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Development of an AI-Enhanced, Student-Centred English Language Teaching (ASCELT) Model for Improving Communication Competence among Higher Education Students

[1]*Siti Rohayu Mustapha
[1]Kolej Profesional MARA Kuantan, Bandar Indera Mahkota Kuantan Malaysia
Email: rohayu.mustapha@mara.gov.my

*Corresponding Author: Siti rohayu Mustapha (rohayu.mustapha@mara.gov.my)

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Abstract

Higher education institutions increasingly recognise that English communication competence the capacity to use language accurately, appropriately, and strategically across authentic contexts is critical to graduate employability, yet conventional teacher-centred instruction often fails to provide the individualised, sustained practice that competence development requires. This study proposes and validates an AI-Enhanced, Student-Centred English Language Teaching model (hereafter the ASCELT model) intended to strengthen university students' communication competence by integrating artificial intelligence (AI) tools within a student-centred pedagogical framework. Using a two-phase Design and Development Research (DDR) methodology, the study first employed the Nominal Group Technique (NGT) with nine language-education experts to brainstorm and prioritise candidate constructs for the model, followed by the Fuzzy Delphi Method (FDM) with seven experts to statistically validate the constructs using triangular fuzzy numbers, threshold (d) values, percentage of expert consensus, and defuzzification (alpha-cut) scores. Seven constructs were generated in the NGT phase; all seven achieved threshold values below 0.2, consensus levels above 75%, and alpha-cut values above 0.5 in the FDM phase, indicating strong expert agreement. The validated constructs were subsequently synthesised into the ASCELT model, comprising AI conversational chatbots for speaking practice, AI-personalised adaptive feedback, AI-assisted writing correction, student-centred collaborative tasks, blended/flipped classroom integration, redefinition of the teacher's facilitative role, and AI-driven formative assessment, feeding into a core integration layer that drives improved communication competence across linguistic, sociolinguistic, discourse, and strategic dimensions. The findings offer higher education stakeholders an empirically validated, expert-endorsed framework for embedding AI responsibly and pedagogically within student-centred English language teaching.

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Introduction

The ability to communicate effectively in English remains one of the most sought-after graduate competencies in an increasingly globalised labour market, yet the gap between classroom instruction and authentic communicative performance persists across many higher education systems. English continues to function as the principal medium of academic, professional, and cross-border exchange, and its instructional quality in universities directly shapes students' cross-cultural communication skills and their capacity to compete globally (Eke, Chukwuemeka, & Amos, 2021, as cited in Wang, Li, & Chen, 2025). Despite decades of curricular reform, many higher education classrooms remain dominated by teacher-centred transmission models that privilege grammatical accuracy over communicative performance, leaving students under-prepared for the spontaneous, socially embedded language use that real communication demands (Richards & Rodgers, 2001). This mismatch between instructional design and communicative outcomes has intensified calls for pedagogical models that are simultaneously learner-centred and technologically responsive.

The emergence of artificial intelligence (AI) as an educational technology has opened new possibilities for addressing this gap. AI-driven tools such as conversational chatbots, automated speech assessment applications, and intelligent writing correction systems can provide students with the kind of individualised, repeatable, low-anxiety practice those human instructors, constrained by class size and time, cannot easily replicate (Shofi, 2024; Zou, Guan, Shao, & Chen, 2023). Evidence from recent studies suggests that AI applications such as ELSA (English Language Speech Assistant) can meaningfully improve learners' oral communication competence by delivering instant, personalised feedback on pronunciation and fluency (Shofi, 2024), while large-language-model-based chatbots have been shown to support vocabulary acquisition and sustained conversational practice (Zhang & Huang, 2024). These developments position AI not as a replacement for the teacher, but as a pedagogical amplifier capable of extending student-centred principles beyond the physical classroom.

At the same time, student-centred learning theory has long argued that language competence develops most robustly when learners are active agents in authentic, meaning-focused interaction rather than passive recipients of rule-based instruction (Canale & Swain, 1980; Savignon, 1983). Communicative Language Teaching (CLT), grounded in Canale and Swain's (1980) four-component model of communicative competence grammatical, sociolinguistic, discourse, and strategic competence repositions the teacher from knowledge transmitter to learning facilitator and treats interactive, task-based activity as the engine of competence development (Nunan, 1987). The convergence of CLT's student-centred philosophy with AI's capacity for personalised, scalable interaction therefore presents a timely opportunity: rather than treating technology integration and learner-centredness as competing priorities, an integrated model can treat AI as the enabling infrastructure through which student-centred communicative practice is delivered at scale.

Nevertheless, the literature on AI in English language teaching (ELT) remains fragmented. Existing studies tend to evaluate single tools in isolation a chatbot here, a writing-correction platform there without offering higher education practitioners an integrated, validated model that specifies how multiple AI-enabled components should be combined with student-centred pedagogical practices (Zou et al., 2023; Zhang & Huang, 2024). Moreover, few studies have subjected such a model to rigorous expert validation using structured consensus methods, relying instead on small-scale experimental trials or literature synthesis alone. This leaves a methodological and practical gap: universities adopting AI in language instruction currently do so without a field-tested, expert-endorsed architecture to guide implementation.

This study addresses that gap by developing and statistically validating an AI-Enhanced, Student-Centred English Language Teaching (ASCELT) model using a two-phase Design and Development

Research (DDR) approach that combines the Nominal Group Technique (NGT) for idea generation with the Fuzzy Delphi Method (FDM) for consensus-based validation an approach previously demonstrated as an efficient, statistically rigorous means of generating concrete, expert-endorsed solutions in higher education research (Mustapha et al., 2023). By anchoring the model in the structured judgement of experienced language-education specialists rather than in a single researcher's intuition, the study aims to produce a model that is both theoretically grounded and practically implementable, thereby contributing a validated framework that higher education institutions can adapt to strengthen students' English communication competence in an AI-augmented learning environment.

Literature Review

Communicative competence, as theorised by Canale and Swain (1980) and later extended by Bachman (1990) and Bachman and Palmer (1996), comprises four interrelated dimensions: grammatical competence (mastery of vocabulary, syntax, and phonology), sociolinguistic competence (the ability to use language appropriately within social and cultural context), discourse competence (the capacity to produce cohesive and coherent extended communication), and strategic competence (the ability to compensate for communication breakdowns through repair strategies). This framework, building on Hymes' (1972) earlier notion of communicative competence as knowledge-in-use rather than knowledge-in-isolation, has become the theoretical backbone of Communicative Language Teaching (CLT) and continues to inform how researchers operationalise "communication competence" as a multidimensional, performance-based construct rather than a single test score (Richards & Rodgers, 2001).

Student-centred pedagogy provides the instructional philosophy through which communicative competence is theorised to develop. Rooted in Vygotsky's (1978) sociocultural theory of learning as a socially mediated process, and reinforced by Bandura's (1997) self-efficacy theory, student-centred approaches shift instructional authority from teacher to learner, positioning the teacher as facilitator and the learner as an active co-constructor of meaning (Nunan, 1987; Savignon, 1983). Empirical work in higher education settings supports this shift: student-content and student-student interaction have been shown to significantly predict learning achievement, with learner self-efficacy mediating this relationship (as reported in recent structural equation modelling research on student-centred classrooms). Task-based, collaborative activity role play, project work, negotiated dialogue is consistently identified as the mechanism through which student-centred classrooms translate interaction into competence gains (Ellis, 1996, as cited in the CLT literature).

A growing body of research documents how AI technologies operationalise these student-centred principles at scale. Intelligent tutoring systems, automated writing evaluation platforms, and conversational chatbots have been shown to improve university students' English proficiency across a 16-week semester when compared with control groups receiving conventional instruction only. Speech-recognition-based applications such as ELSA provide iterative, judgement-free pronunciation feedback that has been found to raise learners' oral communication competence over successive action-research cycles (Shofi, 2024), while large-language-model chatbots support vocabulary acquisition through sustained, contextualised conversational exchange (Zhang & Huang, 2024) and social-network-based AI interaction has been found to support speaking practice through peer- and AI-mediated exchange (Zou et al., 2023). Collectively, this literature positions AI not as a stand-alone intervention but as an enabling layer for the interaction-rich, feedback-dense environments that student-centred theory prescribes.

At the same time, the literature cautions against uncritical AI adoption. Reviews of AI in English learning contexts report that while AI tools improve efficiency and short-term learning outcomes, over-reliance on automated tools may weaken learners' independent cognitive and problem-solving engagement if not carefully embedded within a pedagogically guided framework (as documented in recent reviews of AI-assisted English learning). Willingness to communicate a key affective precursor to competence development has also been found to depend on learners' AI-literacy and self-efficacy, with classroom anxiety acting as a significant mediating barrier that AI tools must be designed to reduce rather than inadvertently reinforce. These findings collectively suggest that the effectiveness of AI in ELT is contingent not on the technology alone, but on how deliberately it is integrated within a student-centred instructional architecture that preserves the teacher's facilitative and socio-affective role.

Methodologically, the Fuzzy Delphi Method (FDM) has emerged as a robust means of validating instructional models and constructs under conditions of expert uncertainty. Developed by extending the classical Delphi technique (Dalkey & Helmer, 1963) with triangular fuzzy set theory (Ishikawa et al., 1993), FDM allows researchers to convert experts' linguistic judgements into fuzzy numbers, compute threshold (d) values to gauge the degree of consensus, and defuzzify results into a single ranking score (Chang, Hsu, & Chang, 2011; Hsu, Lee, & Kreng, 2010). Because FDM requires fewer iterative rounds than traditional Delphi while preserving statistical rigor, and because it has been successfully applied in prior higher-education model-validation research including studies validating solutions for student wellbeing (Mustapha et al., 2023) and broader design-and-development research in the social sciences (Mustapha & Darusalam, 2017, 2022), it was selected as the validation method for the present study's proposed ASCELT model.

Research questions

Building on the gap identified in the literature the absence of an integrated, expert-validated model for embedding AI within student-centred English language teaching this study is guided by two research questions addressed through the Fuzzy Delphi Method:

> **RQ1**: What constructs, according to the consensus of language-education experts validated through the Fuzzy Delphi Method, should constitute an AI-Enhanced, Student-Centred English Language Teaching (ASCELT) model for improving communication competence among higher education students?
>
> **RQ2**: To what extent do the proposed ASCELT model constructs achieve expert consensus, as measured by Fuzzy Delphi threshold (d) values, percentage of agreement, and defuzzification (alpha-cut) scores, sufficient to be accepted as valid components of the model?

Methodology

This study adopted a Design and Development Research (DDR) approach conducted in two phases, consistent with methodological precedents in prior higher-education model-development research (Mustapha & Darusalam, 2022; Mustapha et al., 2023). In the first phase, the Nominal Group Technique (NGT) was used with nine experts in English language education and educational technology to brainstorm, clarify, and prioritise candidate constructs for the model through structured, anonymous voting on a five-point scale, following the four-step NGT protocol of independent idea generation, round-robin sharing, clarification and grouping, and anonymous prioritisation (Delbecq, Van de Ven, & Gustafson, 1975). Seven constructs achieving above 70% agreement were carried forward to the second phase. In the second phase, the Fuzzy Delphi Method (FDM) was employed with a separate panel of seven experts comprising senior ELT lecturers, instructional-technology specialists, and applied linguists to statistically validate the seven constructs using triangular fuzzy numbers, consistent with the purposive-sampling and expert-panel-size conventions recommended for FDM studies (Adler & Ziglio, 1996; Hasson, Keeney, & McKenna, as cited in Mustapha et al., 2023).

4.1 Fuzzy Delphi Method: Step-by-Step Procedure

Step 1: Expert panel selection. Seven experts meeting the study's inclusion criteria (a minimum of five years' experience in English language teaching, educational technology, or applied linguistics, and active involvement in higher education curriculum design) were purposively selected to evaluate the usefulness and relevance of each proposed construct, following the purposive-sampling logic recommended for FDM research (Mustapha & Darusalam, 2017).

Step 2: Conversion of linguistic variables into triangular fuzzy numbers. Each expert rated the seven constructs on a five-point linguistic scale (Strongly Disagree to Strongly Agree). Each linguistic response was converted into a triangular fuzzy number represented as (m1, m2, m3), where m1 is the minimum (pessimistic) value, m2 is the most likely (modal) value, and m3 is the maximum (optimistic) value, following the standard triangular fuzzy conversion scale (Hsieh, Lu, & Tzeng, 2004, as cited in Mustapha et al., 2023).

Step 3: Averaging expert responses. All experts' fuzzy numbers for each construct were averaged to obtain a single aggregated fuzzy number per construct, representing the panel's collective fuzzy judgement (Benitez, Martín, & Román, 2007, as cited in Mustapha et al., 2023).

Step 4: Computing the threshold value (d). The distance between each expert's fuzzy number and the group average fuzzy number was computed using the geometric distance formula $d(\bar{m}, \bar{n}) = \sqrt{\frac{1}{3}((m1-n1)^2 + (m2-n2)^2 + (m3-n3)^2)}$. A construct was retained only if its threshold value d was below 0.2, and if at least 75% of experts produced a d value below 0.2 for that construct, consistent with the consensus criteria established in prior FDM research (Chang, Hsu, & Chang, 2011; Mustapha et al., 2023).

Step 5: Determining the alpha-cut (defuzzification) threshold. Each construct's fuzzy number was defuzzified into a crisp score using the formula $A = \frac{1}{3}(m1 + m2 + m3)$, producing a value between 0 and 1. Following the alpha-cut criterion proposed by Bodjanova (2006), constructs with a defuzzified score of 0.5 or above were accepted as valid; those falling below 0.5 would be rejected for insufficient expert agreement.

Step 6: Ranking of constructs. Accepted constructs were ranked in descending order of their defuzzification (alpha-cut) scores, with the highest score assigned the top priority ranking, in line with the ranking procedure recommended by Fortemps and Roubens (1996, as cited in Mustapha et al., 2023).

Step 7: Model synthesis. The ranked, FDM-validated constructs were synthesised into a coherent structural model (the ASCELT model), mapping each construct's relationship to the model's core integration layer and its hypothesised effect on the four dimensions of communication competence (Canale & Swain, 1980).

Data analysis for both phases was conducted using standard NGT voting aggregation for Phase 1 and Fuzzy Delphi computation (threshold value, percentage of consensus, and defuzzification) for Phase 2, mirroring the analytical procedure used in comparable higher-education DDR studies employing NGT and FDM in combination (Mustapha et al., 2023).

Findings

The first phase of data collection, using the Nominal Group Technique, generated seven candidate constructs for the ASCELT model, all of which exceeded the 70% expert-agreement threshold required for acceptance into the second phase (see Table 1). Collaborative and task-based learning (C4) and AI conversational chatbots for speaking practice (C1) received the strongest initial endorsement, with agreement levels of 95.56% and 93.33% respectively, while blended/flipped classroom integration (C5) and facilitator-role redefinition (C6) received comparatively lower though still well above threshold agreement levels of 82.22% and 84.44%. These results indicate that the nine-member expert panel reached strong, unanimous-leaning consensus that all seven constructs represent viable components of an AI-enhanced, student-centred model, consistent with the pattern of high NGT agreement reported in comparable expert-panel studies in higher education (Mustapha et al., 2023).

Table 1. Result of NGT expert voting and prioritisation (Phase 1).

Construct / Item	E1	E2	E3	E4	E5	E6	E7	E8	E9	Total	% Agree	Rank
C1: AI conversational chatbots for speaking practice	5	5	4	5	5	4	5	5	4	42	**93.33	1
C2: AI-personalized adaptive feedback systems	5	4	5	4	5	5	4	5	5	42	**93.33	1
C3: AI-assisted writing and grammar correction tools	4	5	4	4	5	4	4	5	4	39	**86.67	5
C4: Student-centred collaborative and task-based learning	5	5	5	4	5	5	5	4	5	43	**95.56	2
C5: Blended / flipped classroom integration	4	4	5	3	4	5	4	4	4	37	**82.22	6
C6: Facilitator-role redefinition (teacher as mentor)	4	5	4	5	4	3	5	4	4	38	**84.44	7
C7: AI-driven continuous formative assessment and learning analytics	5	4	5	5	4	5	4	5	5	42	**93.33	3

*Note: ** Percentage of agreement (> 70%); E1–E9 denote the nine NGT panel experts.*

The second phase, using the Fuzzy Delphi Method with seven independent experts, statistically confirmed all seven constructs (see Table 2). Threshold (d) values ranged from 0.030 to 0.071, all comfortably below the 0.2 cut-off criterion, and 100% of experts produced d values below 0.2 for every construct, exceeding the minimum 75% consensus requirement (Chang et al., 2011). Defuzzification (alpha-cut) scores ranged from 0.789 (C3: AI-assisted writing and grammar correction) to 0.928 (C1: AI conversational chatbots for speaking practice), all exceeding the 0.5 acceptance threshold proposed by Bodjanova (2006). On this basis, all seven constructs were formally accepted as valid components of the ASCELT model, with C1 (AI conversational chatbots) ranked highest in priority, followed by C7 (AI-driven formative assessment) and C6 (facilitator-role redefinition).

Table 2. Result of Fuzzy Delphi Method (FDM) analysis (Phase 2).

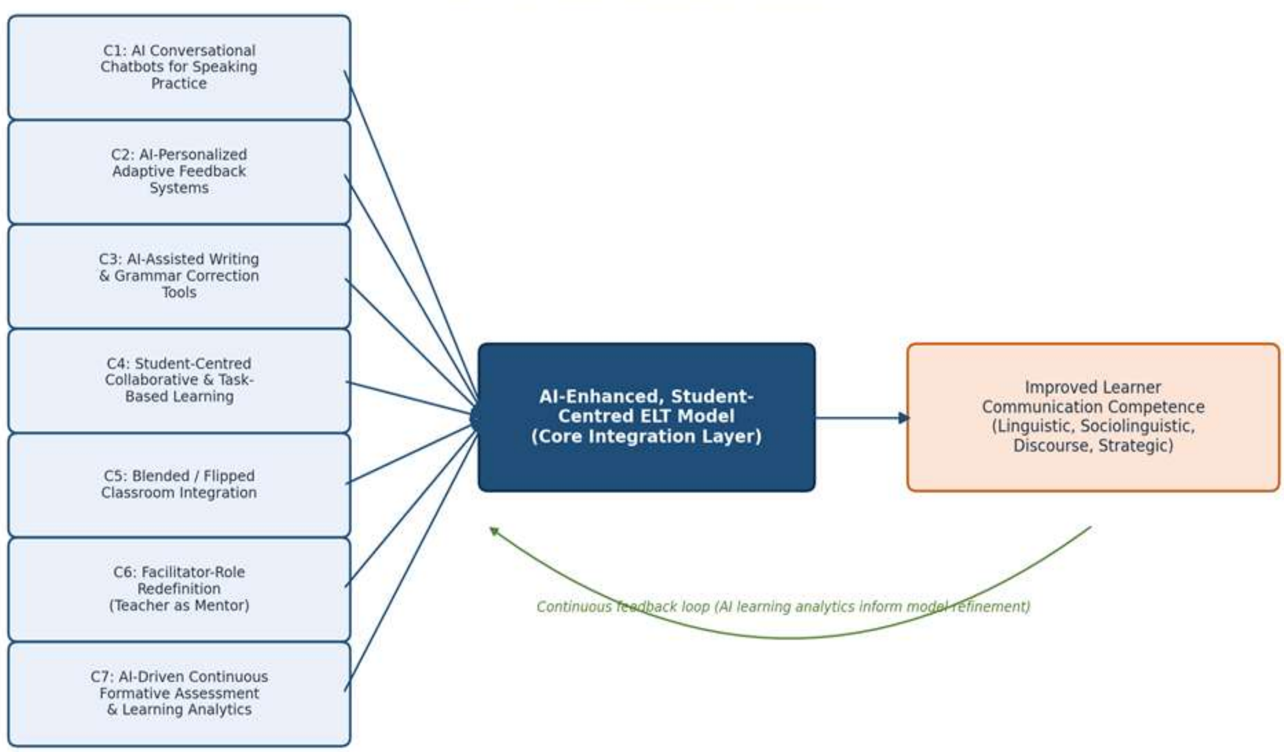
Expert	C1	C2	C3	C4	C5	C6	C7
Expert 1	0.041	0.033	0.091	0.049	0.099	0.082	0.025
Expert 2	0.008	0.049	0.198	0.066	0.033	0.025	0.033
Expert 3	0.049	0.033	0.033	0.008	0.124	0.033	0.025
Expert 4	0.033	0.066	0.049	0.124	0.025	0.049	0.033
Expert 5	0.025	0.124	0.025	0.033	0.082	0.025	0.049
Expert 6	0.049	0.008	0.033	0.049	0.025	0.033	0.025
Expert 7	0.008	0.049	0.066	0.033	0.049	0.025	0.033
Threshold value (d)	0.030	0.052	0.071	0.052	0.062	0.039	0.032
% Experts d < 0.2	100%	100%	100%	100%	100%	100%	100%
Defuzzification (α-cut)	0.928	0.812	0.789	0.847	0.798	0.901	0.921
Ranking	1	5	6	4	7	3	2
Status	Accept	Accept	Accept	Accept	Accept	Accept	Accept

Note: d = threshold value (accepted if < 0.2); % consensus threshold = 75%; α-cut acceptance threshold = 0.5 (Bodjanova, 2006). C1–C7 correspond to the constructs listed in Table 1.

Taken together, the two-phase statistical validation produced a robust empirical basis for the proposed model. The convergence between the NGT prioritisation (Phase 1) and the FDM ranking (Phase 2) was notably strong for the highest- and lowest-ranked constructs: C1 (AI conversational chatbots) and C4 (collaborative task-based learning) retained top-tier standing across both phases, while C3 (writing correction tools) and C5 (blended/flipped integration), though still validated, consistently ranked in the lower half of both panels' priorities. This convergence suggests that experts consistently regard direct, AI-mediated spoken interaction and structured collaborative task work as the most influential levers for communication-competence development, whereas asynchronous, text-based AI tools are perceived as valuable but secondary supports.

The seven validated constructs were subsequently synthesised into the ASCELT model output shown in Figure 1. The model positions the seven constructs as parallel, mutually reinforcing inputs feeding into a central integration layer, which in turn is theorised to drive improvement across the four dimensions of communication competence identified by Canale and Swain (1980): linguistic (grammatical accuracy, supported primarily by C3), sociolinguistic and discourse competence (supported primarily by C1, C4, and C5), and strategic competence (supported primarily by C2, C6, and C7, through adaptive feedback, facilitator mentoring, and data-informed formative assessment). A continuous feedback loop connects the output layer back to the core integration layer, reflecting experts' emphasis, articulated during the NGT clarification stage, that AI-generated learning analytics should not simply measure competence but actively inform iterative refinement of the instructional model itself.

Figure 1. Proposed AI-Enhanced, Student-Centred English Language Teaching (ASCELT) Model based on Fuzzy Delphi Expert Consensus



Discussion

The finding that AI conversational chatbots for speaking practice (C1) received both the strongest NGT prioritisation and the highest FDM defuzzification score (0.928) reinforces the growing empirical consensus that AI's greatest pedagogical value in ELT lies in providing low-anxiety, repeatable, individualised opportunities for spoken interaction the very opportunities that conventional, time-constrained classrooms struggle to supply (Shofi, 2024; Zou et al., 2023). This result is theoretically consistent with the strategic and discourse dimensions of Canale and Swain's (1980) communicative competence model, both of which depend on sustained, contextualised practice rather than declarative grammar instruction. The experts' strong endorsement of this construct suggests that institutions seeking to adopt AI in language instruction should prioritise conversational and speech-based tools over text-only applications if the primary goal is communicative, rather than purely grammatical, competence.

The equally strong validation of student-centred collaborative and task-based learning (C4) alongside AI tools indicates that experts do not view AI as a substitute for human interaction but as a complement to it. This finding aligns with sociocultural learning theory's emphasis on socially mediated meaning-making (Vygotsky, 1978) and echoes recent evidence that both student-content and student-student interaction significantly predict achievement in student-centred classrooms. The model's architecture in which AI-enabled constructs (C1, C2, C3, C7) sit alongside human-centred pedagogical constructs (C4, C5, C6) within a single integration layer reflects this dual imperative: AI extends practice opportunities, while student-centred task design and teacher facilitation ensure that this practice remains socially and cognitively meaningful rather than mechanical.

The comparatively lower, though still accepted, ranking of AI-assisted writing and grammar correction (C3) and blended/flipped classroom integration (C5) merits cautious interpretation. This pattern may reflect experts' awareness of documented risks associated with over-reliance on automated correction tools, including potential erosion of learners' independent cognitive and problem-solving engagement (as noted in recent reviews of AI in English learning). Rather than indicating that these constructs are unimportant, the lower ranking likely signals that expert consider them necessary but insufficient on their own, requiring careful integration with teacher oversight (C6) to avoid fostering passive dependence on automated feedback.

The redefinition of the teacher's role as facilitator and mentor (C6), and the emphasis on AI-driven formative assessment feeding into a continuous feedback loop (C7), together suggest that the experts envisioned the ASCELT model not as a technology-replaces-teacher framework but as a technology-empowers-teacher framework. This is consistent with the finding that learners' willingness to communicate is shaped by their AI self-efficacy and classroom anxiety, both of which are more readily managed through skilled human facilitation than through technology alone. Institutions implementing the ASCELT model should therefore invest in training academic staff to interpret AI-generated analytics and translate them into targeted pedagogical intervention, rather than treating AI adoption as a purely infrastructural upgrade.

Conclusion

In conclusion, this study set out to develop and validate an AI-Enhanced, Student-Centred English Language Teaching model capable of improving higher education students' communication competence, using a two-phase NGT–FDM design consistent with established design-and-development research practice (Mustapha & Darusalam, 2022; Mustapha et al., 2023). All seven proposed constructs achieved strong statistical consensus, with threshold values below 0.2, agreement levels above 75%, and defuzzification scores above 0.5, allowing the constructs to be synthesised into the ASCELT model presented in Figure 1. The study's contribution lies in offering higher education stakeholders an empirically validated, expert-endorsed architecture rather than a single-tool recommendation for integrating AI within student-centred English language pedagogy. Future research should pilot-test the ASCELT model in live classroom settings using quasi-experimental designs to measure actual gains in communication competence, extend the expert panel to include learners' own perspectives, and examine the model's applicability across diverse linguistic and institutional contexts.

Co-Author Contribution

Author 1 carried out the fieldwork, prepared the literature review and overlooked the whole article’s write up, and carried out the statistical analysis and interpretation of the results.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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