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Exploring the Role of Artificial Intelligence in Shaping Teacher Identity and Digital Pedagogy in English Language Education

Jianfang Zhang

School of Foreign Languages, Jining Normal University, Ulanqab, China
jianfangZhang174@outlook.com

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Abstract

In the era of the digital economy, increasing digital literacy has emerged as one of China's key policies, which has led to the crucial goal of English education to develop digital talents. In Zhejiang, 190 higher English teachers participated in an online survey on digital literacy. Data research revealed that English teachers had a comparatively high self-score for digital literacy. Digital literacy's four dimensions are, the Awareness in digital, Thinking Computationally, Innovation and Learning in Digital, Digital Protection and Transparency. The IFSO-DAdaBoost method presents a comprehensive skill evaluation, enhances skill extraction accuracy, facilitates intelligent learning, and improves data representation. When compared to the current method, the proposed IFSO-DAdaBoost strategy shows a significant increase in accuracy. The strategy achieves 99.2% accuracy, 98.6% precision, 99.0% recall, and a 98.9% F1 score. The error performance decreased by RMSE of 0.3524, MAE of 0.1832, and MAPE of 4.24 based on the error measurements.

Keywords: Digital Literacy, Digital Transformation, Artificial Intelligence (AI), English Teachers, Economic Development, Digital Awareness, Pedagogical Integration of AI

Introduction

The term "digital literacy" describes a person's capacity to gather, comprehend, produce, and share information in a digital setting (Ervianti et al., 2023 and Xing & Diao, 2024). It encompasses a number of traits and abilities. The field of education has demonstrated a significant correlation between digital literacy and student learning outcomes (Ding & Wu, 2024). In order to encourage integration of teachers and pupils with the atmosphere of digital technology, researchers have also emphasized the significance at higher education institutes of innovation in digital and digital literacy.Research has demonstrated that incorporating social media into the educational process enhances students' digital literacy (Reddy et al., 2023). However, English education promotes digital transformation to establish sustainable and environmentally friendly schools, thereby contributing to the development of digitally literate and applied talents. Therefore, it is urgent to find out how digitally literate pupils are currently enrolled in English education and suggest improvements. Previous studies have typically focused on a specific student population, such as conducting empirical evaluations of the middle school the digital literacy of students. Others seek to examine college students' digital literacy (Tinmaz et al., 2022 and Chen, 2024).

1.1 the Significance of Universities and Colleges' Digital Transformation

Universities and colleges are undergoing a digital transformation, integrating information technology with education and teaching to improve talent training quality and effectiveness. This process aims to address societal demands, raise educational standards, and build future-ready talent by integrating new technology organically (Farias-Gaytan et al., 2023 and Qiu, 2023). The digital transformation of universities and colleges involves modernizing teaching strategies, transitioning from traditional classroom methods to online and digital approaches, and leveraging technology tools like the Internet, smart devices, and virtual reality for global access and personalized learning.

1.2 Digital Transformation's Obstacles in Universities and Colleges

Universities and colleges' digital transformation has emerged as a crucial component of fostering social and economic progress in the current era of the digital economy's quick and strong development. However, development is not always smooth, and no change can be successful immediately. The actual process of digital transformation at universities and colleges is still fraught with difficulties (Wu & Reyes, 2024 and Zhou et al., 2023).

The proposed work's primary contributions are as follows in: The development of Dynamic Adaptive Boosting-based Intelligent Fish Swarm Optimisation (IFSO-DAdaBoost) technology offers new resources and approaches for teaching digital literacy. Developing higher English teachers' capacity to effectively gather, process, analyse, and assess information is the main objective of digital literacy instruction. Through the use of kernel principal component analysis techniques, AI technology may help students quickly extract the necessary information from vast amounts of data and process and analyse it, making it simpler for them to comprehend and use the information.

Furthermore, by giving tailored learning materials and feedback, IFSO-DAdaBoost technology may give students individualised learning experiences based on their requirements and interests.Students' information literacy can be improved by this individualised learning experience, which can help them better understand digital literacy techniques and skills. To sum up, the creation of the IFSO-DAdaBoost model presents both new possibilities and difficulties for the teaching of digital literacy.

1.3 Research Questions

1. What is the organizational contribution of incorporating the issue of artificial intelligence into the professional identity of English language teachers in the era of digital transformation?
2. How can the artificial intelligence be used to design and improve the digital practices of pedagogy in teaching English language?
3. What is the mediating role of digital literacy and technology acceptance of the teachers in terms of artificial intelligence and digital pedagogy?
4. To what extent will the suggested IFSO-DAdaBoost model be able to evaluate the level of digital literacy and intelligent teaching among English language teachers?

Literature Review

This study examines challenges faced by vocational schools in preparing students for new skills, including limited budgets, inadequate compensation, and curriculum incompatibilities. Recommendations include increased student involvement, funding, ongoing training opportunities, and linking educational applications to competition requirements (Peng et al., 2023).This study evaluates the effectiveness of mandatory modifications in teaching using machine learning, artificial intelligence, and synthetic intelligence. Data from 100 Serbian students at selected higher education institutions was used to assess student adoption of these advancements (Ilić et al., 2021).

Researcher proposes a blended learning paradigm based on CIAP, which includes intellectual, behavior, process, and conceptual elements. This approach helps students become more information technology literate at the college level. The study found that a blended learning strategy significantly affects college students' growth in information literacy. However, the validity of the results may be limited due to response bias and short-term implementation issues (Shi et al., 2022).The Developing AI Literacy (DAILy) class aimed to teach elementary school children about AI principles, ethical implications, and career prospects.

The program helped students identify bias, reduce it, and assess AI's impact on their future careers (Zhang et al., 2022). The study identifies 20 key contextual factors that influence digital literacy among students. These include self-confidence, reading ability, at-home resources, class discussions, and publications. The findings suggest that home factors have a greater influence on digital literacy development, while teaching-related features are more important (Chen et al., 2022).

This study examines the main socioeconomic drivers of digital ability in the population using data analysis techniques. It aims to ascertain when people need to be educated in digital capabilities to positively affect the country's sustainable growth. However, the accuracy of the results may be impacted by feedback bias and the cross-sectional methodology may not account for capacity confounding variables or longitudinal changes in virtual skills (Hidalgo et al., 2020). In order to support the realisation of the modernisation of Chinese higher education, the article suggests a path for college teachers to cultivate digital literacy from the perspectives of boosting endogenous motivation, creating a learning community, implementing diversified evaluation, conducting systematic training, and enhancing safety protection ability (Ren, 2024).

The study discovered that while teacher preparedness and infrastructure must be mediated by online learning, students' digital literacy practices have an impact on online learning, motivation, and technology introduction. The study's conclusions show that in order to develop instruction that emphasises kids' digital skills, teachers, school administrators, and legislators must work together (Jatmoko et al., 2023).

In a meta-analysis, Ekizer (2025) establishes that the AI technologies can effectively stimulate the learning performance, engagement of learners and the effectiveness of instruction on English language learning. In the informal digital setting, Nguyen et al. (2025) indicate that the teachers tend to view the use of AI-mediated tools positively in enhancing ESL writing, whereas students are actively following strategic measures, including the use of automated feedback and self-directed learning as a way of enhancing their career-related written language.

Considering the ecological and identity-based approaches, Satvati et al. (2025) show that AI integration also changes the professional identity of teachers as it works to change their role in instruction, technological agency, and pedagogical faith in dynamic education settings. Altogether, these studies also highlight the multidimensional roles of AI in the contemporary English language teaching on pedagogy, student strategies, and teacher identity.

Methods

3.1 Research Design

The research design of this study was a quantitative survey research design with an intelligent data-driven modeling approach, which constitutes a quasi mixed method research design. The digital literacy level of higher English teachers was investigated using the survey approach, and the advanced machine learning approaches were utilized to model, assess, and verify the digital literacy performance based on the proposed IFSO-DAdaBoost algorithm.

3.2 Process of Selecting the Participants

A stratified convenience sampling strategy was used to select participants in some of the Universities in Zhejiang Province, China. The inclusion criteria were that the participants had to be full-time English teachers and actively involved in digital teaching. Data cleaning resulted in the retention of 190 valid responses. The size of the sample is suitable since it is sufficiently large to perform statistical analysis and machine learning modeling and at the same time has enough representatives of both sexes and age.

3.3 Data Collection

A structured questionnaire on the Internet, comprising four main dimensions of digital literacy, that is, Digital Awareness, Computational Thinking, Innovation and Digital Learning, and Digital Protection and Transparency, was used to collect the data. The questionnaire questions were also based on the existing digital literacy measuring scales, and they were modified according to the review of experts. Three educational technology and applied linguistic experts were used to establish content validity. Factor analysis was used to evaluate construct validity and Cronbachs alpha ($\alpha >$ 0.80 and above) was used to evaluate internal consistency reliability. Appendix A has all the questionnaire tools.

An online questionnaire survey was carried out in a few schools in Zhejiang, China, between December 2023 and January 2025. In all 190 authentic surveys are gathered in an unidentified format. The distribution of the research objects is appropriate, and the sample data revealed a particular proportion of gender, age, and teachers subject.

Variable	**Options**	**Frequency(N-190)**	**Percentage(Frequency of variable/total *100)**
Gender	Male	86	45.26%
	Female	104	54.73%
Age	21-35	92	48.42%
	35-50 years old	98	51.57%
Teachers	English teachers	190 Total:190	100%

Table 1: Basic Information of respondent

Data Cleaning Using Duplicate Removal

Data is improved by eliminating duplication and ensuring the integrity of AI quality and stability by the removal of duplicate or anomalous data points, the use of Euclidean distance algorithms to verify unique entries, and data rectification. Entries that are duplicate in personal students and teacher's data that may have the same attributes.

Duplicates are Identifying

Every entry is compared in order to identify duplicates using an exact match, which is represented by *eq. 1.*

$$Duplicate(i,j) = \begin{cases} 1 & if\ xi = xj \\ 0 & otherwise \end{cases} \qquad (1)$$

For slightly different entries in *eq. 2*, it is advised to use a distance measure, such as Euclidean distance, in order to achieve near matching.

$$d(xi, xj) = \sqrt{\sum_{k=1}^{n} n(xik - xjk)} \qquad (2)$$

xi and xjstand for the i^{th}- and j^{th} entries in the dataset, respectively; $d(xi, xj)$ calculates the Euclidean distance between them; n is the total number of features; and xik andxjkindicate the values of the k^{th} feature for the corresponding entries. $Duplicate(i, j)$ indicates whether these entries are duplicates (1 for an exact match, 0 otherwise).

Duplicates are Removing

Only the initial instance of each duplication is kept in order to maintain unique entries throughout the duplicate removal procedure (*eq. 3*).

$$Cleaned\ Dataset = \{xi \mid xi\ is\ unique\ in\ D\} \qquad (3)$$

3.4 Data analysis and Ethical consideration

The data analysis was done in four phases, namely: (1) cleaning and removing duplicates of the data by using exact matching and Euclidean distance based similarity detection methods; (2) extracting nonlinear features of the data by using Kernel Principal Component Analysis (K-PCA); (3) classifying and making predictions of the data by the use of the proposed IFSO-DAdaBoost model; and (4) evaluating the performance of the analyzed data in terms of accuracy, precision, recall, F1-score, RMSE, MAE, and MAPE. A comparison with Naive Bayes, KNN, and IoT-based models was done to prove the efficiency of the proposed method.

Ethical guidelines were observed to the letter in the course of the research. The informed consent was given by all participants who filled the questionnaire. The process was voluntary and the respondents were advised that they could pull out at any point. Anonymization of all data collected was done to provide privacy and confidentiality, as well as no personal data was stored or revealed. The research adhered to the traditional ethical principles of academic research on human subjects.

3.5 Extracting features using kernel principal component analysis (K-PCA)

Data is transformed into a higher-dimensional space using kernel functions in Kernel Principal Component Analysis (K-PCA), a nonlinear version of conventional PCA. Data from IoT sensors at the mining site, such as gender, age, class, of the students were analyzed for feature extraction to find important trends and insights that improve operating safety and efficiency.This approach is very useful for feature extraction since it makes it possible to find intricate patterns and structures in the data. Through the extraction of the most pertinent features, K-PCA increases ML model accuracy and computational efficiency.The training data matrix $W \in \mathbb{R}^{m\times n}$is assumed to be mapped onto a high-dimensional feature space $\mathcal{F}$ by a nonlinear function$\Phi(.)$, represented as$\Phi(X) \in \mathbb{R}^m \times \mathcal{F}$, where m represents the sample number, n is the variable number, and R is a set of real numbers in *eq.4*.

$$\Phi(X) = \sum_{j=1}^{l} s_j o_j^S + F \qquad (4)$$

3.6 Intelligent Fish Swarm optimization based on Dynamic Adaptive Boosting (IFSO-DAdaBoost)

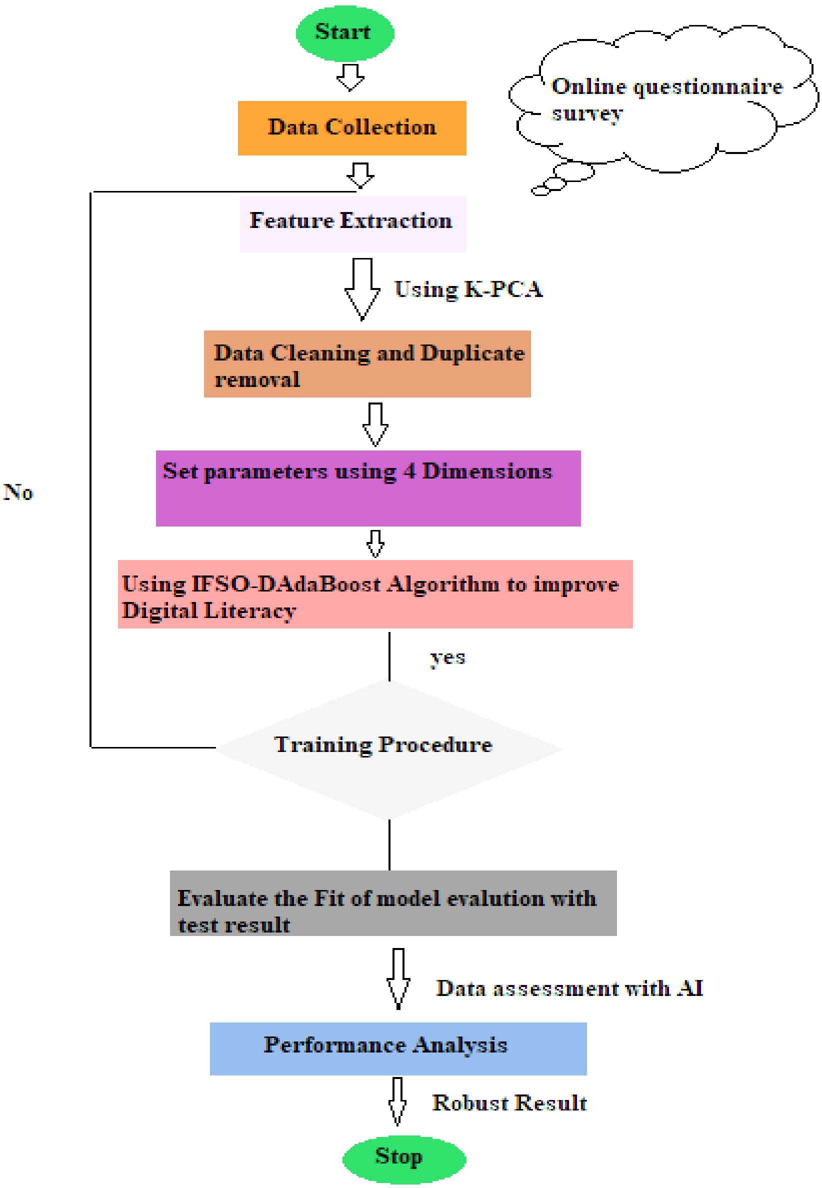

Fig1. Flow Diagram of a proposed method

3.6.1 Dynamic Adaptive Boosting (DAdaBoost)

In mining architecture, DAdaBoost is a sophisticated ensemble learning method in English teachers that modifies the boosting process dynamically to increase model accuracy while removing patterns from intricate data structures. Based on their success, it adjusts the weights assigned to weaker learners, enabling more targeted error remediation. This approach improves, especially well in cases when algorithm is unbalanced or changing. In general, while analyzing a regression problem, the training data set Θin Digital Literacy can be shown as in *eq. 5.*

$$\Theta = \{(W_1, Z_1), (W_2, Z_2), \dots, (W_n, Z_n)\} \qquad (5)$$

Where n is the total sample number, and $(W_j, Z_j)(j = 1, \dots, n)$ represents the j^{th} sample in the training data set; Z_j is the value of output data, while W_j is the input data vector. Samples; $W_j$is the input data vector; $Z_j$is the output data value. Then, using a few particular learning algorithms, it can be used to train a base learning teaching system (or weak learner)$H(W)$. The relative prediction error for each sample can be expressed as *eq. 6.*

$$f_j = K(Z_j - H(W_j)) \qquad (6)$$

Where $K(.)$is the loss function square, exponential, or linear that is commonly used. For simplicity, the linear loss function is utilized in *eq. 7.*

$$f_j = \frac{|Z_j - H(W_j)|}{F} \qquad (7)$$

Where, the highest absolute prediction error of all the samples is expressed as $F = max|Z_j - H(W_j)|$. Since it goes without saying that a single weak learner will perform appallingly, the goal of AdaBoost is to generate a sequence of weak learners, $H_l(W), l = 1,2, \dots, M$, and then combine them Consider that there are two different sorts of teaching system in the aforementioned derivations: $x_{l,j}$, and α_l. The first one $(x_{l,j})$ is used to indicate that samples of training data will have their samples increased in order to improve their learning in the next stage. It is used to identify which samples were erroneously predicted. Regarding weak learners, the second one (α_l) suggests that the final results will be significantly influenced by the weak learner who is more accurate.

Intelligent Fish Swarm Optimization (IFSO)

The fundamental concept of AFSA is as follows: The study has considered an n-dimensional space to contain a fish swarm$M$ artificial fish. An AI fish's location may be written down as $W = \{w_1, w_2, \dots . w_m\}$, where $w_j(j = 1,2, \dots . m)$is the optimizing factors. The simulated fish in position's level of current meal consistency $W$is a kind of objective function$Z = e(W)$artificial fish's seeing area is known as visual, and its maximal movement length is known as step. The separation between two plastic fish in W_j and W_iEuclidean Distance is used to represent locations$c_{ji} = \|w_j - w_i\|$.

Additionally, the bulletin has the optimal fake fish location loaded. The try number specifies the maximum number of times the fake fish tried to find food. The factor for congestion level $\delta(0 < \delta < 1)$denotesthe level of congestion surrounding a certain location, which is intended to prevent crowding or collision with nearby places. The following depicts the fish swarm's disrupted behaviors:

Foraging habits

Let's say that the location of the j^{th} artificial isW_j , and a state $W_i$is chosen at random from its Visual range. If$Z_i < Z_j$, The fish advances in the direction by one step of$\left(W_i - W_j\right)$. Alternatively, choose a state at random$W_i$once again and determine whether the forward condition is met. When a try-number of met the risks has been run repeatedly, and there are still no fulfilled places, random behavior will be used. Following are the guidelines for foraging behavior:

$$W_{next} = \begin{cases} W_j + Rand.Step \quad \frac{W_i - W_j}{\|W_i - W_j\|} if(Z_i < Z_j) \\ randombehavior \quad otherwise \end{cases} \tag{8}$$

where $W_{next}$is the fake fish's current condition, and Rand() is evenly produced between [0,1].

Swarming behavior

When migrating to escape congestion, each fish leans toward the center of its neighboring companions, which is referred to as swarm behavior. LetW_ji be the condition of synthetic fish at the moment$j$, $W_j$to occupy the center of the present field, and $m_e$the quantity of fake fish in the area's visual field W_d position; if $Z_d < Z_j and\, Z_d/m_e < \delta Z_j$, It indicates that there is lots of food but that the area surrounding the couples is not very congested. The fish then advances one step to this partner's middle place. The following is a description of the swarming behavior:

$$W_{next} = \begin{cases} W_j + Rand.Step \quad \frac{W_i - W_j}{\|W_i - W_j\|} if(Z_d < Z_j and\, Z_d/m_e < \delta Z_j\ ) \\ foragingbehavior \quad otherwise \end{cases} \tag{9}$$

where δ ∈ (0, 1) reveals the food's content.

The following behavior

The following behavior demonstrates how each plastic fish swims in the best possible direction at the moment.SupposeW_{min} is inside the immediate area, a local's closest friend of W_j.If $Z_{min}/m_e < \delta Z_j$, and the artificialfish $W_j$tries to take a step in the desired direction $\left(W_{min} - w_j\right)$.The following is a description of the swarming behavior.

$$W_{next} = \begin{cases} W_j + Rand.Step \quad \frac{W_{min} - W_j}{\|W_{min} - W_j\|} if\ (Z_{min}/m_e < \delta Z_j) \\ foragingbehavior \quad otherwise \end{cases} \tag{10}$$

Random behavior

Before advancing a Step, random behavior entails picking at random a new state W_next in its visible region. Actually, it is the accepted course of action.

Theoretical Model: TPACK-TAM Integrated Model

Theoretically, the framework that forms a basis of the present study can be seen as a complex pair of Technological Pedagogical Content Knowledge (TPACK) model and the Technology Acceptance Model (TAM). TPack framework describes how the professional competence of teachers is formed as a result of the dynamic interaction of the technological knowledge, pedagogical knowledge, and content knowledge, which is why it is highly applicable in the context of studying digital pedagogy and the development of teacher identity in English language education. TAM, in its turn, describes how technology adoption is explained based on two foundational determinants the perceived usefulness and perceived ease of use that have a direct effect on the attitude and behavioral intentions of teachers regarding digital technologies.

In this combined model, the four dimensions of digital literacy that were reviewed in this study fit in both models. Digital Awareness and Digital Protection and Transparency are associated with the technological knowledge and perceived ease of use teachers in TAM. Computational Thinking represents the ability of teachers to operationalise technology to solve problems and/or to design instruction, which is associated with the technology-pedagogy cross of TPACK. Innovation and Digital Learning reflect the concept of pedagogical change and perceived usefulness of the digital means in teachers to improve the learning results. Combined, these dimensions show the professional digital competence of teachers (TPACK) as well as their adoption of AI-driven technologies (TAM).

The data analysis and interpretation of this study were directly facilitated by this framework. To evaluate each of the digital literacy dimensions as a quantifiable measure of technological, pedagogical, and adoption-related competencies of teachers, the statistical analysis was done using descriptive and inferential statistics. Secondly, TAM principle of optimizing performance was operationalized by the IFSO-DAdaBoost model that concerned the most significant digital literacy characteristics related to high evaluation accuracy. Third, the comparative performance analysis of all models (Naïve Bayes, KNN, IoT-based methods, and the proposed model) was understood through TAM but as the indicators of the various degrees of technology performance and adoption appropriateness.

Results were interpreted in the light of TPACK-TAM to discuss the fact that high scores in Digital Protection and Transparency demonstrate strong technological awareness concerning the foundations, whereas slightly lower scores in Computational Thinking can be regarded as the sign of the necessity of more profound integration of AI and data-driven technologies into the educational process. The framework facilitates the determination that AI-enhanced assessment models like IFSO-DAdaBoost will empower teacher professional growth through offering a greater number of precise responses, teaching personalization, and transformation of digital pedagogy.

Results And Discussion

4.1 Statistical analysis of Digital Literacy

The average score for digital literacy among upper English teachers in school is 4.03, according to the statistical analysis of the questionnaire *(Table 2).* With an average score of 4.50, Digital Protection and Transparency has the highest score among the specific dimensions of digital literacy, suggesting that students enrolled in vocational education possess a comparatively high capacity for acquiring, comprehending, assessing, and disseminating digital information. The findings of this survey are comparable to those of other study, however they differ significantly based on the data findings of the Hunan Province survey (Shi, 2024). The high level of digital literacy among English teachers may be attributed to Zhejiang Province's successful digital economic development.

Variable	Min_Value	Max_value	Mean	Std_Deviation
Digital Awareness	1.00	5.00	3.98	0.82
Thinking Computationally	1.82	5.00	3.90	0.80
Innovation and Digital Learning	1.27	5.00	3.95	0.83
Digital Protection and Transparency	2.85	5.00	4.50	0.72
Total Average_ Score	1.98	5.00	4.03	0.71

Table 2: Statistical result of Higher English teachers in Digital Literacy (N=190)

4.2 Analyzing Performance metrics

To confirm the effectiveness of the suggested method, IFSO-DAdaBoost, a comparison with several well-known AI approaches is conducted. These methods include RNN (ElHaji & Azmani, 2014), IOT (Rakasiwi et al., 2023), and Naïve Bayes (NB) (Herlambang et al., 2019)

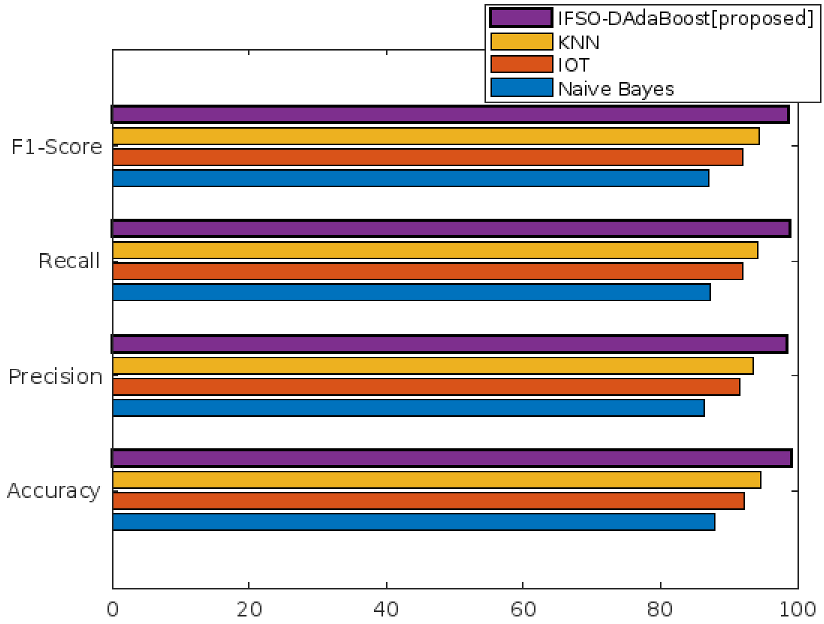

Figure 2: Result of the Overall performance

The suggested IFSO-DAdaBoost model substantially beat the traditional Naïve Bayes, IOT, and KNN approaches in terms of overall performance across a variety of assessment criteria, as shown in Table 3 and Figure 2. With an accuracy of 99.2%, the Proposed version greatly exceeds the Existing model in terms of accuracy, indicating its advanced ability to categorise instances effectively. It may also be able to identify relevant periods while lowering false positives and fake negatives, as the IFSO-DAdaBoost has the best recall (99.0%) and precision (98.6%). The IFSO-DAdaBoost model achieves a much higher F1 score (98.9%), suggesting a better balance between accuracy and F1 score. The comparison reveals that the IFSO-DAdaBoost model outperforms the other current method in terms of accuracy, precision, recall, and F1 score, indicating its effectiveness in classifying.

4.3 Error Metrics

The proposed IFSO-DAdaBoost model outperformed the IOT, KNN, and Naïve Bayes approaches in terms of evaluation metrics, as shown in Table 3. and Figures 3, 4, 5. The proposed model significantly improves the current model in terms of MAPE, reducing the error from 8.64 to 4.24. Comparably, the IFSO-DAdaBoost model obtains a significant reduction in Mean Absolute Error (MAE) from 0.5924 to 0.1832, demonstrating its capacity to produce more accurate predictions with less departures from the actual values. By lowering the error from 0.8865 to 0.3524, the IFSO-DAdaBoost model's Root Mean Square Error (RMSE) shows excellent overall performance and the capacity to successfully reduce the sharpening discrepancies between predicted and real values. Overall, the study demonstrates how well the proposed IFSO-DAdaBoost version performs forecasting tasks by increasing predicting accuracy and decreasing errors when compared to the conventional Existing technique.

Model	RMSE $RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$	MAE $MAE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)$	MAPE (%) $MAPE = \frac{100}{n}\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)$
Naïve Bayes	0.5938	0.4983	8.64
IOT	0.8865	0.5924	10.12
KNN	0.5782	0.4553	8.41
IFSO-DAdaBoost Algorithm	0.3524	0.1832	4.24

Table 3: RMSE, MAE, MAPE outcome result

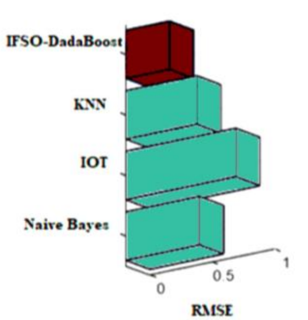

Fig3: RMSE Outcome Value of result

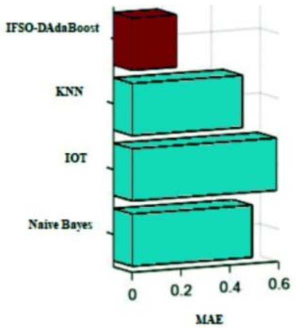

Fig4: MAE Outcome Value of result

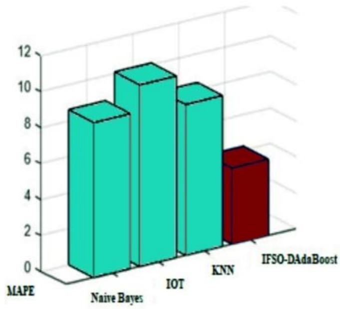

Fig5: MAPE Outcome

Discussion

The research introduced the impact of artificial intelligence on the professional identity of English language educators and digital pedagogy in the educational context of the digital transformation, along with the efficacy of the suggested IFSO-DAdaBoost framework of intelligent assessment. The results have valuable theoretical and pedagogical and societal implications and are in line with recent global studies on AI-enhanced education.

To begin with, the findings show that artificial intelligence has a considerable impact on the professional identity of teachers of English language by redefining the role of teachers, professional agency, and self-concept in the role of a digitally competent teacher. This observation highly argues the ecological view that Satvati et al. (2025) suggest, that one that argues that teacher identity changes via interactions between technology, institutional culture and professional practice. In line with meta-analysis by Ekizer (2025), AI has been shown to boost instructional efficiency, quality of feedback and learner engagement to transform teachers into learners designers and facilitators. This change of identity can be viewed as the change of a data-intensive, technology-driven professionalism, as opposed to the strict traditional pedagogical role.

Second, the use of artificial intelligence was identified as the core of effectiveness in changing digital pedagogical practices in the English language learning. The results indicate that AI-based technologies are useful in personalized learning, automation of feedback, smart assessment, and blended instruction design. These findings are aligned with those made by Nguyen et al. (2025) who have shown that AI-mediated online learning environments transform the instructional approaches used by teachers and the career-oriented writing habits of students. This shift within the construct of the TPACK is evidence of more profound unification of technological knowledge with pedagogical and content knowledge, beyond what the superficial use of ICT entails. Nevertheless, the discrepancies of the rates of innovation-oriented digital practices that were revealed in the findings also reflect previous issues that a great number of teachers have not yet moved past the stage of technology application to pedagogic change (Farias-Gaytan et al., 2023).

Thirdly, digital literacy and technology acceptance of teachers were identified to mediate the association between artificial intelligence and digital pedagogy. More innovative AI-based instructional practices were observed in teachers who were more digital literate and more technology accepting. The result can be related to the Technology Acceptance Model, which identifies the perceived usefulness and ease of use as the essential determinants of the technology adoption. It is also consistent with the empirical research that proved the digital literacy to be a strong predictor of teaching effectiveness and learning outcomes (Ervianti et al., 2023; Rakasiwi et al., 2023). This mediating effect was further supported by institutional support, training systems, and access to intelligent infrastructure, which confirms the findings of previous structural modeling studies of Jatmoko et al. (2023) and Ren (2024). Simultaneously, the existence of sustained digital disparities between institutions and regions still limits the adoption of AI fairly (Hidalgo et al., 2020; Qiu et al., 2023).

Regarding the methodological issue, the high results of the suggested IFSO-DAdaBoost model prove the benefits of the combination of swarm intelligence optimization and ensemble learning that would provide high-accuracy educational assessment. The proposed model also has a higher predictive accuracy and stability, compared to the conventional machine learning methods like KNN and Naive Bayes (ElHaji et al., 2014; Herlambang et al., 2019). This agrees with recent deep learning and soft computing research, which suggests intelligent fuzzy models that may be applied in difficult educational evaluation tasks (Chen, G., 2024; Chen et al., 2022).

The perceived system usefulness within the model is boosted by the high performance as well, which is another element needed to make AI adoption in education sustainable in terms of TAM.

Besides methodological input, this research has significant social and educational implications. At the education level, the results indicate that teacher professional development must go beyond the simple ICT training to the advanced AI literacy, data-driven pedagogy, algorithm thinking, and ethical governance. Universities are recommended to implement the tiered, persistent training system that will be based on the career stage of teachers and the digital transformation objectives. Digitally and AI-capable English teachers at the societal level are crucial in equipping students to be included in the globalized digital economy and mitigating the imminent educational inequalities. Nonetheless, the ethical risk of algorithmic bias, data privacy, and transparency is an essential aspect that continues to pose a challenge, which justifies the responsibility of AI governance in education (Zhang et al., 2022; Reddy et al., 2023).

Although such contributions have been made, there are a number of limitations that are to be noted. To begin with, the sample of the study was confined to one regional context, which can limit the extrapolation of the results. Second, the use of self-reported questionnaire data is subject to possible response and social desirability bias. Third, as much as the proposed IFSO-DAdaBoost model has good predictive capability, the interpretability is low because of the complexity of the ensemble and swarm optimization processes.

In the future research, such limitations should be overcome in several ways. To begin with, the comparative studies among the regions, and nations are required to investigate how AI-guided teacher identity and pedagogy will develop in various policy, culture, and technological settings. Second, the research designs based on longitudinal methods are to be considered to trace the changes in digital literacy, technology acceptance, and professional identity over an extended period. Third, self-reported measures should be accompanied by combining multi-source behavioral data in the learning management system, as well as artificial intelligence teaching systems and classroom analytics in future studies. Lastly, explainable artificial intelligence solutions ought to be implemented to promote a sense of transparency, fairness, and trust in intelligent learning assessment systems.

Altogether, this research not only promotes intelligent assessment methodology via the IFSO-DAdaBoost model but also contributes to theoretical knowledge of how artificial intelligence redefines the identity of a teacher and digital pedagogy as a part of the integrated TPACKTAM model. The study offers a viable insight to the field of intelligent English language education sustainable development by connecting technological innovation and professional development and educational governance.

Conclusion

The preliminary 190-sample survey in Zhejiang, China, concluded that students enrolled in English education demonstrated a comparatively high digital literacy self-score. The metrics encompass 4 dimensions: awareness in digital, computational thinking, innovation learning in digital , digital protection, and transparency. The results of the data analysis indicate that, although Students of various genders and age groups do not significantly vary from one another, there is a substantial variation in digital literacy among English teachers. Therefore, we can conclude that enhancing teachers' digital literacy often necessitates higher levels of English education. Meanwhile, we have conducted a statistical analysis of 4 aspects of literacy in digital. Future studies look into the meaning and application of literacy in digital to examine ways to help English students in secondary school and those in higher vocational education, respectively...

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