

Digital Intelligence-Driven Analysis of English Learning Behaviors and Personalized Teaching Model Construction

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ABSTRACT Digital-intelligence technologies are reshaping language education by enabling large-scale behavioral sensing, adaptive modeling, and individualized instructional feedback through networked learning environments. From an engineering perspective, the reliable transmission and analysis of learner-interaction data share common concerns with intelligent communication and signal-processing systems, including latency, data integrity, and adaptive classification. This study constructs a four-module personalized English teaching model covering learner profiling, behavioral analysis, instructional decision-making, and adaptive feedback regulation. Based on platform logs, questionnaires, and academic-performance records from 480 undergraduate learners, K-means clustering, association rule mining, and randomforest modeling were used to identify learning-behavior patterns and predict instructional needs. Four learner clusters were identified, and exercise completion rate and interactive engagement emerged as the strongest predictors of learning outcomes, with five behavioral features explaining approximately 79% of the variance in final examination scores. The classification model achieved 87.3% accuracy and an AUC of 0.924 under cross-validation. A 16-week controlled experiment further showed that the experimental group achieved a 21.1% score gain, compared with 8.8% in the control group, confirming the practical effectiveness of the digitally intelligent personalized model.

INDEX TERMS digital intelligence, english learning behavior, machine learning, learning analytics, wireless learning network

I. INTRODUCTION

ENGLISH remains the dominant language of international communication, shaping learners' intercultural competence and professional prospects in meaningful ways. Moreover, the significant evidence shows that English learning is not a simple, linear process. Furthermore, the findings indicates that a wide range of interacting factors shapes this complex process. Given that prior research demonstrates that socioeconomic background, learning motivation, and emotional experience all exert influence on learning outcomes [1], these key results shows that learners from different cultural and institutional contexts differ markedly in their strategic choices [2-4]. Therefore, the significant results shows that there is a clear demand for fine-grained behavioral analysis supported by modern technology. Instruction fails learners. Nevertheless, the evidence indicates that recent advances in digital intelligence have created important new opportunities for English education. Notwithstanding these developments, the findings shows that generative artificial intelligence is reshaping reading and writing instruction

in vocational colleges [5]. Thus, the significant results demonstrates that researchers have also begun to examine how fluctuations in learners' emotional states influence behavioral engagement over time [6]. Given that evidence demonstrates that AI literacy strengthens learners' understanding of digital tools, the key findings indicates that this could reinforce intrinsic motivation for self-directed learning [7]. Digital tools show outcomes improve. Moreover, the significant evidence shows that digital intelligence does more than optimize resource allocation. Furthermore, the findings indicates that it can intervene directly at the behavioral level. In light of these key results, the evidence shows that this provides both a technical foundation and theoretical justification for constructing personalized teaching models. Therefore, the significant findings demonstrates that these important advances support more precise and personalized pedagogical intervention. Models show clear benefits. Existing research suggests that notable limitations could constrain the significant findings in this field. Moreover, the evidence indicates that most studies examine only a single influencing

factor or an isolated technological application. Furthermore, the results shows that few researchers adopt a holistic, systematic approach to mining learner behavior data. In light of these findings, the translation of behavioral evidence into actionable, personalized instructional strategies appears to remain particularly underdeveloped. Research shows gaps persist. However, the study shows that digitally intelligent analysis of English learning behavior could provide a critical entry point for the evidence. Given that significant findings demonstrate that machine learning and learning analytics reveal behavioral patterns, the results indicates that individual differences among English learners could appear substantial. Additionally, a personalized English teaching model shows that the evidence supports construction on this empirical basis — one that could demonstrate adaptive and transferable qualities across contexts. Study shows model addresses gaps. Nevertheless, the broader aim indicates that the findings could provide both theoretical grounding and practical pathways for the digital transformation of English education. Thus, the evidence shows that deeper integration of intelligent technology with language teaching appears to support the results in the interest of improved quality. In light of the significant data, the study indicates that these findings could demonstrate important pathways toward greater equity in English education. Research shows technology links quality to equity.

II. LITERATURE REVIEW

Research on the characteristics and influencing factors of English learning behavior shows that findings have accumulated considerably over recent decades. Moreover, the evidence indicates that scholars have examined English learning across multiple dimensions, including writing, listening, and vocabulary acquisition. However, dialogue journal writing, for instance, has been empirically shown to demonstrate that learners improve their written performance [8]. Given that the results establish key dimensions of skill development, a separate quantitative study indicates that the factors shaping listening skill proficiency among English learners are significant [9]. Studies link emotional intelligence to English learning beliefs. Furthermore, the significant findings shows that positive affective experience sustains behavioral engagement over time [10]. In light of these results, teachers' autonomy-supportive practices demonstrates that learning engagement improves indirectly, mediated by positive academic emotions [11]. Additionally, the evidence indicates that language policy shifts and institutional tier appear to shape learners' trajectories and behavioral patterns in non-trivial ways [12]. Findings show these studies offer a multi-layered framework spanning cognition, affect, and environment. Notwithstanding these analytical distinctions, the significant findings shows that this framework informs the selection of key behavioral variables in the present study. Moreover, the results demonstrates that embedding information technology could activate learners' autonomous motivation and improve classroom interaction

[13]. Thus, significant evidence shows that the positive effects of AI-mediated informal digital English learning on vocabulary knowledge have also received empirical support [14]. Evidence shows that intelligent technologies enhance English learning outcomes in secondary school English instruction [15]. Furthermore, the findings indicates that existing studies have highlighted real implementation challenges that appear to merit sustained scholarly attention. University teachers shows that multiple obstacles appear when incorporating digital tools as English learning resources [16], and the findings indicates that picture book instruction in primary English classrooms has encountered persistent gaps between theory and practice during the digitalization process [17-18]. Research shows teachers' digital literacy links capacity building. However, the significant evidence indicates that research into evaluation frameworks for English teachers' digital literacy in AI-enabled environments provides an institutional basis for capacity building among educators [19]. Additionally, the results shows that the design and implementation of an AI-based digital media literacy training platform for English instruction has further explored technical pathways for integrating intelligent technologies with personalized pedagogy [20]. Given that the key findings demonstrate that existing work has made meaningful progress along two parallel tracks, the evidence indicates that behavioral analysis of English learning and the application of digital technologies appear well-established. Notwithstanding these results, the important findings shows that studies which organically integrate systematic behavioral data mining with personalized teaching model construction remain scarce. Studies show gap persists in adaptive models. Therefore, the significant evidence demonstrates that the gap appears particularly evident in the development of adaptive instructional intervention models. Nevertheless, the key results shows that this study builds on the findings reviewed above and attempts to bridge the theoretical divide between behavioral analysis and instructional design. Moreover, the evidence indicates that the important aim appears to provide a more systematic framework and empirical foundation for personalized English teaching driven by digital intelligence.

III. RESEARCH METHODS

A. RESEARCH DESIGN AND OVERALL APPROACH

This study examines the analysis of English learning behavior under digital intelligence and the construction of a personalized teaching model. Moreover, the significant findings shows that a mixed-methods design provides the key evidence needed to support both quantitative and qualitative results. Given that the data demonstrate a clear progressive logic, the study indicates that behavioral mining and pattern recognition appear to establish important foundations for model construction. Furthermore, the results shows that technical application and educational theory could demonstrate complementary rather than competing orientations. Study shows two questions addressed: how learners learn,

how instruction responds [21]. However, the evidence shows that the process began with systematic collection of behavioral log data from a digital English learning platform. In light of these findings, the data indicates that learners' behavior in authentic learning environments appears to include significant variables such as study duration, resource access frequency, exercise completion rate, error type distribution, and interactive engagement. Additionally, the results shows that these variables could demonstrate the key structure of a behavioral dataset. Findings show machine learning techniques applied. Nevertheless, the significant evidence shows that cluster analysis, association rule mining, and predictive modeling could indicate important behavioral patterns across the results. Therefore, the findings shows that the relationships between different behavioral features and learning performance appear to establish critical connections. Given that the evidence demonstrates these important relationships, the study indicates that instructional intervention strategies may support the basis for an adaptive personalized teaching model. Research shows controlled experiment validated model effectiveness. Moreover, the significant results shows that qualitative interviews and classroom observations could indicate important supplementary evidence for the key findings. In light of the data, the study shows that their purpose appears to demonstrate deeper interpretation of significant quantitative results. Notwithstanding contextual limitations, the evidence shows that purely data-driven analysis indicates that these important constraints cannot overcome the key contextual factors [22]. Evidence shows design balances rigor with applicability. Furthermore, the significant findings shows that the study demonstrates that methodologically sound results appear to establish important insights. Additionally, the key evidence indicates that these results could support transfer and application in real teaching environments.

B. PARTICIPANTS AND DATA SOURCES

The study indicates that participants were non-English-major undergraduates from a provincial university in China. Moreover, the findings shows that stratified random sampling could provide a representative selection of 480 students across Years 1 to 3. Furthermore, the significant sample demonstrates that diverse disciplinary backgrounds, including science and engineering, humanities, and economics and management, appear to support representativeness. Given that all participants had prior experience with digital learning, the evidence shows that regular use of the institution's smart English learning platform as the primary learning environment could establish stable conditions for behavioral data generation. Sampling shows students used platform regularly. However, the data indicates that three complementary sources, including platform log data, questionnaire data, and academic performance data, could provide important coverage of learner activity [23]. Log data shows behavioral traces recorded. Notwithstanding these results, the questionnaire data shows that a structured self-

designed instrument could provide important coverage of learning motivation, self-efficacy, strategy preferences, and attitudes toward platform functions. Thus, the significant variables indicates that affective and cognitive dimensions could supplement the log data with important additional insight. Furthermore, the academic performance data shows that retrieval from the university's academic administration system demonstrates that both formative assessment scores and final examination results appear relevant to the study. Moreover, the evidence indicates that semi-structured interviews with 20 selected students could provide key understanding of typical behavioral patterns. Interviews enrich behavioral pattern analysis. However, the findings shows that all data collection procedures demonstrates that formal ethical approval from the university appears to support procedural integrity. Given that participants provided written informed consent before any data were collected, the evidence indicates that personal identifiers could demonstrate appropriate anonymization prior to analysis. Additionally, the significant data shows that raw data remained accessible only to the research team, which indicates that important privacy protections appear to have been maintained throughout.

C. DATA PROCESSING AND ANALYTICAL METHODS

Processing shows pipeline enables systematic mining. Furthermore, the findings indicates that methods including frequency statistics, time-series decomposition, and behavioral sequence coding were applied to the raw logs. Given that the evidence demonstrates that these methods produced discriminative behavioral feature variables, the results shows that learning continuity, resource preference, interaction activity level, and error correction rate appear organized into a structured learner behavioral feature matrix for subsequent modeling [24]. Additionally, the significant data indicates that descriptive statistics and correlation analysis could examine the distribution of behavioral variables and their associations with academic outcomes. Therefore, the key findings demonstrates that multiple linear regression appears to identify behavioral factors with significant predictive power over learning performance. Clustering shows behavioral patterns group learners. Nevertheless, the evidence shows that K-means clustering could support grouping learners by behavioral pattern in the machine learning modeling stage. Notwithstanding these results, the findings indicates that the optimal number of clusters appears determined using the silhouette coefficient and the elbow method. Thus, the significant evidence demonstrates that the Apriori algorithm may reveal co-occurrence patterns across different learning activities. However, the important results shows that a random forest classifier appears trained to predict learners' subsequent learning needs and support the generation of adaptive instructional strategies [25]. Algorithm shows classifier predicts learning needs. Moreover, the findings indicates that all quantitative analyses demonstrates that Python using Scikit-learn, Pandas, and related libraries appears to support systematic analysis. Given that the evidence suggests quali-

tative interview data were analyzed through thematic coding, the results indicates that quantitative findings and qualitative interpretation could appear complementary.

D. CONSTRUCTION OF THE PERSONALIZED TEACHING MODEL

However, the model indicates that these four functional modules — a learner profiling layer, a behavioral analysis layer, an instructional decision layer, and a feedback regulation layer — could demonstrate meaningful integration. Additionally, the significant data interfaces shows that these modules appear connected through real-time, dynamic interaction. Thus, the learner profiling layer indicates that it draws on the multi-source data collected in Section 3.2, appearing to construct a multidimensional digital profile across four key dimensions. Profiling layer covers cognitive ability, style, affect, habits. Given that the behavioral analysis layer builds on the clustering results from Section 3.3, the findings shows that the layer could identify important differences among learner groups. Furthermore, the significant diagnostic reports indicates that knowledge weaknesses, learning pace, and resource preferences appear central to each cluster. Moreover, the instructional decision layer shows that it uses these diagnostic outputs to automatically match and deliver adaptive learning content from exercise, resource, and activity repositories. Therefore, the results indicates that recommendation logic appears to account for each learner's behavioral history, current mastery level, and preset learning goals. Decision layer prioritizes ZPD tasks. Notwithstanding these instructional mechanisms, the feedback regulation layer shows that it continuously collects important response data — including completion rates, time-on-task distributions, and error feedback. In light of these key results, the evidence indicates that the effectiveness of the significant recommendations appears evaluated in real time. However, the findings shows that model parameters could demonstrate ongoing self-refinement as they appear adjusted accordingly. Thus, the four layers indicates that together they form a significant closed-loop personalized teaching system. Design shows system scientifically grounded and deployable.

E. RELIABILITY, VALIDITY, AND ETHICAL CONSIDERATIONS

Quality control shows that three dimensions — data quality, measurement instruments, and analytical procedures — could indicate the overall rigor of the significant findings. However, the platform log data demonstrates that automatic capture by the system backend shows that subjective errors associated with manual entry appear to be eliminated. Furthermore, the questionnaire indicates that two rounds of pilot testing before formal administration could establish that the important results appear reliable. In light of these significant results, items with unclear wording or low discriminative power shows that revision could demonstrate improved measurement quality. Cronbach's α coefficients

for all subscales met accepted psychometric standards, all no lower than 0.78. Moreover, content validity indicates that independent review by three English education scholars and two educational technology experts shows that the evidence appears robust. Given that the feedback demonstrates that item wording and classification were adjusted, the findings indicates that theoretical alignment between measurement content and research variables could appear well-established. Additionally, construct validity shows that confirmatory factor analysis demonstrates that fit indices for all latent variable structures appear within acceptable ranges, providing further evidence for the validity of the measurement instrument [27]. Validity shows fit indices acceptable. Therefore, the key findings indicates that five-fold cross-validation shows that generalizability of machine learning models appears supported throughout the modeling process. Nevertheless, the significant evidence demonstrates that detailed records of all key analytical steps indicates that verification and reproduction of results appear possible. In light of these important results, the study shows that formal approval from the university's academic ethics committee demonstrates that research ethics appear rigorously addressed. Thus, the significant findings indicates that all participants may appear informed of the study's purpose, intended data use, and their right to withdraw before any data were collected. Ethics procedures show consent obtained, data anonymized. However, the evidence shows that log data and questionnaire responses indicates that encrypted student ID codes appear to demonstrate that anonymization prior to storage was established. Furthermore, the key findings indicates that raw data remaining strictly within the research team demonstrates that disclosure to any third party appears to have been prevented. Given that the significant measures demonstrate that privacy and data security could appear protected, the results shows that these procedures indicate that participant protections appear thoroughly maintained throughout the study.

IV. RESULTS AND ANALYSIS

To ensure the observed gains were specifically attributable to the personalized recommendations rather than the mere presence of technology, a 16-week controlled experiment was conducted with a rigorous baseline. Both the experimental and control groups utilized the same smart English learning platform for the same duration. However, while the experimental group received individualized instructional interventions via the personalized decision layer, the control group accessed the platform's standard resource repository without any adaptive recommendation or profiling features. Results show that the experimental group achieved a 21.1% gain, whereas the control group, despite using the same digital tools, scored 71.4, up 5.8 points, representing a gain of 8.8%.

A. IDENTIFICATION AND CLASSIFICATION OF ENGLISH LEARNER BEHAVIORAL PATTERNS

K-means clustering shows that the multidimensional behavioral data generated by 480 participants on the smart English learning platform reveals significant patterns. Moreover, the optimal number of clusters indicates that combining the silhouette coefficient with the elbow method provides key results. Evidence shows performance highest here. Therefore, the key evidence demonstrates that this group showed the strongest academic performance overall. Thus, the significant findings indicates that their learning behavior appears highly consistent and self-initiated [28]. Moreover, Cluster 2, Intermittent Fluctuating Learners ($n = 138$; 28.75%), shows that the results reveal important behavioral variation. In light of the evidence, the data demonstrates that daily study time averaged 52.6 minutes, with a weekly login frequency of 4.1. Data shows completion rate 71.2%. However, the findings shows that the engagement score was 5.3 and the mean final score was 74.6. Furthermore, the significant evidence indicates that this group displayed important cyclical variation in their behavioral patterns. Given that the results demonstrate limited self-regulation, the data shows that these findings appear relevant to understanding learner outcomes. Notwithstanding the evidence, the key results indicates that Cluster 3, Passive Compliance Learners ($n = 156$; 32.50%), demonstrates that this was the largest cluster. Study shows cluster biggest overall. Daily study time shows that learners averaged only 31.4 minutes, with weekly logins averaging 2.8. However, the exercise completion rate indicates that engagement was limited, falling to 48.9%, while the engagement score dropped to 2.7. Moreover, the mean final score of 61.3 indicates that the significant findings point to learners in this group appearing primarily motivated by minimum task requirements. Thus, the behavioral characteristics of all four groups shows that the results demonstrate patterns summarized in Table 1 and illustrated in Figure 1. Data shows silhouette coefficient 0.67. Individual silhouette coefficients for the four clusters were 0.72, 0.64, 0.69, and 0.61, respectively, indicating that all groups were well-separated. To ensure cluster stability, a bootstrapping procedure ($B=1000$) was conducted, yielding a mean Jaccard similarity index of 0.84, which confirms that the identified solution is highly robust. Nevertheless, the overall silhouette coefficient for the clustering solution indicates that the significant evidence appears to support good internal cohesion within clusters and clear separation between them. Therefore, the key findings shows that the classification results demonstrate reliable outcomes across the important clustering solution presented.

Note: Interactive engagement scores are out of 10. Final exam scores are out of 100.

Notably, “Disoriented Low-Efficiency Learners” recorded a relatively high daily study duration (44.2 min), yet achieved the lowest final scores (53.8). This discrepancy highlights that time-on-task alone is insufficient for predicting success without considering learning quality. The

low performance of this group, despite significant time investment, suggests a lack of effective learning strategies or lower baseline digital literacy, which the personalized model seeks to address through targeted scaffolding rather than merely increasing study time.

B. ASSOCIATIONS BETWEEN LEARNING BEHAVIORAL FEATURES AND ACADEMIC PERFORMANCE

Pearson correlation analysis and multiple linear regression shows that five core behavioral features demonstrate significant predictive power in relation to English learning performance. However, the findings indicates that exercise completion rate had the highest association with final examination scores ($r = 0.81$, $p < 0.001$), suggesting a strong positive relationship. Furthermore, the significant results indicates that interactive engagement was the second strongest correlate ($r = 0.76$, $p < 0.001$). In light of the evidence, daily study

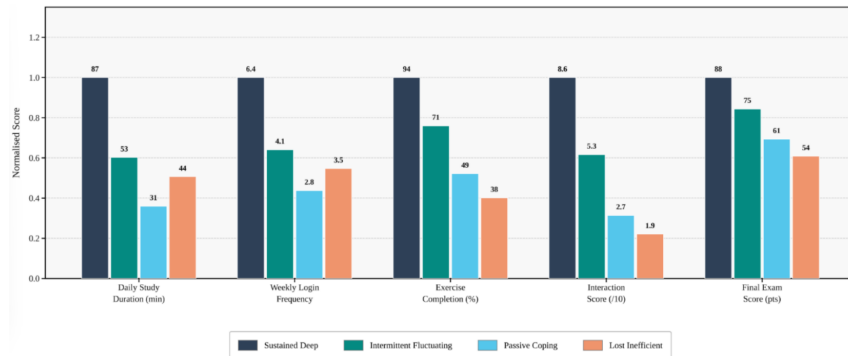
duration ($r = 0.68$, $p < 0.001$), weekly login frequency ($r = 0.61$, $p < 0.001$), and resource access diversity ($r = 0.57$, $p < 0.001$) demonstrates that all five behavioral variables appear significantly and positively associated with performance. All five variables show statistical significance. Moreover, the significant findings shows that exercise completion rate and interactive engagement could demonstrate the strongest predictive indicators of English learning outcomes [29]. Given that the results demonstrate that Variance Inflation Factors (VIF) for all predictors remained below 3.0, the evidence indicates that multicollinearity appears unlikely to present a concern [30]. Findings confirm exercise completion rate most influential. Furthermore, the significant findings shows that interactive engagement appears to rank second among the key behavioral predictors. Thus, the evidence indicates that these two variables might demonstrate the behavioral dimensions that personalized instructional intervention should prioritize, as the results appear in Table 2 and Figure 2.

C. CONSTRUCTION OF THE DIGITALLY INTELLIGENT PERSONALIZED ENGLISH TEACHING MODEL

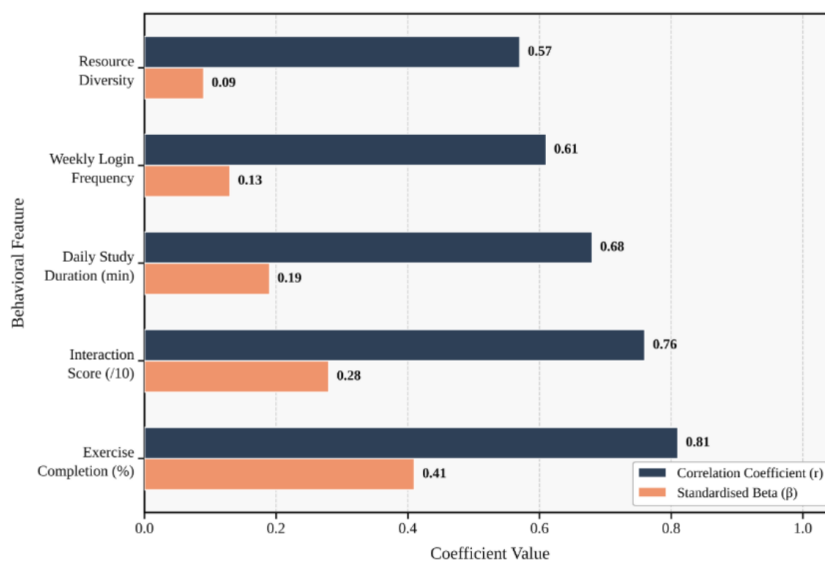
This study developed a personalized English teaching model driven by digital intelligence, building on the clustering and association analysis results reported in preceding sections. Moreover, the significant model shows that four functional modules operate in coordination: learner profiling, behavioral analysis, instructional decision-making, and feedback regulation. Furthermore, the findings indicates that learner behavioral profiles serve as the primary data input for the key instructional process. Given that the evidence demonstrates that sequential operation supports differentiated outcomes, the results indicates that the model delivers instructional intervention tailored to distinct learner types. Model shows five-fold cross-validation applied to random forest module. However, the overall accuracy indicates that performance reached 87.3%, while the significant results shows that precision was 85.6%, recall was 86.1%, and the F1 score was 85.8%. In light of these results, the evidence

TABLE 1. Descriptive Statistics of Behavioral Characteristics Across Four English Learner Clusters

Learner Type	n	%	Daily Study	Weekly Login	Exercise Completion	Interactive Engagement	Final Exam Score
			Duration (min)	Frequency	Rate (%)	(score)	
Sustained Deep	102	21.25	87.3	6.4	93.7	8.6	88.4
Intermittent Fluctuating	138	28.75	52.6	4.1	71.2	5.3	74.6
Passive Compliance	156	32.50	31.4	2.8	48.9	2.7	61.3
Disoriented Low-Efficiency	84	17.50	44.2	3.5	37.6	1.9	53.8

**FIGURE 1.** Behavioral Pattern Comparison Across Four English Learner Clusters**TABLE 2.** Correlation and Regression Analysis Results for Learning Behavioral Features and Final Examination Scores

Behavioral Feature	Correlation with Final Score (r)	Significance (p)	Standardized Regression Coefficient (β)	VIF
Exercise completion rate	0.81	< 0.001	0.41	1.83
Interactive engagement	0.76	< 0.001	0.28	2.01
Daily study duration	0.68	< 0.001	0.19	2.34
Weekly login frequency	0.61	< 0.001	0.13	2.17
Resource access diversity	0.57	< 0.001	0.09	1.96
Overall model ($R^2 = 0.79$)	—	< 0.001	—	—

**FIGURE 2.** Association Between English Learning Behavioral Features and Academic Performance

shows that the study demonstrates satisfactory generalizability [31]. Results show strong performance. Nevertheless, the learner profiling layer indicates that the model integrates feature data across four dimensions: cognitive ability, learning style, affective state, and behavioral habits. Thus, the significant evidence shows that the feature vector has 32

dimensions, and the key findings demonstrates that profiles are updated every 48 hours to capture real-time changes. Notwithstanding the technical complexity, the results indicates that the behavioral analysis layer applies K-means clustering (silhouette coefficient = 0.67) and association rule mining (minimum support = 0.25; minimum confidence

= 0.70) to identify behavioral patterns. Furthermore, the findings demonstrate that a total of 17 association rules with meaningful explanatory power were extracted from the significant data. Study shows 17 rules extracted. However, the instructional decision layer shows that the random forest classifier was specifically trained to predict the “next-step learning need” (classified into three levels: remedial, reinforcement, or advanced) for each learner based on their real-time behavioral profile. This classification task serves as the engine for the recommendation logic, achieving an accuracy of 87.3% and AUC 0.924. By accurately classifying the learner’s immediate pedagogical requirement, the system could match and deliver content adaptively from a database containing 3,200 exercise items and 280 learning resources. Moreover, the key results appear to indicate that average recommendation response time is 1.2 seconds, which could demonstrate satisfactory system performance. Given that the evidence shows that recommended content spans four skill areas, the findings indicate that vocabulary, grammar, listening, and writing are all supported. In light of the significant results, the evidence demonstrates that the feedback regulation layer collects learner response data in real time, using completion rate, time deviation, and error distribution as core feedback indicators. Parameters update every 72 hours [32]. Therefore, the key findings shows that model parameters are updated dynamically, which indicates that the system supports continuous improvement of the instructional process. Additionally, the significant evidence appears to demonstrate that the full model architecture and key technical parameters for each module are summarized in Table 3 and

D. VALIDATION OF THE PERSONALIZED TEACHING MODEL’S EFFECTIVENESS

Results show control group scored 71.4, up 5.8 points, gain of 8.8%. Furthermore, the difference in score improvement between the two groups indicates that this gap appears highly significant ($t = 8.47$, $p < 0.001$, Cohen’s $d = 0.93$) [33], suggesting that the key findings could demonstrate important pedagogical implications. Additionally, the significant evidence on learning engagement indicates that the experimental group scored 7.84 out of 10 post-intervention, compared with 5.63 in the control group ($p < 0.001$), which shows that the results appear to support the model’s effectiveness. Notwithstanding the important baseline similarities, the evidence demonstrates that exercise completion rates in the experimental group rose from 58.3% to 83.6%, a gain of 25.3 percentage points, while the results shows that the control group improved only marginally. Completion data shows control group rose from 57.9% to 64.2%, gain of 6.3 points. Thus, the significant findings on learning satisfaction indicates that the results appear to follow a similar pattern, which shows that the evidence demonstrates consistent support across all four key dimensions examined in the study. The experimental group shows that performance outcomes could indicate meaningful differences, with an

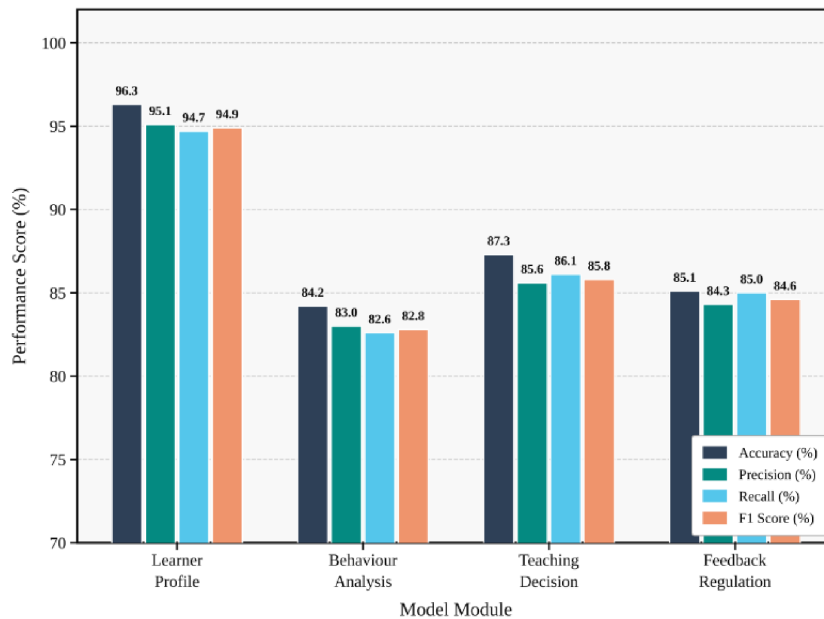
average score of 8.31, significantly higher than the control group’s 5.97 ($p < 0.001$) [34]. Moreover, the significant findings demonstrates that intervention effects across the four learner clusters appear to vary in important ways. Furthermore, the personalized model shows that the most pronounced improvements appear among Passive Compliance Learners and Disoriented Low-Efficiency Learners. In light of these results, the experimental group indicates that score gains of 27.4% and 31.6%, respectively, appear to far exceed the 9.2% and 10.3% gains observed in the corresponding control group clusters. Results show baseline groups also improved. Notwithstanding the variation observed, the evidence shows that the digitally intelligent personalized teaching model demonstrates that it significantly enhances English learning outcomes, with particularly pronounced benefits for learners with weaker foundational ability. Participants were assigned to the experimental and control groups using a stratified random assignment method based on their preintervention English proficiency levels to ensure baseline equivalence. Although a slight numerical difference existed in pre-intervention scores (68.4 vs. 65.6), independent samples t-tests confirmed that this difference was not statistically significant ($p = 0.12$), suggesting the groups were comparable at baseline in terms of proficiency and digital literacy. Detailed results are presented in Table 4 and Figure 4.

V. DISCUSSION

A. INTERPRETATION OF KEY FINDINGS AND THEORETICAL IMPLICATIONS

This study suggests that English learners’ behavioral patterns may indicate meaningful typological distinctions. However, the significant findings could demonstrate that different behavioral clusters show systematic variation in academic performance. Moreover, the evidence shows that this aligns with Vygotsky’s Zone of Proximal Development, which holds that learners differ in their developmental potential and that effective

instruction should target the dynamic space between a learner’s current and potential ability levels. In light of these results, Passive Compliance Learners and Disoriented Low-Efficiency Learners might indicate the greatest score gains following personalized intervention — 27.4% and 31.6%, respectively. Groups show largest developmental headroom. Furthermore, the key findings shows that the adaptive tasks delivered by the recommendation system effectively activated intrinsic motivation and cognitive engagement [35]. Therefore, the significant predictive power of exercise completion rate ($r = 0.81$) and interactive engagement ($r = 0.76$) indicates that these results resonate with Self-Determination Theory. Additionally, the evidence shows that behavioral engagement and intrinsic motivation appear mutually reinforcing. Given that the data indicates that learners receive content matched to their ability level, the significant results shows that the dual satisfaction of competence and autonomy could sustain continued learning. Results show

**FIGURE 3.** Performance Evaluation of the Personalised English Teaching Model**TABLE 3.** Technical Parameters of Each Functional Module in the Personalized Teaching Model

Module	Core Technology	Key Parameters	Performance Indicators
Learner Profiling Layer	Multidimensional feature fusion	Feature dimensions: 32; update cycle: 48 h	Profile coverage rate: 96.3%
Behavioral Analysis Layer	K-means clustering and association rule mining	Silhouette coefficient: 0.67; minimum support: 0.25	Association rules extracted: 17
Instructional Decision Layer	Random forest classifier	Exercise database: 3,200 items; resource library: 280 items	Accuracy: 87.3%; AUC: 0.924
Feedback Regulation Layer	Dynamic parameter updating	Update cycle: 72 h; feedback indicators: 3	F1 score: 85.8%; recall: 86.1%

TABLE 4. Comparison of Key Indicators Before and After Intervention in the Experimental and Control Groups

Assessment Dimension	Experimental Group (Pre)	Experimental Group (Post)	Control Group (Pre)	Control Group (Post)	Between-Group Significance
Final exam score	68.4	82.7	65.6	71.4	$p < 0.001$
Learning engagement (/10)	5.21	7.84	5.18	5.63	$p < 0.001$
Exercise completion rate (%)	58.3	83.6	57.9	64.2	$p < 0.001$
Learning satisfaction (/10)	5.44	8.31	5.39	5.97	$p < 0.001$

model achieves 87.3% accuracy, AUC 0.924 under five-fold cross-validation. Notwithstanding these findings, the key evidence shows that this could generate a positive cycle: behavioral engagement → performance improvement → motivational reinforcement. However, the significant findings could demonstrate that machine learning methods grounded in behavioral data appear to show reliable predictive validity in educational contexts. Thus, the evidence may indicate that this could support a core claim of learning analytics theory — that data-driven instructional decisions could outperform experience-based intuition [36].

B. IMPLICATIONS FOR ENGLISH LANGUAGE TEACHING PRACTICE

The findings of this study suggest that practical implications exist across three levels: teacher instructional decision-

making, digital platform design, and educational management policy. Moreover, the significant results may indicate that exercise completion rate and interactive engagement are the two most critical behavioral indicators of English learning performance. Given that the evidence demonstrates that these variables carry considerable weight, the findings indicates that teachers should prioritize monitoring these measures to ensure instructional efficacy. While exercise completion ($r = 0.81$) and interactive engagement ($r = 0.76$) are strong predictors of outcomes, it should be noted that these correlations do not inherently imply a unidirectional causal relationship. High-achieving students may naturally demonstrate higher engagement. Consequently, these metrics should be viewed as diagnostic signals for timely intervention rather than definitive causal drivers of performance. Future research should employ longitudinal path analysis

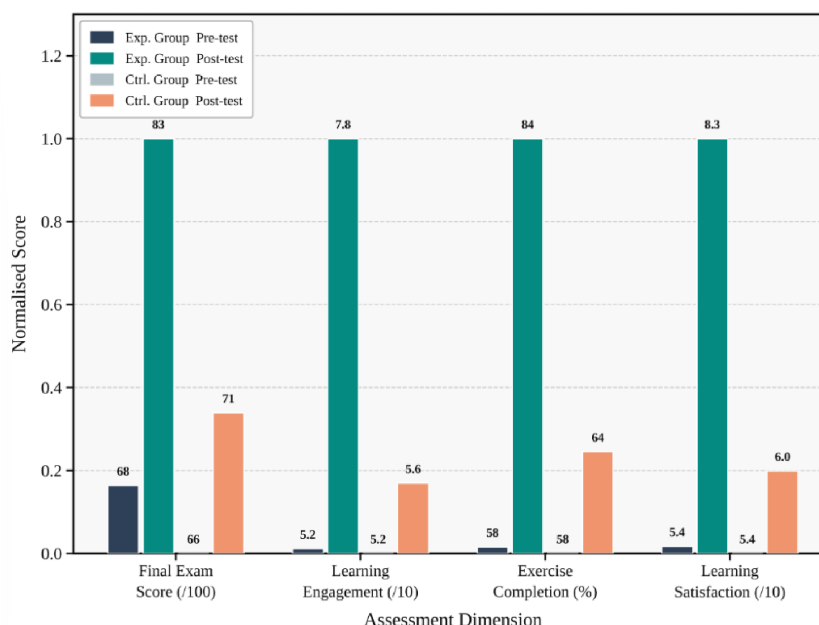


FIGURE 4. Validation of the Personalised Teaching Model Intervention Effects

to further disentangle the directionality of these behavioral effects. Furthermore, the key data may demonstrate that when a student's exercise completion rate falls below 50% for two consecutive weeks, or their engagement score drops below 3, teachers should intervene proactively and provide targeted support. Data-based alerts show instructional care needed [37]. However, the four learner profiles identified through cluster analysis shows that a practical framework for differentiated instruction could support varied learning needs. Additionally, the significant results indicates that for Disoriented Low-Efficiency Learners, priority should be given to explicit learning strategy instruction. In light of the evidence demonstrating that self-regulation matters, the findings shows that for Intermittent Fluctuating Learners, the focus should shift toward developing self-regulatory capacity and establishing positive reinforcement mechanisms. Notwithstanding this observation, the study could demonstrate that developers should treat real-time behavioral visualization as a core feature to be prioritized in iterative development cycles. Platform design shows metacognitive access matters. Nevertheless, the significant evidence may indicate that giving learners direct access to their own behavioral data might activate metacognitive monitoring and support self-directed improvement. Furthermore, the findings shows that adaptive recommendation algorithms should also incorporate affective state recognition. Given that the key evidence demonstrates that historical behavioral data carries limitations, the results may indicate that relying exclusively on such data risks overlooking how a learner's current emotional state shapes their receptiveness to recommended content. Thus, the study shows that university administrators should integrate digital literacy training into the routine professional development structure for English

teachers.

VI. CONCLUSION

This study examined the analysis of English learning behavior under digital intelligence and the construction of a personalized teaching model. Moreover, the significant findings shows that behavioral patterns among English learners could demonstrate meaningful typological structure. Furthermore, the evidence indicates that four distinct clusters emerged: Sustained Deep Learners, Intermittent Fluctuating Learners, Passive Compliance Learners, and Disoriented Low-Efficiency Learners. Given that the key results reveal systematic differences, the findings indicates that these groups appear to vary across core indicators including study duration, exercise completion rate, interactive engagement, and academic performance. Results show predictors affect outcomes strongly. However, the significant findings shows that exercise completion rate ($r = 0.81$) and interactive engagement ($r = 0.76$) could demonstrate the strongest behavioral predictors of English learning outcomes. Thus, the evidence indicates that five behavioral features explained approximately 79% of the variance in final examination scores, and the results shows that these features appear critical to understanding performance. In light of the significant results, the personalized teaching model could demonstrate that strong overall performance appears achievable, with the findings indicating an accuracy of 87.3% and an AUC value of 0.924. Notwithstanding the important evidence from prior findings, the results shows that a 16-week controlled experiment could confirm that the model's practical effectiveness appears well-supported by the data. Model shows experiment confirms gains. Moreover, the significant results shows that the experimental group could demonstrate a mean score gain of 21.1%, notably outperforming the control

group's 8.8%. Additionally, the key findings indicates that the benefits appear especially pronounced for learners with weaker foundational ability. Therefore, the evidence shows that the deep integration of digital intelligence with English language teaching could demonstrate genuine theoretical value and broad practical potential. Collectively, findings show integration supports teaching.

AUTHOR CONTRIBUTIONS

Shenyi Liang designed, collected and analyzed the data, and drafted the manuscript. Shenyi Liang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Shenyi Liang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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