in a specific structure for analysis. Changing every textual content to lower case is also important in order to standardize the text since it is easier to compare lower cases to lower cases from the increased amount of whitespace removed from the text that does not add any value to the meaning of the text. Furthermore, normalization includes enhancement of some occasional contractions to their full bureaucracy, normalization of Unicode character to illustrating equivalent, and erasing normal words like such as those adding semantics. Tokenization process divides the textual content into individual words or tokens which can be lemmatized into their base form so as to reduce variation. Applying these approaches, the textual content is preprocessed: it is normalized and previously analyzed or trained in models, and similarly prepared for further analysis.

*2) Tokenization:* Tokenization is the procedure of dividing textual content into smaller units, known as tokens, which may be character words, phrases, or symbols. This phase is vital in NLP because it converts raw textual input into a structured format that can then be easily evaluated and processed. Splitting the text into tokens, permits algorithms to handle and understand textual statistics greater efficiently, permitting responsibilities which include parsing, evaluation, and modeling. Tokenization simplifies the textual content, making it feasible to carry out operations like counting word frequencies, analyzing sentence structures, and making use of the system mastering model.

$$Tokens = text.split(delimiter) \tag{1}$$

Where $text$ is the original string of text that will be tokenized and $delimiter$ is the character or collection of characters used to divide the text.

### *C. Bi-LSTM*

Bi-LSTM networks are enhanced LSTM networks that capture time-dependent complexity in sequential data without dissimilarity. Standard LSTM networks, sequential in one direction. In the future, Bi-LSTMs process data in both forward and backward orientations. These two modes can integrate past and future knowledge about a specific event in the sequence to provide a thorough comprehension in the context of the mediation. A Bi-LSTM network consists of two LSTM layers: one that processes the input sequence from beginning to end, and another that processes it from end to beginning. The outputs of these two layers are then combined to provide a more complete representation of the data. For a given sequence $X = (x_1, x_2, x_3 \dots., x_T)$, where $T$ is the length of the sequence, the forward LSTM creates hidden states $\overrightarrow{h_t}$. The forward LSTM creates hidden states at each time step $t$, whereas the reverse LSTM generates hidden states at each time step $\overleftarrow{h_t}$. The composite representation for each time step (t) is obtained by concatenating the two hidden states:

$$h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}] \tag{2}$$

In Eq. (2), $h_t$ represents output at time step , which capture the data from both the direction of the sequences. The Input Gate $(i_t)$ controls the quantity of incoming data that is fed into the cell state. The Forget Gate $(f_t)$ regulates the quantity of previous cell state that should be retained. The output gate $(o_t)$ determines the quantity of cell state that will be output.

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{3}$$

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \tag{4}$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{5}$$

$$C_t = tanh(W_C.[h_{t-1}, x_t] + b_C) \tag{6}$$

$$C_t = f_t * C_{t-1} + i_t * C_t \tag{7}$$

$$h_t = o_t * \tanh(C_t) \tag{8}$$

where the hyperbolic tangent function in Eq. (3), Eq. (4), Eq. (5), Eq. (6), Eq. (7) and Eq. (8) is represented by $tanh$, the sigmoid function by $\sigma$, and element-wise multiplication by $*$. Because of these equations, LSTMs may better express complex temporal relationships by keeping a consistent gradient across long time periods.

The Fig. 2 illustrates the architecture of the Bi-LSTM model and briefly describes its work. As an advanced type of LSTM network, the Bidirectional LSTM network analyzes the data sequences both in the backward manner and the forward manner, thus, collects contextual information from both the past and the future for each time step. The forward LSTM scans the sequence from start to end while the reverse LSTM scans from the end to the start. The output of these two LSTM layers are then concatenated together to form a new vector representation for each time step. This bidirectional method enhances the possibility of the model to learn and predict based on the whole context of the input. On the whole, the graphic represents the LSTM cells of both, the forward and backward passes, while the arrows demonstrate the information flow across the layers. Bi-LSTMs are useful in tasks that require exploitable amount of context depth such as language modeling, text classification and sequence prediction, where information flow is bidirectional. This structure is especially useful when the correct forecast depends on context data of both past and future time periods. BiLSTMs are often superior to regular LSTMs in hardnesses that require understanding context not only from the previous but the following data input, and they also can discover more sophisticated relations in sequential signs than unidirectional LSTMs. BiLSTMs can be used in any general purpose, for natural language processing and time series analysis and machine translation.

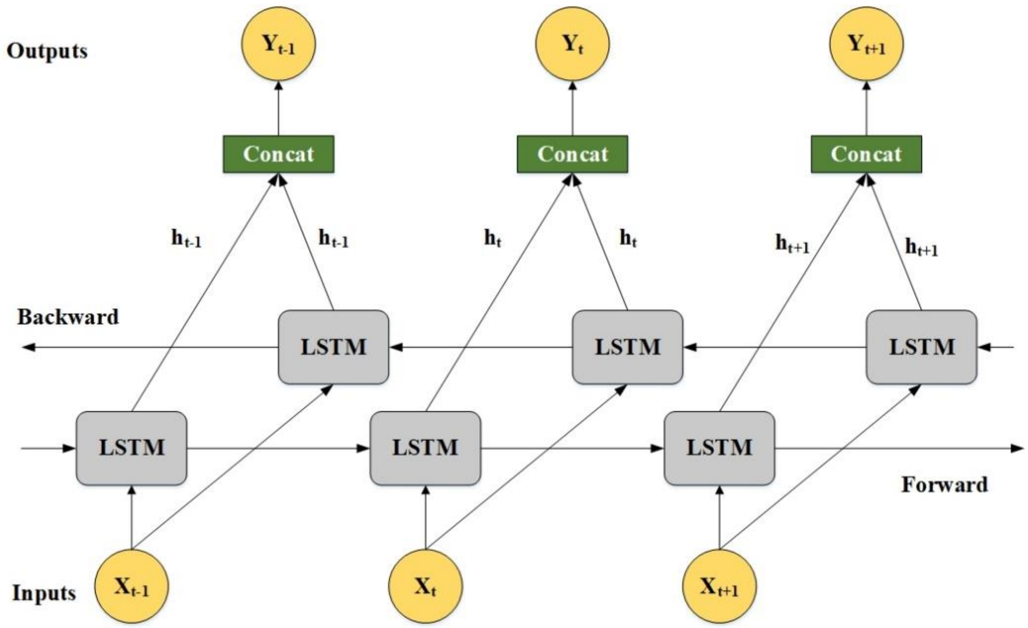


Fig. 2. Architecture of Bi-LSTM.

Bi-LSTM are crucial to investigate and technologically impact the reading theory in MALL for freshmen's reading comprehension. Bi-LSTM interfaces are particularly important in this work, for identifying and applying applications from past and future in contexts, under all comprehending reading tasks. Compared with the single-dimensional model, the Bi-LSTM network can receive textual input in two dimensions that it is more likely to analyse reading and estimating the student comprehension level than the single-dimension model. This bimodal processing assists the communicator to pick the fine details of the language and the context. It also enhances the model's accuracy in forecasting comprehension rates based on engagement with the read theory.

***Algorithm 1: Reading Comprehension Using BI-LSTM***

***Step 1*** *Data Collection*
- *Input the RACE Dataset*

***Step 2*** *Data Pre-Processing*
- *Clean the data*
- *Normalize the text data*
- *Tokenize the text into smaller units*

$$Tokens = text.split(delimiter)$$

*Divide the text*
- *Lemmatization*

***Step 3*** *Model Training*

*//Define the architecture of the Bi-LSTM model*

$$\text{Given sequence } X = (x_1, x_2, \ldots, x_T)$$

$$hidden\ states\ h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}]$$

*//Initialize Model Parameters*

*//Forward LSTM Layer*

$$\text{Input Gate } (i_t) = \sigma(W_i.[h_{t-1}, x_t] + b_i)$$

$$Output\ Gate\ (o_t) = \sigma(W_o.[h_{t-1}, x_t] + b_o)$$

*//Calculate Cell State*

$$\text{Cell State } (C_t) = tanh(W_C.[h_{t-1}, x_t] + b_C)$$

$$C_t = f_t * C_{t-1} + i_t * C_t$$

$$\text{Hidden State } (h_t) = o_t * tanh(C_t)$$

*Train the model using the training data*

***Step 4*** *Model Evaluation*
- *Make Predictions on the test data*
- *Calculate model accuracy*

***Step 5*** *Model Deployment*
- *Evaluate the model*

In practice, the Bi-LSTM network will be used to assess sequences of student interactions with Read Theory content, such as their replies to comprehension questions and feedback received during the learning process. This investigation seeks to uncover trends and insights into how the Read Theory platform enhances reading comprehension abilities. Using the Bi-LSTM's capacity to integrate information from both sides of the text sequence, the research may gain a better grasp of how various parts of the learning material contribute to comprehension growth. Furthermore, the Bi-LSTM's ability to simulate long-range dependencies within text sequences is critical for capturing the intricate links between many aspects of reading comprehension, such as recognizing context, drawing conclusions, and storing knowledge over time. This capacity will allow the research to more properly and thoroughly assess the success of the Read Theory intervention. Finally, the application of Bi-LSTM networks will give significant insights into the efficacy of mobile-assisted learning tools, help to optimize instructional tactics, and improve the overall impact of MALL platforms on engineering students' academic achievement.

## V. RESULT AND DISCUSSION

In the result and discussion section, examining the findings from applying Read Theory inside a MALL framework to engineering freshmen, specializing in studying comprehension upgrades facilitated by using Bi-LSTM networks are done. This section delves into how the gaining knowledge of Read Theory affects comprehension outcomes, inspecting the effectiveness of the Bi-LSTM model in capturing and enhancing reading abilities. The interpretation the statistics to evaluate the realistic implications of these findings, comparing them with existing literature and discussing their relevance for academic techniques in engineering disciplines. Insights gained will highlight the impact of MALL tools on academic performance.

## A. Training and Testing

The Fig. 3 shows a line graph illustrating the training and testing accuracy of a machine learning model over 100 epochs. The x-axis represents the variety of epochs, at the same time as the y-axis shows the accuracy value, starting from zero. The training accuracy, which typically increase as the model learns from the training data. The testing accuracy, which measures the model's performance on unseen data. Initially, the training accuracy hastily increases, at the same time as the testing accuracy indicates a greater slow upward push. However, after round 60 epochs, the training accuracy plateaus, and the testing accuracy starts to decrease slightly. This indicates that the model might be overfitting the training information, learning its patterns too well and struggling to learn new, unseen examples. Overall, the graph indicates that the model achieves a reasonable level of accuracy on both training and testing data.

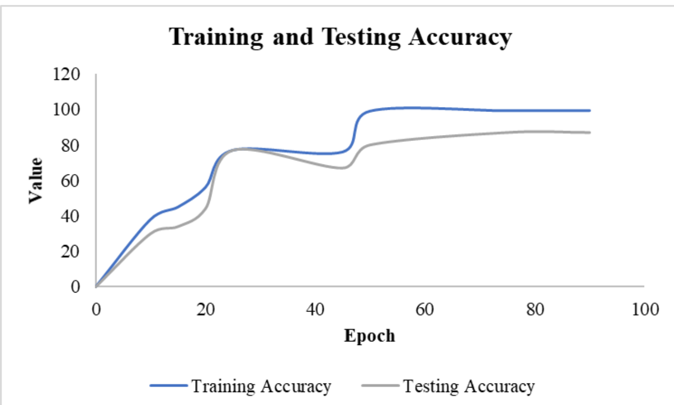


Fig. 3. Training and testing accuracy.


Fig. 4. Training and testing loss.

Fig. 4 shows a line graph illustrating the training and testing loss of a machine learning model over 60 epochs. The x-axis represents the range of epochs, at the same time as the y-axis shows the loss value, starting from zero. The training loss, which commonly decreases because the model learns from the training data. The testing loss, which measures the model's performance on unseen statistics. Initially, both training and testing loss decrease unexpectedly, suggesting that the model is learning efficiently. However, after around 30 epochs, the training loss continues to lower, while the testing loss begins to plateau or even increase slightly. This indicates that the model might be overfitting the training data, learning its patterns too well and struggling to generalize to new, unseen examples. Overall, the graph shows that the model achieves a reasonable level of overall performance.

## B. Performance Metrics

Performance metrics are quantitative values applied in the assessment of how effectively a model meets intended objectives. These include recall that measures the model's performance in selecting all the actual positives from the entire dataset; accuracy which gives an overall measure of the number of correct predictions; precision that quantifies the number of actual positives per hundred fine predictions to demonstrate the capacity of the version in avoiding false positives; the F1 score that is an integrated measure of recall and precision that provides a balanced measure of performance. Hence, every metric provides information about particular aspects of the model's performance. Thus, for the given classes of precise programs, practitioners could use the above points and make knowledgeable selections about the suitability of the proposed metric and guarantee that the system beneath thought of does fulfill the performance degrees wanted for the preferred solution of the intended problems.

*1) Accuracy:* Accuracy is one of the evaluation metrics that define the portion of instances that has been classified correctly in a given set. That is because it provides a full picture of a model's performance for categorization tasks. The formula for accuracy is shown in Eq. (9),

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \tag{9}$$

*2) Precision:* An overall performance indicator called precision assesses how well the model predicts the future with any degree of accuracy. It calculates the percentage of actual positive results among all cases the model has categorized as positive. Because precision is focused on the quality of positive predictions, it is most useful in situations when the cost of false positives is substantial. The formula for precision is shown in Eq. (10),

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{10}$$

*3) Recall:* The efficiency of pattern recognition for future predictions is evaluated using an overall performance score known as precision. It provides information on actual rate of positives, based on the totality of the cases which the model has classified to have positive results. Since precision measures the accuracy of positive instances, the measure is most handy in applications where false positives are very costly. It is given in Eq. (11).

$$Recall = \frac{True\ Positives}{True\ Positives + False\ negatives} \tag{11}$$

*4) F1 score:* The F1 score is an all-around performance statistic that gives a fair assessment of a model's accuracy in classification tasks by integrating recall and precision into a single measurement. When working with unbalanced datasets—where accuracy and recall may differ significantly it is helpful. The F1 score is a means to assess a model's performance by taking into account both false positives and false negatives. It is calculated as the harmonic mean of accuracy and recall. The formulation for the F1 score is given in Eq. (12),

$$F1\ score = \frac{2\times(Precision\times Recall)}{Precision+Recall} \tag{12}$$

Table I show that the study obtained great overall performance in comparing the effectiveness of a model. Accuracy at 99.3% suggests that the model is successful in showcasing its general correctness across all predictions. Precision, at 99.1%, measures the share of actual positive predictions amongst all high-quality identifications made by the model, highlighting its reliability in minimizing false positives. Recall, at 98% indicates the model's ability to find true positives among all cases. Recall, indicates what percentage of positive cases exist in a set of records. It provided an F1 score of 98. 9% is used to balance the precision and recall at once, which gives rather comprehensive information about the model on the whole. This F1 score shows how well the model reduces false positives and how reliable it is, that is how good it is at identifying positive cases. Cumulatively, those measurements show that the version outperforms others in terms of all the measurements which include accuracy, precision, recall, and f1 score making the model extremely useful for the intended purpose. The model's capability in realizing such excessive confirmed the tool's potential in providing practical predictions in practical conditions.

TABLE I. PERFORMANCE METRICS

| Metrics | Efficiency |
|---|---|
| Accuracy | 99.3% |
| Precision | 99.1% |
| Recall | 98.7% |
| F1 score | 98.9% |

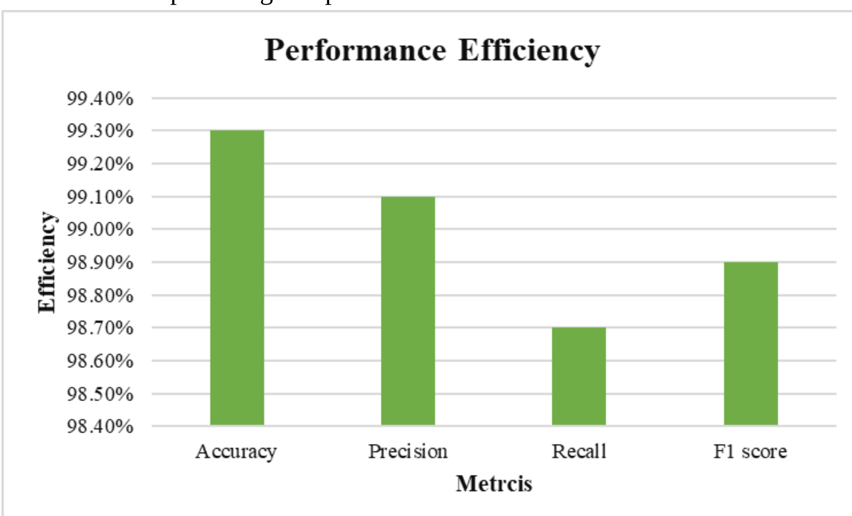


Fig. 5. Performance efficiency of the Bi-LSTM on the proposed study.

Fig. 5 depicts a model's performance parameters, with an emphasis on metrics. The graphic reveals that Accuracy is the highest of the measures, a little over 99.30%, showing that the model's predictions are generally true. Precision follows closely, barely below 99.20%, indicating the model's ability to reliably identify real positive situations while limiting false positives. Recall is significantly lower, slightly around 99.00%, implying that, while the model is reliable and exact, it may miss some actual positive cases, showing a modest trade-off in sensitivity. The F1 Score falls between accuracy and recall, just above 98.90%, indicating a balance between the two measures and reflecting the model's overall strength in classification tasks. The figure's representation of these metrics emphasizes the model's efficiency in performing classification jobs with high accuracy and precision while keeping an acceptable balance with recall, resulting in a strong F1 score. This figure highlights the model's great performance, particularly in circumstances where accuracy and precision are important, but also illustrates the importance of recall in situations when detecting all positive instances is critical.

TABLE II. PERFORMANCE COMPARISON OF THE PROPOSED METHOD WITH DIFFERENT METHOD

| Method | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Decision Tree [22] | 95.0% | 94.5% | 96.0% | 95.2% |
| Random Forest [23] | 92.3% | 91.8% | 93.5% | 92.6% |
| KNN [24] | 98.0% | 97.5% | 98.6% | 98.0% |
| SVM [25] | 89.5% | 88.0% | 90.2% | 89.1% |
| Proposed Method | 99.3% | 99.1% | 98.7% | 98.9% |

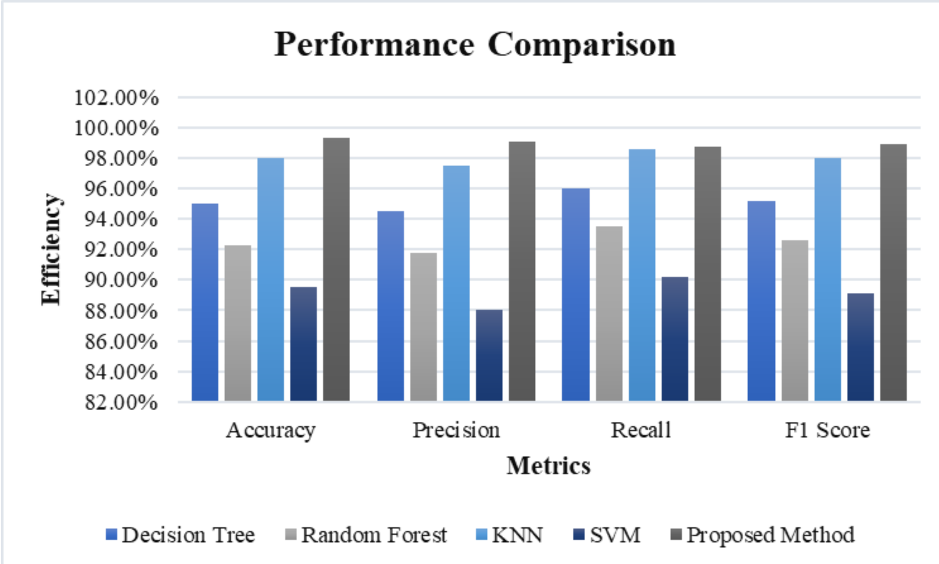


Fig. 6. Performance comparison of the proposed method with different methods.

A comparison of the methodologies across several measures is shown in Table II. The decision tree approach has 95.0% accuracy, 94.5% precision, 96.0% recall, and a 95.2% F1 score. This indicates a strong balance between identifying positive cases and reducing false positives. The Random Forest performs low, with 92.3% accuracy, 91.8% accuracy, 93.5% recall, and 92.6% F1 score, with improved classification but slightly less robust than decision trees K-Nearest Neighbors (KNN) technique achieves 98.0% accuracy, 97.5% precision, 98.6% recall, and 98.0% F1 score, indicating that it performs well in finding positive cases while minimizing error. In contrast, the Support Vector Machine (SVM) method does not perform well, with 89.5% accuracy, 88.0% accuracy, 90.2% recall, and 89.1% F1 score, indicating its low efficiency in comparison. The proposed method outperforms the others by the highest metrics: 99.3% accuracy, 99.1% precision, 98.7% recall, and 98.9% F1 score, demonstrating good performance at all evaluation criteria. This suggests that the suggested strategy gives an accurate and dependable solution to the categorization problem.

Fig. 6 compares the efficiency of five distinct methods such as Decision Tree, Random Forest, KNN, SVM, and the Proposed Method using four major performance metrics. The chart shows that the Proposed Method regularly beats the other approaches, with the highest values in all parameters, including accuracy slightly above 99%, precision just under 100%, recall around 98.7%, and an F1 score close to 99%. KNN also performs well, especially in accuracy and recall, where it outperforms all other approaches save the suggested method. Decision Tree performs well, with accuracy and recall metrics close to 95%, but it falls slightly short in precision and F1 score. Random Forest has balanced performance across all measures but stays lower than the top performers, with values ranging from 92-94%. SVM has the lowest metrics, particularly in accuracy and recall, demonstrating that it fails to compete with the other techniques' efficiency. This comparison demonstrates that the suggested technique outperforms all measures, making it the most trustworthy alternative for classification jobs in this context.

### *C. Discussion*

The limitation of previous research in MALL, on improving reading comprehension, often starts from their lack of ability to evolve to the various learning desires of students. Earlier approaches and methods have failed to deliver in terms of dealing with the dynamic nature of the problem, particularly in the context of specific learning pathways. Most of these methods rarely achieved an optimal blend of accuracy and flexibility which, in turn, affected the performance levels and the progression of students' reading skills. The following shortcomings have been identified with the conventional approach of analysis: The proposed method that uses BI-LSTM networks eliminates these shortcomings. The processing of sequential data in both forward and backward directions, make BI-LSTM capture the requirement of language learning more effectively than the basic models of AI. This allows the model to capture more of the context inherent in language and hence leads to improved prediction and in extension reading comprehension. This high level of accuracy underlines the ability of the strategy to compensate for the problems that have been identified in the previous investigations. The technique enhances the reading comprehension result at the same time establishing a standard of feasibility for the subsequent MALL applications. Such an approach can be successfully spread to other spheres of language learning making the approach more valuable and effective.

## VI. Conclusion and Future Work

Combining Read Theory with Mobile Assisted Language Learning or MALL enhances the first-year engineering students' reading comprehension using BI-LSTM networks. The 99. The achievement of 99.3% accuracy, proved that BI-LSTM is effective for dealing with restrictions that traditional MALL methods have. Previous strategies hardly take into account students' evolving and diverse needs for learning and this has led to poor improvement in reading skills. In fact, due to the bidirectional processing of sequential data, the technique providing a more enlightened picture of language acquisition as well as a more personalized learning model to individuals, BI-LSTM is capable to accomplish the idea. It not only set very high standards for MALL systems but also improves the ways in which understanding-oriented results are interpreted, thus showing how state-of-the-art AI techniques have the potential to dramatically transform teaching resources. The outcomes of the study make suggestions for the use and extension of BI-LSTM in educational technologies and highlight that, given that language proficiency is high, the usefulness of this technique could be of great value in engineering courses. The high reliability of this method highlights how the learning process as well as the classroom setting can be enhanced for better performance.

Future studies should examine how well the BI-LSTM model scales and adapts to various academic situations and topic areas. The efficacy and usefulness of BI-LSTM might be further improved by looking at how it integrates with other adaptive learning technologies and pedagogical approaches. Furthermore, carrying out longitudinal research to evaluate the approach's long-term effects on reading comprehension and general academic performance would offer significant insights into its long-term advantages. Including a wider range of student demographics and educational attainment in the research can improve the model's accuracy and scope of application. Additionally, investigating how to include interactive and gamified learning components with BI-LSTM may provide a more stimulating and engaging learning environment. For the strategy to be refined and implemented on a broader scale, cooperation with educational institutions to pilot the model in real-world situations and collect input from educators and students would be essential.

## REFERENCES

[1] Y. Arifani, “The effectiveness of Pamanpintermu e-reading program on EFL learners’ reading performances,” in 2018 3rd International Conference on Education, Sports, Arts and Management Engineering (ICESAME 2018), Atlantis Press, 2018, pp. 21–24.

[2] M. Gutiérrez-Colón, A. D. Frumuselu, and H. Curell, “Mobile-assisted language learning to enhance L2 reading comprehension: A selection of implementation studies between 2012–2017,” Interact. Learn. Environ., vol. 31, no. 2, pp. 854–862, 2023.

[3] Y. Xu, J. C. Yau, and S. M. Reich, “Press, swipe and read: Do interactive features facilitate engagement and learning with e-Books?,” J. Comput. Assist. Learn., vol. 37, no. 1, pp. 212–225, 2021.

[4] M. P. Vidal, “Effectiveness of Multimedia and Text-Based Reading Approaches to Grade 10 Students’ Reading Comprehension Skills,” AsiaCALL Online J., vol. 13, no. 4, pp. 55–79, Sep. 2022, doi: 10.54855/acoj.221345.

[5] A. Habók, T. Z. Oo, and A. Magyar, “The effect of reading strategy use on online reading comprehension,” Heliyon, vol. 10, no. 2, p. e24281, Jan. 2024, doi: 10.1016/j.heliyon.2024.e24281.

[6] S. G. T. Ong and G. C. L. Quek, “Enhancing teacher–student interactions and student online engagement in an online learning environment,” Learn. Environ. Res., vol. 26, no. 3, pp. 681–707, Oct. 2023, doi: 10.1007/s10984-022-09447-5.

[7] J. M. Muñoz Rodríguez and A. Sánchez Rojo, “On Blended Learning Flexibility: An Educational Approach,” in Blended Learning: Convergence between Technology and Pedagogy, vol. 126, A. V. Martín-García, Ed., in Lecture Notes in Networks and Systems, vol. 126. , Cham: Springer International Publishing, 2020, pp. 21–44. doi: 10.1007/978-3-030-45781-5_2.

[8] M. L. Bernacki, J. A. Greene, and H. Crompton, “Mobile technology, learning, and achievement: Advances in understanding and measuring the role of mobile technology in education,” Contemp. Educ. Psychol., vol. 60, p. 101827, Jan. 2020, doi: 10.1016/j.cedpsych.2019.101827.

[9] M. Wardak, Mobile assisted language learning (mall): teacher uses of smartphone applications (apps) to support undergraduate students’ english as a foreign language (efl) vocabulary development. Lancaster University (United Kingdom), 2020.

[10] N. Nurjannah, K. Nurhadi, A. R. S. Tambunan, and others, “Assessing Student Empowerment in Mobile-Assisted Extensive Reading in a University Setting.,” Qual. Rep., vol. 28, no. 6, 2023.

[11] M. Valizadeh, “Investigating the impacts of mobile assisted reading on EFL learners’ vocabulary knowledge development,” Sak. Univ. J. Educ., vol. 12, no. 3, pp. 573–590, 2022.

[12] C.-C. Lin, V. Lin, G.-Z. Liu, X. Kou, A. Kulikova, and W. Lin, “Mobile-assisted reading development: a review from the Activity Theory perspective,” Comput. Assist. Lang. Learn., vol. 33, no. 8, pp. 833–864, 2020.

[13] O. Viberg, B. Wasson, and A. Kukulska-Hulme, “Mobile-assisted language learning through learning analytics for self-regulated learning (MALLAS): A conceptual framework,” Australas. J. Educ. Technol., vol. 36, no. 6, pp. 34–52, 2020.

[14] M. Mortazavi, M. K. Nasution, F. Abdolahzadeh, M. Behroozi, and A. Davarpanah, “Sustainable learning environment by mobile-assisted language learning methods on the improvement of productive and receptive foreign language skills: A comparative study for Asian universities,” Sustainability, vol. 13, no. 11, p. 6328, 2021.

[15] S. Ebadi and A. Raygan, “Investigating the facilitating conditions, perceived ease of use and usefulness of mobile-assisted language learning,” Smart Learn. Environ., vol. 10, no. 1, p. 30, 2023.

[16] S. Habib, A. Haider, S. S. M. Suleman, S. Akmal, and M. A. Khan, “Mobile assisted language learning: Evaluation of accessibility, adoption, and perceived outcome among students of higher education,” Electronics, vol. 11, no. 7, p. 1113, 2022.

[17] K.-O. Jeong, “Facilitating sustainable self-directed learning experience with the use of mobile-assisted language learning,” Sustainability, vol. 14, no. 5, p. 2894, 2022.

[18] Z. Chen, W. Chen, J. Jia, and H. An, “The effects of using mobile devices on language learning: a meta-analysis,” Educ. Technol. Res. Dev., vol. 68, no. 4, pp. 1769–1789, Aug. 2020, doi: 10.1007/s11423-020-09801-5.

[19] X. Lei, J. Fathi, S. Noorbakhsh, and M. Rahimi, “The impact of mobile-assisted language learning on English as a foreign language learners’ vocabulary learning attitudes and self-regulatory capacity,” Front. Psychol., vol. 13, p. 872922, 2022.

[20] J. Sabatini, T. O’Reilly, J. Weeks, and Z. Wang, “Engineering a twenty-first century reading comprehension assessment system utilizing scenario-based assessment techniques,” Int. J. Test., vol. 20, no. 1, pp. 1–23, 2020.

[21] “datasets/docs/catalog/race.md at master • tensorflow/datasets,” GitHub. Accessed: Aug. 23, 2024. [Online]. Available: https://github.com/tensorflow/datasets/blob/master/docs/catalog/race.md

[22] J. Sinclair, E. E. Jang, and F. Rudzicz, “Using machine learning to predict children’s reading comprehension from linguistic features extracted from speech and writing.,” J. Educ. Psychol., vol. 113, no. 6, p. 1088, 2021.

[23] S. K. D’Mello, R. Southwell, and J. Gregg, “Machine-learned computational models can enhance the study of text and discourse: A case study using eye tracking to model reading comprehension,” Discourse Process., vol. 57, no. 5–6, pp. 420–440, 2020.

[24] L. S. Riza, Y. Firdaus, R. A. Sukamto, Wahyudin, and K. A. F. Abu Samah, “Automatic generation of short-answer questions in reading comprehension using NLP and KNN,” Multimed. Tools Appl., vol. 82, no. 27, pp. 41913–41940, 2023.

[25] Z. Ye et al., “Towards a Better Understanding of Human Reading Comprehension with Brain Signals,” in Proceedings of the ACM Web Conference 2022, Virtual Event, Lyon France: ACM, Apr. 2022, pp. 380–391. doi: 10.1145/3485447.3511966.