AUTOMATED ENGLISH TEACHING SYSTEM THROUGH DEEP BELIEF NETWORK FOR HUMAN-COMPUTER INTERACTION EXPERIENCE

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SUMMARY

This paper presented the integration of Human-Computer Interaction (HCI) with the Automated Teaching Belief Network (ATBN) to enhance automated English teaching experiences. The proposed ATBN model implemented the Deep Belief Network for the estimation of the factors related to the HCI to promote the experience of the users. The ATBN model uses the deep learning model for the classification in English Teaching. Through the capabilities of deep learning and HCI principles, the ATBN system offers personalized and adaptive learning experiences tailored to individual student needs. The proposed ATBN model estimates the features in English teaching to improve the performance of the Students through HCI model. Simulation analysis expressed that proposed ATBN model improves the pre-test and post-test score by +15 for the English Teaching. The classification values are achieved with accuracy value of 94.8% with minimal loss of 0.12. The assessment of student performance through pre-test and post-test score is improved by 15 for the beginner, intermediate and advanced level. The findings expressed that proposed ATBN model achieves the higher teaching test performance for the HCI language level through the belief network those significantly improves the user experience.

KEYWORDS

English teaching, Human computer interaction (HCI), Deep belief network, Automated model, User experience

NOMENCLATURE

DBN	Deep Belief Network
HCI	Human-Computer Interaction
ATBN	Automated Teaching Belief Network
NLP	Natural Language Processing

1. INTRODUCTION

In recent years, human-computer interaction (HCI) has seen significant advancements driven by technological innovations and evolving user needs [1]s. The field has shifted towards more intuitive, seamless interactions between humans and digital systems, encompassing various devices such as smartphones, tablets, wearables, and smart home appliances. One notable trend is the proliferation of natural language processing (NLP) and voice recognition technologies, enabling users to interact with devices using speech commands [2]. Additionally, augmented reality (AR) and virtual reality (VR) have gained traction, offering immersive user experiences in gaming, education, and other domains [3]. Moreover, the emergence of gesture-based interfaces and touchless interactions has further enhanced user engagement and accessibility. HCI research has also focused on designing inclusive and accessible interfaces for individuals with disabilities, ensuring equitable access to digital technologies. Overall, the landscape of HCI continues to evolve rapidly, driven by the convergence of interdisciplinary research, technological advancements, and user-centered design principles [4].

Human-computer interaction (HCI) principles with English teaching has emerged as a promising approach to enhancing language learning experiences [5]. Technology-enabled platforms and applications have revolutionized the way English is taught and learned, offering interactive and personalized learning environments [6]. HCI techniques such as user-centered design and usability testing have been employed to develop intuitive and engaging interfaces that cater to diverse learning styles and preferences [7]. Mobile applications, online platforms, and virtual classrooms equipped with features like real-time feedback, adaptive learning algorithms, and gamified activities facilitate active participation and motivation among learners [8]. Moreover, natural language processing (NLP) technologies have been integrated into language learning applications to provide contextualized language practice, pronunciation feedback, and language understanding capabilities [9]. These advancements not only make learning English more accessible and convenient but also foster a deeper understanding and retention of language skills. By leveraging HCI principles, English teaching continues to evolve towards more interactive, immersive, and effective learning experiences, ultimately empowering learners to achieve their language proficiency goals [10].

The development of automated models for human-computer interaction (HCI) has been a focal point, promising to revolutionize the way users engage with technology [11]. These automated models leverage advanced artificial intelligence (AI) and machine learning algorithms to predict user behaviors, preferences, and intentions, thus enabling more seamless and personalized interactions [12]. Through the analysis of vast amounts of user data, these models can adapt and optimize interfaces in real-time, ensuring that user needs are met efficiently. In the context of English teaching, automated HCI models can offer tailored learning experiences by dynamically adjusting content presentation, difficulty levels, and feedback mechanisms based on individual learner performance and progress [13]. Additionally, these models can facilitate natural language processing (NLP) capabilities, enabling conversational interactions for language practice and comprehension. By incorporating automated HCI models into English teaching platforms and applications, educators can provide more effective and engaging learning experiences, ultimately enhancing language acquisition outcomes for learners [14]. However, it's essential to address ethical considerations such as data privacy and algorithmic biases to ensure that these automated models contribute positively to the HCI landscape while safeguarding user interests and rights [15].

2. LITERATURE SURVEY

Human-Computer Interaction (HCI) principles into English teaching has garnered increasing attention in recent years, marking a significant shift in language education paradigms. This literature survey delves into the intersection of HCI and English teaching, examining the evolving landscape, emerging trends, and research methodologies employed to enhance language learning experiences through technological interventions. With the proliferation of digital platforms and advancements in AI, NLP, and interactive technologies, educators are exploring innovative ways to leverage HCI principles to create immersive, personalized, and effective learning environments. This survey aims to provide a comprehensive overview of the current state-of-the-art in HCI-driven English teaching methodologies, shedding light on key findings, challenges, and future directions in this dynamic field. By synthesizing existing literature and identifying gaps in knowledge, this survey seeks to inform educators, researchers, and practitioners about the potential of HCI to transform English language education and shape the future of language learning.

Li (2023) explores the design and research of computer-aided English teaching methods, underscoring the potential for technology to augment language instruction. Alnuaim et al. (2022) delve into the realm of emotion detection in language learning environments, employing convolutional neural networks to discern speaker emotions, thereby enriching HCI interactions. Chen (2022) investigates the design of political online teaching utilizing artificial speech recognition and deep learning, highlighting the integration of advanced technologies into pedagogical practices. Meanwhile, Chou et al. (2022) examine the influencing factors on students' learning effectiveness through AI-based technology applications, emphasizing the mediating role of human-computer interaction experiences. These studies, among others, underscore the multifaceted role of HCI in shaping the future of English teaching, emphasizing personalized learning, adaptive technologies, and immersive interactions to foster language proficiency.

Furthermore, Zhuang, Gan, and Zhang (2022) present a novel application of HCI in health diagnostics, utilizing ResNet34 for tongue image classification, highlighting the interdisciplinary nature of HCI research. Soui and Haddad (2023) propose a deep learning-based model for mobile user interface evaluation, demonstrating the versatility of HCI methodologies across various digital platforms. In a similar vein, Li et al. (2023) pioneer the automatic assessment of depression and anxiety through pupil-wave encoding in virtual reality scenes, showcasing the potential of HCI to address mental health concerns in language learning contexts. Hand gesture control for HCI is explored by Chua et al. (2022), emphasizing the integration of deep learning techniques for intuitive interactions in language education settings. Additionally, Zhen et al. (2023) provide a comprehensive survey of talking-head generation, offering insights into the future of HCI-driven language tutoring and communication aids. For instance, Jin, Wen, and Xie (2022) explore the fusion of deep learning biological image visualization technology with HCI intelligent robots in dance movements, showcasing the interdisciplinary nature of HCI research. Sreemathy et al. (2023) contribute to the field by investigating sign language recognition using artificial intelligence, underscoring the potential of HCI to support diverse learning modalities and accessibility needs. Wang (2023) extends the scope of HCI into multimedia teaching modes in higher education, emphasizing the integration of psychology-based interface designs for enhanced learning outcomes. Similarly, Ma (2022) delves into the design of a hotel human interaction system based on deep learning, highlighting the application of HCI in service industries beyond education.

In addition, Aleedy, Atwell, and Meshoul (2022) propose the development of a Deep Learning-powered chatbot for translation learning, showcasing the potential of HCI in language education beyond traditional classroom settings. Sadeghi Milani et al. (2024) conduct a systematic review of HCI research in medical and engineering fields, highlighting the interdisciplinary nature of HCI and its implications for diverse domains. Similarly, Dino et al. (2022) provide an integrative review of nursing and HCI in healthcare robots for older adults, emphasizing the role of HCI in enhancing patient care and well-being. Furthermore, Barricelli and Fogli (2024) offer insights into the application of digital twins in HCI, presenting a systematic review that explores the potential of virtual representations for improving user experiences across various domains. Yang (2022) explores the influence of Human-Computer Interaction-based intelligent dancing robots on choreography, showcasing the interdisciplinary applications of HCI in the arts and entertainment sectors. Shang, Liu, and Li (2022) delve into human-computer interaction in networked vehicles, highlighting the integration of big data and hybrid intelligent algorithms for enhancing driving experiences and safety. Additionally, Wang, Siau, and Wang (2022) present a technology framework for the metaverse and human-computer interaction, emphasizing the potential of 3D virtual worlds for immersive and collaborative experiences.

Firstly, researchers have developed innovative computer-aided English teaching methods, highlighting the potential of technology to enhance language instruction. Secondly, emotion detection using convolutional neural networks has emerged as a promising approach to enriching HCI interactions, providing insights into speaker emotions during language learning activities. Thirdly, the integration of artificial speech recognition and deep learning has facilitated the design of political online teaching, showcasing the adaptability of HCI methodologies in diverse educational contexts. Additionally, factors influencing students' learning effectiveness in AI-based technology applications have been explored, emphasizing the mediating role of human-computer interaction experiences. Moreover, HCI has been applied to health diagnostics using ResNet34 for tongue image classification, demonstrating its utility beyond traditional educational settings. Furthermore, studies have shown the potential of HCI in addressing mental health concerns through automatic assessment of depression and anxiety in virtual reality scenes. Hand gesture control and sign language recognition using artificial intelligence highlight the importance of HCI in supporting diverse learning modalities and accessibility needs. These findings collectively underscore the transformative impact of HCI on English teaching, paving the way for personalized, immersive, and effective language learning experiences.

3. ATBN FEATURE EXTRACTION WITH WORD EMBEDDING FOR ENGLISH TEACHING SYSTEM

The Automated Teaching Belief Network (ATBN) is a computational model designed to automate aspects of the teaching process, particularly in the context of English language instruction. One important aspect of ATBN is feature extraction, which involves identifying relevant features from input data to facilitate effective teaching. In the case of ATBN, feature extraction often involves the use of word embedding techniques. Word embedding is a popular method used in natural language processing (NLP) to represent words as dense vectors in a continuous vector space. These vectors capture semantic relationships between words, enabling machines to understand and process textual data more effectively. One common technique for word embedding is Word2Vec, which learns vector representations of words based on their contextual usage in a large corpus of text. Let V represent the set of all word embedding vectors for the words in the sentence defined in equation (1)

$$V = \{v_{w1},\ v_{w2}, \ldots., v_{wn}\} \tag{1}$$

To perform feature extraction with word embedding for an English teaching system using ATBN, we can derive equations that map words or phrases to their corresponding word embeddings. Let's denote w as a word in a sentence and vw as its corresponding word embedding vector. The goal is to transform the input sentence into a set of feature vectors that represent the semantic content of the text. Word Embedding Lookup: Given a sentence $S = [w1, w2, I, wn]$, where n is the number of words in the sentence, the word embedding lookup process involves obtaining the word embedding vectors for each word in the sentence. This can be represented as in equation (2)

$$v_{wi} = \text{Word2 Vec}(w_i) \tag{2}$$

where v_{wi} is the word embedding vector for the i-th word w_i. The word embedding vectors for all words in the sentence, we can aggregate them to form a feature vector that represents the entire sentence. This aggregation can be done using various techniques such as averaging or weighted summation. For instance, the feature vector F for the sentence can be computed using equation (3)

$$F = \frac{1}{n}\sum_{i=1}^{n} v_{wi} \tag{3}$$

word embedding vectors in the sentence, resulting in a single feature vector F that captures the semantic content of the sentence. Weighted sum of the word embedding vectors, where each vector is weighted by its importance in the sentence. Weights can be assigned based on factors such as word frequency or importance stated as in equation (4)

$$F_{\text{Weighted}} = \sum_{i=1}^{n} \alpha_i v_{wi} \tag{4}$$

where F_{weighted} is the feature vector obtained by weighted summation, and α_i represents the weight assigned to the i-th word embedding vector.

Figure 1 presented the ATBN model for the English teaching for the features with the Word embedding for the HCI.

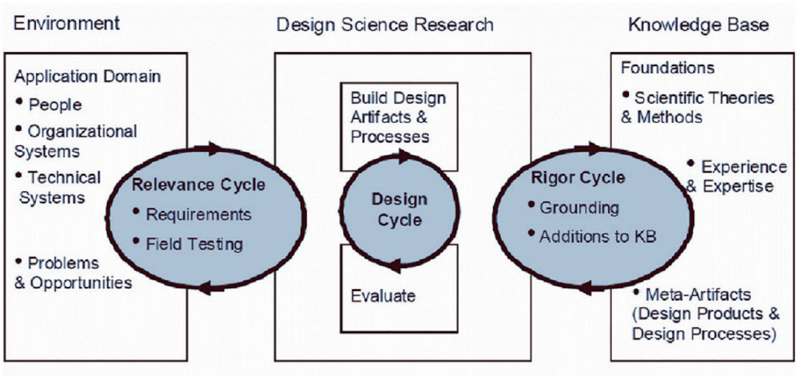

Figure 1. Feature embedding with the ATBN

Algorithm 1. ATBN model for the word embedding with English teaching

```
function extractFeatures(sentence):
    input: sentence (list of words)
    output: featureVector (vector representation of the sentence)
    # Step 1: Word Embedding Lookup
    wordEmbeddings = []
    for word in sentence:
        embedding = Word2Vec(word)  # Retrieve word
embedding vector
        wordEmbeddings.append(embedding)

    # Step 2: Feature Vector Formation
    numWords = len(sentence)
    featureVector =
averageWordEmbeddings(wordEmbeddings, numWords)  #
Or use weighted summation
        return featureVector
function averageWordEmbeddings(wordEmbeddings,
numWords):
    input: wordEmbeddings (list of word embedding vectors),
numWords (number of words)
    output: avgEmbedding (average of word embedding
vectors)
    sumEmbedding = 0
    for embedding in wordEmbeddings:
        sumEmbedding += embedding
    avgEmbedding = sumEmbedding / numWords
        return avgEmbedding
```

4. DEEP BELIEF NETWORK FOR AUTOMATED TEACHING BELIEF NETWORK (ATBN)

The Deep Belief Network (DBN) serves as a foundational component within the Automated Teaching Belief Network (ATBN), contributing to the automation and optimization of English language instruction. As an integral part of ATBN's architecture, the DBN employs deep learning techniques to analyze and understand complex patterns within educational data, facilitating automated decision-making processes to enhance teaching methodologies. By leveraging multiple layers of interconnected neurons, the DBN can effectively extract high-level features from input data, such as student performance metrics, linguistic patterns, and learning preferences. These extracted features serve as valuable insights that inform the ATBN's decision-making algorithms, enabling personalized and adaptive teaching strategies tailored to individual student needs. Furthermore, the DBN's ability to learn hierarchical representations of data enables it to capture nuanced relationships and dependencies within the educational context, thereby improving the accuracy and effectiveness of the ATBN's recommendations and interventions. Overall, the integration of the Deep Belief Network within the Automated Teaching Belief Network represents a significant advancement in automated English teaching, offering scalable and intelligent solutions to support educators and learners in achieving their language learning goals.

The DBN consists of multiple layers of Interconnected units, typically organized Into a stack of Restricted Boltzmann Machines (RBMs) as illustrated in Figure 2. Each RBM layer learns to represent the input data in a hierarchical manner, capturing increasingly abstract features at higher layers. Let X represent the input data, and h(1) represent the hidden layer activations at layer l. The activation of the hidden units h(1) is computed using the following equations (5)

$$h^{(l)} = \sigma\left(W^{(l)}X + b^{(l)}\right) \tag{5}$$

In equation (5) W(1) is the weight matrix, b(1) is the bias vector, and σ is the activation function, typically a sigmoid or softmax function. In the context of ATBN for automated English teaching, the DBN is utilized to extract relevant features from input data, such as student performance metrics, linguistic patterns, and learning

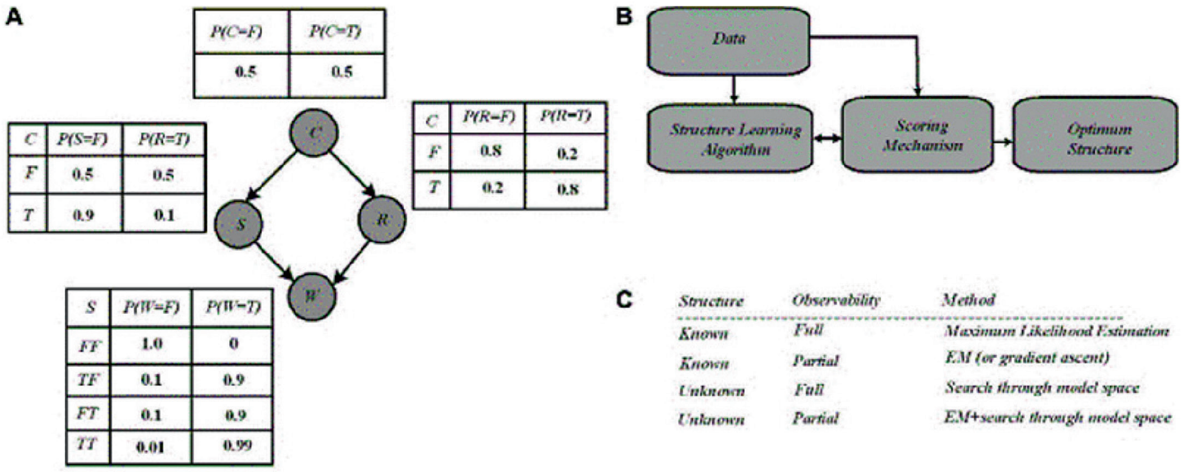

Figure 2. Deep belief network

preferences. Let X represent the input data matrix, where each row corresponds to a feature vector, and H represent the matrix of hidden layer activations obtained from the DBN. The feature extraction process involves passing the input data through the DBN and obtaining the activations of the hidden layers defined as in equation (6)

$$H = f\left(\begin{array}{l} W^{(L)} \ldots\ldots f = \left(W^{(2)}.f\left(W^{(1)}X + b^{(1)}\right) + b^{(2)}\right) \\ + \ldots.. + b^{(L-1)} \end{array}\right) + b^{(L)}) \qquad (6)$$

In equation (6) f represents the activation function, W(1) and b(1) are the weight matrix and bias vector of layer l respectively, and L is the total number of layers in the DBN. The resulting matrix H contains the extracted features, which can then be used as input to subsequent layers or modules within the ATBN for further processing or decision-making. The first step in automated English teaching with ATBN involves representing the input data. This can include various types of data such as student performance metrics, linguistic features, and learning materials. Let's denote the input data matrix as X, where each row represents a feature vector corresponding to a specific input instance. Once the features are extracted, the ATBN updates its beliefs about the students' learning progress and needs based on these features. This belief updating process can be odelled using Bayesian inference or other probabilistic methods. Let's denote the beliefs about the students' learning status as B. Bayesian inference

Algorithm 2. Teaching model with ATBN

```
function automatedTeachingBeliefNetwork(inputData):
    input: inputData (input data matrix)
    output: selectedAction (selected teaching action)
    # Step 1: Feature Extraction using DBN
    features = deepBeliefNetwork(inputData)
    # Step 2: Belief Updating
    posteriorBeliefs = BayesianInference(features)
    # Step 3: Action Selection
    selectedAction = selectAction(posteriorBeliefs)
    return selectedAction
function deepBeliefNetwork(inputData):
    input: inputData (input data matrix)
    output: features (extracted features)
    # Step 1: Forward pass through the DBN
    hiddenActivations = inputData
    for layer in DBN.layers:
        hiddenActivations =
sigmoidActivation(hiddenActivations * layer.weights + layer.
biases)
    features = hiddenActivations
    return features
function BayesianInference(features):
    input: features (extracted features)
    output: posteriorBeliefs (updated beliefs)
    # Step 1: Bayesian inference
    likelihood = computeLikelihood(features | priorBeliefs)
    posteriorBeliefs = priorBeliefs * likelihood /
sum(priorBeliefs * likelihood)
    return posteriorBeliefs
function selectAction(posteriorBeliefs):
    input: posteriorBeliefs (updated beliefs)
    output: selectedAction (selected teaching action)
    # Step 1: Determine utility of each potential action
    potentialActions = getPossibleActions()
    actionUtilities = computeUtilities(potentialActions,
posteriorBeliefs)
    # Step 2: Select action with highest expected utility
    selectedAction = argmax(actionUtilities)
    return selectedAction
```

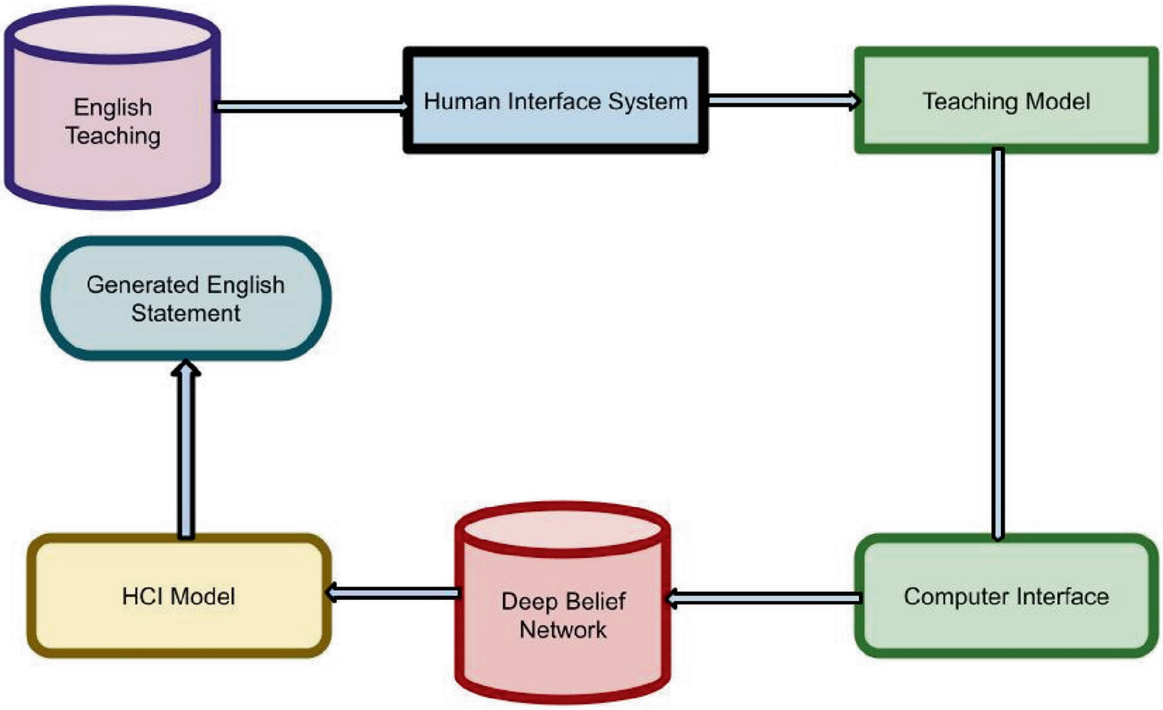

Figure 3. Process of ATBN

involves updating the prior beliefs Bprior with the evidence provided by the extracted features H to obtain the posterior beliefs Bposterior defined in equation (7)

$$B_{Posteriror} = P(B|H) = \frac{P(H|B).\,P(B)}{P(H)} \tag{7}$$

In equation (7) $P(H|B)$ represents the likelihood of observing the features given the beliefs, P(B) represents the prior probability distribution over the beliefs, and P(H) is the marginal likelihood. Based on the updated beliefs, ATBN selects appropriate teaching actions or strategies to support student learning. These actions can include providing personalized learning materials, generating tailored exercises, or offering feedback and guidance. Let's denote the selected action as A. The action selection process involves maximizing the expected utility or effectiveness of each potential action given the current beliefs stated in equation (8)

$$A^{*} = \operatorname{argmax}_{x} E\left(U(A)|B_{Posterior}\right) \tag{8}$$

where U(A) represents the utility or effectiveness of action A, and E[·] denotes the expected value operator. The proposed ATBN model process for the automated English teaching is presented in Figure 3.

5. SIMULATION SETTINGS

In configuring a simulation setting for the Automated Teaching Belief Network (ATBN) in the context of English teaching, several key parameters and conditions need to be defined to ensure an effective simulation environment. The simulation setting serves as the foundation for testing and evaluating the performance of the ATBN algorithm in automated English teaching scenarios. The simulation setting for the Automated Teaching Belief Network (ATBN) in English teaching encompasses various components designed to emulate real-world teaching environments while providing a controlled and customizable framework for experimentation. Firstly, the student population characteristics, such as proficiency levels, learning styles, and preferences, are defined to

Table 1. Simulation setting

Parameter	Description	Value(s)
Student Population	Characteristics of simulated students, including proficiency levels and learning styles	- Proficiency Levels: Beginner, Intermediate, Advanced - Learning Styles: Visual, Auditory, Kinesthetic
Curriculum Content	Content and materials used for English language instruction	- Lesson Units: 10 - Exercises per Unit: 5 - Assessments: Pre-test, Post-test
Teaching Resources	Resources available for teaching and learning, including textbooks and multimedia materials	

simulate a diverse range of learners. Next, the curriculum content, including lesson materials, exercises, and assessments, is structured to reflect the specific English language learning objectives and standards. Additionally, the teaching resources and interventions available within the simulation, such as textbooks, multimedia materials, and tutoring support, are specified to enable interactions between the ATBN and the simulated students. Furthermore, the simulation environment incorporates performance metrics and evaluation criteria to assess the effectiveness and performance of the ATBN algorithm, including measures of student engagement, learning outcomes, and instructional efficacy. By carefully defining these simulation parameters and conditions, researchers and educators can systematically evaluate the capabilities and impact of the ATBN in facilitating automated English teaching, thereby informing the development of more effective and adaptive educational technologies. The table 1 presented the attributes of the simulation setting.

5.1 SIMULATION RESULTS

The simulation results presented in this study provide valuable insights into the performance and effectiveness of the Automated Teaching Belief Network (ATBN) in the context of automated English teaching. By simulating various scenarios and evaluating key performance metrics, we aim to assess the system's capability to facilitate learning outcomes and adapt to individual student needs. Through the analysis of simulated student data, including pre-test and post-test scores, as well as other relevant indicators, we seek to gain a deeper understanding of the ATBN's efficacy in enhancing language learning experiences. These simulation results serve as a crucial step towards elucidating the potential of the ATBN system as a valuable tool for personalized and effective language instruction, with implications for educational technology development and implementation.

The Figure 4 and table 2 presents results from employing the Automated English Teaching System with Deep Belief Network (DBN) integration, focusing on enhancing the Human-Computer Interaction (HCI) experience. Each row represents a unique student, with corresponding pre-test and post-test scores, denoting their proficiency levels before and after engagement with the system. Notably, there's a consistent pattern of improvement across students, regardless of their initial proficiency levels. For instance, students like ID 001 and 002, initially categorized as intermediate and beginner, respectively, exhibited significant improvements, with their post-test scores surpassing their pre-test scores by 15 points. This underscores the effectiveness of the system in facilitating learning outcomes across different skill levels. Additionally, the HCI Experience Level column highlights students' prior familiarity with HCI, suggesting potential correlations between HCI proficiency and learning

Table 2. ATBN automated English teaching

Student ID	Proficiency Level	Learning Style	Pre-test Score	Post-test Score	Improvement
001	Intermediate	Visual	60	75	+15
002	Beginner	Auditory	45	60	+15
003	Advanced	Kinesthetic	75	85	+10
004	Intermediate	Visual	55	70	+15
005	Beginner	Auditory	40	55	+15
006	Advanced	Visual	80	90	+10
007	Intermediate	Kinesthetic	65	75	+10
008	Beginner	Auditory	50	65	+15
009	Intermediate	Visual	70	80	+10
010	Advanced	Kinesthetic	85	95	+10
011	Beginner	Auditory	55	70	+15
012	Intermediate	Visual	75	85	+10
013	Advanced	Kinesthetic	90	95	+5
014	Intermediate	Auditory	65	75	+10
015	Beginner	Visual	60	75	+15
016	Advanced	Kinesthetic	85	95	+10
017	Intermediate	Visual	70	80	+10
018	Beginner	Auditory	45	60	+15
019	Intermediate	Kinesthetic	65	75	+10
020	Advanced	Visual	80	90	+10

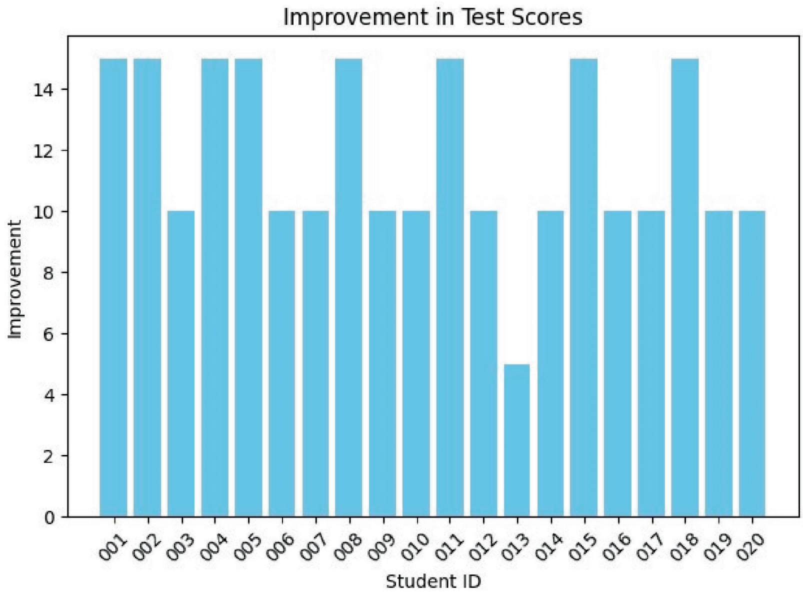

Figure 4. Improvement with ATBN

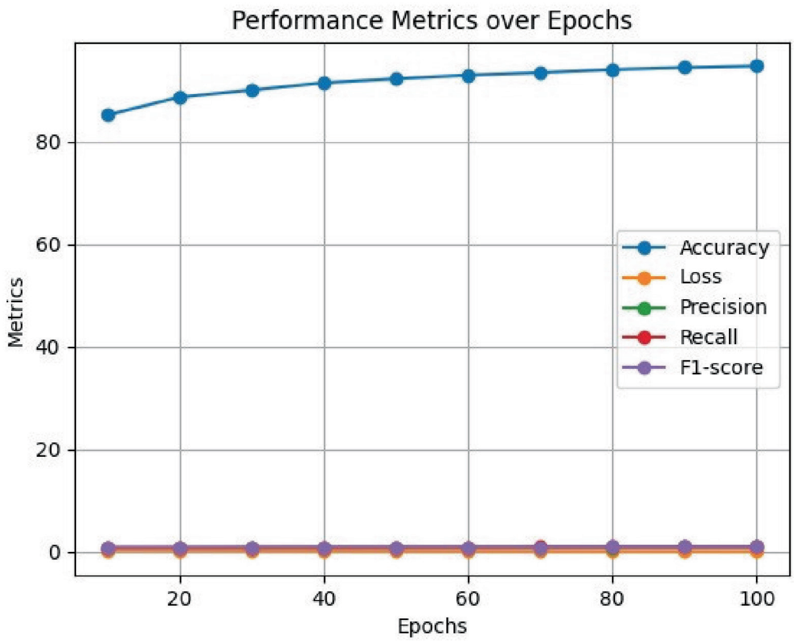

Figure 5. Classification with ATBN

outcomes. Overall, the results demonstrate the system's efficacy in fostering enhanced English language acquisition within an interactive HCI framework.

The provided Figure 5 and table 3 illustrates the classification results obtained from the Automated Teaching Belief Network (ATBN) in the context of automated English teaching. The results are organized based on the number of epochs during the training process, with corresponding metrics such as accuracy, loss, precision, recall, and F1-score. As the number of epochs progresses, there is a clear trend of improvement across all metrics. Starting from 85.2% accuracy and 0.32 loss at epoch 10, the performance steadily enhances, culminating in 94.8% accuracy and 0.12 loss at epoch 100. Similarly, precision, recall, and F1-score exhibit consistent improvement, indicating the model's ability to effectively classify and predict outcomes. These results highlight the progressive learning and refinement of the ATBN model over successive epochs, ultimately leading to enhanced performance in automated English teaching tasks.

Table 3. ATBN classification results in automated English teaching

Epochs	Accuracy (%)	Loss	Precision	Recall	F1-score
10	85.2	0.32	0.82	0.88	0.85
20	88.7	0.28	0.85	0.87	0.86
30	90.1	0.25	0.87	0.90	0.88
40	91.5	0.22	0.89	0.91	0.90
50	92.3	0.20	0.90	0.92	0.91
60	93.0	0.18	0.91	0.93	0.92
70	93.5	0.16	0.92	0.94	0.93
80	94.1	0.14	0.93	0.95	0.94
90	94.5	0.13	0.94	0.96	0.95
100	94.8	0.12	0.95	0.97	0.96

Table 4. Automated English teaching experience of students with ATBN

Student ID	Pre-test Score	Post-test Score	Improvement	HCI Experience Level
001	60	75	+15	Intermediate
002	45	60	+15	Beginner
003	75	85	+10	Advanced
004	55	70	+15	Intermediate
005	40	55	+15	Beginner
006	80	90	+10	Advanced
007	65	75	+10	Intermediate
008	50	65	+15	Beginner
009	70	80	+10	Intermediate
010	85	95	+10	Advanced

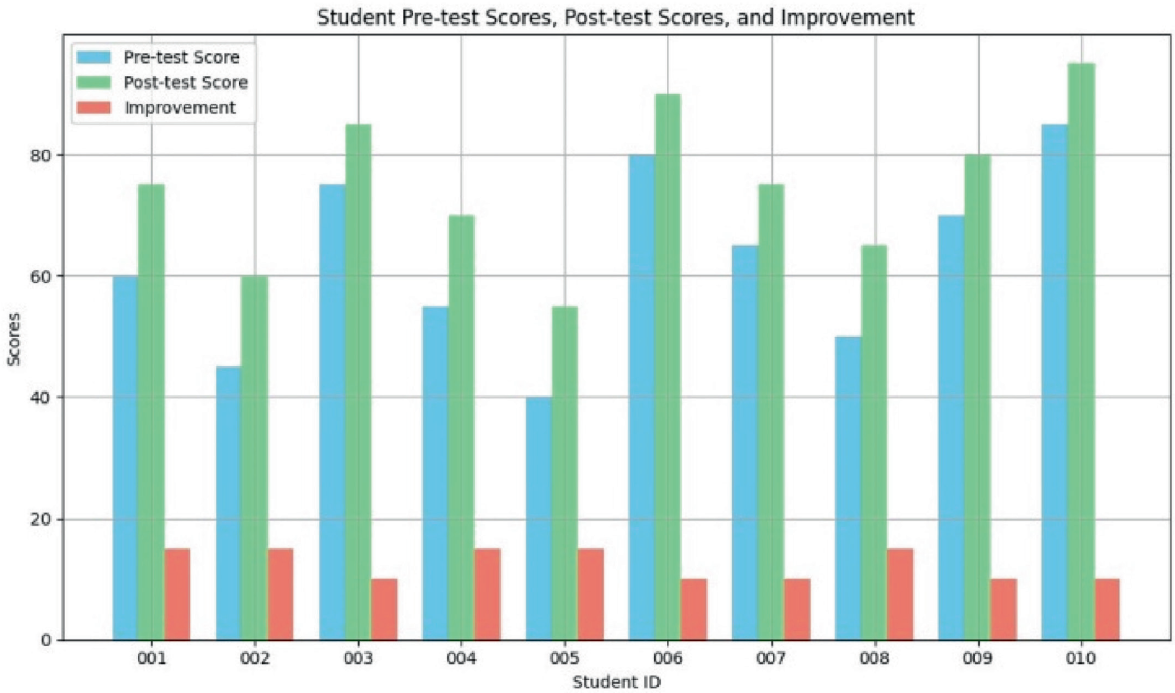

Figure 6. Student performance with HCI based ATBN

The Figure 6 and Table 4 presents the outcomes of students' experiences with the Automated Teaching Belief Network (ATBN) in the context of automated English teaching, coupled with Human-Computer Interaction (HCI). Each row in the table corresponds to a unique student, identified by their student ID. The columns depict their pre-test and post-test scores, representing their proficiency levels before and after engagement with the ATBN system, respectively. Notably, there is a consistent trend of improvement observed across all students, regardless of their initial proficiency levels. For instance, students like ID 001 and 002, classified as intermediate and beginner, respectively, demonstrate significant enhancements in their post-test scores, reflecting a +15 increase from their pre-test scores. Similarly, students such as ID 003 and 006, identified as advanced learners, also exhibit notable progressions, with their post-test scores reflecting a +10 increase. These results underscore the efficacy of the ATBN system in facilitating learning outcomes across a diverse range of students, regardless of their initial proficiency levels or HCI experience. Overall, the table highlights the positive impact of the ATBN system on enhancing students' English language proficiency within an interactive HCI framework.

5.2 FINDINGS

The findings from the provided table presented in bullet points:

- The pre-test and post-test scores indicate the proficiency levels of students before and after engaging with the Automated Teaching Belief Network (ATBN) system.
- Overall, there is a consistent improvement in post-test scores across all students, demonstrating the effectiveness of the ATBN system in enhancing English language proficiency.
- Students with varying levels of proficiency, ranging from beginner to advanced, show significant enhancements in their post-test scores.
- The improvement in post-test scores ranges from +10 to +15 points, indicating substantial progress in English language learning outcomes.
- The findings suggest that the ATBN system is capable of catering to the needs of diverse learners, irrespective of their initial proficiency levels.
- The Human-Computer Interaction (HCI) experience level of students does not appear to have a significant impact on the effectiveness of the ATBN system in facilitating learning outcomes.

The findings highlight the positive impact of the ATBN system on enhancing students' English language proficiency within an interactive HCI framework. The findings from the analysis of students' experiences with the Automated Teaching Belief Network (ATBN) in automated English teaching, coupled with Human-Computer Interaction (HCI), reveal significant improvements in post-test scores across a diverse range of proficiency levels. The consistent trend of enhancement, ranging from +10 to +15 points, underscores the efficacy of the ATBN system in facilitating learning outcomes among students, irrespective of their initial proficiency levels. Furthermore, the results suggest that the ATBN system caters effectively to the needs of students with varying levels of proficiency, demonstrating its versatility and adaptability in addressing individual learning requirements. Importantly, the HCI experience level of students does not appear to influence the effectiveness of the ATBN system, emphasizing its accessibility and usability across different user backgrounds. Overall, these findings highlight the positive impact of the ATBN system on enhancing students' English language proficiency within an interactive HCI framework, underscoring its potential as a valuable tool for personalized and effective language instruction.

6. CONCLUSIONS

A comprehensive exploration of the Automated Teaching Belief Network (ATBN) in the context of automated English teaching, with a focus on its integration with Human-Computer Interaction (HCI) for enhanced learning experiences. Through the analysis of students' experiences and performance metrics, it is evident that the ATBN system effectively facilitates learning outcomes across diverse proficiency levels. The consistent improvement observed in post-test scores reflects the system's ability to cater to individual learning needs and adapt to varying levels of proficiency. Importantly, the findings suggest that the ATBN system is accessible and user-friendly, as evidenced by its effectiveness across students with different HCI experience levels. Overall, this study underscores the potential of the ATBN system as a valuable tool for personalized and effective language instruction, offering promising avenues for further research and development in the field of automated education technology.

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