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ORIGINAL

Research on Multimodal College English Teaching Model Based on Genetic Algorithm

Investigación sobre el modelo multimodal de enseñanza universitaria del inglés basado en el algoritmo genético

Anber Abraheem Shlash Mohammad[1,2], Mai alshebel[3], Badrea Al Oraini[4], Asokan Vasudevan[5], Suleiman Ibrahim Shelash Mohammad[6,7], Huiying Jiang[8], Aktham Al Sarayreh[9]

[1]Digital Marketing Department, Faculty of Administrative and Financial Sciences, Petra University, Jordan.
[2]Research follower, INTI International University, 71800 Negeri Sembilan, Malaysia.
[3]Assistant Professor of Business Administration, Faculty of Business Studies, Arab Open University, Riyadh, Saudi Arabia.
[4]Department of Business Administration, Collage of Business and Economics, Qassim University, Qassim - Saudi Arabia.
[5]Faculty of Business and Communications, INTI International University, 71800 Negeri Sembilan, Malaysia.
[6]Department of Business Administration, Business School, Al al-Bayt University, Jordan.
[7]Research follower, INTI International University, 71800 Negeri Sembilan, Malaysia.
[8]Faculty of Liberal Arts, Shinawatra University, 99 Moo 10, Bangtoey, Samkhok, Pathum Thani, Thailand.
[9]Al Balqa Applied University / Amman University College Financial & Managerial Science, Jordan.

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ABSTRACT

Analyzing College English texts is essential for quantitatively evaluating their grammar, phrases, and words to enhance their use in writing, conversation, and other contexts. The precise and clear use of College English words, phrases, and sentences is essential to knowledge-based and foundational learning systems. Text data analytics run into problems with data amount, data diversity, data integration and interoperability. It is challenging to accomplish human-computer interaction in spoken College English communication and to assist students with corrections using the conventional methodology of teaching College English. Therefore, this paper proposed the Genetic Algorithm-based intelligent English course optimization system (GA-IECOS) to handle the scheduling above issue of college English classes and optimize college English teaching courses. The results demonstrate that the conventional BP neural network's local scheduling optimization issue may be resolved using the multidirectional mutation genetic BP neural network method. Subsequently, a mix of formative and summative assessments will be used to establish a couple of groups to evaluate the effectiveness using a control population and a trial group of a GA-IECOS for English language classes using a multidirectional mutation genetic algorithm and an optimization neural network. The results demonstrate that the GA-IECOS algorithm is more effective in the classroom and may greatly improve students' English performance.

Keywords: Genetic Algorithm (GA); College; Students; English Course; BP Neural Network; Teaching// Education.

RESUMEN

Analizar textos de inglés universitario es esencial para evaluar cuantitativamente su gramática, frases y palabras para mejorar su uso en la escritura, la conversación y otros contextos. El uso preciso y claro de palabras, frases y oraciones en inglés universitario es esencial para los sistemas de aprendizaje fundamentales y basados en el conocimiento. El análisis de datos de texto tiene problemas con la cantidad de datos, la diversidad de datos, la integración de datos y la interoperabilidad. Es un desafío lograr la interacción persona-computadora en la comunicación hablada en inglés universitario y ayudar a los estudiantes con las correcciones utilizando la metodología convencional de enseñanza de inglés universitario. Por lo tanto, este artículo propuso el sistema inteligente de optimización de cursos de inglés basado en algoritmos genéticos (GA-IECOS) para manejar la programación mencionada anteriormente de las clases de inglés universitario y optimizar los cursos de enseñanza de inglés universitario. Los resultados demuestran que el problema de optimización de la programación local de la red neuronal BP convencional puede resolverse utilizando el método de red neuronal BP genética de mutación multidireccional. Posteriormente, se utilizará una combinación de evaluaciones formativas y sumativas para establecer un par de grupos para evaluar la efectividad utilizando una población de control y un grupo de prueba de un GA-IECOS para clases de inglés utilizando un algoritmo genético de mutación multidireccional y una red neuronal de optimización. . Los resultados demuestran que el algoritmo GA-IECOS es más efectivo en el aula y puede mejorar en gran medida el rendimiento en inglés de los estudiantes.

Palabras clave: Algoritmo Genético (GA); Universidad; Estudiantes; Curso de Inglés; Red Neuronal BP; Enseñanza//Educación.

INTRODUCTION

Amidst the backdrop of economic integration, basic literacy in English has emerged as a prerequisite for higher-level talent, raising the bar for English language instruction and posing new obstacles for higher education institutions.[1] Teachers of English at the university level would do well to keep up with the latest research in the field, make full use of the opportunities presented by innovative pedagogy in today's classrooms, and strive for the utmost scientific rigour in their lessons. For the greater good of society, they should likewise seek to develop more practical, high-quality skills.[2]

To increase the optimization efficiency, one of the most common conventional optimization strategies is the optimization of traditional instructional courses. However, the optimization algorithm can't see the big picture since course selection is based on past performance, current teaching methods, and results from several trials; moreover, the accuracy of approximation analysis drops dramatically when the need for individualized instruction rises.[3,4] New optimization approaches have recently been the subject of much investigation and study. One avenue of inquiry in the optimization of curricula is the use of BP neural networks. In light of the current state of research on graded instruction, the emotional and psychological challenges faced by students, and the challenges associated with its implementation in the realm of teaching management, this body of literature provides, based on optimization research on the instructional method, a set of efficiency metrics for college English language education modules.[5,6]

As the article explains, reforming foreign language instruction aims to integrate demand analysis theory with graded teaching. Based on demand analysis theory, graded instruction is a powerful tool for shifting the focus of college English instruction away from standardized, one-size-fits-all lessons and toward more individualized plans for each student.[7,8] Some have argued that the methodological concepts of scientifically directing instruction and properly structuring the teaching process are upheld by the notion of genetic algorithms used to optimize the teaching process. Interior and outside factors, as well as the rules, ideals, obligations, formats and procedures of modern education, form the foundation of the teaching system's features. Among the many possible applications of this theory in College English instruction, it serves as a theoretical foundation for graded teaching.[9,10]

Formative and summative assessments are increasingly used in university student evaluations of College English classes. Class participation, homework, attendance, and the outcomes of group projects are all examples of formative assessment.[11] Typically, the instructor or learning committee will assist in recording the data of the total number of participants and their performances. Teachers have a hard time accurately calculating the matching normal scores for each student when it comes time to tally up all students' test results after the study session. So, people tend to accept random ratings or scores based on first impressions. An assessment like this hinders the growth of teacher-classroom connection and makes it hard to increase students' motivation to study.[12,13]

A means of evaluating educational progress Utilizing an improved neural set network with a genetic algorithm and an autonomous characteristic connecting the neural set system, this research uses college English to conduct extensive and classified assessments.[14] Because of this, the network can be generalized well and exhibit the nonlinear properties of the system. Matching the evaluation factor weights is crucial to many of these index types; the weights' value directly impacts the assessment outcomes. As database sizes skyrocket, optimizing queries becomes a massivechallenge.[15] Using a multimodal GA first to decrease the search space improves the algorithm's search accuracy by maximizing the amount of relevant documents retrieved if there are too many or too few. Smart scheduling for classes may use adaptive genetic algorithms because of their simplicity, low price, and capacity to handle the easy and difficult class scheduling needs. Due to its diverse coding style, exceptional parameter robustness, and novel population search strategy, genetic algorithms are perfect for optimizing schedules with many objectives and constraints. College English scheduling uses genetic algorithms because of its novel population search approach, diverse and adaptable coding, and outstanding parameter robustness.[16,17]

The main objectives are:

a) Multimodal methods of instruction show learners a variety of educational forms and platforms, which can deepen their knowledge regarding the courses and enhance classroom instruction while improving the quality of education.

b) The College English scheduling problem optimization task in BP networks has been assigned to the Genetic Algorithm based on its exceptional parameter resilience, diversified and flexible coding, and distinctive population search technique.

c) This research presents a novel approach to optimizing College English language teaching. It draws on the multidirectional mutation Genetic Algorithm and its optimized BP neural network based on the proposed GA-IECOS.

This section of the paper follows: section 2 provides a literature overview of the pertinent works. The suggested strategy for teaching College English using many media is then laid out in Section 3. Section 4 gives the experimental findings after the presentation of the proposed approach. Conclusions and an outline of the study are included in Section 5, which concludes the article.

Related survey

Generalization and self-learning allow the neural set network to represent complicated nonlinear mapping precisely and learn from samples and abstract applicable rules. In recent years, numerous academics have used neural set networks to evaluate College English course teaching models. Forecasters use neural set networks. College English course teaching quality has been under-tested compared to other areas where academics have used neural set networks improved by genetic algorithms for evaluation purposes. Using a genetic algorithm optimization neural set network, this study enhances the quality evaluation model for university college English courses, addressing the shortcomings and offering a more efficient solution.

Qin[18] have developed an IoT-based grading system for spoken College English education that considers students' use of many senses. At first, certain fixed-dimensional visual and auditory elements from the IoT are extracted and quantified using a trained convolutional neural network (CNN) model. By obtaining the top ranks and an accuracy of 88,8 %, our scoring model for oral College English education outperforms others by more than 2 %, as shown in our data.

Compared to the traditional way of instruction, the multimodal approach was demonstrated to be more effective in improving students' learning outcomes from the midterm to the conclusion of the term by Qin et al.[19], where they were previously proficient in just College English. Because class B typically had a higher College English level, students' grades improved by 24 % between the midterm and final before and after implementing multimodal instruction. Using textbooks with the same level of difficulty, this paper's experimental findings demonstrated that most students' final grades would improve in the class with poor college English proficiency.

Zhang et al.[20], one decision-making method is the analytic hierarchy process (AHP), which uses quantitative thinking to deal with qualitative problems. Using four facets—students' attitudes and beliefs regarding implementing multimodal teaching—the author offers AHP-based techniques for boosting the effect of multimodal instructional materials in upper technical College English. Among these aspects are creating a multimodal teaching environment, using multimodal teaching materials, and creating multimodal activities for instruction.

Based on research into college English instructors' practices, Fan[21] examines how to build multimodal experiential teaching from the ground up using the idea of allosteric learning. A multimodal experiential learning model grounded on metamorphic learning is put out to examine the need for multimodal instruction in college English courses. A multimodal experiential teaching approach is suggested for use in college English classes following the notion of multimodal experience learning.

Chen[22] proposes a method for instructing graduate students in multimodal academic English writing using the field's history of IT applications as a foundation. Because it encourages the digital and three-dimensional evolution of English education, multimodal teaching is typical of reinventing the English teaching system. Graduate students' ability to do independent research and articulate their scholarly opinions depends critically on their mastery of academic English writing.

Using activities derived from multimodal Vocabulary theory, the experimental class by Jin[23] teaches English, while the control class sticks with the tried-and-true technique of teaching English vocabulary. Research findings indicate that linguistic symbols and the multimodal vocabulary instruction method work together to contribute to the meaning-making process. Their collaboration can enhance students' holistic abilities in hearing, speaking, reading, writing, and translating while simultaneously mobilizing their initiative to acquire new words.

Proposed framework

Learning College English is the foundational public offering. In the educational system, the impact on student learning and the quality of college English instruction directly affects other teaching aspects. Higher education English teaching that relies on conventional methods has struggled with student engagement and the impact of its lessons for a long time despite implementing reforms to these courses. Education and teaching are transforming profoundly, driving this change by providing new techniques and resources. Smart and efficient classroom teaching can be achieved via the thorough integration and innovation of neural network systems with academic English instruction and study. Students' excellent value orientation and ideological quality can be better fostered. Digital education is made feasible by combining algorithms with sophisticated equipment in the classroom. The advancements in science and technology, as well as the fast-paced growth of the economy, are connected to the development of College English skills in college smart classrooms that rely on neural networks. This article primarily examines an automated smart classroom paradigm for teaching College English at the university level. Throughout the lesson, instructional tasks are carried out with the help of human-computer interaction technology. Teachers and students may engage in real-time engagement via the e-mobile Internet. Students may get lesson materials over the Internet in advance. Instructors have more freedom to move around and concentrate on student engagement. The students may easily and adaptably arrange the tables and chairs into a circular pattern for group discussions. Through mobile devices, group members may improve communication and involvement by discussing concerns, creating visualizations, and more.

The control group follows the prior model's instructions for teaching college English, while the participants in the experiment use a smart classroom approach that lasts for semesters. The entire textbook is structured per the same unit format. The experimental class units' hearing, speaking, reading, and writing instruction is delivered using smart classroom methods. Lessons in the experimental class included introducing the curriculum, students engaged in autonomous listening and speaking, and instructors facilitating debate and exchange. Figure 1 is the instructional activity framework of the experimental class. It shows that each unit's reading materials should be distributed to students before class. In class, students use the micro-videos of these materials for background learning to lead in topics through illumination, inquiry, and guidance.

This helps students understand the topic better, builds their knowledge of related concepts, and prepares them for the development of listening activities. The platform is then sent to the instructor with the listening materials and learning assignments. The students finish the work according to their rhythm by adjusting the record speed. The system provides quick feedback on the outcomes. In autonomous listening, the steps are as follows: students listen to the recordings, do the activities, get rapid feedback from the system, and then listen to the recordings again. Teachers will also provide students with visuals and textual examples to help them better grasp the College English reading materials they are reading. Teachers are capable of facilitating student participation in communication activities. The significance of thinking is highlighted here, and pupils are asked to ponder for one minute. Teachers may enrich their pupils' learning by assigning real-world issues that motivate them to express themselves via language. Concurrently, educators may have students engage in man-machine communication to encourage active participation from all participants. The assessment and correction of mistakes tasks are best completed after class, so instructors should remind pupils to participate. Students know enough to contribute after the first two phases of speaking and listening. Students should be required to engage in additional activities to apply what they have learned; for instance, they may practice speaking before writing. As their knowledge grows, they will be able to encourage higher-level cognition. Instead of emphasizing the teacher's "teaching" and the students' "learning," the two groups should work together to succeed.

Along with assessing how well students have learned, it is important to consider how engaged they are, how much they know, how well they can apply what they have learned, and how conscious they are of collaboration and communication in the learning process. No one other than instructors, parents, and students should be considered when assessing the impact of learning. Student self-evaluation has the dual benefit of fostering self-education and mobilizing learning passion. Hence, pupils should not only be motivated to self-evaluate their learning but also to have their performance evaluated by instructors.

In this work, the paper experiments in class using the factors above and compares their learning outcomes before and after using the smart class College English teaching methodology. In contrast, the dynamic teaching method calls for more than fact sorting and activity provision when planning sessions. While students' knowledge and abilities are strengthened, their thinking is challenged. The hallmark of dynamic instruction is the ability of instructors to take course materials and turn them into practical lessons while also planning engaging classroom activities that will challenge students' thinking and help them retain more information. Lesson content modification by teachers is crucial, and classroom activities reflect the results of teachers' knowledge point change.

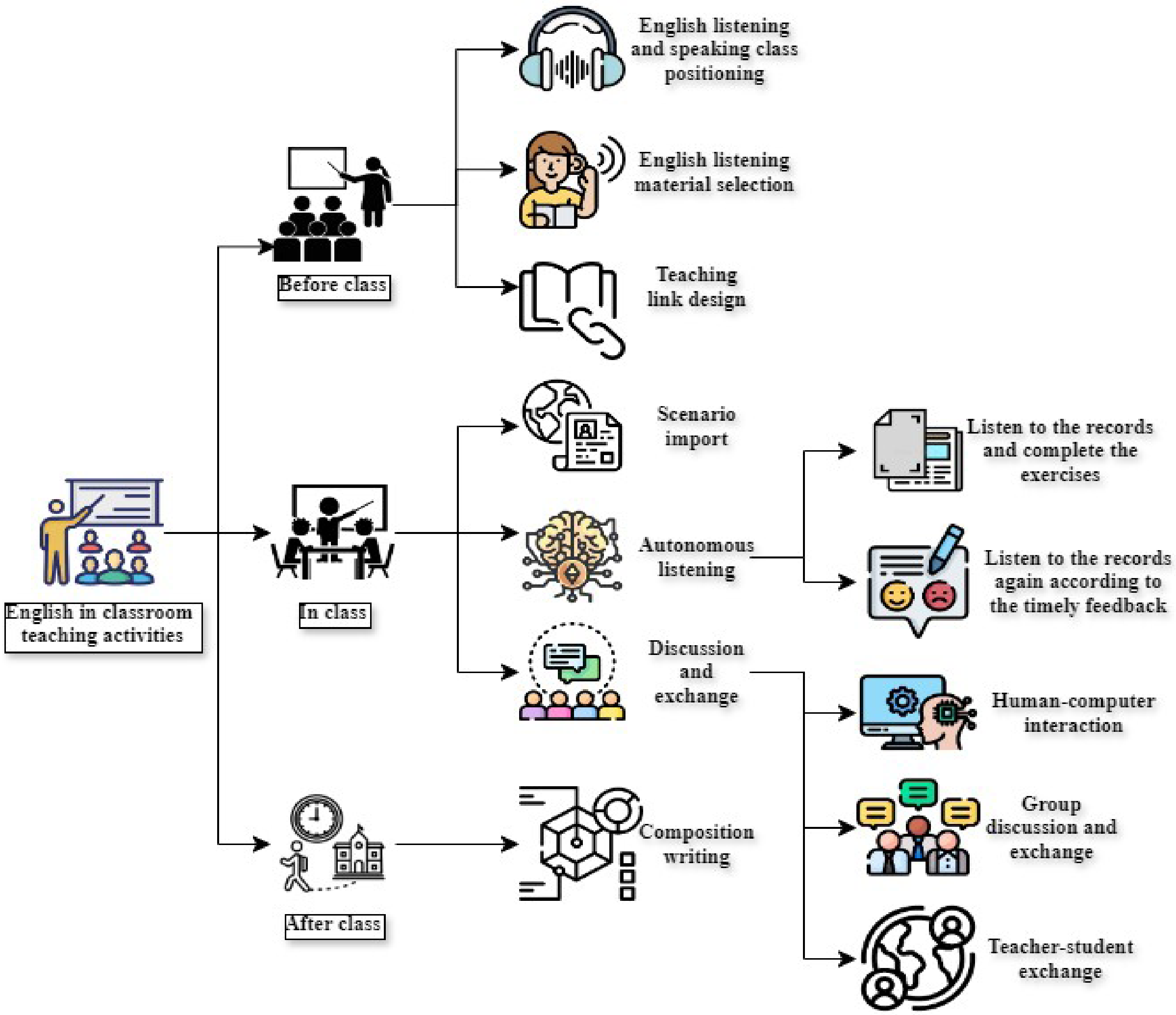

Figure 1. College EnglishTeaching Activity Model

The Internet has permeated educational institutions in the same way that it permeates employment factor distribution; both use information technology to reasonably optimize teaching environments in educational institutions for College English and improve pupils' educational results in these courses. The significance of actively incorporating computer and network technology into college English education has been highlighted. Using a developed at-random genetic algorithm isn't the way to go regarding college English education. When supplies are restricted, professors are forced to teach numerous courses under different grades, and classrooms may have to plan several courses. There are still unanswered questions about the College English scheduling problem, even though many scholars have made substantial efforts to find a better solution. An example is the need for the starting population not to have any persons involved in conflicts. Furthermore, the fitness function's design lacks the flexibility to adjust to new conditions adequately. The teacher will indeed put restrictions on the classroom setting, but these are the only restrictions for which the fitness function in this research accounts. There will be future maintenance challenges with the scheduling system because of this. Present scheduling methods, such as intelligent scheduling systems, do not adequately address certain schools' complex and unique needs regarding things like school-based course scheduling, tutor classes, long and short courses, and other similar issues. Starting from these problems, instead of considering potential conflicts in class schedules when generating the starting population, we implement a method to automatically split the teaching courses, thereby resolving the College English scheduling issue. As a result, the initial population doesn't require any practical solutions. We can automatically identify and eliminate on-target possibilities by integrating altering genes into the variability operator. The results of the practical evaluation section show how well the algorithm works when faced with real-life class scheduling problems. In addition, this research delves into the pedagogical practices of a university College English class and creates a genetic algorithm-driven social network for ESL students.

A meta-heuristic technique like the genetic algorithm (GA) could be useful when looking for the best possible answers. The genetic algorithm was implemented throughout its development, as shown in figure 2, a flow diagram. Genetic algorithms in the classroom are highly recommended due to their high imitative qualities, artificial intelligence capabilities, and practical usefulness.

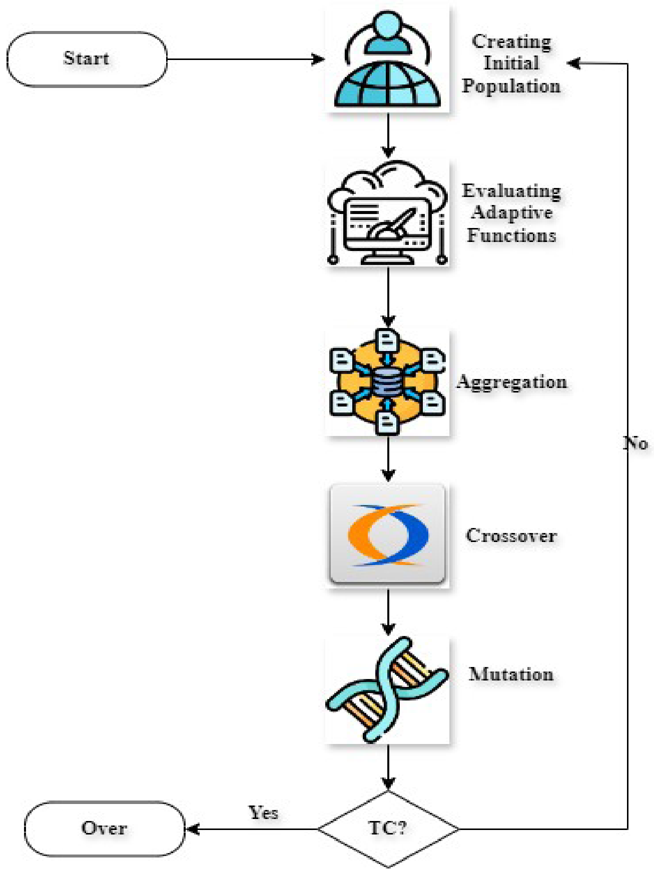

Figure 2. GA for class scheduling problem optimization

Each of the five steps of the genetic algorithm—initialization, assessment of the fitness function, aggregation, crossover, and mutation—involves five operations, as shown in figure 2. Three separate types of issues, each with its specific specification, are amenable to genetic algorithms: Many population variables have their labels specified by the adaptable operation, while the chosen procedure follows the "choose the most effective and exclude the rest" methodology. Genetic studies make use of molecular genetic operators such as instability and recombination. Mutations result from alterations to the crossover operation, while players executing crossovers are responsible for swapping sets of genes within a chosen population. Each chromosome represents a cluster grouping according to the clustering criteria, and a single tweet represents a population. Similar to how a gene is an object with clustered allele values, each tweet is grouped along with chromosomal genes with the same allele value. To implement these two concepts, computer scientists must see genetic code and genomes as collections of arrays. The first method separates allele values to create bigger clusters or strengthen existing ones, while the second involves combining them. Each mapper receives equal input, revealing the selection, adaptive function, and startup phases. Following this, the reducer receives the data derived by the fitness parameter cross-tracking and mutation at different points in time. The fundamental objective of the scheduling problem is to arrange courses, teachers, and classrooms in a manner that does not conflict while satisfying the instructor's needs and providing ideal or almost ideal results. Figure 1 shows a computational representation of the scheduling issue, which consists of the following elements: sessions (AC), groups (FC), teachers (GC), learning environments (HC), and scheduled intervals (QC) are shown in equation (1):

$$\begin{aligned} FC &= \{f_1, f_2, \dots, f_k\}, \\ AC &= \{a_1, a_2, \dots, a_k\}, \\ GC &= \{g_1, g_2, \dots, g_k\}, \\ HC &= \{h_1, h_2, \dots, h_k\}, QC = \{q_1, q_2, \dots, q_k\}. \end{aligned} \quad (1)$$

Finding two lecture periods that work within the parameters and avoid scheduling conflicts amongst teaching resources is the key to solving the scheduling dilemma. Class schedules for each grade level may then be determined. After that, we can determine the connection between learning environments, instructors, groups, and programmes. Finally, we can form a set of lectures, denoted as R={f,a,g,h,q}.

Requirements for Carrying Out Work

When making a class schedule, it's important to think about how much time and space each element will take up and whether or not they will adhere to certain restrictions the faculty sets. These restrictions should prevent schedule elements from conflicting with one another, allow for the most efficient combination and allocation of teaching resources, and ensure that regular teaching can occur. You may think of constraints in two ways: hard and soft.

The following picture illustrates the scheduling process and its hard constraints, which are the criteria that must be satisfied. We can only be sure that the scheduled resources will not collide if the schedule fulfils the hard constraints.

During any instructional session, no more than one course, including the same instructor, may be arranged as shown in equation (2).

$$\sum_{y=1}^{AC}\sum_{n=1}^{QC}\sum_{m=1}^{FC} c_y\, q_n f_m e_i w_s \leq 1 \quad (2)$$

No more than one class may be booked in the same classroom during any given time period as shown in equation (3).

$$\sum_{s=1}^{HC}\sum_{n=1}^{QC}\sum_{m=1}^{FC} c_y\, q_n f_m e_i w_s \leq 1 \quad (3)$$

A single instructor may set up a limit of one course per teaching time as shown in equation (4).

$$\sum_{i=1}^{GC}\sum_{n=1}^{QC}\sum_{m=1}^{FC} c_y\, q_n f_m e_i w_s \leq 1 \quad (4)$$

We can't have teachers who have mutually exclusive rules and teach simultaneously.

$$q_1 \neq q_2 \quad (5)$$

According to equation (5), in scheduling, "soft constraints" refer to pre-scheduling faculty requirements that aren't strictly necessary but have a major impact on the schedule's logic and the satisfaction of its users.

A schedule's performance is affected in the following ways by how strictly it follows these rules:

1. As much as feasible, space out the weeks of the same class.
2. Priority courses should be arranged in the most prioritized session; for example:
    a) The beginning of the day is the best time to arrange the major course.
    b) The teacher's arranged scheduling will show you the number of recurrent courses.
    c) The order of the classes is not always sequential.

The Function of Fitness

Because it details the individual's strengths and weaknesses (class schedule), fitness is a major signal in genetic algorithms. Individuals are selected based on their fitness during the algorithm's iterative phase. If the genetic algorithm can find the global optimal solution, it depends on how the fitness function is built. This paper presents a fitness function that accounts for a high school course load's specific by considering course priority and schedule uniformity. It also includes a penalty for students who fail to adhere to strict and more lenient requirements.

A course scheduling approach may be evaluated using section priority criteria. The teacher may decide which classes are most important before they're scheduled; for instance, the first session may be scheduled first thing in the morning. The instructor would likely assign higher priorities to classes if more of them in the schedule meet the priority rule. In this work, the section priority is defined as l_1, and the equation (6) for l_1 is:

$$l_1 = \delta^{vios} \quad (6)$$

Where δ is usually between 0,90 and 0,991, the impact factor of the importance of the course sections. This value indicates the number of times the scheduling scheme's course arrangement violates the section priority rule, and a smaller value for l_1 is obtained for a higher number of violations.

Course uniformity, denoted as s_f, is a way to quantify the degree to which a class's courses are spread throughout the week. There shouldn't be excessive concentration on any subject at any time of the week;

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therefore, classes should be distributed equally as feasible.

As a starting point, let's think about the consistency of s_{ffor} one class and one course, which may be expressed in equation (7):

$$s_f = \frac{1}{1+1/R\sum_{n=1}^{R}|q_n-\acute{q}|} \qquad (7)$$

The next thing to consider is the consistency of a class's course schedule, represented by ρ_c, which is determined as $\rho_c=1/F\ \Sigma_{(F=1)}sb$.

Here, R stands for the weekly schedule, F for how many lessons are covered in the course, q_n for the amount of time allotted for that particular day, q´ for the typical daily duration, as shown in equation (8).

$$\acute{q} = \frac{q_{period}}{r} \qquad (8)$$

Where q_{period} is the number of hours per week and r is the number of days per week of the course; for the sake of this paper, we will assume r= 5. The study defines l_2 as the uniformity of course scheduling for all classes. A better scheduling solution is achieved with a bigger value of l_2, which is computed in equation (9):

$$l_2 = \frac{1}{C}\sum_{c=1}^{C}\rho_c \qquad (9)$$

Where C is the number of courses.

The schedule's fitness is reduced if it does not adhere to the requirements by checking for hard and soft constraint violations. The level of adaptive compromise increases as the frequency of transgressions increases. Following the indication of the penalty degree by is the corresponding equation (10).

$$\beta = \alpha_1^{hard\_vios} \cdot \alpha_2^{soft\_vios} \qquad (10)$$

The formula indicates that the frequency with which a person disobeys strict regulations is represented by hard_vios, and the percentage of the time a person breaks loose restrictions is represented by soft_vios. The penalty factors α_1 and α_2 are from 1 to 10, with $\alpha_1<\alpha_2<1$. The priority is to eliminate conflicts involving hard constraints. The evolutionary effect is significantly affected by the values of α_1 and α_2. A small value will cause other elements to have a minor influence on overall fitness, while a big value will cause a tiny penalty on the fitness value. A small value will also cause a huge rise in fitness.

Before developing a multimodal teaching model for college English, it is necessary to understand the group characteristics of college students. College students are distinct from their high school counterparts. College students have matured psychologically, gained much life experience, and entered the adult growth stage. Their varied backgrounds and experiences can shape the dynamic social landscape. Concurrently, it displays an obvious defiance of authority. The characteristics of college students inform the design of College English multimodal instruction. Our second topic is the fundamentals of controlling the computer's haptic, aural, and visual effects. The visual, aural, and tactile senses help college students learn English. The purpose of using the multimodal approach to teaching college English is to help students learn the language by capitalizing on their unique combination of visual, auditory, and tactile learning styles and taking into account their unique physiological and psychological makeup.

The approach to ideas of college English curriculum teaching is to look at machine intelligence theory and its techniques for teaching development through the lens of multiple intelligences, to be objective, and to coordinate the development of all intelligences. An example of how pupils' language expression may be improved is via the organic coupling of mathematical logic intelligence and language speech intelligence. By fusing visual-spatial intelligence with mathematical, logical intelligence, one may transform abstract thought into graphical picture memory and build schema associations rich in reason. Learning via play is possible when physical awareness and social intelligence work together. The second goal is to find common ground between MI theory and other theories of language education so that we may create an interdisciplinary method for teaching vocabulary. At its heart, this idea is based on the idea that integration and optimization are biologically one and that there is no need for a singular theory to inform effective classroom practice. Consequently, the following is a diagram depicting the algorithm that stands for the optimal neural network that drives the multidirectional mutation genetic algorithm.

First, the system gathers data from College English language classes and vocabulary courses and stores it in a central location (Figure 3). This data includes information on College English words, phrases, grammar, logic, and logical structure. Feature extraction provides data on the instructor's background, methods, courses, attitude, and students' grades to BPNN. Next, the BPNN is fine-tuned using the **GA-IECOS** algorithm, which can make BPNN more accurate.

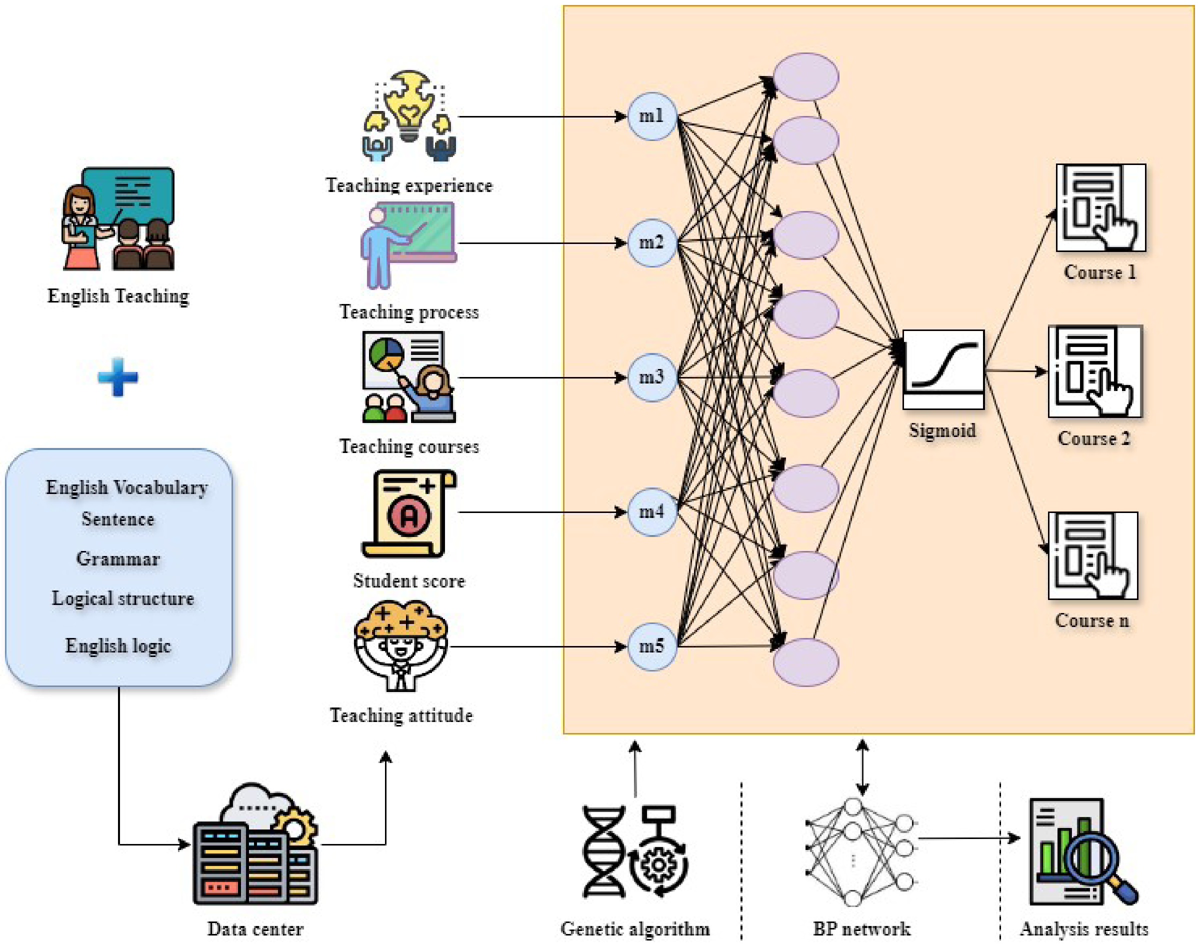

Figure 3. Multimodel College English Teaching Framework

Genetic algorithms may benefit from binary single-point or two-point crossovers, which widen populations. Still, random mating, like biological "reproduction solitude," will wipe out parents' genetic knowledge and thereby halt population growth. Also, in many functional optimization experiments, the author found that the operations in fundamental genetic algorithms, especially the genetic operators of the floating-point coding scheme, would lead the population at large to be dispersed in a "+" shape. It is unlikely that all chromosomal gene segments would change in a true coded genetic operator (Cross or Mutation). Instead, a "cross" distribution, in which some genes change and others stay the same, is the most common occurrence. This research presents a genetic technique for hybrid coding that combines binary mutation with floating-point crossover. The population may easily escape the trap and progress towards the ideal search hyperplane thanks to the algorithm's multidirectional mutation capability, violating the "ten" word distribution rule. This research also suggests a strategy for dynamic coding based on this. When performing genetic operations on small populations, a dynamic coding scheme ensures that individuals won't stray too far from the centre's ideal value.

The following parameters must be known before the algorithm can be run: popsize, maxgen, the two populations' crossover and mutation rates, chromlen, nvars, and chromlen, nb, and the dynamic coding mutation range interval. Additionally, the current evolutionary algebra generation must be set to 0. (1) Setup: the algorithm takes the two fields for defining variables in the algorithm's decisions. It uses them to start the population randomly. To make implementation easier, floating-point numbers are generally utilized as coding methods, even though the algorithm uses a mixed coding strategy. Converting floating-point numbers to their appropriate codes is a common practice when further coding operations are needed. A random generator is used to create popsize people as population A, and one individual is generated randomly throughout the solution space. In other words, everyone in population B uses this one person as a jumping-off point for their searches.

(2) Elitist preservation technique: this paper suggests that a better algorithm will likewise use this strategy, but it will preserve the two populations' ideal members inside their respective interiors. The ideal personal data will be stored in the memory areas designated for population [popsize] and constructor [popsize]. (3) This study uses the greatest evolutionary algebra as a halting condition. In real-world scenarios, particular circumstances may be correctly introduced without impacting the algorithm's performance. The roulette selection approach, often called the fitness proportion method, is used in this study. (4) Each population member determines its own proportional selection probability based on its fitness value. (5) To generate two new persons (the chromosomes of the progeny) from two-parent individuals that fulfil the crossover requirements, the algorithm's crossover operator employs the single-point crossover approach. This is accomplished by exchanging genes' segments before and after a randomly chosen location. As mentioned in the previous chapter, the crossover procedure of each population in this research uses floating-point coding to ensure that the genetic information of the parent generation may be passed on to the offspring. By switching to binary coding, Population A can circumvent "cross" distribution and improve its global search capabilities. To enhance their local search capabilities, members of Population B employ dynamic coding to modify within a defined limited range. Notably, the population's variation rate PCB may be suitably enhanced due to the short search range of population B. Local optimization is more likely to occur when the variation rate is high and the variation range is short. (6) The migration operator is bigger than population A's and population B's constructors or their respective populations. Population A discovers a better person if the population size is more significant. The current state of affairs is to duplicate the whole population of B and use it as the new beginning point for the search, which is population.

As the multimodal teaching idea has grown in popularity, an increasing number of College English instructors are experimenting with different ways to impart College English language skills to their students to boost their proficiency in multimodal communication and learning. On the other hand, Multimodal instruction is more involved than single-mode instruction, requiring more advanced skills from educators and catering to a broader range of student learning styles. The College English pedagogical practices and attitudes of many educators are somewhat outdated. Under examination supervision, they primarily engage in single-channel and single-mode instruction. Indoctrination is the primary method of imparting information and skills to students; nevertheless, it cannot provide "multimode input," which diminishes students' motivation to study English.

Additionally, there is a noticeable lack of proficiency and understanding of multimodal learning among pupils. There is a clear trend among students to "emphasize reading and writing and neglecting listening and speaking" when it comes to learning English, and this is true across all educational levels, from elementary to university. This is likely a result of the pervasiveness of exam-oriented education thought. Multimodal learning is not something they have gotten into the habit of doing well. Even with multimodal College English instruction, some pupils struggle to adapt. This demonstrates that College English learning students lack the necessary knowledge and skills in multimodal learning. Lastly, there isn't a conducive setting for lecturing using several media in higher education. Universities and colleges have a building standard for their College English teaching environments that is behind. There are limited chances to see a high-standard voice room or multimedia classroom, and most College English classes are held in regular classrooms. The limited integration of various modes in teaching College English and the relatively single presentation form of College English knowledge in teaching materials make it difficult to organize and implement multimodal teaching activities in College English effectively.

The multimodal teaching paradigm of College English teaching relies heavily on the contributions of teachers. Instructors direct their students' acquisition of the College English language following the tenets of the multimodal instruction theory. Consequently, college English instructors should study more about multimodal instruction, develop views about multimodal instruction, and use a variety of multimodal approaches to teach College English. In addition to enhancing the impact of environmental activities, environmental elements may influence how individuals perceive and behave in the world.

RESULTS AND DISCUSSIONS

Students' motivation to learn is strongly correlated with the logicalness of the teaching strategies used in College English classes and the calibre of the students' attitudes about learning College English. Among the various approaches to teaching College English as a foreign language in college and university settings, this research has shown that 82 % of instructors use group discussions and that 39,2 % of instructors can use a combination of the strategies above. Even though 62,9 % of educators are adept at selecting effective methods of instruction for their College English classes, those who stick to just one approach would do well to broaden their pedagogical horizons, and experiment with other approaches to pique their students' interest and boost their retention rates.

Dataset Description: this mixed-method research study examined EFL classroom multimodal resources and students' perspectives. The research included fifty Mattayom five (grade 11) science-math students from a Nonthaburi public school. A questionnaire was based on a teacher interview on classroom multimodal materials.

Mean and SD were calculated using questionnaire data.[24] Data was scored and interpreted using a 5-point Likert Scale. Qualitative narrative analysis examined open-ended questions. The survey found that textbooks were the most often utilized multimodal resource in classrooms. High-level students indicated good evaluations of all multimodal classroom resources. Most students learned well using PowerPoint and proposed using additional multimodal tools in class.

Student's performance based on GA-IECOS

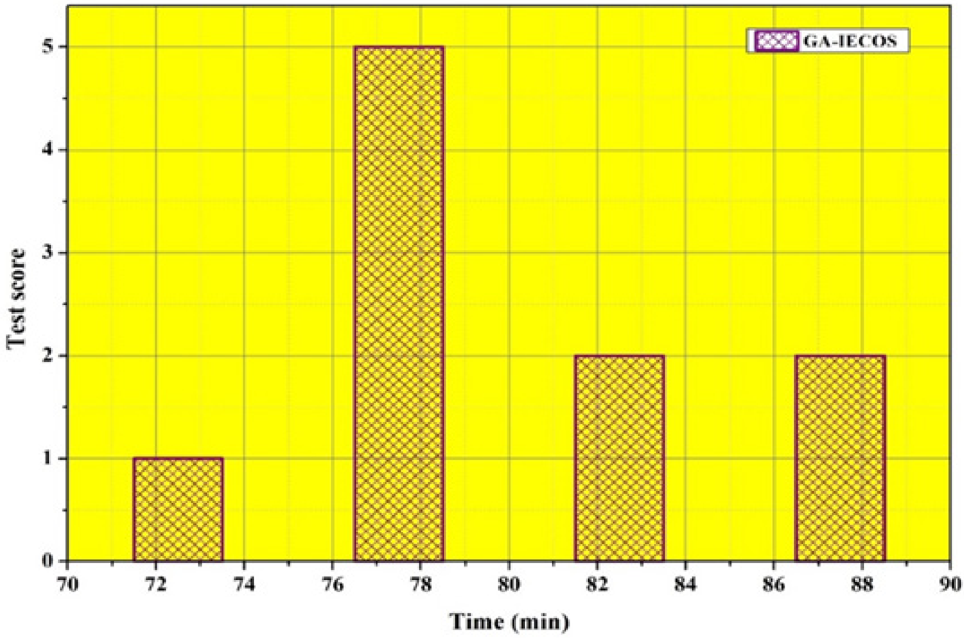

Figure 4. Student's Performance based on GA-IECOS

To measure the impact of College English learning on students, it is important to look at their engagement, self-assurance, level of comprehension and application of information, level of collaboration and communication awareness, and the extent to which they participate in the learning process. Teachers, parents, and students are all involved in evaluating learning effects. The student's motivation to learn and their capacity for independent study may be enhanced via self-evaluation. Consequently, not only should professors assess their students' progress, but students should also be motivated to assess their learning. The experimental class was surveyed before and after the effective College English teaching model had been used to examine the changes in the students' learning effects. The evaluation was administered using the elements above. The outcomes may be seen in figure 4.

Teaching Level based on GA

Figure 5 shows that the research carefully studied the GA algorithm's effect on student participation in college English language classrooms, noting that engagement is crucial to education. This demonstrates that most students can accurately identify what they want to learn and create a strategy. It also suggests that students may adapt and enhance their learning plans based on the teaching levels. Students may build or enhance their self-confidence via multimodal College English teaching, emphasizing determination and control. With a mean score of 4,75, students entirely agreed with the statement, "Well, it could overcome difficulties in learning College English", suggesting that students may develop or enhance their self-efficacy beliefs via self-motivation after multimodal teaching. For example, "students can get a sense of accomplishment from reading in College English," over half of the students gave a full yes, indicating that students in multimodal College English courses did feel accomplished. They learned new things and came to see the world in a different light. Still, Teachers should strive to achieve a balanced blend of modalities since some pupils struggle to comprehend due to an unwillingness to embrace variety in resources.

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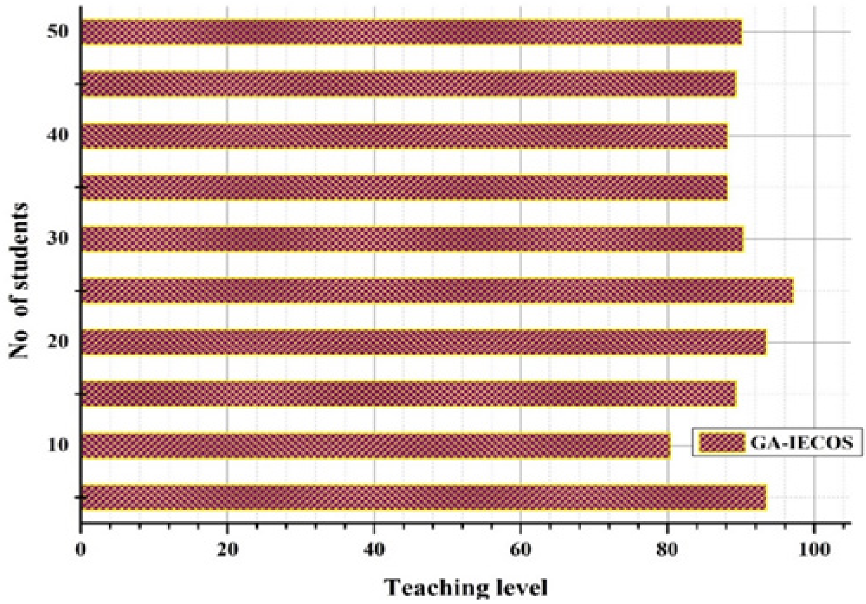

Figure 5. Teaching Level based on GA

Student's English learning Improvement

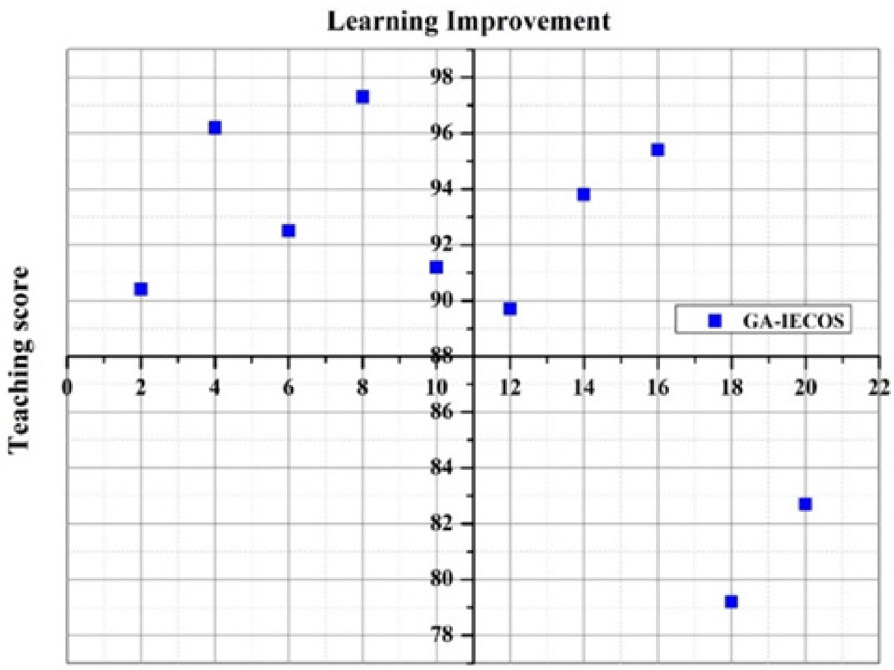

Figure 6. Student's English learning Improvement

Figure 6 shows that according to the research findings, using the method resulted in a considerable improvement in the performance of individuals in college English. Students in the experimental group demonstrated constant improvement in their test scores over the length of the trial, exceeding the students in the control group who were instructed using conventional methodological approaches. Several formative and summative evaluations were carried out to quantify this improvement. Ratings showed that the study participants learned and retained more than the control group. The improved results show that GA-IECOS can change language learning. The algorithm's customized method, which adjusts to each student's learning demands and speed, helped achieve this remarkable achievement.

Accuracy in implementing GA algorithm

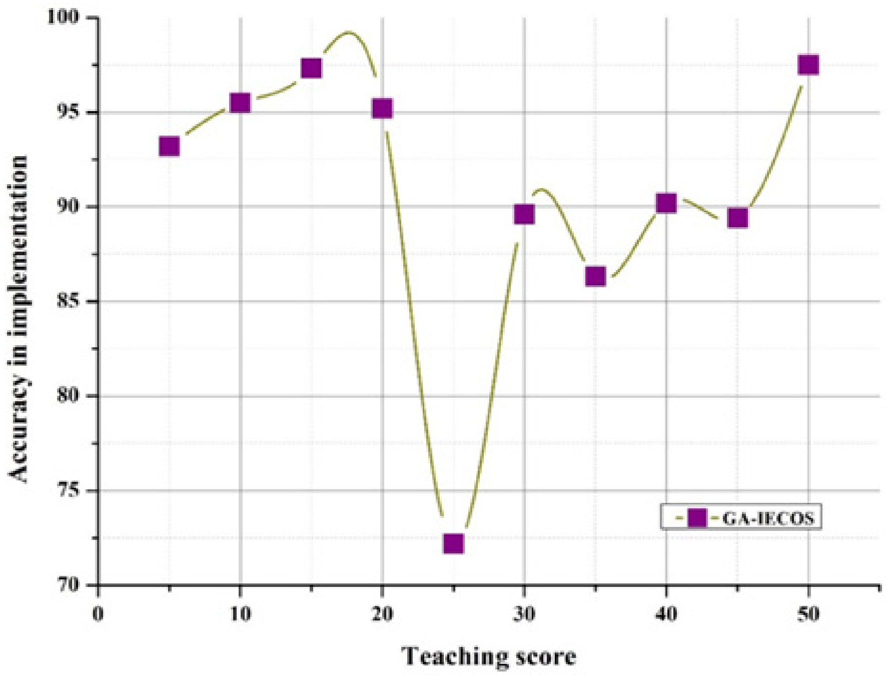

Figure 7. Accuracy in implementing GA algorithm

The GA algorithm's accuracy for college English lectures significantly improved throughout the study, as seen in figure 7. Implementing a strict grading system resulted in fewer mistakes on exams and assignments and more accurate questions. There was consistent improvement in this area's writing, reading comprehension, vocabulary, and grammar. Experimenters overcame their weaknesses with the support of the College English learning technique. This method allowed teachers to give pupils more feedback and chances to improve. The intervention helped students gain self-assurance and improve their College English skills, which led to higher exam scores and overall academic achievement. This research's multimodal College English teaching strategy was successful because it prioritized accuracy.

CONCLUSIONS

According to this research, college English language learners' engagement and performance are improved using an advanced adaptive learning genetic algorithm. After implementing these unique teaching tactics, the experimental group outperformed the control group in terms of engagement, test scores, and mistake rates. The promise of GA-IECOS to improve both English language teaching and student achievement in higher education is shown by this substantial improvement. According to the study, academic performance improved significantly. Throughout the research, the experimental group's test scores improved significantly. Improve your grammar, vocabulary, reading comprehension, and writing skills by enrolling in a college English language program. Students in the experiment may work on their weak spots with the aid of the adaptive system's individualized comments and specific exercises. Improved learning and retention were outcomes of using this individualized approach. Adaptive learning's benefits were most apparent compared to the control group's negligible gains via traditional instruction. Students in the experimental group were far more engaged and achieved higher academic success. Students who are more invested in their schoolwork boost learning, involvement, and enthusiasm. By making language teaching more engaging and personalized, the College English system that the experimental group utilized improved language training.

There is an increase in the student's concentration and interest in their coursework. The experimental group showed more positive engagement markers than the control group. By presenting more interesting and entertaining ways of learning, the GA-IECOS framework may have increased student motivation. The pupils' accuracy was also highlighted in the report. The rating accuracy was better in the experimental group. Improved accuracy and confidence in College English were seen across various language skills when the adaptive learning technique was used. Students could better comprehend and perform better since the adaptive algorithm offered them individualized feedback that helped them see and fix their mistakes. The capacity of College English learning technology to significantly improve academic performance and student engagement demonstrates its revolutionary potential. One way to make learning more successful and enjoyable for pupils is to tailor lessons to their specific requirements. Teachers may improve student performance by adapting to each student's learning speed and providing timely, individual feedback.

Improving pupils' capacity for critical thinking and bridging cultures has become more important as the new millennium has begun. Reforming education in different nations is not an easy undertaking. If College English majors, in particular, want to improve their discipline's reputation and the employability of their graduates, they must prioritize the development of students' critical thinking abilities. To improve the efficacy of College English instruction, we musten sure pupils learn more deeply. Encouraging students to engage in active investigation and discovery rather than passively absorbing information requires us to prioritize independent inquiry learning. Secondly, teachers must provide more direction while giving their pupils room to think critically and rationally about other cultures. Teaching college-level English with the use of a multimodal approach yields excellent results. This paper presents a more thorough and practical discussion of the main factors, constraints, and solution targets in the planning issue of universities and colleges. It then utilizes a genetic algorithm to address the arranging programming problem, designs a simple but effective fitness function, and conducts scheduling simulation experiments to determine the influence of factors like population size, crossover probability, and variation probability on scheduling. Finally, iterative experiments are conducted to find the optimal solution. This led to the proposal of a broad framework and notion for addressing the scheduling issue using evolutionary algorithms and successfully implementing this method in academic settings. According to the test results, the method can handle the class scheduling issue reasonably and efficiently. This will be the focus and direction of future studies if there is a way to dynamically enhance how College English is taught and track the most recent teaching status in real-time.This paper wants to keep investigating evolutionary algorithms' potential uses in the information retrieval domain in the future. A more extensible and flexible version of the suggested strategy will be applied to a bigger dataset. It will investigate other potentials to include in the information retrieval system. Additionally, additional performance metrics will be used to evaluate the retrieval technique.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHOR CONTRIBUTION

Conceptualization: Anber Abraheem Shlash Mohammad, Mai alshebel, Badrea Al Oraini, Asokan Vasudevan.

Methodology: Anber Abraheem Shlash Mohammad, Mai alshebel, Asokan Vasudevan, Suleiman Ibrahim Shelash Mohammad.

Investigation: Anber Abraheem Shlash Mohammad, Badrea Al Oraini, Aktham Al Sarayreh.

Data Curation: Badrea Al Oraini, Asokan Vasudevan, Huiying Jiang.
Writing - Original Draft: Anber Abraheem Shlash Mohammad, Suleiman Ibrahim Shelash Mohammad, Mai Alshebel.
Writing - Review & Editing: Badrea Al Oraini.