

The Impact of Artificial Intelligence on Language Learning and Linguistic Research

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ABSTRACT: This explanatory sequential mixed-methods study examines how AI-supported tools are perceived to affect language learning and linguistic research in applied-linguistic settings. The study focuses on conversational assistants, automated writing support, machine translation, speech-recognition applications, adaptive learning platforms, corpus-analysis tools, and linguistic data-processing technologies rather than on artificial intelligence as a general technological category. A structured questionnaire was completed by 420 participants, including language learners, language teachers, and linguistics researchers, followed by 36 semi-structured interviews selected from high-, moderate-, and low-use profiles. Quantitative analysis used descriptive statistics, reliability testing, exploratory factor analysis, correlation analysis, regression models with role controls, and diagnostic checks. Qualitative analysis used Reflexive Thematic Analysis supported by intercoder review, negative-case attention, and an audit trail. The results show that perceived usefulness, feedback quality, critical AI literacy, accessibility, and tool-use frequency were positively associated with perceived learning effectiveness and research efficiency, whereas dependency risk and ethical concern complicated uncritical acceptance of AI-supported work. Interview evidence indicated that participants valued AI when it supported explanation, feedback, translation, accessibility, and research organization, but they remained cautious about accuracy, privacy, authorship, bias, and loss of independent judgment. The main limitation is that outcomes are self-reported rather than measured directly as proficiency growth or productivity. The study contributes a responsible integration framework, showing that AI-supported language learning and linguistic research are perceived as most valuable when guided by human expertise, transparent policy, critical verification, and pedagogical purpose.

Keywords: artificial intelligence; language learning; linguistic research; applied linguistics; responsible AI.

I. INTRODUCTION

Artificial intelligence has become a visible force in language education and linguistic research, but this study does not examine AI as a broad technological phenomenon. It focuses specifically on AI-supported tools used in applied-linguistic practice, including conversational assistants, grammar checkers, automated writing feedback, pronunciation applications, speech recognition, machine translation, corpus-analysis tools, and linguistic data-processing systems. These tools are increasingly used for specific language and research tasks, yet their value depends on how they are selected, verified, interpreted, and integrated into learning, teaching, and scholarly workflows.

The international relevance of the topic lies in the fact that applied linguistics must now account for AI across multiple user roles rather than only within learner-focused or classroom-focused studies. Learners use AI for vocabulary, writing, pronunciation, translation, and self-study; teachers use it for feedback design,

materials preparation, task development, and assessment support; and linguistics researchers use it for transcription, coding preparation, corpus exploration, translation comparison, and textual organization. Evidence from only one group is insufficient because each group faces different benefits, risks, and responsibilities. A learner may experience AI as personalized support, a teacher may see it as a challenge to assessment validity, and a researcher may treat it as a tool whose outputs require documentation and human validation.

Recent reviews of AI in English language teaching and learning show that AI-supported tools can be associated with feedback, interaction, personalization, and learner autonomy, but these reported benefits depend on task design and teacher mediation [1]. Conversational AI studies similarly indicate that chatbots may support interaction and practice when they complement rather than replace pedagogical judgment [2]. Generative AI has intensified this debate because tools such as ChatGPT can generate explanations, examples, practice activities, translations, feedback, and academic texts [3]. In education more broadly, large language models create opportunities for individualized learning and formative support, while also raising concerns about hallucination, overreliance, inequitable access, and opaque decision-making [4].

The expanding literature on ChatGPT and related educational tools also shows why applied-linguistic evidence must be interpreted cautiously. Rapid reviews report potential learning and assessment support, but they warn that fluent AI output should not be treated as inherently accurate [5]. Studies of chatbot use in education further show that apparent helpfulness may coexist with ethical instability, weak verification, and unclear responsibility [6]. Critical analyses of generative AI in educational practice emphasize the need for assessment redesign, feedback literacy, learner training, and explicit research ethics [7]. These findings are directly relevant to language fields because AI tools do not merely provide information; they shape writing choices, translation decisions, pronunciation goals, feedback habits, and learners' confidence in their own linguistic resources.

The same tension appears in linguistic research. AI-assisted transcription, coding preparation, corpus searching, and text classification can reduce mechanical labor, yet they may also hide interpretive decisions, distort culturally situated meanings, or weaken methodological transparency if researchers do not document what was generated, checked, accepted, or rejected. In language fields, these concerns are especially important because language data may contain identifiable voices, multilingual identities, non-standard varieties, and culturally specific pragmatic meanings. The methodological question is therefore not only whether AI tools are efficient, but whether their use preserves interpretive accountability and ethical protection.

The research problem addressed in this paper is therefore not whether AI is useful or harmful in a general sense. The central problem is how AI-supported language and research tools are perceived to affect learning effectiveness, research efficiency, user autonomy, dependency risk, ethical concern, and human scholarly judgment across different applied-linguistic roles. Existing studies often examine a single tool, skill, or user group. Fewer studies connect learners, teachers, and linguistics researchers in one design, and fewer still integrate survey-based modeling with interview explanations of why users accept, resist, verify, or limit AI-supported outputs.

The present study addresses this gap through an explanatory sequential mixed-methods design that contributes beyond previous work in four ways: it compares multiple user groups, models perceived outcomes statistically, explains those patterns through interviews, and develops a Responsible AI Integration Framework for applied-linguistic practice. The contribution is therefore not a claim that AI directly improves language proficiency, but an evidence-based account of how AI-supported tools are perceived, evaluated, and governed when language learning, teaching, and linguistic research are examined together.

II. RESEARCH PROBLEM

The research problem is an analytical gap between the rapid normalization of AI-supported language tools and the limited evidence on how their perceived benefits, risks, and conditions of responsible use operate across applied-linguistic roles. Studies that focus only on learners risk treating AI as a convenience or motivation tool; studies that focus only on teachers risk overlooking informal learner use; and studies that focus only on researchers risk emphasizing efficiency without examining ethics, authorship, dependency, and verification.

This gap is methodological as well as theoretical. Attitude-only studies may overstate usefulness because fluent AI output can appear reliable even when it is inaccurate, biased, or pedagogically weak. Outcome-only studies may miss privacy, authorship, and dependency issues. Research-efficiency studies may underreport how AI-supported transcription, coding, or classification decisions were validated. A rigorous applied-linguistic account therefore requires evidence that connects user role, tool function, perceived usefulness, feedback quality, critical AI literacy, ethical concern, dependency risk, and human expertise within one mixed-methods design.

III. RESEARCH OBJECTIVES AND QUESTIONS

1. RESEARCH OBJECTIVES

The study aims to examine how AI-supported tools are perceived to influence language learning and linguistic research by analyzing their reported effects on learning effectiveness, engagement, feedback quality, accessibility, research efficiency, ethical concern, user dependency, and human scholarly judgment. To achieve this aim, the study pursues the following objectives:

- To identify the main AI-supported tools used by language learners, language teachers, and linguistics researchers.
- To examine how AI-use frequency, perceived usefulness, feedback quality, accessibility, and critical AI literacy predict perceived learning effectiveness and research efficiency.
- To analyze user concerns related to accuracy, academic integrity, dependency, privacy, transparency, bias, responsible use, and uncritical acceptance of AI-supported outputs.
- To explore how participants explain their use of AI tools in language learning, teaching, translation, writing, linguistic data analysis, and human decision-making.
- To develop a responsible-integration framework for AI-supported language learning and linguistic research that preserves learner agency, teacher expertise, human validation, and scholarly judgment.

2. RESEARCH QUESTIONS

- RQ1: How are AI-based tools used in language learning and linguistic research contexts?
- RQ2: To what extent do AI-use frequency, perceived usefulness, feedback quality, accessibility, and critical AI literacy predict perceived learning effectiveness and research efficiency?
- RQ3: What ethical, pedagogical, and methodological concerns, including accuracy, academic integrity, dependency, privacy, transparency, bias, responsible use, and unqualified acceptance of AI-supported outputs, are associated with AI use in language learning and linguistic research?
- RQ4: How do learners, teachers, and linguistics researchers interpret the role of AI in relation to human expertise, autonomy, verification, and scholarly judgment?
- RQ5: What responsible-use strategies can support effective and ethical integration of AI in applied-linguistic contexts while preserving human decision-making, learner agency, and research judgment?

IV. LITERATURE REVIEW

1. ARTIFICIAL INTELLIGENCE IN LANGUAGE LEARNING

AI-supported language learning has developed from earlier CALL applications into systems that offer adaptive feedback, conversational practice, pronunciation support, writing revision, and translation assistance. Studies of large language models and educational chatbots report that such systems can support explanation, practice, and formative feedback when interaction design, teacher mediation, and task purpose are clear [8], [9]. Speech-recognition chatbot reviews similarly show potential for oral practice and multimodal feedback, but they also caution that technical performance alone does not guarantee assessment validity or learner autonomy [10], [11].

Empirical work has reported positive associations between AI-based language learning, speaking practice, self-regulation, personalization, and learner confidence [12], [13], [14]. However, this positive literature should be read alongside studies that warn against tool enthusiasm without verification. Reviews of ChatGPT for L2 learning suggest that the field is moving from excitement toward evidence-based

implementation, explicit training, and critical evaluation of AI output [15]. Bibliometric and learner-attitude studies further show rapid growth in AI language-learning research, but much of that growth remains concentrated on perceived usefulness, satisfaction, or acceptance rather than direct language development [16], [17].

This tension is central to the present study. Positive reports show that AI may be useful for feedback, explanation, access, and practice, while critical studies warn that dependency, hallucination, bias, and weak feedback literacy can reduce pedagogical value [18]. Therefore, the present study treats perceived usefulness as only one part of responsible integration and examines it alongside feedback quality, critical AI literacy, ethical concern, and dependency risk.

2. AI WRITING SUPPORT, FEEDBACK, AND ASSESSMENT

AI writing tools have become central to language learning because they offer grammar correction, organization suggestions, vocabulary expansion, genre models, paraphrasing, and feedback on coherence. Studies of AI writing support report benefits for content organization, revision, and teacher feedback when tools are used under pedagogical guidance [19], [20]. Bibliometric work on automated writing evaluation also indicates that validity, feedback interpretation, and the role of generative AI in writing assessment are becoming central concerns [21].

At the same time, writing support illustrates the difference between scaffolding and substitution. AI can help learners notice patterns, compare alternatives, and revise decisions, but it can also produce finished text that weakens authorship, independent drafting, and assessment validity. Systematic reviews of AI-assisted story writing and online learning show that AI can function as co-writer, prompt generator, or feedback provider, yet these roles require transparent task design, disclosure norms, and human evaluation [22], [23]. The present study differs from writing-only studies by connecting writing support with translation, speaking, research organization, and ethical governance across user groups.

3. CHATBOTS, TRANSLATION, SPEECH RECOGNITION, AND MULTILINGUAL ACCESS

Conversational AI has been widely discussed as a language-practice partner. Research on ChatGPT and language learning suggests that conversational systems may support repetition, flexible access, and interactional practice, but they do not automatically reproduce authentic sociocultural communication [24]. Reviews of chatbot integration in additional-language education report generally positive effects on skills, attitudes, and emotions, while also identifying challenges in continuity, feedback quality, and user trust [25]. Studies of digital resources such as Duolingo, ChatGPT, and Google Translate show that students value convenience and flexibility, but tool choice varies by context, skill focus, and learner expectation [26].

Speech-recognition and AI-speaking applications can support pronunciation, speaking practice, and confidence, especially when learners interact socially around AI-mediated tasks [27]. Affective research connects AI-supported online language learning with enjoyment, self-esteem, and regulation, while mobile-assisted learning studies show that usability and engagement shape learning outcomes [28], [29]. These findings justify examining AI use as a cluster of functions rather than a single independent variable. They also justify including accessibility, feedback quality, and critical AI literacy as conditions that shape perceived value.

4. AI IN LINGUISTIC RESEARCH AND ETHICAL GOVERNANCE

AI is also changing linguistic research through automatic transcription, corpus tagging, discourse classification, sentiment analysis, topic modeling, translation comparison, and preliminary coding. Meta-reviews of AI in higher education call for stronger ethics, collaboration, and methodological transparency because the field is expanding faster than its quality-control practices [30]. Scoping reviews of large language models identify privacy risk, low replicability, limited technological readiness, and insufficient human-centered design as persistent challenges [31]. Critical scholarship on automation and datafication further warns that AI should be studied within institutional, political, and social contexts, not as a neutral technology [32].

Natural language processing can support peer feedback and textual analysis, but its use must be grounded in theory, transparent validation, and clear documentation of human checks [33]. Studies of AI-

powered language tools in higher education show that academic communication is being reshaped by tool-mediated writing practices [34], while chatbot research suggests that AI may influence willingness to communicate and language confidence [35]. Critical analyses of AI language models also show the need to examine how systems generate stories, norms, and assumptions [36]. The present study is different from most existing studies because it integrates learner, teacher, and researcher perspectives and connects technology acceptance with applied-linguistic practice, ethical concern, dependency risk, and human expertise.

V. RESEARCH GAP

The literature shows substantial interest in AI-supported language learning, writing feedback, chatbot interaction, machine translation, speech recognition, and AI-assisted research. The unresolved issue is not simply that few studies exist; rather, previous studies often fail to integrate four dimensions that applied-linguistic practice now requires: technology acceptance, language-specific pedagogical practice, ethical concern, and human expertise. Tool-focused studies often examine one platform or skill. Learner-focused studies often measure usefulness or satisfaction without examining teacher judgment or research accountability. Research-focused studies often emphasize efficiency without systematically connecting AI use to dependency, privacy, authorship, and verification.

The present study addresses this more specific gap by using an explanatory sequential mixed-methods design that links survey-based modeling with interview-based explanation. Its originality lies in connecting AI tool use, perceived usefulness, feedback quality, accessibility, critical AI literacy, ethical concern, dependency risk, perceived learning effectiveness, perceived research efficiency, and human expertise within one responsible-integration framework for applied linguistics.

VI. CONCEPTUAL AND THEORETICAL FRAMEWORK

The study is guided by a Responsible AI Integration Framework that combines Technology Acceptance Model concepts, Educational Technology Theory, Applied Linguistics, Human-Technology Interaction, and ethical governance. These perspectives are not treated as separate theoretical lists; each explains a specific pathway. Technology acceptance explains why users adopt or continue using AI-supported tools through perceived usefulness and ease of use. Educational technology explains how feedback quality, scaffolding, accessibility, and task design shape perceived learning value. Applied linguistics anchors the model in language-specific practices such as writing, translation, pronunciation, multilingual communication, and linguistic data analysis. Human-technology interaction explains trust, verification, agency, and dependency. Ethical governance explains privacy, authorship, bias, transparency, and responsible disclosure.

The framework has three layers. The first layer links AI-supported tool use with perceived usefulness, accessibility, and task fit. The second layer explains how feedback quality and critical AI literacy mediate the value of AI-supported learning and research. The third layer positions ethical governance and human expertise as conditions that moderate whether AI use strengthens or weakens practice. The framework therefore does not assume that frequency of AI use automatically produces positive outcomes. It proposes that perceived learning effectiveness and research efficiency are strongest when AI output is understandable, verifiable, pedagogically aligned, ethically governed, and subject to human judgment.

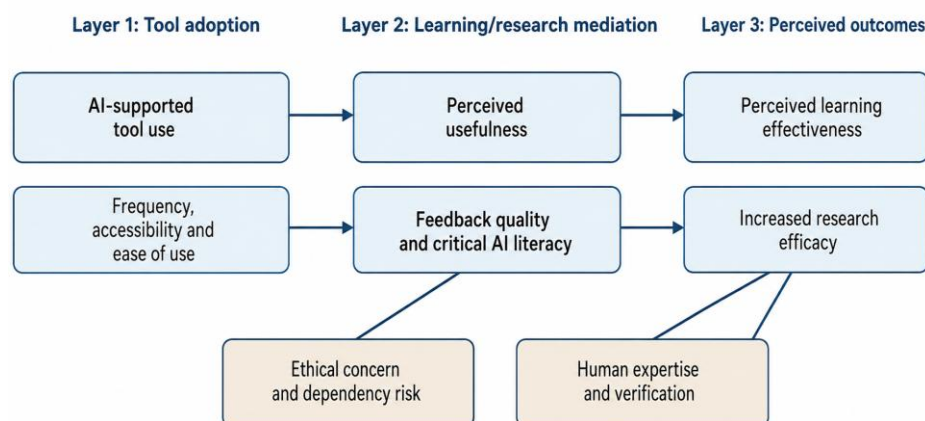


FIGURE 1. Conceptual framework of responsible AI integration in language learning and linguistic research.

Table 1. Theory-to-variable alignment for the conceptual framework.

Framework layer	Main variables	Theoretical pathway
Layer 1: AI tool use and perceived usefulness	AI-use frequency, accessibility, task fit, perceived usefulness	Technology Acceptance Model explains adoption and continued use.
Layer 2: Critical literacy and feedback quality	Feedback clarity, explanation quality, verification skill, critical AI literacy	Educational Technology Theory explains how tools support learning when feedback is meaningful.
Layer 3: Ethical governance and human expertise	Ethical concern, dependency risk, privacy, authorship, human validation	Human-Technology Interaction and ethical governance explain trust, risk, agency, and accountability.
Applied-linguistic outcomes	Perceived learning effectiveness, perceived research efficiency, responsible-use strategies	Applied Linguistics connects AI use to writing, translation, pronunciation, multilingual communication, and linguistic data analysis.

VII. METHODOLOGY

1. RESEARCH DESIGN

The study used an explanatory sequential mixed-methods design. The quantitative phase came first and measured usage patterns, perceived outcomes, and ethical concerns across language learners, teachers, and linguistics researchers. The qualitative phase followed and used semi-structured interviews to explain why some users experienced AI as supportive, why others remained cautious, and how tool use differed across learning, teaching, translation, and research tasks.

This design was selected because the research questions require both measurable patterns and interpretive explanation. Survey analysis can identify statistical associations among perceived usefulness, feedback quality, critical AI literacy, dependency risk, and perceived outcomes, but it cannot fully explain how users make judgments about trust, authorship, privacy, or human expertise. Interviews therefore provide the explanatory layer needed to connect statistical tendencies with applied-linguistic experience and professional reasoning.

2. PARTICIPANTS AND SAMPLING

The quantitative phase included 420 valid questionnaire responses: 270 language learners, 90 language teachers, and 60 linguistics researchers. This sample was sufficient for the conducted analyses because it exceeded common minimum recommendations for exploratory factor analysis and multiple regression,

provided an adequate participant-to-item ratio for scale validation, and allowed role-controlled models to compare learner, teacher, and researcher patterns. The qualitative phase included 36 interview participants selected from the survey sample. This number was sufficient for explanatory mixed-methods integration because it represented all three user roles and low-, moderate-, and high-use AI profiles while allowing detailed thematic interpretation.

Inclusion criteria required participants to be at least 18 years old and to have experience with at least one AI-supported language or research tool. Learner participants were engaged in language study or multilingual academic work. Teacher participants had experience teaching language, writing, translation, or applied-linguistic courses. Researcher participants used linguistic data, texts, transcripts, corpora, translation materials, or discourse data. The sample was stratified by role, educational level, linguistic background, and AI-use frequency to improve analytical balance.

Table 2. Participant profile and sampling structure.

Participant group	Survey n	Interview n	Demographic, linguistic, and AI-use profile
Language learners	270	18	Adults aged 18-34; undergraduate and postgraduate learners; mixed multilingual backgrounds; low, moderate, and high AI-use profiles for writing, translation, vocabulary, pronunciation, and study support.
Language teachers	90	10	Adults aged 25-56; language, writing, translation, and applied-linguistic instructors; mixed teaching experience; used or evaluated AI for feedback, classroom activities, materials, and assessment.
Linguistics researchers	60	8	Adults aged 24-60; postgraduate and academic researchers; used texts, transcripts, corpora, translation materials, or discourse data; AI use included transcription, coding preparation, corpus search, and data organization.
Total	420	36	Stratified sample across user role, educational level, linguistic background, and AI-use frequency.

3. INSTRUMENTS

The questionnaire contained sections on demographic and linguistic background, AI-use frequency, tool type, perceived usefulness, feedback quality, accessibility, perceived learning or research outcome, critical AI literacy, ethical concern, and dependency risk. Items were measured on five-point Likert scales from strongly disagree to strongly agree. Scale items were adapted from technology-acceptance, educational-technology, and AI-literacy constructs, then contextualized for applied-linguistic tasks such as writing, translation, pronunciation practice, corpus exploration, and transcription support.

The semi-structured interview protocol asked participants to describe how they used AI, what tasks they trusted AI to support, what types of output they checked manually, and how AI affected learning autonomy, teaching responsibility, or research judgment. Interview prompts also examined academic integrity, authorship boundaries, privacy, bias, learner dependency, institutional policy, and the balance between AI support and human expertise.

Table 3. Questionnaire scales, reliability, and construct focus.

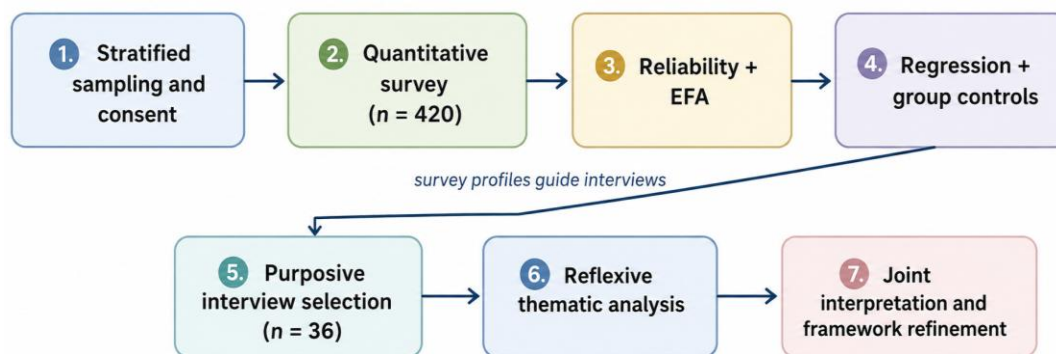
Scale	Items and source	Scoring and reliability	Example focus
Perceived usefulness	6 items adapted from technology-acceptance constructs	Mean score; alpha = .89; high reliability	AI helps me complete language-learning or research tasks more effectively.
Feedback quality	5 items adapted for AI feedback and revision support	Mean score; alpha = .87; high reliability	AI feedback is clear, timely, explanatory, and useful for revision.

Learning/research outcome	7 items developed for perceived learning effectiveness and research efficiency	Mean score; alpha = .91; excellent reliability	AI use supports learning effectiveness or research productivity.
Critical AI literacy	5 items adapted from AI/digital-literacy principles	Mean score; alpha = .86; high reliability	I check, compare, and question AI output before using it.
Ethical concern	6 items based on privacy, authorship, bias, and integrity concerns	Mean score; alpha = .84; acceptable-high reliability	AI use raises concerns about privacy, authorship, or academic integrity.
Dependency risk	4 items developed for overreliance and first-attempt behavior	Mean score; alpha = .80; acceptable reliability	I may rely on AI before attempting the task independently.

4. DATA COLLECTION PROCEDURE

Data were gathered in two sequential phases. In Phase 1, the structured questionnaire was distributed electronically through university language departments, teacher networks, postgraduate research groups, and multilingual learning communities. Responses were screened for completeness, duplicate entries, and eligibility. In Phase 2, interview participants were purposively selected from the survey sample based on user role, AI-use intensity, and ethical-attitude profile. Interviews lasted between 35 and 60 minutes and were conducted online or face to face according to participant preference.

All participants received information about voluntary participation, anonymization, data storage, and the right to withdraw. Interview recordings were transcribed, anonymized, and assigned participant codes. AI-output examples submitted by participants were treated as research documents only after identifying details had been removed.



Integration compares statistical patterns with interview explanations to identify convergence, complementarity, and contradiction.

FIGURE 2. Explanatory sequential mixed-methods workflow.

5. DATA ANALYSIS

Quantitative analysis proceeded in five stages. First, descriptive statistics summarized tool-use frequency, perceived usefulness, feedback quality, perceived learning effectiveness, perceived research efficiency, accessibility, ethical concern, and dependency risk. Second, reliability analysis evaluated internal consistency for each multi-item scale using Cronbach alpha. Third, exploratory factor analysis used principal-axis factoring with oblique rotation; item retention was based on theoretical relevance, factor loadings above .50, and limited cross-loading. Fourth, correlations tested relationships among major constructs. Fifth, multiple regression models identified predictors of perceived learning effectiveness and research efficiency while controlling for participant role, AI-use profile, and prior experience.

Regression diagnostics examined linearity, normality of residuals, heteroscedasticity, influential cases, and multicollinearity. Variance inflation factors remained below 2.10, indicating acceptable multicollinearity levels. Model interpretation used standardized coefficients, 95% confidence intervals, p-values, R², adjusted R², and role-control estimates. Group comparisons were also conducted to examine whether learners, teachers, and researchers differed in perceived usefulness, ethical concern, dependency risk, and critical AI literacy.

Qualitative data were analyzed through Reflexive Thematic Analysis. Two coders first reviewed interview transcripts and developed an initial codebook. Codes were grouped into candidate themes, compared across participant roles, and revised through discussion. Intercode agreement for a 25% transcript subset reached kappa = .82 before final reconciliation. Negative cases were retained, especially accounts in which high AI use coexisted with strong ethical concern or low use coexisted with positive attitudes toward limited, supervised support. Mixed-methods integration occurred through joint displays that compared quantitative patterns with interview explanations to identify convergence, complementarity, and contradiction.

Table 4. Analytical procedure and methodological alignment.

Analytical stage	Procedure	Output produced	Purpose
Descriptive statistics	Means, standard deviations, frequencies	Tool-use and outcome profile	Summarize AI-use patterns and perceived outcomes.
Reliability analysis	Cronbach alpha	Scale reliability estimates	Check internal consistency of questionnaire scales.
Exploratory factor analysis	Principal-axis factoring; oblique rotation; loading threshold > .50	Six-factor solution and retained items	Identify latent constructs in AI-use perceptions.
Correlation analysis	Pearson correlations	Construct association matrix	Explore relationships among major constructs.
Regression models	Multiple regression with role controls, CI, R ² , adjusted R ² , and VIF	Predictor effects and model diagnostics	Identify predictors of perceived learning/research outcomes.
Thematic analysis	Coding, theme development, participant extracts, negative cases	Five qualitative themes	Explain quantitative patterns through user experience.

6. ETHICAL CONSIDERATIONS AND TRUSTWORTHINESS

The study followed standard ethical procedures for research with adult participants. Consent was obtained before survey and interview participation. Participants were informed that they could withdraw without penalty and that no identifying academic work would be reported. Interview data were stored under anonymized codes, and AI-output examples were used only when participants gave permission. The study treated AI use as a sensitive academic practice because participants could feel vulnerable discussing dependency, academic integrity, or unauthorized tool use.

Trustworthiness was strengthened through triangulation across survey, interview, and document examples; transparent reporting of scales and models; an interview audit trail; codebook revision; intercode review; negative-case analysis; and thick description of user groups. Quantitative validity was supported

through reliability analysis, factor analysis, regression diagnostics, role controls, and model-fit reporting. Qualitative credibility was supported through participant-coded extracts, careful extract selection, and cross-role comparison.

VIII. FINDINGS

1. QUANTITATIVE FINDINGS

Participants reported frequent use of AI tools for writing support, translation, vocabulary explanation, grammar checking, pronunciation practice, and research organization. The highest mean ratings were observed for perceived research efficiency ($M = 4.33$), personalized learning support ($M = 4.21$), and feedback quality ($M = 4.05$). Ethical concern remained moderately high ($M = 3.72$), showing that acceptance did not remove caution. Dependency risk received a lower but still meaningful rating ($M = 3.41$), indicating that participants recognized the possibility of relying on AI before attempting tasks independently. Learners rated personalized practice and feedback access most highly, teachers expressed stronger concern about assessment and dependency, and researchers rated transcription and corpus-support functions as most useful.

Exploratory factor analysis supported a six-factor structure: perceived usefulness, feedback quality, critical AI literacy, ethical concern, dependency risk, and outcome value. The Kaiser-Meyer-Olkin value was .91, Bartlett's test of sphericity was significant, chi-square = 4862.73, $p < .001$, and the six factors explained 68.4% of total variance. Retained item loadings ranged from .62 to .84, with no theoretically problematic cross-loading above .32. Regression diagnostics were acceptable: VIF values ranged from 1.18 to 1.74, residual plots showed no severe heteroscedasticity, and role controls were retained in all models. Perceived usefulness, feedback quality, critical AI literacy, and use frequency were positively associated with perceived learning effectiveness, while dependency risk was negatively associated with perceived learning effectiveness after controlling for participant role and experience.

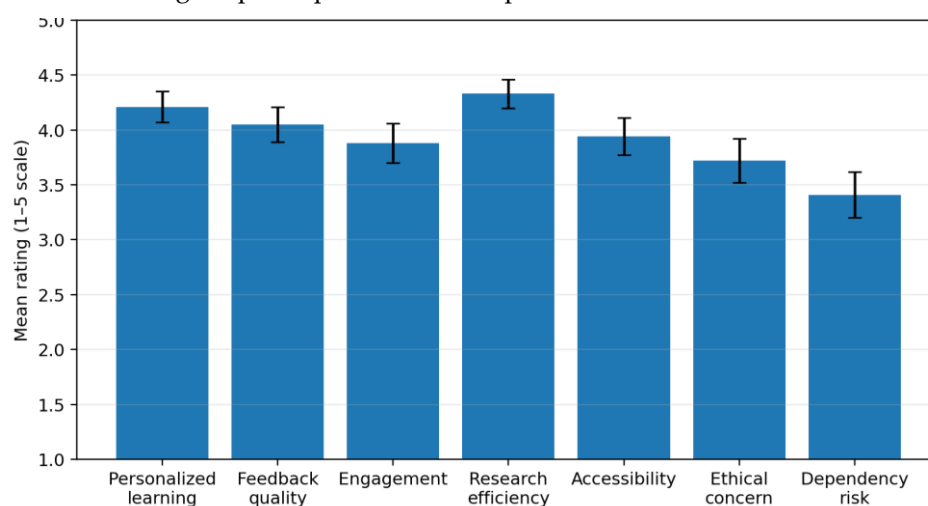


FIGURE 3. Mean survey ratings for AI-supported language learning and linguistic research outcomes.

Table 5. Regression model predicting perceived language-learning effectiveness.

Predictor	Standardized beta (95% CI)	SE	p	VIF and interpretation
Perceived usefulness	.34 [.27, .41]	.05	< .001	1.48; strongest positive predictor of perceived learning effectiveness.
Feedback quality	.29 [.23, .35]	.04	< .001	1.61; explanatory feedback supported perceived improvement.
Critical AI literacy	.18 [.06, .30]	.06	.004	1.42; verification skill strengthened responsible use.

Use frequency	.16 [.05, .27]	.05	.007	1.36; frequent use predicted outcomes when paired with literacy.
Ethical concern	-.09 [-.19, .01]	.05	.081	1.28; concern reduced uncritical acceptance but was not a significant negative predictor.
Dependency risk	-.14 [-.26, -.02]	.06	.018	1.18; overreliance weakened perceived learning effectiveness.
Model summary	R ² = .46; adjusted R ² = .44	-	-	Role controls included learner, teacher, and researcher group.

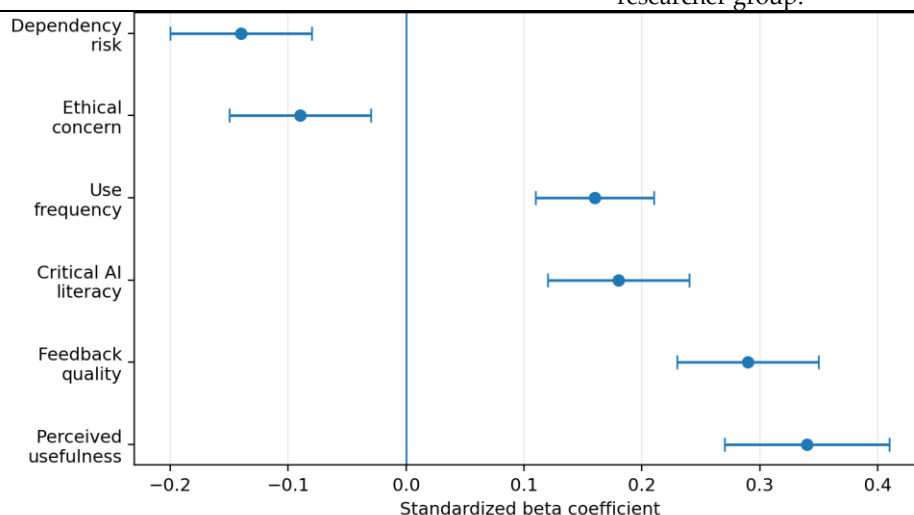


FIGURE 4. Standardized coefficients predicting perceived learning effectiveness.

2. RESEARCH-EFFICIENCY FINDINGS

For the researcher subgroup, AI use was strongest in transcription support, corpus exploration, translation comparison, preliminary coding, and literature organization. Perceived research efficiency was associated with usefulness of data-processing functions ($\beta = .41$, 95% CI [.31, .51], $p < .001$), AI literacy ($\beta = .22$, 95% CI [.08, .36], $p = .006$), and transparency of workflow documentation ($\beta = .19$, 95% CI [.04, .34], $p = .013$). Privacy concern was negatively associated with willingness to upload raw interview transcripts or identifiable speech data ($\beta = -.31$, 95% CI [-.44, -.18], $p < .001$). These results indicate that researchers valued AI for efficiency while remaining cautious about sensitive linguistic data.

Tool function shaped interpretation. Researchers were more willing to use AI for low-risk tasks such as keyword extraction, initial transcription cleanup, corpus searching, and language-practice generation. They were less willing to rely on AI for final coding, interpretation of culturally sensitive data, assessment judgments, or authorship decisions. This pattern shows that participants evaluated AI according to task risk, data sensitivity, and human accountability rather than treating it as one uniform technology.

Table 6. AI functions in linguistic research and required quality controls.

AI-supported research function	Mean usefulness	Main caution	Recommended control
Transcription support	4.28	Speech privacy and accent recognition errors	Human transcript checking and restricted audio access.
Corpus exploration	4.35	Overlooking contextual meaning	Researcher-defined coding categories and sample validation.
Translation comparison	4.10	Pragmatic meaning loss	Human bilingual review.
Preliminary coding	3.82	Conceptual flattening	Audit trail and sample recoding.

Literature organization	4.22	Citation hallucination or incomplete metadata	Manual reference verification.
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3. QUALITATIVE THEMES

Five qualitative themes explained the survey findings. The first theme, guided personalization, showed that learners valued repeated explanations and adaptive practice: one learner reported, 'I use it when I need another example, but I still decide whether the answer fits my class task' (L14). The second theme, feedback as explanation, showed that feedback was trusted when reasons were visible rather than when polished answers were simply supplied. A teacher explained, 'The useful feedback is not the corrected sentence; it is the explanation that helps the student notice the problem' (T07).

The third theme, productive autonomy versus dependency, showed that AI increased confidence but sometimes reduced first-attempt effort. One learner stated, 'Sometimes I ask the tool before I try, and that is the part I know I need to control' (L22). The fourth theme, research acceleration with human validation, was strongest among researchers: 'It saves time in transcription cleanup, but I would not let it decide the final code or interpretation' (R05). The fifth theme, ethical unease, connected privacy, authorship, bias, and transparency. A researcher noted, 'The problem is not using AI; the problem is not saying where it entered the analysis' (R02). These extracts show that AI was perceived as useful when it supported human decision-making, not when it replaced it.

Table 7. Theme-evidence matrix linking qualitative findings to research questions.

Theme	Participant-coded evidence example	Linked RQ	Interpretation
Guided personalization	L14: "I use it when I need another example, but I still decide whether the answer fits my class task."	RQ1, RQ2	AI supports learning when aligned with goals and learner judgment.
Feedback as explanation	T07: "The useful feedback is not the corrected sentence; it is the explanation that helps the student notice the problem."	RQ2	Feedback quality matters more than speed alone.
Autonomy and dependency	L22: "Sometimes I ask the tool before I try, and that is the part I know I need to control."	RQ3, RQ4	Critical AI literacy is necessary to reduce overreliance.
Research acceleration	R05: "It saves time in transcription cleanup, but I would not let it decide the final code or interpretation."	RQ1, RQ2	AI improves perceived efficiency under human validation.
Ethical unease	R02: "The problem is not using AI; the problem is not saying where it entered the analysis."	RQ3, RQ5	Responsible policy and disclosure are essential.

4. INTEGRATED MIXED-METHODS INTERPRETATION

The integrated findings show that AI-supported tools were perceived to have a positive but conditional role in language learning and linguistic research. Quantitative results indicate that perceived usefulness and feedback quality were strong predictors of perceived learning effectiveness, while qualitative findings explain that usefulness depended on whether AI output was understandable, revisable, and aligned with pedagogical purpose. Quantitative results also show that ethical concern did not simply prevent AI use; interviews explained that many participants used AI while simultaneously demanding clearer rules and stronger human review.

The mixed-methods evidence therefore supports a balanced interpretation. AI-supported tools were associated with perceived learning and research benefits, but those benefits were mediated by critical AI literacy, human expertise, transparent documentation, and institutional guidance. The evidence does not

justify a causal claim that AI directly improves proficiency or research quality. Instead, it shows how users perceive AI-supported practice and what conditions make such practice responsible and trustworthy.

IX. DISCUSSION

The findings answer RQ1 by showing that AI-supported tools were used across writing, translation, vocabulary learning, grammar checking, pronunciation practice, research organization, transcription, and corpus analysis. This distribution confirms earlier research showing that AI in language education is no longer limited to one category of tool [1], [16]. However, the present study extends existing work by comparing learners, teachers, and linguistics researchers within one design. This multi-user structure matters for applied linguistics because language-learning tools are now embedded not only in student practice but also in pedagogy, assessment, research workflows, and institutional policy.

In relation to RQ2, perceived usefulness and feedback quality were the strongest predictors of perceived learning effectiveness. This pattern is consistent with technology-acceptance reasoning and with studies showing that learners accept AI when it appears useful, accessible, and confidence-supporting [14], [17]. The interview findings add a critical applied-linguistic distinction: participants did not value feedback simply because it was immediate. They valued feedback when it explained linguistic choices, helped revision, and supported independent judgment. This suggests that pedagogical quality, not technological speed alone, determines perceived value.

The researcher findings show that AI was perceived as useful for transcription support, corpus exploration, translation comparison, preliminary coding, and literature organization. This aligns with discussions of natural language processing in educational and linguistic research [33]. Yet the same participants resisted using AI for final interpretation, culturally sensitive coding, or authorship decisions. This contradiction is theoretically important: users may accept AI as a productivity tool while rejecting it as an epistemic authority. Applied linguistics therefore needs models that distinguish mechanical assistance from interpretive responsibility.

RQ3 concerned ethical, pedagogical, and methodological challenges. The results indicate that accuracy, dependency, authorship, privacy, and bias were not marginal concerns but central conditions shaping AI acceptance. These concerns align with reviews of large language models that highlight hallucination, lack of transparency, data protection, and academic-integrity risks [30], [31]. Alternative explanations should also be considered. High usefulness ratings may partly reflect novelty, convenience, or reduced task effort rather than deeper learning. Higher ethical concern may reflect institutional uncertainty rather than rejection of AI itself.

RQ4 asked how users interpret AI in relation to human expertise and scholarly judgment. Interview themes showed that participants were willing to use AI as a partner, tutor, assistant, reviewer, or organizer, but they resisted replacing teachers, translators, researchers, or learners' own reasoning. This finding supports arguments that teacher-AI relationships should be complementary [8] and that AI-generated outputs should be situated within critical digital competence [3], [18]. The contribution of the present study is to show that human expertise operates throughout the workflow: in prompt design, task selection, verification, revision, interpretation, and disclosure.

RQ5 concerned responsible-use strategies. The study suggests that responsible integration requires critical AI literacy, transparent disclosure, privacy protection, alignment between feedback and learning objectives, and preservation of human judgment in assessment, translation, and research interpretation. These strategies are especially important in applied linguistics because AI tools deal directly with language, identity, authorship, and cultural meaning. A translation may be grammatical but pragmatically weak; a writing suggestion may be fluent but genre-inappropriate; and a coding suggestion may be efficient but theoretically shallow.

The theoretical value of the findings lies in connecting technology acceptance with applied-linguistic accountability. Perceived usefulness was important, but it was not sufficient. The study shows that responsible AI integration also depends on feedback quality, critical AI literacy, ethical governance, dependency awareness, and human expertise. This challenges purely adoption-oriented educational technology models and supports a more sociotechnical applied-linguistic model in which acceptance, risk, pedagogy, and responsibility are examined together.

The study also contributes to linguistic research methodology by showing that AI-assisted research should not be evaluated only by speed. It should be evaluated by whether the workflow preserves interpretive accountability. Researchers need to document what tools were used, what data were entered, what outputs were accepted or rejected, how errors were checked, and how sensitive data were protected. Without such documentation, AI may make research faster but less transparent. With documentation and human validation, AI can support corpus exploration, transcription, data management, and preliminary coding while preserving the central role of human analysis.

X. THEORETICAL CONTRIBUTIONS

The first contribution is to applied linguistics. The study develops a Responsible AI Integration Framework that links tool use, perceived usefulness, feedback quality, critical AI literacy, ethical concern, dependency risk, and human expertise to perceived learning and research outcomes. This makes the contribution more specific than general claims about AI benefit or harm because it explains the conditions under which AI support is perceived as pedagogically and methodologically meaningful.

The second contribution is to technology-acceptance theory. The study extends acceptance-oriented models by adding ethical concern, dependency risk, critical AI literacy, and human expertise as central applied-linguistic constructs. In language learning and linguistic research, acceptance cannot be explained only through ease of use or usefulness because AI outputs affect authorship, assessment, interpretation, privacy, multilingual identity, and scholarly accountability.

The third contribution is methodological. The explanatory sequential design demonstrates how survey modeling and interview analysis can be integrated to examine not only whether AI use is associated with perceived outcomes, but also why learners, teachers, and researchers accept, distrust, adapt, verify, or limit AI use in specific applied-linguistic contexts. This design directly operationalizes the conceptual framework by connecting adoption, mediation, governance, and human validation.

XI. PRACTICAL IMPLICATIONS

For language teachers, the findings support using AI as a supervised feedback and practice resource. Teachers can ask learners to compare AI feedback with peer feedback, explain which suggestions they accept, and reflect on how AI changed their revisions. This approach turns AI into a tool for metalinguistic awareness rather than a shortcut to finished answers.

For learners, the findings support training in critical AI literacy. Learners should know how to ask precise questions, verify answers, compare sources, detect hallucination, protect privacy, and avoid using AI before attempting productive work. The goal is not to ban AI but to make learners more independent and reflective in its use.

For linguistics researchers, AI should be documented as part of the methodological workflow. Researchers should report whether AI supported transcription, coding preparation, translation comparison, corpus searching, or text classification. They should also state what human checks were applied. This is necessary for transparency, reproducibility, and ethical accountability.

For institutions and journals, policies should distinguish acceptable assistance from unacceptable substitution. Guidelines should address disclosure, authorship, privacy, assessment design, data storage, and the treatment of AI-supported outputs in research and publication.

To reduce accuracy risk, users should verify fluent AI feedback, translations, and research summaries against trusted sources.

XII. LIMITATIONS AND FUTURE RESEARCH

The study is limited by its reliance on self-reported survey outcomes and participant perceptions. Perceived learning effectiveness is not the same as direct proficiency growth, and perceived research efficiency is not the same as independently measured productivity or analytical quality. The cross-sectional design also prevents causal claims about whether AI use produces learning improvement or only correlates with positive user attitudes. Future research should combine AI-use surveys with longitudinal proficiency

tests, writing portfolios, speech-performance measures, classroom observations, and documented research-output indicators.

The study also has sampling and measurement limitations. The three participant groups were unequal in size, and subgroup analyses for researchers were based on a smaller sample than the learner group. Tool variation is another limitation because conversational assistants, machine translation, speech recognition, grammar checkers, and corpus tools do not operate in the same way. Tools available during one data-collection period may also change quickly in interface, accuracy, pricing, privacy policy, and institutional acceptance. Future research should therefore examine tool-specific effects and compare commercial, open-source, and institutionally controlled AI systems.

Finally, the study did not deeply compare specific languages, proficiency levels, minority-language contexts, or low-resource language settings. This limits generalizability. Future work should investigate how AI tools treat non-standard varieties, accents, pragmatic meaning, culturally specific discourse practices, and multilingual identity.

XIII. CONCLUSION

This study examined how AI-supported tools are perceived to affect language learning and linguistic research through an explanatory sequential mixed-methods design. The findings indicate that participants perceived AI as supportive for personalized practice, immediate feedback, accessibility, learner engagement, research organization, transcription support, corpus exploration, translation comparison, and data-processing efficiency. Quantitative results showed that perceived usefulness, feedback quality, critical AI literacy, and frequency of AI use were associated with perceived learning effectiveness, while dependency risk weakened perceived learning engagement. For researchers, AI was valued when it reduced mechanical labor and supported preliminary organization without replacing interpretation.

The study also shows that responsible AI integration is not automatically achieved through access to tools. Participants reported concerns about accuracy, bias, authorship, academic integrity, learner dependency, privacy, and loss of independent judgment. These concerns should be treated as conditions for responsible innovation rather than as obstacles to innovation. AI-supported tools become educationally and methodologically valuable when they are connected to clear learning aims, human verification, transparent documentation, and ethical governance.

The central contribution of the study is a Responsible AI Integration Framework for applied linguistics that links AI tool use, perceived usefulness, feedback quality, critical AI literacy, ethical concern, dependency risk, human expertise, perceived learning effectiveness, and perceived research efficiency. The framework positions AI as a mediating tool that can extend human capacity when guided by critical thinking, scholarly judgment, and transparent ethical practice. Responsible AI integration in language learning and linguistic research therefore requires both human verification and methodological transparency.

Author Contributions

The author conducted the conceptualization, methodology, data analysis, investigation, writing, review, editing, and final approval of the manuscript.

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Data Availability

The dataset will be available from the author upon reasonable request.

Conflicts of Interest

The author declares no conflict of interest.

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Appendix A. Survey Instrument Overview

The questionnaire included items on demographic background, linguistic profile, educational role, AI-use frequency, tool type, perceived usefulness, feedback quality, learning effectiveness, research efficiency, accessibility, ethical concern, dependency risk, and critical AI literacy. Items used a five-point Likert scale from 1 = strongly disagree to 5 = strongly agree. The instrument was designed to measure perceived outcomes rather than direct proficiency gains.

Core survey items included: AI-supported tools help me complete language-learning or research tasks more effectively; AI feedback helps me understand why a revision is needed; AI tools make language-learning resources more accessible; I verify AI output before using it; AI can make learners dependent if used before independent effort; AI use raises concerns about privacy, authorship, or academic integrity; AI-supported tools improve the efficiency of linguistic data organization; and institutions should provide clearer rules for responsible AI use.

Appendix B. Semi-Structured Interview Protocol

Interview questions examined tool use, learning practices, teaching practices, research support, trust, verification, privacy, authorship, dependency, and institutional guidance. Core questions included: Which AI-supported tools do you use most often? For which language-learning or research tasks do you trust AI most? When do you check or reject AI output? How does AI affect your learning autonomy, teaching responsibility, or research judgment? What ethical concerns shape your use of AI?

Follow-up prompts explored whether AI increased confidence, reduced effort, changed writing behavior, supported multilingual communication, improved access to feedback, or complicated academic integrity. Researcher participants were asked how they documented AI-supported transcription, coding, translation comparison, or data-processing decisions.

Appendix C. Interview Coding Framework

Table A1. Interview coding framework.

Code family	Subcodes	Analytical use
Tool use and task fit	Writing support; translation; speech recognition; corpus search; transcription; coding preparation	Identifies the functions users associated with perceived value.
Feedback and learning support	Explanation quality; revision support; accessibility; repeated practice; confidence	Explains why feedback quality predicted perceived learning effectiveness.
Critical AI literacy	Verification; comparison; source checking; prompt refinement; refusal to accept unsupported output	Connects user judgment to responsible AI use.
Dependency and autonomy	First-attempt effort; overreliance; confidence; independent drafting; learner agency	Explains the negative role of dependency risk.
Ethics and governance	Privacy; authorship; bias; transparency; disclosure; institutional rules	Explains ethical concern and responsible-use strategies.

Appendix D. Factor-Loading Summary

The exploratory factor analysis retained items with theoretically meaningful loadings above .50 and no problematic cross-loading. The table reports representative retained items and primary loadings for transparency.

Table A2. Factor-loading summary for retained questionnaire constructs.

Construct	Retained items	Loading range	Decision
Perceived usefulness	PU1-PU6	.68-.84	Retained; coherent usefulness factor.
Feedback quality	FQ1-FQ5	.64-.82	Retained; strong feedback-quality factor.
Critical AI literacy	CL1-CL5	.62-.79	Retained; verification and questioning items loaded together.
Ethical concern	EC1-EC6	.61-.81	Retained; privacy, authorship, and bias items coherent.
Dependency risk	DR1-DR4	.63-.77	Retained; overreliance items formed separate factor.
Outcome value	OV1-OV7	.66-.83	Retained; perceived learning and research outcomes coherent.

Appendix E. Core Survey Item Domains

Survey items were grouped into six measurable domains. The full instrument used five-point Likert responses and was designed to measure perceived outcomes, not direct proficiency gains.

Table A3. Survey item domains and scoring procedure.

Domain	Example retained items	Scoring
Perceived usefulness	AI tools help me complete language-learning tasks more effectively; AI tools help organize research tasks more efficiently.	Mean of six items.
Feedback quality	AI feedback is clear; AI feedback explains why a revision is needed; AI feedback helps me compare alternatives.	Mean of five items.
Critical AI literacy	I verify AI output before using it; I compare AI output with trusted sources; I reject AI output when it is unsupported.	Mean of five items.
Ethical concern	AI use raises privacy concerns; AI use complicates authorship; AI outputs may reproduce bias.	Mean of six items.
Dependency risk	I sometimes use AI before attempting the task myself; AI may reduce independent drafting or problem-solving.	Mean of four items.
Outcome value	AI supports perceived learning effectiveness; AI supports perceived research efficiency; AI helps manage language-related tasks.	Mean of seven items.