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RESEARCH ARTICLE

Predicting Chinese Character Recognition Achievement: The Roles of Perceived Blended Learning Environment, Self-Efficacy, and Social-Affective Learning Strategies

CHEN ZHANG[1], MOHD SHAHRIL NIZAM BIN SHAHAROM[1], WONG SENG YUE[2], (Senior Member, IEEE), AND WEI ZHAO[3]

[1]Department of Curriculum and Instructional Technology, Faculty of Education, Universiti Malaya, Federal Territory of Kuala Lumpur 50603, Malaysia
[2]Academy of Malay Studies, Universiti Malaya, Federal Territory of Kuala Lumpur 50603, Malaysia
[3]Universiti Malaya, Federal Territory of Kuala Lumpur 50603, Malaysia

Corresponding author: Mohd Shahril Nizam bin Shaharom (nizamsaril@um.edu.my)

ABSTRACT Recent advances in digital technologies, including artificial intelligence (AI), have accelerated the integration of technology-enabled learning components into blended language learning. However, how learners' evaluations of the technology-enabled dimension of blended learning are associated with Chinese character recognition achievement remains insufficiently understood. Guided by the Stimulus–Organism–Response (S-O-R) framework and integrating the Technology Acceptance Model, Self-efficacy Theory and Oxford's language learning strategy perspective, this study examined the relationships among perceived blended learning environment (PBLE), self-efficacy, social-affective learning strategies (SLS), and Chinese character recognition achievement. Data were collected from 325 Chinese as a Second/Foreign Language (CSL/CFL) learners enrolled at Malaysian public universities. Following sample splitting, exploratory factor analysis was conducted using 124 participants, and the measurement and structural models were evaluated using PLS-SEM with an independent subsample of 201 participants. The results showed that PBLE significantly predicted self-efficacy, and self-efficacy significantly predicted social-affective learning strategies. Social-affective learning strategies significantly predicted Chinese character recognition achievement, whereas PBLE and self-efficacy did not significantly predict achievement directly. These findings support the proposed S-O-R framework, suggesting that learners' evaluations of the technology-enabled dimension of blended learning are associated with Chinese character recognition achievement through successive psychological and behavioral processes rather than through direct prediction. This study extends the application of the S-O-R framework by integrating TAM, Self-efficacy Theory and Oxford's strategy perspective to explain technology-supported Chinese character learning. The findings suggest that, alongside technology implementation, supporting learners' self-efficacy and social-affective learning strategies may better facilitate learners' achievement with Chinese character learning in blended learning environments.

INDEX TERMS Perceived blended learning environment, self-efficacy, social-affective learning strategies, Chinese character recognition achievement, stimulus–organism–response framework.

I. INTRODUCTION

The rapid advancement of digital technologies in the artificial intelligence (AI) era has fundamentally reshaped educational practices, particularly within technology-enhanced language education [1], [2], [3]. Recent advances in deep learning and intelligent perception algorithms have further expanded the capabilities of AI across diverse application domains, including object detection and human–computer interaction [4], [5]. This macro-backdrop has accelerated the integration of

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diverse digital platforms, mobile applications, and interactive tools into mainstream university blended learning architectures [6], [7]. Within these contemporary instructional settings, technology-integrated applications are embedded across online and face-to-face modalities to support flexible, adaptive, and learner-centered experiences [8], [9]. Rather than examining an isolated digital tool, contemporary educational research requires a comprehensive evaluation of how learners perceive the utility and usability of these integrated technological configurations. Understanding the precise pathways through which students behaviorally and psychologically process these technology-enhanced spaces is crucial for maximizing their academic potential.

The urgency of this exploration is highly pronounced in Chinese as a Second Language (CSL) instruction. According to the US Foreign Service Institute (FSI), Chinese is officially classified as a Category V' super-hard language. Notably, Chinese character acquisition remains one of the most demanding aspects of the learning process [10]. Unlike alphabetic writing systems, Chinese orthography is characterized by visually complex structures, stroke sequences, radicals, and spatial arrangements, requiring learners to simultaneously develop orthographic awareness, visual recognition abilities, and writing skills [11], [12]. Such characteristics impose substantial cognitive demands on CSL learners and often hinder sustained engagement and learning performance [13]. Conventional instructional approaches, which largely rely on repetitive memorization and mechanical writing practice, have been criticized for their limited capacity to accommodate individual learning needs and maintain learner motivation over time [14]. Consequently, higher education institutions increasingly deploy technology integrated blended learning environments to deliver the multi-modal scaffolding and structural flexibility required to alleviate the heavy memory burdens of logographic script acquisition [15].

Recent advances in digital educational technologies, including generative AI and other intelligent learning applications, have further enriched blended learning environments by providing immediate feedback, flexible learning resources, learning analytics, and personalized instructional support [16]. Rather than representing a single digital application, these technologies function as integrated components of blended learning that facilitate learner interaction, collaboration, and knowledge co-construction [17]. Prior studies have demonstrated that digital interaction and peer engagement can positively influence learning outcomes, participation, and academic performance [18], [19]. However, evidence regarding their direct contribution to objective language achievement remains inconsistent. In particular, little is known about how learners' perceptions of technology-integrated blended learning environments influence Chinese character recognition achievement through successive psychological and behavioral mechanisms. Addressing this gap requires moving beyond technology acceptance alone to examine the internal processes through which external technological support is translated into learning performance.

Beyond technological affordances, psychological and affective factors also play a critical role in shaping learners' academic performance. Among these factors, self-efficacy has consistently been identified as a significant predictor of learners' confidence, persistence, and engagement in learning tasks [20]. In studies related to online and mobile learning, self-efficacy has frequently been employed to explain learners' acceptance and effective use of educational technologies [21]. At the same time, social-affective strategies, as an important dimension of language learning strategies, may help learners regulate emotions, reduce anxiety, and enhance motivation through social interaction and collaborative engagement. However, existing studies have primarily emphasized technological acceptance, cognitive perceptions, or learning attitudes, while comparatively limited attention has been paid to the role of social-affective strategies in technology-assisted language learning environments [22]. More specifically, there remains insufficient understanding of how learners utilize social interaction and affective regulation within blended learning contexts to improve Chinese character recognition achievement.

To address these theoretical and empirical gaps, the present study investigates perceived blended learning environment (PBLE), conceptualized as learners' evaluative perceptions of the technology-enabled components embedded within a blended learning environment, operationalized through perceived usefulness and perceived ease of use. To explain how these perceptions are translated into learning outcomes, the study integrates the Technology Acceptance Model (TAM), Self-efficacy Theory, and Oxford's strategy perspective within the Stimulus–Organism–Response (S-O-R) framework. Specifically, it explains how learners' perceptions of blended learning influence Chinese character recognition achievement through successive psychological (self-efficacy) and behavioral (social-affective learning strategies) mechanisms. By extending the S-O-R framework to technology-integrated blended learning, this study contributes to a better understanding of Chinese character learning in digitally supported instructional contexts and provides practical implications for the design of technology-integrated language learning environments.

II. LITERATURE REVIEW

A. PERCEIVED BLENDED LEARNING ENVIRONMENT AND CHINESE CHARACTER RECOGNITION ACHIEVEMENT

In the present study, perceived blended learning environment (PBLE) refers specifically to learners' evaluative perceptions of the technology-enabled dimension of a blended learning environment rather than its overall pedagogical, social, or institutional characteristics. Contemporary blended learning integrates various digital learning components, such as learning management systems, communication platforms, and automated feedback tools, to support teaching and learning. Rather than evaluating any single technology in isolation, PBLE captures learners' overall perceptions of these technology-enabled learning components as part of the

blended learning environment. Grounded in the Technology Acceptance Model (TAM) [23], PBLE is operationalized through perceived usefulness (PU) and perceived ease of use (PEOU), which represent learners' evaluations of the usefulness and usability of these digital learning components. Perceived usefulness reflects learners' beliefs that the technology-enabled learning components enhance their language learning performance, whereas perceived ease of use reflects the extent to which these components are perceived as easy and convenient to use.

Although positive perceptions of the technology-enabled dimension of blended learning have generally been associated with favorable learning experiences, whether such perceptions directly translate into objective learning achievement remains theoretically inconclusive. Consistent with Cognitive Load Theory (CLT), Chinese character learning requires learners to process orthographic forms, phonological information, and semantic meanings simultaneously, imposing substantial intrinsic cognitive load [25], [26], [27], [28]. Under such conditions, favorable perceptions of the technology-enabled learning environment may provide supportive learning conditions but may not directly improve character recognition unless learners effectively regulate their psychological and learning processes. Accordingly, PBLE is expected to be associated with Chinese character recognition achievement primarily through learners' internal psychological and behavioral adaptation rather than through a direct association. Previous empirical findings have also reported inconsistent results regarding the direct relationship between technology-supported learning and learning achievement. Therefore, the direct relationship remains worthy of empirical examination.

H1: Perceived blended learning environment is positively associated with Chinese character recognition achievement.

B. SELF-EFFICACY AND CHINESE CHARACTER RECOGNITION ACHIEVEMENT

Self-efficacy, defined as individuals' belief in their capacity to accomplish tasks successfully, has been consistently linked to academic achievement across disciplines [29], [30], including language learning [31], vocational education [32], and online learning [33]. It shapes students' motivation, persistence, and behavioral engagement in the face of academic adversity [34]. In blended learning contexts, self-efficacy represents a critical internal psychological state, reflecting a learner's confidence in navigating both instructional tasks and digital demands. However, empirical findings regarding its direct impact on performance remain highly inconsistent. For instance, Luo et al. [35] demonstrated that learning engagement fully mediated the link between self-efficacy and achievement, while. Huang and Wang [36] highlighted that cognitive and strategic variables frequently disrupt or carry this relationship, pointing to substantial contextual complexity.

This theoretical variance is particularly acute in the domain of Chinese character acquisition. According to Bandura [37], self-efficacy operates as a motivational belief rather than an objective cognitive competence. Believing in one's capacity to learn Chinese characters can mitigate the debilitating emotional anxiety triggered by the daunting orthographic complexity of the logographic script. However, psychological confidence alone cannot substitute for the actual working memory processing required to decode, store, and retrieve intricate stroke patterns. Without translating this internal psychological readiness into concrete, effortful strategic actions, the direct conversion of self-efficacy into objective recognition achievement is structurally limited. Therefore, although self-efficacy has been associated with academic performance in previous studies, its association with Chinese character recognition achievement remains worthy of empirical examination. Accordingly, we hypothesize:

H2: Self-efficacy is positively associated with Chinese character recognition achievement.

C. SOCIAL-AFFECTIVE LEARNING STRATEGIES AND CHINESE CHARACTER RECOGNITION ACHIEVEMENT

In recent years, research has demonstrated that Social-affective Learning competencies exert broad and long-lasting positive effects on students' academic achievement [38]. In the domain of language learning, the role of social-affective learning strategies is particularly pronounced [39]. According to Cognitive Load Theory, human working memory has a strictly limited capacity when processing novel, high-element information. The intricate visual-spatial configurations of Chinese characters demand extensive cognitive resources for pattern recognition, inducing a heavy intrinsic cognitive load that is frequently compounded by learning anxiety and frustration [40].

Social-affective learning strategies help learners cope with these cognitive and emotional challenges. Affective strategies, such as emotional regulation and anxiety management, reduce unnecessary cognitive interference, whereas social strategies, including help-seeking, peer collaboration, and interaction within technology-supported learning environments, provide feedback and learning support. By facilitating more effective use of limited cognitive resources, these strategies may facilitate schema construction and be associated with better Chinese character recognition achievement [39], [41]. Accordingly, the following hypothesis is proposed:

H3: Social-affective learning strategies are positively associated with Chinese character recognition achievement.

D. PERCEIVED BLENDED LEARNING ENVIRONMENT AND SELF-EFFICACY

Learners' perceptions of blended learning environments play an important role in shaping their self-efficacy. According to the Technology Acceptance Model (TAM), perceived usefulness (PU) and perceived ease of use (PEOU) reflect learners' evaluations of the effectiveness and usability of

the technology-enabled dimension of a blended learning environment [23]. When learners perceive blended learning environments as useful and easy to use, they are more likely to experience successful learning and develop confidence in completing learning tasks.

According to Bandura's Social Cognitive Theory, mastery experiences are the primary source of self-efficacy development [42]. Empirical evidence supports this theoretical proposition. For example, Hanham et al. [43] reported that the perceived usefulness of an online tutoring service positively predicted students' academic self-efficacy, indicating that learners who regarded the technology as beneficial for understanding course content and completing learning tasks demonstrated greater confidence in their academic abilities. Similarly, Chen et al. [44] found that positive perceptions of educational technologies were associated with stronger self-efficacy in technology-enhanced learning environments.

Within the S-O-R framework, learners' perceptions of the blended learning environment represent an external environmental stimulus (Stimulus), whereas self-efficacy reflects learners' internal psychological responses (Organism). Accordingly, favorable perceptions of the technology-enabled dimension of blended learning are expected to enhance learners' confidence in successfully completing Chinese language learning tasks, thereby strengthening their self-efficacy. Therefore, the following hypothesis is proposed:

H4: Perceived blended learning environment positively predicts self-efficacy.

E. SELF-EFFICACY AND SOCIAL-AFFECTIVE LEARNING STRATEGIES

According to Bandura's Social Cognitive Theory, self-efficacy influences learners' behavioral choices, effort, and persistence when facing learning challenges [37]. Consequently, learners with stronger self-efficacy are more likely to adopt adaptive learning strategies to achieve their learning goals.

Empirical studies have shown that learners with higher self-efficacy are more likely to employ social-affective learning strategies, such as emotional regulation, help-seeking, peer interaction, and collaborative learning [45], [46]. In blended learning environments, learners with greater confidence are also more likely to make effective use of available learning resources and engage actively in learning, thereby promoting strategic learning behaviors that may facilitate language learning [47], [48].

Within the S-O-R framework, self-efficacy represents learners' internal psychological state, whereas social-affective learning strategies reflect their behavioral adaptation. In Chinese character learning, learners with stronger self-efficacy are expected to regulate emotions, seek support, and engage in collaborative learning to cope with the cognitive demands of character acquisition. Therefore, self-efficacy is expected to promote the adoption of social-affective learning strategies. Accordingly, the following hypothesis is proposed:

H5: Self-efficacy positively predicts social-affective learning strategies.

F. THEORETICAL INTEGRATION WITHIN THE S-O-R FRAMEWORK

Although the Technology Acceptance Model (TAM) explains learners' perceptions of technology, Self-efficacy Theory explains learners' psychological confidence, and Oxford's language learning strategy framework explains strategic learning behaviors, each theory focuses on a specific aspect of the learning process [23], [42], [49]. To provide a more comprehensive explanation of how learners' evaluations of the technology-enabled dimension of blended learning are translated into learning achievement, the present study integrates these complementary perspectives within the Stimulus–Organism–Response (S-O-R) framework [50].

Within this framework, perceived blended learning environment (PBLE) represents the Stimulus (S), reflecting learners' evaluations of the usefulness and ease of use of the technology-enabled dimension of a blended learning environment. Self-efficacy (SE) and social-affective learning strategies (SLS) together constitute the Organism (O), representing learners' internal psychological and strategic adaptation to the learning environment. Chinese character recognition achievement (CCRA) serves as the Response (R), representing the final learning outcome.

Accordingly, more favorable evaluations of the technology-enabled dimension of blended learning are expected to be associated with higher levels of self-efficacy, which may subsequently facilitate the use of social-affective learning strategies. In Chinese character learning, these strategies help learners regulate the cognitive and emotional demands associated with the complex orthographic characteristics of Chinese characters. This explanation is consistent with Cognitive Load Theory, which suggests that successful learning under high cognitive demands depends on effective regulation of cognitive and emotional resources rather than external learning conditions alone [51]. Therefore, the association between PBLE and Chinese character recognition achievement is expected to be explained through learners' successive psychological and strategic adaptation processes. Accordingly, the following hypothesis is proposed:

H6. Self-efficacy and social-affective learning strategies sequentially mediate the association between perceived blended learning environment and Chinese character recognition achievement.

III. MATHODS

A. PARTICIPANTS AND DATA COLLECTION PROCEDURE

This study employed a cross-sectional survey design to examine the relationships among the study variables. The target population comprised Chinese as a Second/Foreign Language (CSL/CFL) learners enrolled at two Malaysian public universities offering Chinese language courses. The target population of this study was intentionally limited to undergraduate CSL learners enrolled in Malaysian public

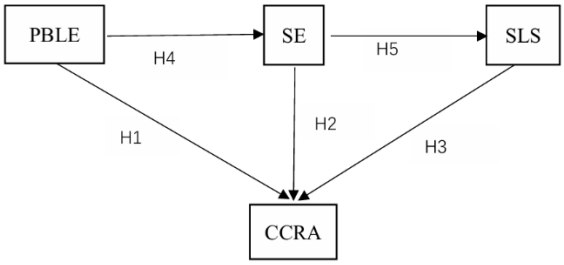

FIGURE 1. Conceptual framework.

universities because they shared relatively comparable curricula, instructional arrangements, and exposure to blended learning, thereby reducing contextual variability during theory testing. Restricting the sampling frame to this relatively homogeneous population was intended to strengthen the internal validity of the proposed theoretical model rather than to maximize population representativeness.

An a priori power analysis was conducted using G*Power 3.1. Assuming a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = .05$, statistical power of.95, and three predictors for the most complex endogenous construct, the required minimum sample size was 119 participants. To support both exploratory factor analysis (EFA) and structural equation modeling, a substantially larger sample was collected.

A multi-stage probability sampling procedure was employed. First, proportional stratified sampling was used to determine the required sample size for each participating university according to student enrollment. Subsequently, 12 intact Mandarin classes were selected using simple random sampling, including three classes from University A and nine classes from University B. The cluster sizes were relatively homogeneous, ranging from 25 to 30 students per class, with an average cluster size of 27.1 students. All students enrolled in the selected classes were invited to participate. Intact classes were selected to preserve the natural instructional setting and to minimize disruption to regular classroom teaching. A total of 365 students were approached, of whom 325 returned valid questionnaires, yielding a valid response rate of 89.0%. Because participants were recruited through intact classes, the data had a clustered sampling structure. All participating classes were beginner-level Chinese language courses following comparable course syllabi and intended learning outcomes.

To strengthen construct validation and reduce potential overfitting, the dataset (N = 325) was randomly divided into two independent subsamples: one for EFA (n = 124) and one for measurement and structural model evaluation using PLS-SEM (n = 201). Accordingly, all PLS-SEM results reported in this study are based on the independent validation sample (Table 1).

Participation was voluntary and anonymous. Electronic informed consent was obtained before participation, and no personal identifiable information was collected. Participants completed both the questionnaire and the Chinese character recognition test under closed-book conditions. To reduce potential common method bias, the questionnaire and the Chinese character recognition test employed different response formats, with the latter being scored objectively by predefined scoring criteria. The study was approved by the relevant ethics committee of University of Malaya, University of Malaya (Approval No. UM.TNC(P&I)/UMREC_4654).

TABLE 1. Participant characteristics (N = 325).

Characteristic	Category	N	%
Gender	Male	110	33.8
	Female	213	65.5
	Prefer not to say	2	0.7
Chinese proficiency	Beginner	325	100.0
Learning Duration	Year 1	203	62.5
	Year 2	122	37.5

B. INSTRUMENTS AND PILOT TEST

The questionnaire consisted of five sections: demographic information, perceived blended learning environment (PBLE), self-efficacy (SE), social-affective learning strategies (SLS), and Chinese character recognition achievement (CCRA). All scales were adapted from validated instruments and rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Content validity was confirmed via expert review (3 educational technology and MFL specialists), yielding satisfactory I-CVI and S-CVI values. Two items (affective strategies 3 and 4) were removed from the initial 29 items due to low I-CVI (0.67). The Chinese character recognition test was evaluated for internal consistency using Kuder–Richardson formula 20 (KR-20). The pilot test (N = 35) was conducted to refine item clarity and evaluate internal consistency. The complete questionnaire used in the pilot study is provided in Appendix.

The PBLE scale is adapted from Ibrahim et al. [52] and consists of two dimensions with a total of nine items: perceived usefulness (5 items; $\alpha = .968$) and perceived ease of use (4 items; $\alpha = .929$). In the present study, these items were used to operationalize learners' perceptions of the technology-supported component of the blended learning environment rather than the overall quality of blended learning. Accordingly, PBLE reflects learners' evaluations of how useful and easy the technology integrated into blended learning is perceived to be, rather than evaluations of instructional design, teacher support, or other pedagogical characteristics. A sample item is "The blended learning environment can be helpful to my learning." This operationalization is consistent with the objective of the present study, which focuses on learners' perceptions of technology-supported learning experiences embedded within blended learning rather than broader institutional or pedagogical characteristics of the learning environment.

Self-efficacy was measured using an adapted version of the Student Self-Efficacy Scale [53], which consists of 10 items

($\alpha = .966$). A representative sample item states: "I am convinced that I am able to successfully learn all relevant Chinese content even if it is difficult."

The social-affective learning strategies were measured using the Chinese learning strategy scale [54]. This scale consists of two sub-scales: affective strategies (5 items; $\alpha = .790$) and social strategies (5 items; $\alpha = .784$). For example, "I always encourage myself to use Chinese Characters as much as possible." and "I ask native Chinese speakers to correct my Chinese Characters mistakes."

Chinese character recognition achievement (CCRA) was assessed using an adapted Chinese character recognition test based on the instrument developed by Zhang et al. [10]. Rather than measuring overall Chinese language proficiency, the test was designed to evaluate learners' recognition of basic Chinese characters taught during the participating courses. Accordingly, the outcome variable was renamed Chinese character recognition achievement (CCRA) throughout the manuscript to more accurately reflect the construct being assessed.

The test consisted of 20 basic Chinese characters selected from the course syllabus and instructional materials used by the participating universities. The selected characters represented core vocabulary that all participants had been formally taught before data collection and were considered appropriate for their proficiency level. Three experts in Mandarin education and instructional technology reviewed the test to evaluate the representativeness and alignment of the selected characters with the course learning objectives, providing evidence of content validity.

For each character, participants received one point for correctly identifying the pinyin and one point for correctly providing the corresponding meaning, resulting in a maximum possible score of 40 points. The test demonstrated acceptable internal consistency (KR-20 = .706). Descriptive statistics indicated that the test scores ranged from 7 to 38 (out of 40) ($M = 31.65$, $SD = 5.66$), suggesting adequate score variability with no evidence of severe ceiling or floor effects. The observed distribution indicates that the instrument was able to capture meaningful individual differences in Chinese character recognition achievement.

C. ANALYTICAL PROCEDURE

Before conducting the main data analysis, a series of data screening procedures was conducted to ensure data quality. No missing values were identified. Normality was assessed via skewness and kurtosis values, all of which fell within acceptable thresholds (skewness between -2 and +2; kurtosis between −7 and +7), indicating no significant deviation from normality [55]. Although a few outliers were detected, they were retained as they were considered representative [45].

Because PBLE, self-efficacy, and social-affective learning strategies were measured using self-report questionnaires, several procedural remedies were implemented to reduce the risk of common method bias (CMB). Participation was voluntary and anonymous, responses were confidential, and Chinese character recognition achievement (CCRA) was measured separately using an objective performance test rather than a Likert-type questionnaire. Harman's single-factor test showed that the first unrotated factor explained 35.51% of the total variance, below the recommended 50% threshold [46], suggesting that no single factor dominated the covariance among the measured variables. Nevertheless, this statistical procedure alone cannot conclusively rule out the presence of common method bias.

As the original instruments were adapted and contextualized to blended Chinese language learning environments, exploratory factor analysis (EFA) was first conducted to examine the underlying factor structure and item appropriateness. Items with low loadings or substantial cross-loadings were removed where necessary.

The measurement and structural models were subsequently evaluated using PLS-SEM in SmartPLS 4.0. Although the proposed framework was theory-informed, the primary objective of the study was to examine the predictive relationships among learners' perceptions of the blended learning environment, self-efficacy, social-affective learning strategies, and Chinese character recognition achievement. PLS-SEM was therefore considered appropriate because it is well suited to prediction-oriented research involving multiple latent constructs and reflective higher-order constructs [48].

Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (CR), while convergent and discriminant validity were examined using average variance extracted (AVE) and the heterotrait–monotrait ratio (HTMT) [47]. Social-affective learning strategies (SLS) were modeled as a reflective second-order construct. After the measurement model was established, the structural model was assessed using bias-corrected and accelerated (BCa) bootstrapping with 5,000 resamples. Hypotheses were evaluated using standardized path coefficients (β), t-values, p-values, and 95% confidence intervals. Model quality was further assessed using the coefficients of determination (R^2), effect sizes (f^2), and Stone–Geisser's predictive relevance (Q^2).

Finally, to examine the robustness of the proposed model, gender, Chinese learning duration, and university were included as control variables. The robustness of the structural relationships was evaluated by comparing the path estimates before and after the inclusion of these control variables.

IV. RESULTS

A. EXPLORATORY FACTOR ANALYSIS

To enhance construct validation and reduce potential overfitting, the total sample ($N = 325$) was randomly divided into two independent subsamples. The first subsample ($n = 124$) was used for exploratory factor analysis (EFA), whereas the second subsample ($n = 201$) was reserved for measurement model evaluation and structural model assessment using PLS-SEM. This split-sample approach enabled

preliminary factor exploration followed by cross-validation using an independent dataset.

Exploratory factor analyses were conducted using Principal Axis Factoring. The Kaiser–Meyer–Olkin (KMO) values for PBLE (.933), SLS (.882), and SE (.926), together with significant Bartlett's tests of sphericity (all $p < .001$), confirmed the suitability of the data for factor analysis. Factors were extracted using the eigenvalue-greater-than-one criterion and were further confirmed through inspection of the scree plot. Items were retained when they exhibited primary factor loadings $\geq .50$, communalities $\geq .30$, and no substantial cross-loadings (cross-loading difference $\geq .20$). As summarized in Tables 2 and 3, all retained items demonstrated acceptable communalities and factor loadings.

For PBLE and SE, EFA supported unidimensional structures, with all retained items loading strongly on a single factor. PBLE explained 80.21% of the total variance, whereas SE explained 69.05%. Although perceived usefulness and perceived ease of use were originally conceptualized as distinct but related dimensions within TAM, all adapted PBLE items converged on a single latent factor in the present sample. Accordingly, PBLE was operationalized as a unidimensional construct representing learners' overall perceptions of the blended learning environment. This operationalization reflects the empirical measurement structure observed in the present study rather than theoretical revision of TAM.

Because social-affective strategies were theoretically expected to be correlated, the SLS scale was analyzed using Principal Axis Factoring with Direct Oblimin rotation. The analysis yielded two correlated factors ($r = .651$), explaining 50.75% of the common variance. Items SS2 and SS5 loaded more strongly on the affective strategy factor than on the social strategy factor. Their reassignment was based not only on the empirical factor structure but also on conceptual interpretation. Although both items involve interaction with other people, the primary function of these behaviors in the context of Chinese character learning is to reduce uncertainty, alleviate communication-related anxiety, maintain learning confidence, and regulate negative emotions. Thus, interpersonal interaction serves as a means of affective regulation rather than the primary construct being measured. This interpretation is consistent with Oxford's view that language learning strategies are context-dependent and may serve multiple functions [56]. Therefore, these items were conceptually classified as affective strategies rather than purely social strategies.

Following this refinement, all retained items exhibited satisfactory factor loadings and acceptable communalities without substantial cross-loadings, supporting the final two-factor structure of the SLS construct. Considering the relatively high correlation between affective and social strategies (HTMT = .847), these findings suggest that the two dimensions are closely related but remain empirically distinguishable. Therefore, they were retained as theoretically related first-order dimensions of the higher-order social-affective learning strategies construct rather than being merged into a single factor.

TABLE 2. Summary of exploratory factor analysis results.

Construct	Item	Communality	Factor 1	Factor 2	Final dimension
PBLE	PU1	0.831	0.912	—	PBLE
	PU2	0.759	0.871	—	PBLE
	PU3	0.904	0.951	—	PBLE
	PU4	0.808	0.899	—	PBLE
	PU5	0.880	0.938	—	PBLE
	PEOU1	0.564	0.751	—	PBLE
	PEOU2	0.743	0.862	—	PBLE
	PEOU3	0.810	0.900	—	PBLE
	PEOU4	0.709	0.842	—	PBLE
SE	SE1	0.637	0.798	—	SE
	SE2	0.696	0.834	—	SE
	SE3	0.687	0.829	—	SE
	SE4	0.735	0.858	—	SE
	SE5	0.586	0.765	—	SE
	SE6	0.630	0.794	—	SE
	SE7	0.553	0.743	—	SE
	SE8	0.673	0.820	—	SE
	SE9	0.754	0.869	—	SE
	SE10	0.615	0.784	—	SE
SLS	AS1	0.704	0.789	0.075	AS
	AS2	0.506	0.628	0.120	AS
	AS5	0.579	0.792	-0.050	AS
	SS2	0.496	0.539	0.222	AS (reassigned)
	SS5	0.382	0.680	-0.104	AS (reassigned)
	SS1	0.367	0.131	0.512	SS
	SS3	0.690	-0.119	0.903	SS
	SS4	0.568	0.174	0.629	SS

Notes: Factor 1 and Factor 2 represent the pattern matrix loadings. PBLE and SE yielded one-factor solutions; therefore, cross-loadings are not applicable. SLS was extracted using Direct Oblimin rotation (factor correlation = .651). All KMO values exceeded .88 and Bartlett's tests were significant (all $p < .001$).

B. MEASUREMENT MODEL ASSESSMENT

In the main study stage, the measurement model was evaluated as an integrated structure including all constructs simultaneously. The model consisted of reflective first-order constructs, while social-affective learning strategies (SLS) was specified as a reflective second-order construct comprising affective strategies (AS) and social strategies (SS). The assessment focused on internal consistency reliability, convergent validity, and discriminant validity.

Prior to the PLS-SEM analysis, data distributions and collinearity were examined. Although PLS-SEM is a nonparametric method that does not require distributional normality, skewness and kurtosis values were verified to ensure

TABLE 3. Item refinement process.

Item	Stage	Decision	Reason
AS3	Content validation	Deleted	Expert review indicated semantic redundancy.
AS4	Content validation	Deleted	Expert review indicated limited content relevance.
SS2	EFA	Reassigned	Higher loading on affective factor (0.539 vs 0.222) and conceptually reflected emotional regulation.
SS5	EFA	Reassigned	Higher loading on affective factor (.680 vs −.104) and conceptually reflected emotional regulation.
PU3	PLS-SEM	Deleted	VIF > 5.
PU5	PLS-SEM	Deleted	VIF > 5.
SE5	PLS-SEM	Deleted	Loading < 0.70.
SE6	PLS-SEM	Deleted	Loading < 0.70.

the absence of extreme non-normality that could distort bootstrapping results [48]. Additionally, full-collinearity variance inflation factor (VIF) values were examined as an additional diagnostic indicator [57]. All VIF values were below the conservative threshold of 5.0, indicating that multicollinearity was unlikely to pose a concern. However, consistent with recent methodological recommendations, these VIF values were interpreted only as supplementary evidence and should not be regarded as conclusive evidence that common method bias was absent.

The measurement model was estimated by SmartPLS 4.0. As shown in Table 2, all retained indicators exhibited satisfactory factor loadings above the recommended .70 threshold. The constructs demonstrated robust internal consistency reliability, with Cronbach's alpha values ranging from .67 to .93 and composite reliability (CR) values ranging from .82 to .94. Although the Cronbach's alpha for SS (.67) was slightly below the conventional.70 threshold, its CR value (.823) substantially exceeded the acceptable benchmark, ensuring adequate reliability for exploratory research contexts [58]. Furthermore, all average variance extracted (AVE) exceeded .50, supporting convergent validity.

Discriminant validity was evaluated exclusively using the heterotrait–monotrait ratio (HTMT), which has been established as a superior and more rigorous criterion compared to traditional approaches in PLS-SEM contexts [47]. As presented in Table 4, all HTMT values among the first-order constructs were safely below the conservative threshold of 0.85, thereby demonstrating satisfactory discriminant validity and confirming that all constructs are empirically distinct from one another.

To evaluate the second-order construct (SLS), the disjoint two-stage approach was deployed in SmartPLS 4.0. The second-order measurement model demonstrated strong and significant higher-order loadings of its first-order dimensions (AS = 0.907; SS = 0.893), coupled with high composite reliability (CR = 0.895) and AVE (0.810), confirming acceptable psychometric soundness at the hierarchical level. As shown in Table 5, discriminant validity at the second-order level was fully established, as all HTMT values remained safely below the 0.90 threshold, verifying that SLS is empirically distinct from PBLE and SE.

TABLE 4. Reliability, convergent validity, and discriminant validity (HTMT) (First-Order Constructs).

Construct	Cronbach's alpha	CR	AVE	AS	PBLE	SE	SS
AS	0.755	0.836	0.508	–			
PBLE	0.932	0.944	0.683	0.283	–		
SE	0.917	0.930	0.573	0.445	0.464	–	
SS	0.678	0.823	0.607	0.847	0.150	0.438	–

Notes: CR = Composite Reliability; AVE = Average Variance Extracted. Values below the diagonal represent HTMT ratios. All HTMT values are below 0.85, demonstrating established discriminant validity according to Henseler, et al. [47].

TABLE 5. Reliability, convergent validity, and discriminant validity (Second-Order Construct).

Construct	CR	AVE	SLS	PBLE	SE
SLS	0.895	0.810	–		
PBLE	0.945	0.683	0.223	–	
SE	0.931	0.573	0.468	0.464	–

Notes: CR = Composite Reliability; AVE = Average Variance Extracted. Values below the diagonal represent HTMT ratios.

C. DESCRIPTIVE STATISTICS AND CORRELATIONS

Table 6 presents the descriptive statistics and Pearson correlation coefficients for the study variables. Overall, participants reported relatively positive perceptions of the blended learning environment, high self-efficacy, and moderate-to-high use of social-affective learning strategies.

Pearson correlation analysis indicated that Chinese character recognition achievement (CCRA) was positively correlated with self-efficacy ($r = 0.171$, $p < 0.05$) and social-affective learning strategies ($r = 0.314$, $p < 0.001$), whereas its correlation with PBLE was weak and not statistically significant ($r = 0.097$, $p > 0.05$). In addition, PBLE was positively correlated with self-efficacy ($r = 0.426$, $p < 0.001$) and social-affective learning strategies ($r = 0.200$, $p < 0.01$), and self-efficacy was positively correlated with social-affective learning strategies ($r = 0.393$, $p < 0.001$). These findings provide preliminary support for the proposed relationships and justify subsequent structural model assessment.

TABLE 6. Descriptive statistics and correlations.

Variable	M ± SD	1	2	3	4
1. CCRA	**31.65 ± 5.66**	1			
2. PBLE	**3.87 ± 0.71**	0.097	1		
3. SLS	**3.68 ± 0.65**	0.314***	0.200**	1	
4. SE	**4.08 ± 0.54**	0.171*	0.426***	0.393***	1

Notes: M = mean; SD = standard deviation; PBLE = Perceptions of Blended Learning Environment; SE = Self-efficacy; SLS = Social-affective Learning Strategies; CCRA = Chinese-character recognition achievement. $p < .05$, ** $p < .01$, *** $p < .001$.

D. STRUCTURAL MODEL ASSESSMENT

Following the evaluation of the measurement model, the structural model was assessed to examine the proposed relationships among Perceptions of Blended Learning Environment (PBLE), self-efficacy (SE), social-affective learning strategies (SLS), and Chinese character recognition achievement (CCRA). Prior to hypothesis testing, collinearity diagnostics were conducted using the variance inflation factor (VIF). According to Hair et al. [59], all VIF values were below the recommended threshold of 3.0, indicating that multicollinearity was not a concern.

The structural relationships were evaluated using bootstrapping with 5,000 resamples. Figure 2 illustrates the final structural model. As shown in Table 7, PBLE did not exhibit a significant direct association with CCRA ($\beta = 0.016$, $p = .848$, 95% BCa CI [−0.137, 0.186]); therefore, H1 was not supported. Likewise, the direct association between SE and LA was not statistically significant ($\beta = 0.055$, $p = .552$, 95% BCa CI [−0.129, 0.225]), leading to the rejection of H2. In contrast, SLS was positively associated with CCRA ($\beta = 0.291$, $p < .001$, 95% BCa CI [0.155, 0.431]), supporting H3.

Regarding the relationships among the antecedent variables, PBLE was positively associated with SE ($\beta = 0.437$, $p < .001$, 95% BCa CI [0.259, 0.583]), supporting H4. Similarly, SE was positively associated with SLS ($\beta = 0.395$, $p < .001$, 95% BCa CI [0.200, 0.512]), supporting H5. These findings suggest that learners reporting more positive perceptions of the blended learning environment also tended to report higher levels of self-efficacy, and learners with higher self-efficacy tended to report greater use of social-affective learning strategies.

To further examine the proposed mediation relationships, indirect effects were estimated using the same bootstrapping procedure. The results are presented in Table 8.

The indirect association between PBLE and CCRA through self-efficacy alone was not statistically significant ($\beta = 0.024$, $p = .586$, 95% BCa CI [−0.058, 0.115]). In contrast, the indirect association between SE and CCRA through SLS was significant ($\beta = 0.111$, $p = .001$, 95% BCa CI [0.055, 0.193]). More importantly, the sequential indirect effect of PBLE on CCRA through SE and SLS was statistically significant ($\beta = 0.049$, $p = .003$, 95% BCa CI [0.024, 0.090]). Because the confidence interval did not include zero, H6 was supported.

However, the total indirect effect of PBLE on CCRA was not statistically significant ($\beta = 0.074$, $p = .096$, 95% BCa CI [0.000, 0.174]). Likewise, the total effect of PBLE on CCRA remained non-significant ($\beta = 0.090$, $p = .127$, 95% BCa CI [−0.023, 0.206]).

The structural model was further evaluated in terms of its explanatory capability using the coefficients of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2). As shown in Table 9, the model explained 19.1% of the variance in SE, 15.7% of the variance in SLS, and 10.3% of the variance in Chinese character recognition achievement (CCRA). According to Hair et al. [48], these findings indicate weak-to-moderate explanatory capability, suggesting that additional learner- and context-related factors may also contribute to Chinese character recognition achievement.

Effect sizes (f^2) were further examined to assess the contribution of each exogenous construct to the endogenous variables. Following. Cohen [60], f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. PBLE exerted a medium effect on SE ($f^2 = 0.236$), whereas SE had a small-to-medium effect on SLS ($f^2 = 0.139$). The effect of SLS on Chinese-character recognition achievement was small ($f^2 = 0.080$). In contrast, the effects of PBLE on CCRA ($f^2 = 0.000$), SE on CCRA ($f^2 = 0.002$), and PBLE on SLS ($f^2 = 0.001$) were negligible (see Table 10).

Stone–Geisser's Q^2 values obtained through the blindfolding procedure were positive for all endogenous constructs (SE = 0.105, SLS = 0.118, CCRA = 0.075), indicating acceptable in-sample predictive relevance of the structural model.

TABLE 7. Hypotheses testing.

Relationship	β	S.E.	t	p	95% CI	Results
H1: PBLE → CCRA	0.015	0.082	0.192	0.848	[-0.133, 0.184]	rejected
H2: SE → CCRA	0.055	0.093	0.594	0.552	[-0.124, 0.226]	rejected
H3: SLS → CCRA	0.291	0.071	4.121	< .001	[0.154, 0.428]	supported
H4: PBLE → SE	0.437	0.082	5.306	< .001	[0.264, 0.593]	supported
H5: SE → SLS	0.395	0.079	4.800	< .001	[0.200, 0.512]	supported

Notes: PBLE = Perceived blended learning environment; SE = Self-Efficacy; SLS = Social-affective Learning Strategies; CCRA = Chinese Character Recognition achievement. β = standardized path coefficient; S.E. = standard error; CI = bias-corrected confidence interval.

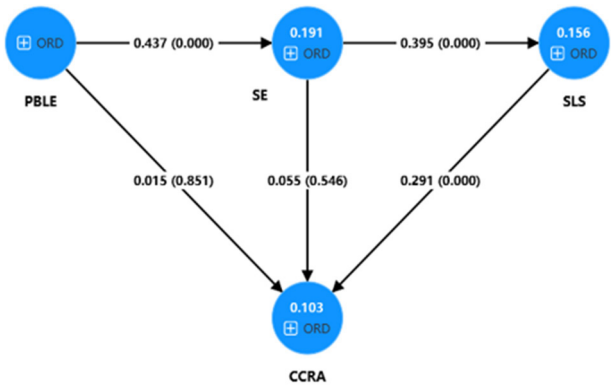

FIGURE 2. Structural model.

E. ROBUSTNESS AND MULTIGROUP ANALYSES

To examine the robustness of the proposed structural model, gender, learning duration, and university were incorporated as control variables. Table 11 presents the structural model estimates before and after the inclusion of the control variables.

TABLE 8. Bootstrapped estimates of specific indirect, total indirect, and total effects.

Effect Type	Path	β	SE	t	p	95% BCa CI	Interpretation
Specific indirect	PBLE → SE → CCRA	0.024	0.044	0.544	0.586	[-0.058, 0.115]	Not significant
	SE → SLS → CCRA	0.111	0.035	3.217	0.001	[0.055, 0.193]	Significant
	PBLE → SE → SLS → CCRA	0.049	0.016	2.965	0.003	[0.024, 0.090]	Supported (H6)
Total indirect	PBLE → CCRA	0.074	0.045	1.666	0.096	[0.000, 0.174]	Not significant
	SE → CCRA	0.115	0.032	3.624	<.001	[0.062, 0.188]	Significant
Total effect	PBLE → CCRA	0.090	0.059	1.525	0.127	[-0.023, 0.206]	Not significant
	PBLE → SLS	0.173	0.044	3.931	<.001	[0.094, 0.265]	Significant
	SE → CCRA	0.170	0.088	1.937	0.053	[-0.015, 0.327]	Not significant

TABLE 9. Structural model quality assessment.

Endogenous construct	R^2	Q^2
SE	0.191	0.105
SLS	0.157	0.118
CCRA	0.103	0.075

TABLE 10. Effect size (f^2).

Structural path	f^2	Interpretation
PBLE → SE	0.236	Medium
SE → SLS	0.139	Small–medium
SLS → CCRA	0.080	Small
PBLE → CCRA	0.000	Negligible
SE → CCRA	0.002	Negligible
PBLE → SLS	0.001	Negligible

The R^2 values of the endogenous constructs increased slightly after incorporating the control variables, from 0.108 to 0.123 for Chinese character recognition achievement, from 0.181 to 0.198 for self-efficacy, and from 0.166 to 0.188 for social-affective learning strategies, indicating a modest improvement in the model's explanatory power.

The hypothesized relationships remained highly consistent across the two models. Specifically, PBLE continued to exert a significant positive effect on self-efficacy ($\beta = 0.425$ vs. 0.414, $p < .001$), self-efficacy remained a significant predictor of social-affective learning strategies ($\beta = 0.408$ vs. 0.424, $p < .001$), and social-affective learning strategies continued to significantly predict Chinese character recognition achievement ($\beta = 0.303$ vs. 0.296, $p < .001$). Likewise, the non-significant effects of PBLE and self-efficacy on Chinese character recognition achievement remained unchanged after including the control variables.

TABLE 11. Robustness check of direct structural relationships after including control variables.

Path	Model 1(Without controls) β	p	Model 2(With controls) β	p
PBLE → CCRA	0.004	0.955	0.006	0.939
PBLE → SE	0.425	<0.001***	0.414	<0.001***
SE → CCRA	0.051	0.570	0.073	0.440
SE → SLS	0.408	<0.001***	0.424	<0.001***
SLS → CCRA	0.303	<0.001***	0.296	<0.001***
Control variables				
Gender → CCRA	—	—	-0.078	0.579
Gender → SE	—	—	0.099	0.501
Gender → SLS	—	—	-0.150	0.234
Learning duration → CCRA	—	—	-0.005	0.943
Learning duration → SE	—	—	0.046	0.511
Learning duration → SLS	—	—	-0.122	0.074
University → CCRA	—	—	0.235	0.084
University → SE	—	—	-0.235	0.114
University → SLS	—	—	0.075	0.596

None of the control variables showed statistically significant effects on the endogenous constructs (all $p > .05$). More importantly, the inclusion of these control variables did not materially change the magnitude, direction, or statistical significance of the hypothesized relationships, indicating that the proposed structural model is robust to demographic and contextual differences among the participants. The serial mediation effect (PBLE → SE → SLS → CCRA) also remained significant after including the control variables ($\beta = 0.052$, $p = .002$).

A bootstrap-based PLS-MGA was conducted to compare the structural model across the two universities. The results indicated no significant differences between the two groups at the 5% significance level. Only the path from self-efficacy to social-affective learning strategies (SE → SLS) approached significance at the 10% level (two-tailed $p = 0.069$), indicating a marginal difference between the two universities (see Table 12).

V. DISCUSSION AND IMPLICATIONS

A. PREDICTIVE RELATIONSHIPS WITH CHINESE CHARACTER RECOGNITION ACHIEVEMENT

The present study found that perceived blended learning environment (PBLE) did not significantly predict Chinese

TABLE 12. Multigroup analysis (University A vs. University B).

Path	Difference (University A − University B)	1-tailed (University A vs. University B) p value	2-tailed (University A vs. University B) p value
PBLE → CCRA	0.094	0.288	0.575
PBLE → SE	0.023	0.453	0.905
SE → CCRA	0.118	0.269	0.538
SE → SLS	0.235	0.035	0.069
SLS → CCRA	-0.008	0.533	0.935

character recognition achievement. This finding suggests that learners' evaluative perceptions of the technology-enabled dimension of a blended learning environment, operationalized through perceived usefulness and perceived ease of use, were not directly associated with objective Chinese character recognition achievement. Although this finding differs from previous studies reporting positive relationships between technology-supported learning and academic achievement [61], [62], [63], [64], it is theoretically consistent with Cognitive Load Theory (CLT).

Chinese character learning requires learners to process complex orthographic, phonological, and semantic information simultaneously, imposing substantial intrinsic cognitive load. Positive evaluations of the usefulness and usability of technology-enabled learning components may not correspond directly to deeper cognitive processing required for Chinese character learning. In fact, when technological tools are primarily used for task completion, they may encourage surface-level engagement rather than deep cognitive processing [65]. Therefore, in the context of Chinese language learning, which imposes exceptionally high cognitive demands, deep processing strategies such as orthographic analysis, comparative induction, and collaborative interaction are more critical than system usability alone. Accordingly, favorable evaluations of the technology-enabled dimension of blended learning may be associated with positive learning experiences but may not correspond directly to schema construction or long-term retention of Chinese characters. Rather, the association between PBLE and Chinese character recognition achievement may be better understood by considering learners' psychological and behavioral characteristics. This finding is consistent with the proposed S-O-R framework, in which PBLE is conceptualized as the external stimulus associated with learners' subsequent psychological and behavioral responses.

Similarly, self-efficacy did not significantly predict Chinese character recognition achievement. Although previous studies have frequently identified self-efficacy as a positive predictor of academic performance [66], [67], [68], [69], the present findings indicate that its predictive relationship with achievement may depend on specific learning contexts. According to Bandura's Social Cognitive Theory, self-efficacy reflects learners' confidence rather than their actual cognitive competence. In Chinese character learning, confidence alone cannot substitute for the intensive cognitive processing required to recognize complex orthographic structures. Therefore, higher self-efficacy may not necessarily predict better learning achievement unless it is accompanied by appropriate learning strategies. This finding is also consistent with the proposed S-O-R framework, in which self-efficacy represents an internal psychological state rather than a direct predictor of objective learning outcomes.

In contrast, social-affective learning strategies significantly predicted Chinese character recognition achievement, indicating that learners who actively regulate emotions, seek support, and engage in collaborative learning achieve better learning outcomes. This finding is consistent with previous studies demonstrating the positive contribution of social-affective strategies to academic performance [63], [70], [71], [72]. Evidence suggests that learners actively engaging in group discussions and seeking feedback in blended learning environments are better able to transform rote memorization into higher-order cognitive processing, such as advanced orthographic analysis, structural comparison, and morpho-semantic decoding. Learners using social-affective strategies may better regulate their learning through peer interaction and the effective use of technology-enabled learning resources embedded within blended learning environments.

Overall, the findings are consistent with the proposed theoretical framework. Neither perceived blended learning environment nor self-efficacy significantly predicted Chinese character recognition achievement directly, whereas social-affective learning strategies significantly predicted achievement. Furthermore, the observed pattern of results is consistent with the proposed sequential relationships among PBLE, self-efficacy, social-affective learning strategies, and Chinese character recognition achievement, providing empirical support for integrating the Technology Acceptance Model, Self-efficacy Theory, Oxford's strategy perspective, Cognitive Load Theory, and the S-O-R framework in explaining technology-supported Chinese character learning.

B. ASSOCIATIONS AMONG PERCEIVED BLENDED LEARNING ENVIRONMENT, SELF-EFFICACY, AND SOCIAL-AFFECTIVE LEARNING STRATEGIES

The present study found that perceived blended learning environment (PBLE) significantly predicted self-efficacy. Specifically, learners who reported higher perceived usefulness and perceived ease of use of the technology-enabled dimension embedded within a blended learning environment also reported higher levels of self-efficacy. This finding is consistent with previous studies showing that favorable perceptions of technology-supported learning are positively associated with learners' confidence in completing academic

tasks [15], [67], [73], [74]. In the present study, PBLE does not represent the overall quality of the blended course but rather learners' evaluations of technology-enabled dimension of the blended learning environment. Therefore, TAM was adopted to operationalize learners' perceptions of technology as the external stimulus within the S-O-R framework, rather than to explain technology usage intention.

The results also showed that self-efficacy significantly predicted social-affective learning strategies. Learners reporting higher self-efficacy were more likely to report greater use of emotional regulation, help-seeking, peer interaction, and collaborative learning strategies. This finding agrees with previous studies suggesting that self-efficacy is positively associated with learners' strategic learning behaviors in technology-enabled learning contexts [75], [76].

Within the proposed S-O-R framework, PBLE, self-efficacy, and social-affective learning strategies correspond to the Stimulus, Organism, and behavioral adaptation components of the learning process, respectively. The significant associations among these variables provide empirical support for the proposed theoretical sequence from learners' perceptions of blended learning to internal psychological responses, and subsequently to adaptive learning strategies. Combined with the non-significant direct relationships between PBLE and Chinese character recognition achievement and between self-efficacy and achievement, these findings further support the proposition that, in the cognitively demanding context of Chinese character learning, learners' perceptions of blended learning and their confidence are more closely associated with achievement through strategic learning behaviors than through direct prediction. Although the cross-sectional design does not permit causal inference, the observed relationships are consistent with the theoretical expectations derived from the integrated TAM, Self-efficacy Theory, Cognitive Load Theory, and S-O-R framework.

The significant serial indirect relationship (PBLE → SE → SLS → CCRA) further supports the proposed integration of TAM, Self-efficacy Theory, Oxford's strategy perspective and the S-O-R framework. This finding is consistent with previous studies suggesting that learners' evaluations of technology-enabled learning environments are associated with learning outcomes through learners' psychological and strategic characteristics rather than through direct prediction [67], [74], [76]. In the context of Chinese character learning, favorable perceptions of the technology-enabled dimension of blended learning may strengthen learners' self-efficacy, but confidence alone may not predict achievement unless accompanied by adaptive social-affective learning strategies. This sequential pattern is consistent with the substantial cognitive demands of processing Chinese orthography and suggests that learners' perceptions of technology are associated with achievement through successive psychological and behavioral adaptation. These findings also extend the application of TAM by conceptualizing perceived usefulness and perceived ease of use as environmental stimuli within the S-O-R framework rather than as direct predictors of technology usage intention.

C. IMPLICATIONS

This study contributes to literature in two respects. First, it extends technology-enhanced language learning research by integrating the Technology Acceptance Model (TAM), Self-efficacy Theory, Oxford's strategy perspective, and the Stimulus–Organism–Response (S-O-R) framework into a unified model. Rather than adopting the original TAM outcome of technology usage intention, this study conceptualizes perceived blended learning environment (PBLE) as learners' evaluations of the technology-enabled dimension of a blended learning environment, thereby adapting TAM to explain learners' psychological and behavioral processes in educational contexts. The findings further support the proposed sequential relationships among learners' evaluations of the technology-enabled dimension of blended learning, psychological readiness, and strategic learning behaviors in Chinese character learning.

Second, the study has practical implications for the design of blended learning environments. Enhancing the usefulness and ease of use of technology-enabled learning components alone may not be sufficient to correspond to better Chinese character recognition achievement. Instead, instructional design should incorporate activities that strengthen learners' self-efficacy, facilitate emotional regulation, and promote peer interaction and collaborative learning. Such learner-centered support may better facilitate learners' strategic engagement with Chinese character learning within blended learning environments.

VI. CONCLUSION

This study examined the relationships among perceived blended learning environment (PBLE), self-efficacy (SE), social-affective learning strategies (SLS), and Chinese character recognition achievement among Chinese as a Second/Foreign Language learners in blended learning contexts. Using PLS-SEM, the findings showed that PBLE significantly predicted self-efficacy, self-efficacy significantly predicted social-affective learning strategies, and social-affective learning strategies significantly predicted Chinese character recognition achievement. However, PBLE and self-efficacy did not directly predict Chinese character recognition achievement.

These findings provide empirical support for the proposed theoretical framework integrating TAM, Self-efficacy Theory, Oxford's strategy perspective, and the S-O-R framework. The results suggest that learners' perceptions of learners' evaluations of the technology-enabled dimension of a blended learning environment are associated with Chinese character recognition achievement through successive psychological and behavioral processes rather than through direct prediction. The proposed framework provides a useful perspective for understanding technology-enabled Chinese

language learning and may serve as a foundation for future studies employing longitudinal or experimental research designs.

A. LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

This study has several limitations that provide directions for future research. First, although demographic robustness analyses were conducted by including gender, learning duration, and university as control variables, and additional PLS-MGA results confirmed that the proposed structural relationships were generally consistent across the two participating universities, the sample was still limited to undergraduate Chinese as a Second/Foreign Language (CSL/CFL) learners from two Malaysian public universities. Therefore, the generalizability of the findings to private universities, other educational settings, or learners with different proficiency levels remains limited. Future studies should validate the proposed model using more diverse samples across different institutions, regions, and learning contexts.

Second, this study employed a cross-sectional survey design. Although PLS-SEM was used to examine the hypothesized predictive relationships, the cross-sectional nature of the data does not permit causal or temporal inferences. Future research should adopt longitudinal or experimental designs to further examine the temporal relationships among perceived blended learning environment, self-efficacy, social-affective learning strategies, and Chinese character recognition achievement.

Third, most constructs were measured using self-report questionnaires. Although the measurement model demonstrated satisfactory reliability and validity, self-reported responses may still be affected by common method bias, recall bias, or social desirability. Future studies could combine questionnaire data with qualitative interviews, classroom observations, learning analytics, or digital interaction logs to provide a more comprehensive understanding of learners' psychological and behavioral processes.

Finally, the present study focused on self-efficacy and social-affective learning strategies as the primary psychological and behavioral variables within the S-O-R framework. Other potentially important factors, such as language learning anxiety, self-regulated learning, cognitive strategies, motivation, or technology usage behaviors, were not included in the proposed model. Future studies may incorporate these variables to further refine the theoretical framework and provide a more comprehensive understanding of technology-enabled blended Chinese language learning.

APPENDIX
QUESTIONNAIRE AND CHINESE CHARACTER RECOGNITION TEST

A. PERCEIVED BLENDED LEARNING ENVIRONMENT

The following statements refer specifically to the technology-enabled dimension of your blended Chinese language learning environment. Accordingly, the term "blended learning environment" in the following items refers to learners' evaluations of the usefulness and ease of use of the digital learning technologies integrated into blended learning, rather than the overall pedagogical, social, or institutional characteristics of the learning environment.

The blended learning environment can help my learning be more efficient.

The blended learning environment can help me acquire the information I want to acquire.

The blended learning environment can be helpful to my learning.

The blended learning environment would improve my learning performance.

The blended learning environment would increase academic productivity.

Interacting with the blended learning environment does not require a lot of my mental effort.

I find the blended learning environment to be easy to use.

It is easy to become skillful at using the blended learning environment.

It would be easy for me to find information in the blended learning environment.

B. SOCIAL-AFFECTIVE LEARNING STRATEGY

I always encourage myself to use Chinese Characters as much as possible.

I try to relax before reading Chinese Characters when nervous.

Small mistakes when writing Chinese Characters do not prevent me from continuing to practice.

I reward myself when making progress in learning Chinese Characters.

I share experiences of learning Chinese Characters with other learners.

I believe that communicating with Chinese people is important for learning Chinese Characters.

I often exchange and practice Chinese Characters with others who are learning the language to encourage myself to keep learning.

I ask native Chinese speakers to correct my Chinese Characters mistakes.

When unable to understand Chinese Characters spoken by others, I ask them to speak slower or repeat.

I often communicate in Chinese with classmates because learning together helps me stay motivated when learning Chinese characters.

C. SELF-EFFICACY

I am convinced that I am able to successfully learn all relevant Chinese Character content even if it is difficult.

I know that I can maintain a positive attitude toward Chinese Character course even when tensions arise.

When I try really hard, I am able to learn even the most difficult Chinese Character content.

I am convinced that, as time goes by, I will continue to become more and more capable of learning the Chinese Character content of this course.

Even if I get distracted in class, I am confident that I can continue to learn Chinese Characters well.

I am confident in my ability to learn Chinese Characters, even if I am having a bad day.

If I try hard enough, I can obtain the academic goals I desire.

I am convinced that I can develop creative ways to cope with the stress that may occur while taking this Chinese Character course.

I know that I can stay motivated to participate in the Chinese Character course.

I know that I can finish the assigned projects and earn the grade I want, even when others think I can't.

D. CHINESE CHARACTERS RECOGNITION TEST

1 你 Pronunciation A. nǐ B. tā C. wǒ D. nǚ
Meaning A. She B. You C. Me D. Big
2 我 Pronunciation A. nǐ B. bù C. wǒ D. le
Meaning A. He B. Buy C. Me D. Sun
3 他 Pronunciation A. tā B. hǎo C. nǚ D. rì
Meaning A. He B. Buy C. Me D. Sun
4 不 Pronunciation A. bú B. bù C. bīng D. dà
Meaning A. Big B. Not C. Thank D. Moon
5 二 Pronunciation A. èr B. liǎo C. rì D. sān
Meaning A. Big B. Not C. Two D. Moon
6 女 Pronunciation A. nǚ B. bù C. bīng D. dà
Meaning A. Woman B. Learn C. Buy D. She
7 吃 Pronunciation A. lǐ B. lǎo C. chī D. le
Meaning A. Not B. Eat C. Sun D. Good
8 日 Pronunciation A. rì B. yuè C. dà D. ér
Meaning A. Moon B. Big C. Sun D. Learn
9 买 Pronunciation A. mài B. mǎi C. xiè D. hào
Meaning A. Sell B. Buy C. You D. Woman
10 谢 Pronunciation A. xǐ B. xué C. xiè D. shì
Meaning A. You B. Thank C. Sell D. Not
11 您 Pronunciation A. nín B. nǚ C. nǐ D. tā
Meaning A. She B. Thank C. You (polite form) D. Ten
12 大 Pronunciation A. dà B. dài C. shí D. tài
Meaning A. Small B. Big C. Buy D. Moon
13 好 Pronunciation A. hǎo B. hěn C. hào D. rì
Meaning A. Woman B. Good C. I D. Two
14 一 Pronunciation A. yí B. yī C. yǐ D. yì
Meaning A. Three B. One C. Ten D. Buy
15 三 Pronunciation A. sān B. èr C. sì D. shí
Meaning A. One B. Three C. Ten D. Not
16 十 Pronunciation A. sān B. shí C. bù D. dà
Meaning A. Ten B. Moon C. Woman D. Two
17 她 Pronunciation A. nǚ B. tā C. mǎi D. yī
Meaning A. He B. Woman C. She D. Good
18 月 Pronunciation A. yuè B. rì C. dà D. shí
Meaning A. Sun B. Woman C. Moon D. Learn
19 卖 Pronunciation A. mài B. mǎi C. xiè D. shì
Meaning A. Buy B. Sell C. Learn D. Thank
20 学 Pronunciation A. xué B. xuè C. shì D. xǐ
Meaning A. Buy B. Learn C. Sell D. Two

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CHEN ZHANG received the M.S. degree from Yunnan University, China. He is currently pursuing the Ph.D. degree with the Faculty of Education, Universiti Malaya. His research focuses on technology-enhanced Chinese as a second/foreign language (CSL/CFL) learning and learner development in digital learning environments. His current research interests include blended learning, learner self-efficacy, language learning strategies, self-regulated learning, and the application of generative artificial intelligence in language education.



MOHD SHAHRIL NIZAM BIN SHAHAROM received the Ph.D. degree in instructional technology from the Universiti Malaya, Malaysia. He is currently a Senior Lecturer with the Faculty of Education, Universiti Malaya. His research interests include educational technology, instructional design, artificial intelligence in education, digital skills development, online learning, and technology-enhanced learning.



WONG SENG YUE (Senior Member, IEEE) received the Ph.D. degree in information science and the Master of Education Management degree from the Universiti Kebangsaan Malaysia (UKM). He is currently an Associate Professor with the School of Malay Studies, Universiti Malaya, Malaysia. His research interests include educational technology, e-learning, game-based learning, virtual and augmented reality, digital innovation, and technology entrepreneurship. His work focuses on leveraging emerging technologies to enhance teaching and learning effectiveness. He is a Professional Member of British Computer Society (BCS).



WEI ZHAO received the M.S. degree from Yunnan University, China. His academic and research pursuits are centered around the domains of foreign language education and the advancement of pedagogical technology.