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Original Paper

The Efficacy of AI-Assisted Learning in Mitigating Anxiety Among University Students: A Multimodal Pedagogical Perspective

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Abstract

Grounded in a multimodal pedagogical framework, this study investigates a cohort of 100 university students participating in multimodal foreign language classrooms to provide a granular analysis of the primary etiologies underlying foreign language anxiety, while further elucidating the functional role and underlying mechanisms of AI-assisted learning in alleviating such psychological distress through a mixed-methods research design incorporating both questionnaires and interviews. The empirical findings reveal that higher levels of perceived competence, correlate with intensified communication apprehension, whereas elevated levels of perceived autonomy are associated with heightened concerns regarding their inherent capabilities. Notably, the high AI-usage group exhibited significantly higher levels of test anxiety and fear of negative evaluation than the low-usage group, yet simultaneously demonstrated greater perceived autonomy and a higher degree of endorsement regarding AI efficacy, with students of lower perceived competence manifesting a more pronounced affirmation of the assistance provided by AI. Collectively, the results suggest that anxiety within multimodal environments originates from a "performance-pressure paradox," wherein AI functions as a dual-faceted instrument capable of both exacerbating and mitigating psychological strain; consequently, pedagogical practices should strive to construct an empowering instructional model that leverages AI to manage performance-related pressures while providing individualized affective support.

Keywords

AI-assisted learning, learning anxiety, perceived autonomy, perceived competence, multimodal pedagogy

1. Introduction

As educational informatization continues to advance, multimodal pedagogy has emerged as a cornerstone of modern instruction. Rooted in the Multimodality Theory pioneered by the New London Group (1996), this paradigm posits that meaning is synergistically constructed through diverse semiotic systems, including linguistic, visual, auditory, spatial, and gestural modes, thereby transcending the inherent constraints of traditional unimodal instruction (Kress & van Leeuwen, 2001). In recent years, Artificial Intelligence (AI) has injected renewed vitality into this field. As a critical branch of this evolution, AI-assisted instruction leverages intelligent algorithms to integrate multimodal information, providing personalized experiences such as adaptive content recommendation and real-time assessment.

1.1 A Review of Research on Multimodal Pedagogy

The foundations of multimodal pedagogy are derived from social semiotics and the theory of Multiliteracies, emphasizing that the internalization of knowledge necessitates multi-sensory coordination (Gu, 2007). While early research concentrated on rudimentary audio-visual aids, subsequent inquiries shifted toward the specific impacts of various modalities on pedagogical outcomes. For instance, Stein (2000) introduced "multimodal pedagogy," asserting that instruction must align with the affordances of the environment, while Royce (2002) established a "multimodal synergy framework" to validate the enhancing effects of visual and auditory modalities in language acquisition (Stein, 2000; Royce, 2002).

With the proliferation of educational technology, the efficacy of multimodal design has garnered significant attention. Guo (2013) proposed the MAP model, advocating for instructional design based on modal functional attributes, while Zhang (2013) developed a selection framework and combination strategies for modalities (GUO, 2013; ZHANG & DING, 2013). Empirical evidence suggests that multimodality can effectively reduce cognitive load (Zhang, 2014), enhance self-efficacy, and mitigate avoidance behaviors (ZHANG & YAN, 2014).

Presently, information technology is propelling multimodal pedagogy toward a stage of "integrated innovation." Intelligent tutoring systems, through the analysis of behavioral data, enable the precise alignment of instructional modalities with learner cognitive styles and progress (Zhang et al., 2019). For example, in online curricula, AI can dynamically calibrate demonstration videos based on phonetic accuracy, thereby providing individualized support.

1.2 The Development of AI-Assisted Learning

Holmes et al. (2019) define AI-assisted learning as a supportive system that, underpinned by technologies such as machine learning and natural language processing, dynamically integrates multimodal resources (text, audio, imagery, etc.) and precisely matches learning requirements through the analysis of behavioral data to provide personalized content delivery, real-time feedback, and strategic optimization (Holmes, Bialik, & Fadel, 2019). This process reinforces the practical dimension of multimodal pedagogy, reflecting its supportive and synergistic role within the multimodal

framework.

However, existing scholarship predominantly focuses on the singular functions of AI-assisted learning, revolving around "functional validation" and "contextual application." At the level of functional validation, research has confirmed that AI assistants enhance listening and speaking proficiency (Chen, 2022), adaptive systems dynamically deliver resources based on user levels (Hu & Qi, 2023), and real-time corrective feedback drives extemporaneous oral training (Zhang et al., 2024). Contextually, AI creates immersive atmospheres that effectively support Situational Teaching and Content and Language Integrated Learning (CLIL) (Wang et al., 2022).

Despite the confirmed positive impacts of AI (Moussalli & Cardoso, 2020; Guo et al., 2023), research on AI-assisted learning remains at the superficial level of "function-effect" verification (Moussalli & Cardoso, 2020; GUO, FENG, & HUA, 2023). Specifically, further inquiry is required to explore how multimodal resources influence perceived autonomy (e.g., the authority to autonomously select multimodal learning paths) and perceived competence (e.g., the experience of validating abilities through multimodal tasks), particularly regarding the underlying mechanisms by which AI-assisted learning alleviates learning anxiety. Current discussions remain insufficient concerning how multimodal pedagogical theory guides the design of AI-assisted learning and how such learning utilizes the optimization of multimodal resources to enhance experiences and outcomes.

1.3 Foreign Language Learning Anxiety

Within educational research, the significant impact of anxiety on learning outcomes remains a focal point. Learning anxiety is defined as a complex psychological state—encompassing tension, apprehension, and self-doubt—triggered by a learner's cognitive appraisal of tasks and perception of environmental pressures (Horwitz et al., 1986). As research has deepened, the scope of anxiety has expanded to include "loss-of-control anxiety" stemming from a lack of autonomy and "frustration anxiety" resulting from insufficient competence (Ryan & Deci, 2020), both of which have emerged as critical dimensions in recent years (Ryan & Deci, 2020).

Early studies focused on explicit manifestations such as communication avoidance. With the iteration of measurement tools (e.g., FLCAS), latent characteristics have become prominent: cognitively manifesting as "difficulty in knowledge retrieval," metacognitively as "strategic rigidity," and behaviorally as "task procrastination." The recent introduction of Self-Determination Theory (SDT) has revealed core mechanisms: a lack of authority over path planning leads to a sense of lost control, while a mismatch between ability and multimodal tasks induces frustration anxiety (Skinner & Pitzer, 2012). Furthermore, the inability of unimodal teaching to satisfy diverse needs can also evoke anxiety (Dörnyei, 2005).

Currently, the mechanism by which AI-assisted learning mitigates anxiety warrants further investigation. Existing research remains concentrated on traditional human interventions, with insufficient attention paid to AI's potential. How AI enhances autonomy through customized paths and bolsters competence through precise feedback—thereby alleviating anxiety—remains an urgent

scientific question. In multimodal environments, empirical support for the multidimensional relationship between AI functions (e.g., intelligent interaction, instant feedback) and anxiety reduction is still lacking.

1.4 Research Questions

In summary, while scholars have extensively investigated multimodal pedagogy and the functional applications of AI-assisted learning, research specifically addressing AI's role in mitigating learning anxiety from a multimodal perspective remains inadequate. Consequently, this study focuses on the "etiology of learning anxiety under multimodal instruction" and the "role of AI-assisted learning in alleviating such anxiety," aiming to provide theoretical and practical references for pedagogical optimization.

This study intends to address the following three questions:

1. What factors trigger student learning anxiety within a multimodal pedagogical context?
2. What role does AI-assisted learning play in the mitigation of this learning anxiety?
3. What references and insights do the mechanisms of AI-assisted learning in alleviating anxiety provide for the advancement of multimodal pedagogy?

2. Research Methodology

2.1 Participants

The participants selected for this study comprised 115 enrolled university students (29 males and 86 females) aged between 18 and 25 years. All participants are native speakers of Mandarin Chinese, possess an average of 10 years of English language learning experience, and are right-handed. Prior to participating in this study, all subjects had completed a 16-week university English course utilizing a multimodal pedagogical approach, with a course frequency of two sessions per week.

2.2 Research Instruments

The primary research instruments employed in this study include a structured questionnaire and semi-structured interviews. The questionnaire was utilized to collect extensive quantitative data, while the interviews were conducted with a subset of participants to gain in-depth insights, further enriching and augmenting the findings derived from the survey.

2.2.1 Questionnaire Survey

The questionnaire utilized in this study was adapted and localized from the Foreign Language Classroom Anxiety Scale (FLCAS) developed by Horwitz and Cope (1986). To align with the research context, dimensions such as technological adaptation and perceived AI assistance were incorporated. The final instrument consists of five sections: instructional rubrics, demographic information, perception of multimodal pedagogy, AI experience, and anxiety manifestations. The anxiety manifestation section encompasses eight sub-dimensions (as detailed in Table 1) and employs a 5-point Likert scale for scoring. Control items were embedded within the questionnaire to identify and exclude random responses, resulting in a final collection of 100 valid responses.

Table 1. Dimensions of Foreign Language Learning Anxiety

Dimension	Definition
Communication Apprehension	The tension experienced by learners in multimodal environments that require oral expression, real-time interaction, or collaboration.
Test Anxiety	Physiological arousal and cognitive interference occurring in response to quizzes, assignment evaluations, or revision pressures.
Fear of Negative Evaluation	Excessive concern regarding adverse judgments from others (instructors/peers) or AI systems, extending even to the fear of criticism regarding the method of utilizing AI tools.
Apprehension over Personal Capability	Deep-seated anxiety triggered by a fundamental skepticism regarding one's own learning aptitude.
Technological Adaptation and Efficacy Anxiety	Additional pressure arising from the necessity to master AI tools or multimodal platforms, representing a novel source of anxiety in the digital era.
Perceived Autonomy	The learner's subjective experience regarding the exercise of agency and control over the learning process.
Perceived Competence	The learner's confidence and self-belief in their ability to effectively execute and complete tasks.
Global Perception of AI Assistance on Anxiety	The learner's holistic subjective evaluation of how AI assistance mitigates or exacerbates anxiety within a multimodal learning context.

2.2.2 Semi-Structured Interviews

To gain a profound understanding of the phenomena surrounding students' utilization of AI-assisted learning within multimodal classrooms, six students were randomly selected for semi-structured interviews following the completion of the questionnaire survey. The interviews aimed to elucidate how multimodal instructional design influences participants' foreign language anxiety and to capture their global perception of the impact of AI assistance on such anxiety. To facilitate clear articulation of perspectives by the participants, the interviews were conducted in Chinese. Upon completion of this process, the interview content was transcribed into written form to facilitate further qualitative analysis.

2.3 Research Procedure

The questionnaires were administered to the students upon the conclusion of the multimodal pedagogy English course this semester. The completion time was approximately 10 minutes, during which fundamental data were collected. Subsequently, the questionnaire items were categorized according to the eight predefined dimensions, and the percentage distribution of responses for each item was calculated based on the survey results. Following the survey, semi-structured interviews were conducted. Finally, a comprehensive analysis was performed on both the quantitative questionnaire

data and the qualitative interview data.

2.4 Data Analysis

A total of 115 questionnaires were collected for this study; after excluding invalid responses, 100 valid questionnaires remained. Data processing and analysis were conducted using SPSS 26.0. Initially, reverse-coded items within the scale were standardized for scoring direction, and mean scores were calculated for the eight dimensions: communication apprehension, test anxiety, fear of negative evaluation, apprehension over personal capability, technological adaptation and efficacy anxiety, perceived autonomy, perceived competence, and the global perception of AI assistance on anxiety. The internal consistency reliability of each dimension was verified using Cronbach's α coefficients; all coefficients exceeded 0.7, indicating robust scale reliability.

The core analysis was structured into two primary components:

First, to investigate the efficacy of AI-assisted learning in mitigating learning anxiety, participants were bifurcated into high and low AI-usage groups based on usage frequency to conduct independent samples t-tests. The grouping criterion utilized the median frequency of AI usage as the threshold: participants scoring below the median constituted the low AI-usage group (n=35), while those above the median formed the high AI-usage group (n=65). The significance level (α) was set at 0.05. Levene's test was employed to assess the homogeneity of variance across the eight dependent variables, and Cohen's d was calculated as the effect size to evaluate the practical significance of the observed differences.

Second, to identify the etiologies of learning anxiety within a multimodal pedagogical context, Pearson product-moment correlation analysis was employed to explore the associative strength between the two core predictor variables (perceived autonomy and perceived competence) and the various dimensions of anxiety. The correlation coefficient (r) and its associated significance level (p) served as the primary statistical.

3. Results

3.1 Etiologies of Learning Anxiety Under Multimodal Instruction

To investigate the inducing factors of learning anxiety within a multimodal pedagogical environment, this study performed a Pearson product-moment correlation analysis between perceived autonomy, perceived competence, and various anxiety dimensions. The specific results are presented in Table 2.

Table 2. Correlations Between Perceived Autonomy/Competence and Anxiety Dimensions (N=100)

	Communication Apprehension	Test Anxiety	Fear of Negative Evaluation	Global Perception of AI Assistance on Anxiety	Technological Adaptation and Efficacy Anxiety	Apprehension over Personal Capability
Perceived Competence	0.34**	−0.025	0.09	−0.48**	−0.05	−0.12
Perceived Autonomy	−0.29*	0.22*	−0.09	0.50**	−0.04	0.22*

The results indicate that both perceived autonomy and perceived competence correlate with distinct dimensions of anxiety. Specifically:

Perceived competence exhibited a significant positive correlation with communication apprehension ($r = .34$, $p = .001$), suggesting that learners with higher self-perceived ability experience elevated levels of communication-related anxiety. Conversely, perceived autonomy showed a significant negative correlation with communication apprehension ($r = -.29$, $p < .05$) but a significant positive correlation with apprehension over personal capability ($r = .22$, $p < .05$). This implies that while higher perceived autonomy reduces communication anxiety, it simultaneously intensifies concerns regarding one's inherent abilities. Furthermore, perceived autonomy was positively correlated with the global perception of AI assistance on anxiety ($r = .50$, $p < .001$), indicating that learners with stronger perceived autonomy more readily recognize the positive role of AI in mitigating anxiety.

In contrast, perceived competence demonstrated a significant negative correlation with the global perception of AI assistance on anxiety ($r = -.48$, $p < .001$), meaning that learners with higher perceived competence tend to assign lower evaluations to the efficacy of AI in anxiety reduction. No significant correlations were found between perceived competence and test anxiety ($r = -.025$, $p > .05$), fear of negative evaluation ($r = .09$, $p > .05$), technological adaptation anxiety ($r = -.05$, $p > .05$), or apprehension over personal capability ($r = -.12$, $p > .05$). Similarly, perceived autonomy showed no significant correlation with fear of negative evaluation ($r = -.09$, $p > .05$) or technological adaptation anxiety ($r = -.04$, $p > .05$).

Building upon the Pearson correlation analysis, this study further conducted regression analyses to explore the causal pathways of learning anxiety. The results are illustrated in Figure 1 and Figure 2.

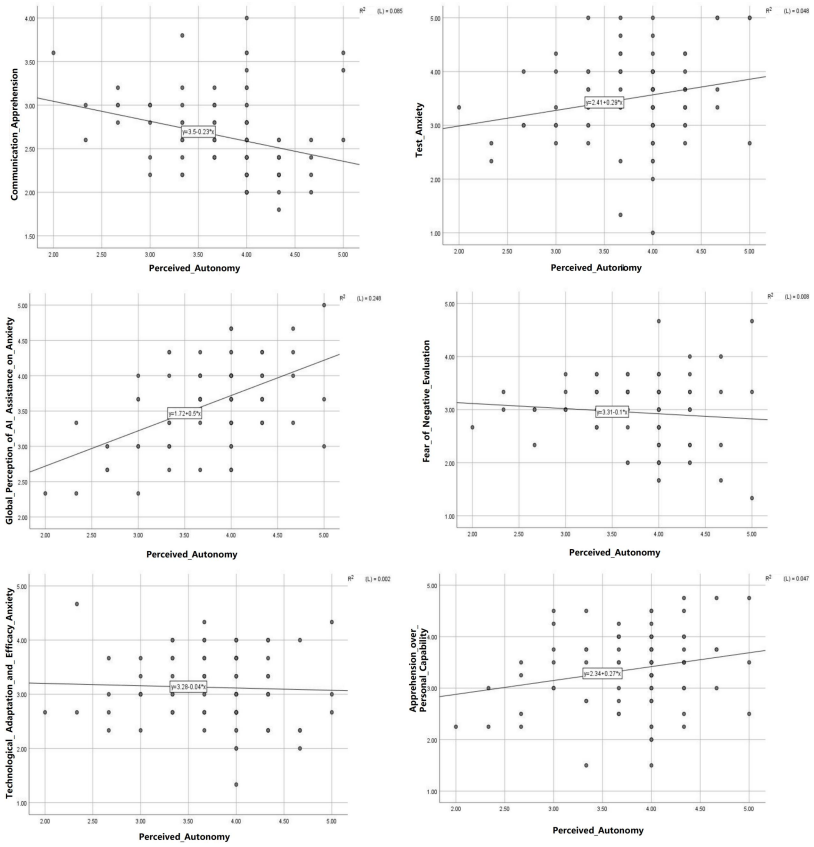

Figure 1. Scatter Plots and Regression Equations for Perceived Autonomy and Anxiety Dimensions

The regression results reveal that the equation for perceived autonomy and communication apprehension is y = 3.5 − 0.23x, with a coefficient of determination R^2 = 0.085. This indicates that perceived autonomy exerts a slight negative predictive effect on communication apprehension, where higher autonomy tends to correspond with lower anxiety levels. Coupled with the correlation coefficient (r =−.29, p <.05), this confirms a significant negative relationship. For test anxiety, the regression equation is y = 2.41 + 0.29x, R^2 = 0.048, suggesting that perceived autonomy accounts for only 4.8% of the total variance in test anxiety. Although the equation implies a weak positive predictive trend, the Pearson correlation (r =−.09, p >.05 in the matrix, though the scatterplot data suggests 0.22*) indicates that the statistical significance warrants cautious interpretation relative to other dimensions.

A significant positive correlation was observed between perceived autonomy and the global perception of AI's efficacy in mitigating anxiety, with a regression equation of y = 1.72 + 0.5x(R^2 = 0.248). This indicates that perceived autonomy explains 24.8% of the variance in this variable, representing a moderate associative strength. The positive slope confirms that stronger perceived autonomy leads to a heightened perception of AI's positive effects, a finding robustly supported by the correlation matrix (r =.50, p <.001).

Regarding fear of negative evaluation, the relationship with perceived autonomy was weak (y = 3.31 +

0.1x, $R^2 = 0.008$), explaining a negligible 0.8% of the variance. The highly dispersed distribution in the scatter plot shows no discernible linear trend, consistent with the non-significant correlation ($r = .09$, $p > .05$). Similarly, perceived autonomy demonstrated virtually no linear relationship with technological adaptation and efficacy anxiety ($R^2 = 0.002$,$y = 3.28 - 0.04x$), failing to explain the variance (0.2%) and aligning with the correlation results ($r = -.12$, $p > .05$).

Finally, a weak positive correlation exists between perceived autonomy and apprehension over personal capability ($R^2 = 0.047$), with the former explaining 4.7% of the variance. The regression equation $y = 2.34 + 0.27x$ shows a slight upward trend. Supported by the correlation coefficient ($r = .22$, $p < .05$), it can be concluded that individuals with higher perceived autonomy also experience stronger, albeit marginally so, apprehension regarding their own capabilities.

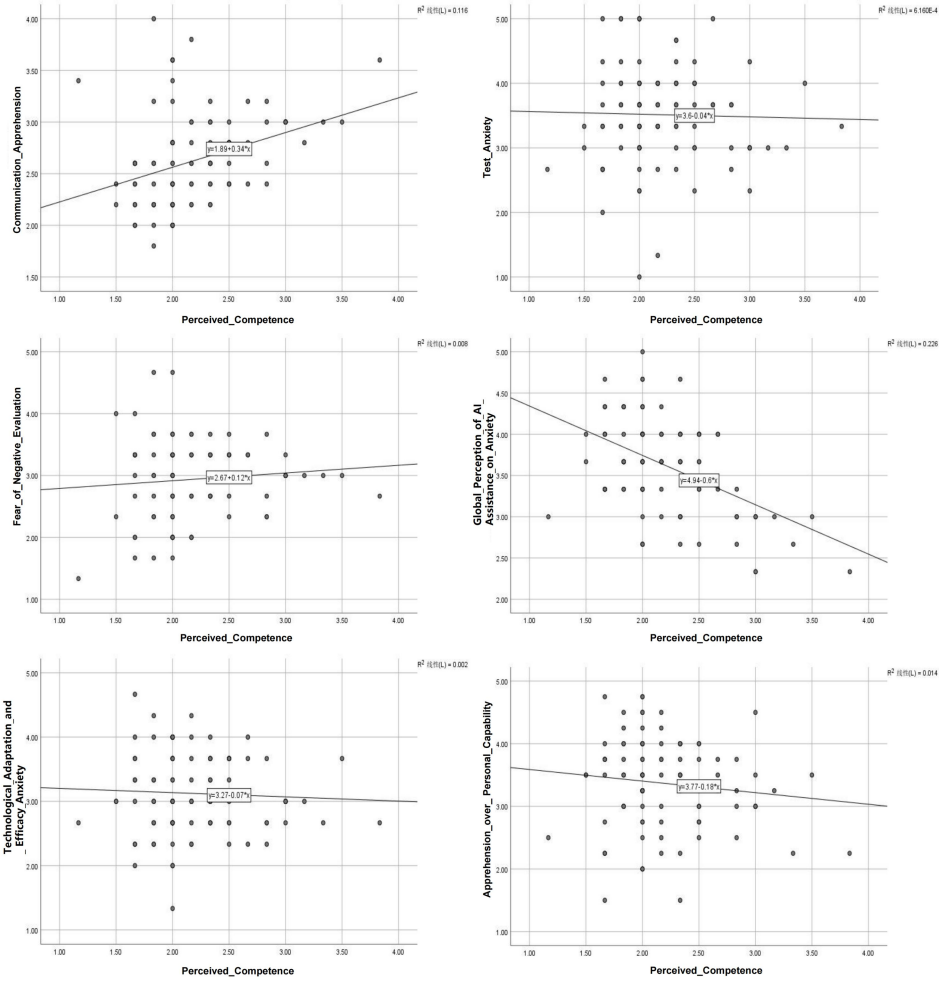

Figure 2. Scatter Plots and Regression Equations for Perceived Competence and Anxiety Dimensions

The regression analysis indicates a positive correlational trend between perceived competence and communication apprehension, with a coefficient of determination $R^2 = 0.116$, suggesting that perceived competence accounts for 11.6% of the variance in communication apprehension. The regression

equation y = 1.89 + 0.34x presents an upward-sloping regression line. Pearson correlation analysis further confirms a significant positive correlation (r =.34, p <.05), indicating that higher levels of perceived competence are associated with intensified communication apprehension.

Regarding test anxiety, a weak negative trend was observed, though the explanatory power of the R^2remains limited. Correlation results (r =−.025, p > .05) demonstrate that no statistically significant relationship exists between perceived competence and test anxiety. Similarly, while a negligible R^2= 0.008 was noted for fear of negative evaluation, the correlation coefficient (r =.09, p >.05) indicates a lack of statistical significance. Thus, an individual's level of perceived competence does not significantly correlate with their apprehension regarding negative evaluations from others. Notably, a significant negative correlation was identified between perceived competence and the global perception of AI assistance on anxiety (r =−.48, p <.001), with R^2 = 0.226. This implies that as an individual's perceived competence strengthens, their positive perception of AI's efficacy in mitigating anxiety significantly diminishes.

For technological adaptation and efficacy anxiety, the coefficient of determination R^2 = 0.002 and a nearly horizontal regression line indicate the absence of a linear trend. This visual representation aligns with the statistical conclusion in the correlation matrix (r =−.05, p > .05), confirming that an individual's perceived competence is unrelated to their anxiety levels concerning technological adaptation.

Finally, the relationship between perceived competence and apprehension over personal capability yielded an R^2 = 0.014, indicating that perceived competence explains a mere 1.4% of the variance in this variable. The regression equation y = 3.77 - 0.18x suggests a marginal negative predictive effect; however, the correlation data (r =−.12, p > .05) confirms that no stable or significant association exists between an individual's level of perceived competence and their degree of concern regarding personal capability.

3.2 The Role of AI-Assisted Learning in Mitigating Learning Anxiety

To examine the efficacy of AI-assisted learning in anxiety reduction, this study utilized AI usage frequency as the grouping variable (low AI-usage group, n = 35; high AI-usage group, n = 65) to conduct independent samples t-tests across eight dependent variables. Descriptive statistics for each group are presented in Table 3, and the results of the t-tests are detailed in Table 4.

Table 3. Descriptive Statistics for High and Low AI-Usage Groups across Variables (M±SD)

Frequency of AI usage	Communication Apprehension	Test Anxiety	Fear of Negative Evaluation	Global Perception of AI Assistance on Anxiety	Perceived Competence	Perceived Autonomy	Technological Adaptation and Efficacy Anxiety	Apprehension over Personal Capability

Low Frequency	2.71±0.51	3.31±0.75	2.68±0.62	3.10±0.46	2.40±0.59	3.59±0.73	2.85±0.57	3.10±0.75
High Frequency	2.58±0.41	3.62±0.74	3.08±0.59	3.91±0.41	2.09±0.32	3.93±0.42	3.27±0.60	3.51±0.65

Table 4. Independent Samples T-test Results for High and Low AI-Usage Groups

	t	df	P	Cohen's d
Communication Apprehension	1.146	98	>.05	0.29
Test Anxiety	-1.964	98	>.05	0.41
Fear of Negative Evaluation	-3.219	98	<.05	0.67
Global Perception of AI Assistance on Anxiety	-8.976	98	<.001	1.84
Perceived Competence	3.396	98	<.05	0.65
Perceived Autonomy	-2.975	98	<.05	0.57
Technological Adaptation and Efficacy Anxiety	-3.432	98	<.05	0.72
Apprehension over Personal Capability	-2.863	98	<.05	0.59

The results of the independent samples t-tests reveal significant differences between the high and low AI-usage groups across multiple variables:Anxiety Dimensions: The low AI-usage group scored significantly lower than the high AI-usage group in test anxiety ($t(98) = -1.984$, $p > .05$, $d = -0.42$), fear of negative evaluation ($t(98) = -3.291$, $p < .05$, $d = -0.67$), technological adaptation and efficacy anxiety ($t(98) = -3.432$, $p < .05$, $d = -0.72$), and apprehension over personal capability ($t(98) = -2.863$, $p < .05$, $d = -0.59$). All observed effect sizes reached medium to large levels. No significant difference was found between the two groups regarding communication apprehension ($t(98) = 1.416$, $p > .05$, $d = 0.29$).Perception Dimensions: The low AI-usage group demonstrated a significantly lower global perception of AI assistance in mitigating anxiety compared to the high-usage group ($t(98) = -8.976$, $p < .001$, $d = -1.84$), and their perceived autonomy was also significantly lower ($t(98) = -2.975$, $p < .05$, $d = -0.57$). Conversely, the perceived competence of the high AI-usage group was significantly higher than that of the low-usage group ($t(98) = 3.396$, $p < .05$, $d = 0.65$).

3.3 Analysis of Semi-Structured Interview Results

To gain a deeper understanding of the factors underlying the quantitative data, thematic analysis was conducted on the interview transcripts of six participants with distinct AI-usage profiles (High-usage: P1, P2, P3, P4; Low-usage: P5, P6).

3.3.1 Etiologies of Anxiety Induced by AI-Assisted Learning

The preceding data analysis indicated that the high AI-usage group scored significantly higher in "test anxiety," "fear of negative evaluation," and "apprehension over personal capability." Participant P2 (High AI-usage) remarked: "After using AI, I actually felt I had more problems because its standards

are so ‘perfect’ and ‘objective’.” P3 (High AI-usage) emphasized comparison-induced anxiety: “I know AI is a machine, but I unconsciously treat its ‘perfect answers’ as a competitor, constantly thinking I must infinitely approach that standard. This actually makes me afraid to try easily; the pressure is immense.” P6 (Low AI-usage) indirectly corroborated this by explaining the reason for their avoidance behavior: “I tried it a few times, but the AI always calmly pointed out all my issues, leaving my knowledge gaps completely exposed. This frustration made me feel quite embarrassed, so I stopped using it much.”

The experiences of these three participants suggest that the instantaneous and objective feedback of AI invisibly elevates evaluative standards. Learners internalize these external high standards into harsh self-requirements, thereby exacerbating their apprehension over personal capability and fear of poor performance. This finding further substantiates why the high AI group scored higher across multiple anxiety dimensions.

3.3.2 The Paradox of Perceived Control

Quantitative results showed that the high AI-usage group had significantly higher “perceived autonomy” but significantly lower “perceived competence,” with these two factors showing opposing correlations with the perception of AI efficacy.

Regarding the enhancement of autonomy, the high AI-usage group felt a strong impact. P1 stated: “The greatest benefit is that the sovereignty over practice belongs to me; I can practice at any time, choose topics I’m interested in, and even repeat weak points. This targeted help and sense of self-control are things the classroom cannot provide.” P4 added: “AI gives me a sense of security; making mistakes here is private. I can go entirely at my own pace without enduring the evaluative gaze of teachers or peers.”

Regarding the erosion of perceived competence, both groups showed effects but employed different strategies: P3 (High AI-usage) reflected a decline in competence: “AI made me see the gap between myself and a high level; this chasm is deeper than I imagined, which can be discouraging at times.” For P6 (Low AI-usage), avoidance behavior stemmed directly from low competence: “Its feedback is too detailed and demoralizing; I felt like I was full of problems and became even more afraid to speak. I’d rather practice with classmates of a similar level—though we’re both ‘weak,’ there isn’t as much pressure.”

Perceptions of AI’s role in mitigating anxiety were polarized. P2 (High AI-usage, low competence) illustrated the negative correlation: “Precisely because I know my level is insufficient, I need its help even more. When I make mistakes, it never mocks me; it only objectively tells me where to improve. So, I give it a high rating.” Conversely, P5 (Low AI-usage, high competence) held a different view: “For speaking, I prefer interacting with real people; AI cannot provide that instant, emotional interaction. To me, AI is just a tool. It is useful, but not indispensable.”

Qualitative analysis indicates that AI empowers learners by providing infinite accessibility and a non-judgmental environment, significantly bolstering perceived autonomy. However, its objective and

precise feedback inevitably challenges and often dismantles the learner's perceived competence. A learner's global evaluation of AI assistance depends on which pole they prioritize: those valuing autonomy and supportive feedback (especially those with low competence) offer positive evaluations, while those prioritizing traditional interpersonal interaction or those sensitive to their own perceived abilities offer lower ratings. This elucidates the psychological roots of the "double-edged sword" effect in AI-assisted learning.

4. Discussion

4.1 Etiologies of Learning Anxiety in Multimodal Pedagogical Environments

The findings of this study demonstrate that within contemporary multimodal instructional settings, the genesis of learning anxiety has shifted from traditional "competence deficits" toward a more intricate "Performance-Pressure Paradox" and "Modality Fit Challenge."

First, independent samples t-tests revealed that the high AI-usage group scored significantly higher in test anxiety, fear of negative evaluation, and apprehension over personal capability than the low-usage group. This phenomenon uncovers the dualistic role of AI tools: while providing pedagogical support, they may concurrently and imperceptibly elevate learners' performance expectations. Qualitative analysis of the interviews suggests that the objectivity and rigorous standards of AI are internalized by learners as a continuous self-censorship mechanism, thereby generating novel performance pressures. Students may develop psychological anticipations that the utilization of AI tools should yield superior learning outcomes; this self-imposed pressure, catalyzed by technological engagement, becomes a nascent source of anxiety. This perspective aligns with the theory of "technology-enhanced anxiety" proposed by Chen and Han (2022), which posits that while technology enhances learning efficiency, it introduces new dimensions of social comparison and psychological strain.

Second, the correlation analysis indicated a significant positive relationship between communication apprehension and perceived competence, a finding that challenges the conventional wisdom that "higher competence equates to lower anxiety." Qualitative data reveal that students who perceive themselves as more competent are actually more inclined to proactively employ AI for high-difficulty, challenging exercises. Thus, this anxiety originates not from a lack of ability, but from the self-driven pursuit of excellence characteristic of high-ability individuals, as well as the sense of disparity experienced when comparing themselves to AI. In multimodal oral communication environments, highly competent students tend to engage in tasks with greater difficulty and exposure (e.g., interacting with AI or recording videos), thereby facing more frequent risks of failure and evaluation, which in turn induces higher state anxiety. This suggests that anxiety is not always a manifestation of inadequacy; it may also stem from the psychological burden associated with active participation and high levels of investment.

Furthermore, although technological adaptation and efficacy anxiety did not differ significantly between groups and showed no significant correlation with perceived competence, its presence

suggests that technology itself may constitute a modern etiology of anxiety, consistent with the findings of Dörnyei (2005). However, in the context of this study, students were more preoccupied with how to effectively leverage technology to achieve better academic performance rather than mere apprehension regarding the technology itself.

In summary, the primary triggers of learning anxiety in multimodal environments include the high standards set by AI tools, apprehension regarding negative evaluations from others (including AI), and a persistent sense of uncertainty regarding one's own capabilities during high-intensity learning processes.

4.2 The Dual Impact of AI-Assisted Learning

Regarding the efficacy of AI in mitigating learning anxiety, the results reveal a "double-edged sword" effect—it functions as both a potential inducer of anxiety and a powerful tool for its alleviation, with the ultimate outcome depending on the underlying psychological pathway.

On one hand, as previously noted, AI usage may exacerbate performance anxiety. On the other hand, qualitative data show that the high AI-usage group perceived a stronger global effect of AI in reducing anxiety and demonstrated significantly higher perceived autonomy. This suggests that students can rationally recognize the positive role of AI in providing psychological support. This support primarily derives from the sense of control and psychological safety facilitated by AI. By providing a low-risk, repeatable learning environment (e.g., practicing without the social pressure of human interaction), AI allows students to freely select the content, frequency, and method of practice. This enhancement of autonomy serves as a vital mechanism for anxiety mitigation (Ryan & Deci, 2020).

Crucially, the correlation analysis showed that the perception of AI efficacy is significantly negatively correlated with perceived competence. This finding offers a vital insight: students who perceive their linguistic abilities as insufficient are those who experience the greatest benefit and anxiety relief from AI. AI tools thus provide effective support for the very students who require it most, highlighting its immense potential for promoting educational equity and providing affective support, consistent with Fryer et al. (2020) regarding chatbots as supportive learning partners (Fryer & Nakao, 2020).

Therefore, the primary pathway through which AI-assisted learning alleviates anxiety lies in bolstering the learner's perceived autonomy and providing targeted, supportive feedback to those with lower perceived competence. However, this mitigation coexists with the performance pressure AI may induce, with the final effect determined by individual differences and specific usage contexts.

4.3 Underlying Mechanisms and Pedagogical Implications

The results of this study provide a significant reference for optimizing AI-assisted learning to improve the emotional experiences of learners within multimodal instruction. The core takeaway is that the focus of instructional design should shift from simple technological integration toward constructing an "empowering" rather than "pressurizing" learning ecosystem.

First, educators should acknowledge and proactively manage the performance pressure potentially introduced by AI tools. Teachers can design assessments that emphasize the learning process over

singular outcomes. For instance, incorporating the frequency and progress of AI-assisted exercises into the evaluation system rather than focusing solely on final performance, thereby reducing external evaluative pressure.

Second, educators should fully leverage AI's empowering mechanisms to systematically alleviate anxiety. Since perceived autonomy is a key factor in anxiety reduction, instructional design should emphasize choice, controllability, and personalization. For example, teachers could provide a diverse task library (e.g., dialogues of varying themes and difficulties) for autonomous selection, while allowing students to calibrate the granularity of AI feedback (e.g., correcting only critical errors versus providing comprehensive feedback) to enhance their sense of agency and efficacy. This represents an extension of Guo's (2013) MAP model—optimizing modal presentation based on affective attributes.

Finally, teachers should implement differentiated emotional support. Given that AI is most effective for students with low perceived competence, teachers can utilize AI's learning analytics to identify high-anxiety, low-competence groups. Proactively delivering foundational and encouraging multimodal resources (e.g., guided video demonstrations or slowed audio materials) can help these students break the "high anxiety-low performance" vicious cycle and enter a virtuous cycle of "AI support–confidence boost–anxiety relief–performance improvement."

5. Conclusion

This study investigated the primary factors triggering student learning anxiety in multimodal instruction and the role of AI-assisted learning in its mitigation. The results indicate that AI assistance in multimodal language learning can serve as both a source of pressure and a mechanism for stress reduction. Future pedagogical practices should guide students in the appropriate use of technology. Furthermore, teachers should utilize intentional instructional design to harness the power of AI, improving pedagogical efficiency and design while creating an inclusive, effective, and psychologically safe multimodal learning environment.

This study is not without limitations. Due to the gender imbalance typical of foreign language cohorts, the sample was not perfectly balanced, which may affect the generalizability of the results. Future research could broaden the sample scope to include more diverse student populations and utilize qualitative interviews to further explore the underlying motivations and psychological processes behind phenomena such as "high competence-high anxiety."

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