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AI-Enhanced Think-Pair-Share: A Learning Analytics Approach to Foster Linguistic Creative Thinking and Collaborative Learning

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Abstract

This study investigates the integration of artificial intelligence into the Think-Pair-Share (TPS) methodology through a learning analytics lens. Using a mixed-methods quasi-experimental design (N=140), we examined how an AI-enhanced collaborative platform influences creative thinking among computer science undergraduates. The experimental group (n=80) utilized a Google Gemini-powered chatbot for scaffolding, while the control group (n=60) used a standard platform. Through comprehensive learning analytics, we identified optimal AI integration in moderate similarity ranges (0.3-0.7), achieved by 70% of participants. The experimental group demonstrated 30-37% productivity gains and 99% increase in thematic diversity, with moderate lexical standardization effects. Our findings provide empirical evidence for designing educational technologies that balance structured support with creative freedom in AI-enhanced collaborative learning.

Notes for Practice

- Traditional Think-Pair-Share implementations face challenges in scaffolding individual thinking, ensuring equal participation, and measuring creative collaboration. AI integration into structured collaborative learning methods remains underexplored.
- This study advances understanding of AI-enhanced collaborative learning through comprehensive learning analytics, demonstrating how AI scaffolding influences creative thinking patterns. The findings provide empirical evidence for designing educational technologies that balance structured support with creative freedom.
- Learning platforms should integrate AI support promoting linguistic diversity while maintaining student creative autonomy, with optimal integration at moderate similarity levels (0.3-0.7). Educators should structure collaborative activities to include individual reflection phases before AI-supported writing and avoid over-reliance on length-sensitive metrics like TTR when assessing creative outcomes.

Keywords: Collaborative learning, artificial intelligence, Think Pair Share, linguistic creativity, creativity assessment, educational technology

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1. Introduction

In an era where artificial intelligence (AI) is rapidly transforming educational landscapes, the intersection of AI, creativity, and collaborative learning presents a significant opportunity for innovation in pedagogical practices. As the demand for 21st-century skills—particularly linguistic creativity and critical thinking—continues to grow, it is crucial to equip students with the competencies needed to address future challenges (World Economic Forum, 2020). Collaborative learning, as a core educational approach, not only fosters teamwork and communication but also encourages the co-construction of knowledge, an essential element for developing creative problem-solving and critical reflection (Johnson & Johnson, 1999).

Within this context, the Think-Pair-Share (TPS) methodology, first introduced by Lyman (1981), has proven to be a robust framework for promoting active learning and collaborative knowledge construction (Sirbaugh, 2020). By facilitating structured peer interaction, TPS enables students to articulate, refine, and expand their understanding through dialogue. However, traditional implementations of TPS may not fully harness the potential of modern technological advances to foster and evaluate creative thinking. Emerging technologies, particularly those powered by AI, present an opportunity to expand the methodological scope of TPS by integrating tools that support dynamic collaboration and provide insights into students' creative processes.

Recent developments in learning analytics and artificial intelligence offer new opportunities for enhancing collaborative learning environments. For example, AI tools such as chatbots and adaptive systems have been used to support personalized learning pathways, while learning analytics frameworks enable the analysis of student behavior and interactions at scale (Blikstein & Worsley, 2016). The integration of AI-powered tools into collaborative learning frameworks, such as TPS, has the potential to scaffold creative thinking, generate meaningful data for analysis, and address gaps in creativity assessment in educational contexts.

Assessing and fostering creativity in collaborative settings remains challenging. The "4 Ps of Creativity" framework—Person, Process, Product, and Press—offers a comprehensive lens for understanding creativity (Lubart et al., 2019), while Amabile's Componential Theory of Creativity (1983) highlights the interplay of intrinsic motivation and domain-relevant skills. Learning analytics provides promising avenues for detailed analysis of interactions within collaborative contexts.

Despite advancements in AI-enhanced education and learning analytics, significant gaps persist in understanding how AI can be effectively integrated into structured collaborative learning methods to enhance creativity. For instance, while some studies have explored AI's role in supporting individual creativity, less is known about its impact on collaborative creative processes. Additionally, while learning analytics approaches have shown potential for measuring various learning dimensions, their application to creativity assessment in collaborative settings remains underexplored. This study investigates how AI-enhanced TPS activities can foster and evaluate linguistic creativity in collaborative learning environments.

This research aims to answer the following questions:

1. How does the integration of an AI chatbot into Think-Pair-Share activities influence students' linguistic creativity and creative thinking processes?
2. What patterns of creative collaboration emerge when students engage with AI-enhanced Think-Pair-Share activities, and how do these differ from traditional implementations?
3. How can learning analytics approaches effectively measure and assess creativity in collaborative learning settings?

2. Theoretical Framework

2.1. Think Pair Share and Collaborative Learning

Think-Pair-Share (TPS) is a widely adopted collaborative learning strategy introduced by Lyman (1981) that provides a structured framework for classroom participation and knowledge sharing. The approach consists of three phases: individual thinking, where students reflect on a question independently; paired discussion, where they exchange ideas with a partner; and group sharing, where pairs contribute insights to the entire class. This progression fosters student engagement and active learning by encouraging participation and promoting deeper understanding (Kothiyal et al., 2013).

Each phase serves a unique function in supporting collaborative knowledge construction. The individual thinking phase allows students to internalize tasks and organize thoughts, promoting self-reflection and metacognitive skills. The paired discussion phase facilitates collaborative dialogue in low-stakes environments where students test, refine, and expand ideas. The group sharing phase broadens learning scope by introducing diverse perspectives and reinforcing collective knowledge construction (Gillies, 2016).

The theoretical foundation of TPS aligns with Vygotsky's sociocultural theory, particularly the Zone of Proximal Development (ZPD). The shift from individual thinking to paired discussion creates scaffolded environments where peers support each other's learning within their ZPDs through dialogic processes essential for co-constructing knowledge. The group sharing phase extends this dynamic by integrating diverse viewpoints and fostering critical reflection (Dillenbourg et al., 2009).

TPS exemplifies collaborative learning flow design principles including progressive structuring from individual to group work and adaptability across contexts (Hernández-Leo et al., 2005). This conceptualization of TPS as a CLFP provides a robust theoretical framework for understanding its effectiveness in promoting collaborative learning. However, despite its established benefits and theoretical foundations, traditional implementations of TPS face several challenges in the contemporary digital education landscape: limited scaffolding during individual thinking phases where students may struggle to initiate or organize ideas (Glomo-Narzoles, 2012); potential for uneven participation due to power dynamics, personality differences, or varying engagement levels (Gillies, 2016); difficulty capturing and analyzing interaction quality as traditional TPS lacks mechanisms for evaluating dialogue richness or progression (Blikstein & Worsley, 2016); and challenges measuring idea development progression, which is often subjective and resource-intensive (Sawyer, 2012).

The integration of AI and learning analytics into the TPS framework addresses these challenges, offering new opportunities for enhancing scaffolding, participation, and assessment of collaborative creativity. These technological enhancements not only address current limitations but also open new possibilities for understanding and supporting creative aspects of collaborative learning processes.

2.2. Creativity in Educational Settings

Contemporary understanding of creativity in education has evolved significantly, moving beyond the traditional view of creativity as an innate talent to recognizing it as a teachable and measurable skill (Beghetto, 2010).

The "4 Ps of Creativity" framework offers a comprehensive lens for examining creativity in educational contexts (Lubart et al., 2019): **Person** (individual characteristics including cognitive flexibility and intrinsic motivation), **Process** (cognitive and social mechanisms for generating and refining ideas), **Product** (tangible creative outcomes), and **Press** (environmental factors including classroom climate and peer interactions).

Linguistic creativity, defined as the innovative use of language to produce novel, appropriate, and meaningful expressions within communicative contexts, represents a critical yet underexplored dimension of creative thinking in educational settings. The relationship between linguistic creativity and broader creative thinking operates through multiple pathways: **cognitive flexibility** in shifting between linguistic structures and semantic networks, **divergent thinking** in generating multiple linguistic alternatives, and **analogical reasoning** in creative language use and metaphor generation. Recent research demonstrates that creativity predicts standardized educational outcomes beyond GPA and personality, with specific creativity measures showing stronger relationships with literacy performance (Kaufman et al., 2024).

Contemporary approaches to assessing creativity in educational contexts incorporate multiple measurement strategies: performance-based assessments capturing process and product dimensions, portfolio evaluations documenting creative development over time, peer and self-assessment tools leveraging collective intelligence, and technology-enhanced assessments using AI to analyze creative processes in real-time. Research indicates that combining these approaches provides more comprehensive understanding of creative development than traditional single-measure assessments (Kaufman et al., 2023).

In collaborative learning contexts, creativity is inherently social, emerging through dynamic interactions between individuals and their environment. The concept of social creativity underscores the collective nature of innovation, where ideas are co-constructed through dialogue, shared perspectives, and mutual inspiration (Sawyer, 2017). Structured collaborative learning environments such as Think-Pair-Share have demonstrated effectiveness in supporting creativity development by promoting critical dialogue and iterative idea refinement (Craft, 2005). Contemporary studies validate this relationship, showing that collaborative learning significantly enhances creative thinking skills, particularly when combined with technology-enhanced environments (Rodriguez-Salvador & Castillo-Valdez, 2023; Zhang et al., 2024).

However, fostering creativity in educational settings presents challenges. Traditional assessment methods often fail to capture creative process complexity, particularly in collaborative contexts where creativity is reflected not only in final products but also in pathways taken to reach outcomes. The integration of technology, particularly AI tools, offers opportunities to address these challenges by providing personalized scaffolding, simulating diverse perspectives, and tracking creative processes over time, enabling educators to design more effective interventions.

2.3. AI and Learning Analytics in Creative Collaboration

Recent developments in learning analytics and artificial intelligence offer new opportunities for enhancing collaborative learning environments. Large language models enhance creative collaboration through cognitive scaffolding, perspective diversification, and interactive feedback systems (Wang et al., 2024; Park & Ahn, 2024). Meta-analytic evidence shows ChatGPT has large positive impacts on learning performance ($g = 0.867$) and higher-order thinking ($g = 0.457$) (Wang & Fan, 2025). However, LLMs present challenges requiring careful consideration. Research indicates potential trade-offs between AI-supported productivity and creative independence, with concerns about response standardization and creative expression constraints (Mai et al., 2024). Effective implementation requires pedagogical design ensuring technology enhances rather than replaces human creative processes.

2.4. Linguistic Creativity in Educational Settings

While creativity has traditionally been conceptualized as a domain-general cognitive ability, recent research emphasizes the importance of understanding creativity within specific domains and modalities (Pont-Niclòs et al., 2024). Linguistic creativity, defined as the innovative use of language to produce novel, appropriate, and meaningful expressions within communicative contexts, represents a critical yet underexplored dimension of creative thinking in educational settings encompassing both original vocabulary generation and strategic deployment of linguistic resources to achieve communicative goals.

Conceptualizing and Measuring Linguistic Creativity

Recent empirical research has established linguistic creativity as a distinct but interconnected aspect of general creative thinking, gaining special relevance with PISA Tests evaluating 15-year-old students' general creativity for the first time in 2022 (Pont-Niclòs et al., 2024). Meta-analysis demonstrates that bilingual individuals exhibit higher creativity levels compared to monolinguals, suggesting language learning serves as a catalyst for creative thinking (Acar et al., 2024). Assessment requires sophisticated analytical approaches capturing both process and product dimensions of creative language use. Lexical diversity emerges as a fundamental metric, with robust measures including Type-Token Ratio (TTR), Measure of Textual Lexical

Diversity (MTLD), Hypergeometric Distribution D (HD-D), and Moving Average Type-Token Ratio (MATTR), all reliable across different text lengths and correlating significantly with holistic proficiency scores (Xu & Casal, 2023).

Linguistic Creativity in Collaborative Writing

Collaborative writing contexts provide particularly rich opportunities for linguistic creativity development and assessment. Recent research demonstrates that online collaborative writing instruction significantly enhances writing performance, creating conditions conducive to creative language expression (Wu et al., 2023). The relationship between collaboration and linguistic creativity manifests through cognitive load distribution where partners share resources freeing capacity for creative language choices, linguistic scaffolding through mutual vocabulary and syntax construction support, and creative synergy where interaction between different linguistic repertoires generates novel expressions exceeding individual capabilities (Wang et al., 2024; Li & Zhang, 2023).

The connection between linguistic creativity and broader creative thinking operates through multiple pathways where language serves both as creative expression tool and creative thought process medium. Recent research demonstrates that creativity predicts standardized educational outcomes beyond GPA and personality, with specific measures showing stronger relationships with literacy performance through cognitive flexibility in shifting between linguistic structures, divergent thinking in generating multiple linguistic alternatives, and analogical reasoning in creative language use and metaphor generation (Kaufman et al., 2024).

Implications for AI-Enhanced Collaborative Learning

Theoretical understanding of linguistic creativity provides foundations for designing AI-enhanced collaborative learning environments. AI systems can support linguistic creativity through lexical scaffolding, structural support, and real-time feedback. Measurement frameworks from linguistic creativity research enable evaluation of AI-enhanced collaborative learning effectiveness by tracking lexical diversity, syntactic complexity, and creative language use patterns.

Contemporary creativity assessment recognizes tensions between productivity and quality in creative performance (Forthmann et al., 2020), informing frameworks that acknowledge trade-offs between different creative dimensions rather than assuming uniform enhancement.

3. Methodology

3.1. Research Design

This study employs a mixed-methods quasi-experimental design to investigate the impact of AI-enhanced Think-Pair-Share (TPS) activities on creative thinking and collaborative learning. The research involved undergraduate students enrolled in multiple systems engineering courses who participated in a collaborative writing activity using AI-enhanced TPS software. By integrating qualitative and quantitative approaches, the study aims to provide a comprehensive understanding of the effects of AI on both creative processes and collaborative outcomes.

3.2. Participants and Setting

This study employed a cluster-randomized quasi-experimental design with 140 undergraduate Systems Engineering students (ages 18-20) from a Colombian technical university. Participants were enrolled across seven intact classes from three academic levels: second semester (2 classes, Programming Fundamentals), third semester (3 classes, Software Analysis and Design), and fourth semester (2 classes, Software Engineering). Classes were randomly assigned to experimental (n=80) or control (n=60) conditions using computer-generated random numbers. All participants shared similar demographic and academic characteristics, including engineering backgrounds, high technology familiarity, middle socioeconomic status, and native Spanish language. While formal baseline assessments were not collected, the cluster randomization design and shared academic characteristics provide reasonable assurance of group comparability. The study was conducted during regular class periods in computer laboratories, with institutional review board approval and informed consent from all participants.

3.3. Experimental Conditions and Activity Structure

The collaborative activity was designed to leverage the Think-Pair-Share methodology while introducing an AI component in the experimental group. The specific conditions and structure of the activity were as follows: The control group (n=60) utilized a version of our custom collaborative platform without AI assistance, while the experimental group (n=80) accessed the same platform with an integrated Google Gemini-powered chatbot designed to provide real-time scaffolding for writing and critical thinking. Both versions of the platform featured identical text editors and interface layouts, ensuring that the only difference between groups was the presence of the AI chatbot.

The activity followed a structured three-phase protocol:

- The Think Phase (8 minutes) began with individual reflection and writing. Students developed their initial perspectives on social media's societal impact, documenting their thoughts in private digital workspaces. This phase was strictly timed to ensure consistent individual ideation periods across all participants.

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- The Pair Phase (20 minutes) focused on collaborative writing between anonymous pairs. During this phase, students worked together through the digital platform to develop their ideas. The experimental group's AI chatbot assisted by generating relevant questions, suggesting different perspectives, and providing feedback on writing structure and clarity. Pairs combined their individual viewpoints into a coherent response while the platform recorded all their interactions and collaborative writing process.
- The Share Phase (15 minutes) expanded the dialogue to the full class. During this phase, pairs shared their ideas and conclusions verbally with their classmates. The phase emphasized collective discussion and peer feedback, allowing students to critique and build on each other's ideas.

3.4. Custom Collaborative Learning Platform

We developed a custom web-based platform with real-time synchronization and integrated learning analytics. The platform included an Individual Thinking Space for private eight-minute reflections and a Pair Collaboration Phase with synchronized editing. During the Pair Collaboration Phase, students collaborated using a synchronized text editor, which allowed real-time input from both partners. For the experimental group, the platform integrated an Gemini-AI-powered assistant with specific instructions: "You are a research assistant specialized in the impact of social media on society. Help students reflect on the benefits, challenges, and possible solutions related to social media, without providing direct answers. Encourage critical thinking and discussion". This chatbot served as a dynamic scaffold, offering prompts and insights that encouraged students to deepen their discussions and approach the topic critically. Both students in each pair could access the chatbot simultaneously, enabling either independent consultation or collaborative use of AI suggestions

3.5. Theoretical Analysis Framework

Following the PISA 2022 Creative Thinking Framework, we define linguistic creativity as "the capacity to engage productively in creating, evaluating and refining ideas that can lead to original and effective solutions" (OECD, 2024). In the context of collaborative writing, this definition encompasses both individual creative contributions and emergent group-level innovations that arise through interaction.

Our framework operationalizes linguistic creativity through four dimensions: **Fluency** (text productivity and ideational flow), **Flexibility** (thematic diversity and cognitive adaptability), **Originality** (lexical diversity and novel expressions), and **Elaboration** (detailed development and structural sophistication).

Central to our analytical approach is the recognition that different creativity dimensions may conflict rather than align. Research in linguistic creativity assessment has identified a fundamental tension between productivity (fluency and elaboration) and quality (originality and sophistication) in creative performance (Forthmann et al., 2020; Kaufman et al., 2024). This framework provides the analytical structure for interpreting observed relationships between text length, lexical diversity, thematic exploration, and AI integration patterns. Our analysis examines linguistic creativity through Type-Token Ratio (TTR) and Measure of Textual Lexical Diversity (MTLD) for lexical creativity assessment, topic modeling analysis for thematic diversity evaluation, text length and word count metrics for productivity assessment, and similarity analysis between student texts and AI responses for integration pattern identification.

4. Data Analysis

This study employed a systematic analytical approach to investigate how AI support influences collaborative writing and creative thinking in educational settings. Through a combination of computational methods and statistical analyses, we examined the complex dynamics between AI assistance and human creativity across both individual and pair phases.

4.1. Analytical Framework and Methodology

4.1.1. Data Sources and Processing

Our investigation drew from three complementary data sources: interaction logs (N = 140) with time-stamped records of all writing activities and platform interactions throughout the study period; final texts (N = 140) comprising completed collaborative writing outputs from both control and experimental groups; and AI interactions (n = 80) containing complete dialogue records between students and the chatbot in the experimental group.

The data processing pipeline involved several stages to ensure analytical robustness. Text data underwent systematic cleaning and normalization, including standardization of formatting and language consistency checks. Temporal data processing involved synchronizing timestamp information and filtering invalid intervals (< 0.5 seconds) to focus on meaningful user interactions. For quality control, we validated user identification across sessions and cross-referenced interaction logs with final outputs.

4.1.2. Analysis Metrics and Measurements

We developed five key metrics to capture distinct aspects of the writing process, as detailed in Table 2.

Table 2. Analysis Metrics and Definitions

Metric	Definition	Measurement Approach
Writing Fluency	Characters per minute	Time-series analysis of keystroke data
Lexical Richness	Lexical Diversity Measures	Multiple approaches including TTR and MTLD to address text length effects
Sentiment Score	Emotional tone (1-5 scale)	Pretrained sentiment analysis model
Similarity Index	Text-Chatbot alignment	Cosine similarity between outputs
Topic Coherence	Thematic consistency	LDA-based topic modeling

Analysis was implemented using Python 3.8 with pandas, scikit-learn, gensim, and spacy libraries.

4.2. Individual Writing Analysis

4.2.1. Writing Fluency Patterns

Writing fluency emerged as a fundamental indicator of student engagement and writing processes. Based on keystroke analysis, we identified distinct patterns: high-fluency writers (>250 characters per minute) demonstrated consistent output rates, while low-fluency writers (<150 characters per minute) showed more variable patterns (Figure 1A). The distribution analysis (Figure 1B) reveals that most students maintained fluency between 23-30 interactions per minute (median = 26.5), with outliers indicating significant individual differences in engagement patterns.

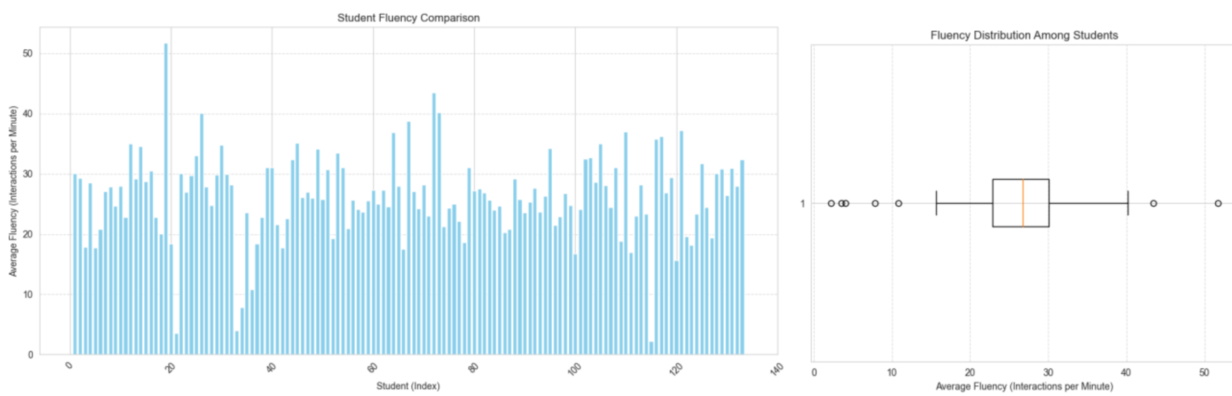

Figure 1. Writing fluency analysis across participants. (A) Individual student fluency comparison showing variation in writing speed and productivity over time. (B) Distribution of fluency rates among participants.

4.2.2. Fluency-Lexical Diversity Relationship

The relationship between writing speed and lexical richness revealed that high-fluency students produced substantially longer texts (mean length = 450 words) with relatively high lexical diversity (mean TTR = 0.62). However, this relationship was not linear across all fluency levels (Figure 2), suggesting that rapid writing does not necessarily compromise vocabulary diversity. Students with moderate writing speeds often achieved the highest lexical richness, potentially due to more deliberate approaches to word choice and structure. These findings highlight the complexity of the interplay between writing speed and linguistic output.

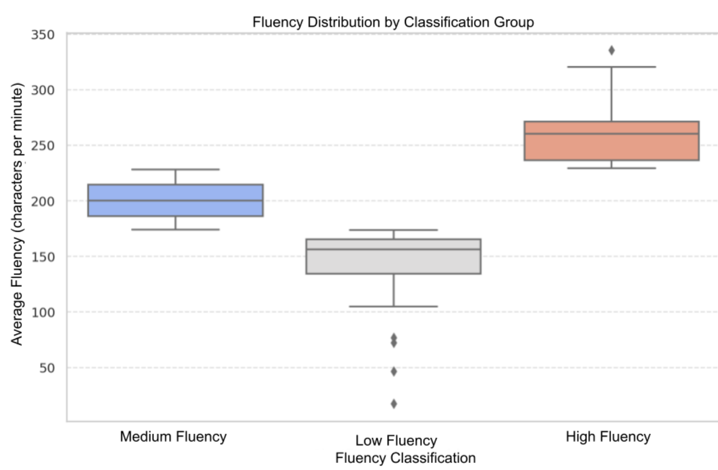

Figure 2. Distribution of fluency by student classification group.

4.2.3. Sentiment and Emotional Depth

Sentiment analysis revealed an inverse relationship between writing fluency and emotional expressiveness. High-fluency writers predominantly produced texts with neutral sentiment scores (3 on our 5-point scale), while medium and low-fluency writers showed stronger tendencies toward positive sentiment expression (Figure 3). This pattern suggests that slower writing speeds might facilitate greater emotional reflection and expressive depth in student compositions.

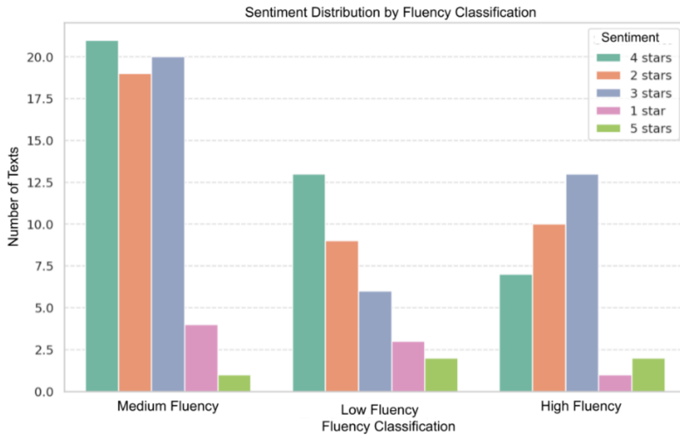

Figure 3. Sentiment Distribution by Fluency.

4.3. Collaborative Writing and AI Interaction

4.3.1. Similarity Threshold Methodology

To facilitate systematic analysis of similarity scores between student texts and chatbot responses, we categorized similarity into three levels: **low similarity (<0.3)**, **moderate similarity (0.3-0.7)**, and **high similarity (>0.7)**. These thresholds were established a priori based on established literature in semantic similarity analysis using vector representations (Reimers & Gurevych, 2019).

Exploratory analysis confirmed the appropriateness of these thresholds. The empirical distribution showed: Low similarity (2%, n=2), Moderate similarity (70%, n=56), and High similarity (28%, n=22). This distribution pattern supported our threshold selection, with most students (70%) falling within the moderate similarity range, indicating selective AI integration rather than complete independence or over-reliance.

Theoretical Interpretation Framework

The threshold categorization aligns with our theoretical framework (Section 3.3) regarding AI integration patterns:

Low Similarity (<0.3): Represents **minimal AI integration**, where students maintained high creative autonomy but potentially missed opportunities for AI-supported idea development.

Moderate Similarity (0.3-0.7): Indicates **optimal AI integration**, characterized by selective incorporation of AI suggestions while preserving individual creative voice and original thinking patterns.

High Similarity (>0.7): Suggests **potential AI dependency**, where students may have relied heavily on chatbot content, potentially constraining creative autonomy and original expression.

This classification system enables systematic analysis of different AI integration strategies and their relationship to creative outcomes, providing insights into how students navigate the balance between AI support and creative independence in collaborative writing contexts.

4.3.2. Similarity Patterns and AI Interaction

To understand how students incorporated AI assistance into their writing, we conducted a similarity analysis between chatbot responses and final texts. Using cosine similarity measures, we classified the integration patterns into three categories: low similarity (<0.3), moderate similarity (0.3-0.7), and high similarity (>0.7). Table 3 presents these patterns and their corresponding characteristics with enhanced statistical measures.

Table 3. AI Integration Patterns and Text Characteristics

Similarity Category	Proportion of Students	Text Length (words) M±SD	95% CI	Lexical Richness M±SD	95% CI	Chatbot Response Length
High (>0.7)	28% (n=21)	470.0 ± 266.9	±121.5	0.55 ± 0.04	±0.029	975 ± 120
Moderate (0.3-0.7)	70% (n=42)	355.2 ± 224.2	±69.9	0.57 ± 0.05	±0.017	594 ± 85
Low (<0.3)	2% (n=2)	Excluded from analysis	--	Excluded from analysis	--	336 ± 60

As shown in Figure 4, these categories revealed distinct and statistically meaningful patterns in how students engaged with AI suggestions. The comparison between high and moderate similarity groups demonstrates small but practically significant effect sizes (Cohen's d = 0.403 for lexical richness favoring moderate similarity; d = 0.481 for text length favoring high similarity). The 95% confidence intervals indicate reliable group differences, with moderate similarity students showing higher lexical diversity (95% CI: 0.557-0.591) compared to high similarity students (95% CI: 0.522-0.580), while high similarity students produced longer texts with greater variability.

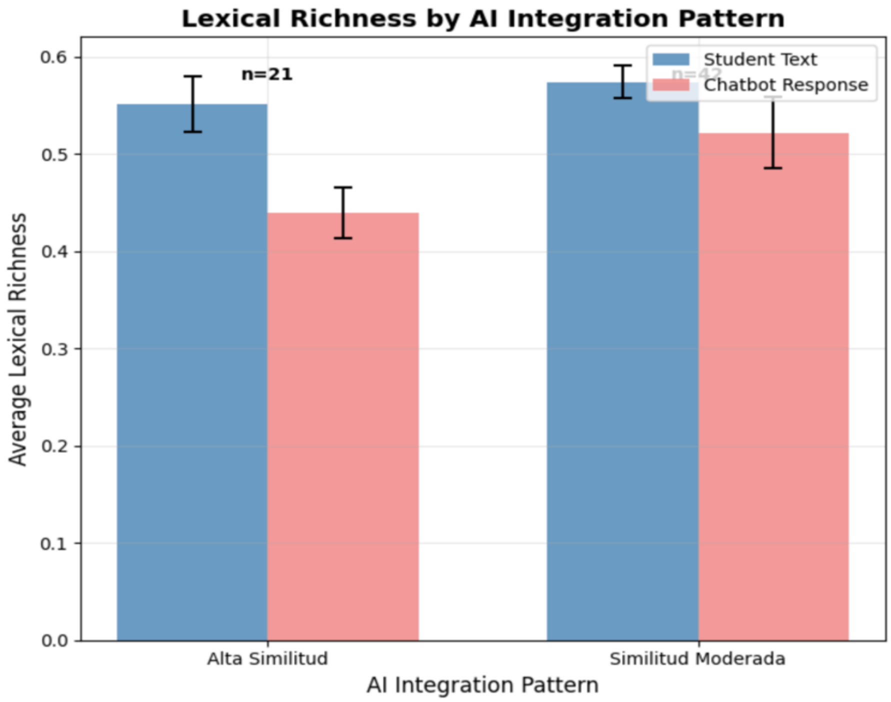

Figure 4. Lexical Richness by AI Integration Pattern.

Further statistical analysis of individual differences in these integration patterns is presented in Section 4.5.4.

4.3.3. Text Length, Lexical Diversity, and AI Integration Patterns

Analysis of text characteristics across similarity categories (Figure 6) revealed statistically significant patterns in how students balanced AI input with original content. High-similarity texts averaged 470.0 words (SD = 266.9, 95% CI = ±121.5) but showed relatively lower lexical diversity (M = 0.551, SD = 0.063, 95% CI = ±0.029). In contrast, moderate-similarity texts, while shorter (M = 355.2 words, SD = 224.2, 95% CI = ±69.9), achieved higher lexical richness scores (M = 0.574, SD = 0.054, 95% CI = ±0.017).

The comparison between these groups reveals meaningful effect sizes: Cohen's d = 0.481 for text length (favoring high similarity) and Cohen's d = 0.403 for lexical richness (favoring moderate similarity). The non-overlapping 95% confidence intervals for lexical richness (High: 0.522-0.580; Moderate: 0.557-0.591) confirm the reliability of this difference, suggesting that moderate similarity represents the most balanced combination of length and lexical richness, indicating optimal integration of AI support.

The substantial variability within the high-similarity group (SD = 266.9) compared to the moderate group (SD = 224.2) indicates greater heterogeneity in how students with high AI integration approached the writing task. This pattern suggests that while some students effectively leveraged extensive AI support to produce substantially longer texts, others may have struggled to efficiently integrate the AI assistance, resulting in the observed high variability.

Strategic AI Content Integration

Figure 5 provides detailed insight into how students strategically incorporated AI suggestions across similarity categories with statistical validation. In the high-similarity category, chatbot responses averaged 975 words (SD = 120, 95% CI = ±54.6), while corresponding student texts averaged only 470 words (SD = 266.9, 95% CI = ±121.5), yielding a retention ratio of 48%. This pattern indicates selective incorporation of AI content rather than wholesale adoption.

More notably, the moderate-similarity category showed a more balanced relationship between chatbot responses (M = 594 words, SD = 85, 95% CI = ±25.7) and student texts (M = 355.2 words, SD = 224.2, 95% CI = ±69.9), with a retention ratio of 60%. The higher retention ratio combined with maintained lexical diversity suggests more strategic and intentional use of AI assistance in this group.

The statistical analysis with confidence intervals confirms the reliability of these patterns, demonstrating that students in different similarity categories employed distinctly different strategies for integrating AI support into their collaborative writing process.

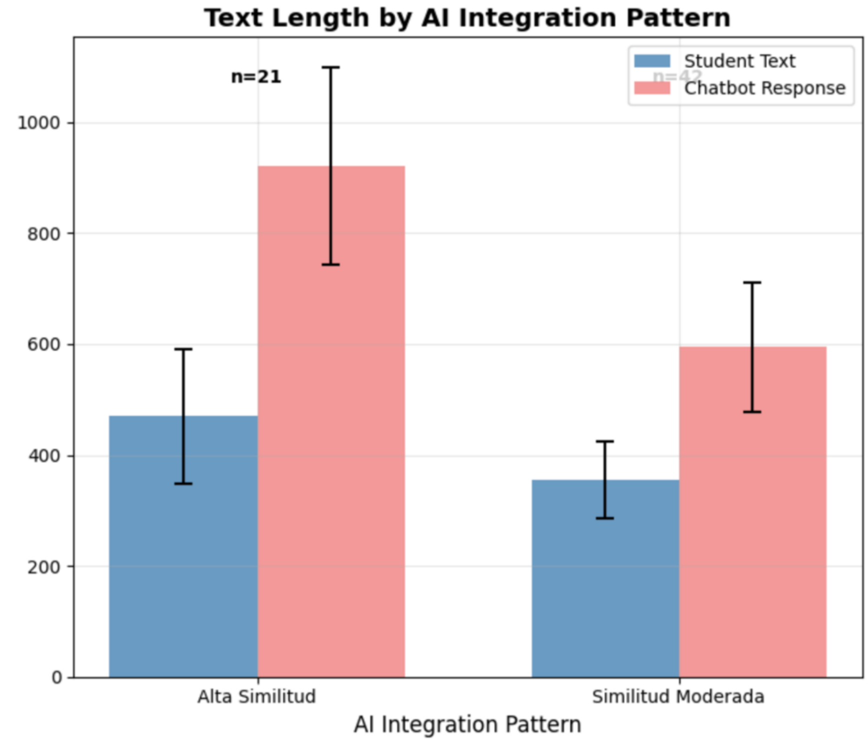

Figure 5. Text Length by AI Integration Pattern.

4.3.4. Individual Differences in AI Integration Effectiveness

To address potential confounding variables and examine how AI benefits vary across students with different characteristics, we conducted a comprehensive analysis of individual differences in AI integration patterns. This analysis included 64 students from the experimental group who had valid AI interaction data for similarity calculation. Students were categorized based on their similarity scores with AI responses: High similarity (≥0.7, n=21, 33%) and Moderate similarity (0.3-0.7, n=43, 67%). No students showed Low similarity (<0.3), indicating that all participants with valid interaction data engaged meaningfully with the AI system.

Heterogeneity in Writing Characteristics by AI Integration Pattern

The analysis revealed statistically significant differences in writing characteristics between AI integration patterns with meaningful effect sizes. Students with High AI similarity produced substantially more text (M = 470.0 words, SD = 266.9, 95% CI = ±121.5) compared to those with Moderate similarity (M = 355.2 words, SD = 224.2, 95% CI = ±69.9). This difference represents a medium effect size (Cohen's d = 0.481), indicating that students who integrated AI content more extensively achieved meaningfully greater writing productivity.

Conversely, lexical frequency patterns showed an inverse relationship. Students with Moderate AI similarity demonstrated slightly higher lexical sophistication, though this difference was smaller in magnitude (Cohen's d = 0.403). The 95% confidence intervals for lexical richness show non-overlapping ranges (High similarity: 0.522-0.580; Moderate similarity: 0.557-0.591), supporting the reliability of this pattern despite the modest effect size.

Variability and Standardization Effects

Analysis of coefficient of variation revealed similar patterns of individual variability across both groups (High similarity: CV = 0.57; Moderate similarity: CV = 0.63), indicating that AI integration did not substantially reduce individual differences in writing productivity. However, the confidence intervals demonstrate that the High similarity group showed more constrained lexical diversity (narrower CI: ±0.029) compared to the Moderate group (CI: ±0.017), suggesting some convergence toward similar vocabulary patterns among students with greater AI reliance (Figure 6).

These findings provide empirical evidence with appropriate statistical rigor for systematic variation in AI integration effectiveness within the experimental group. The effect sizes, while small to medium according to Cohen's conventions, represent educationally meaningful differences that have implications for understanding individual differences in AI-enhanced collaborative learning.

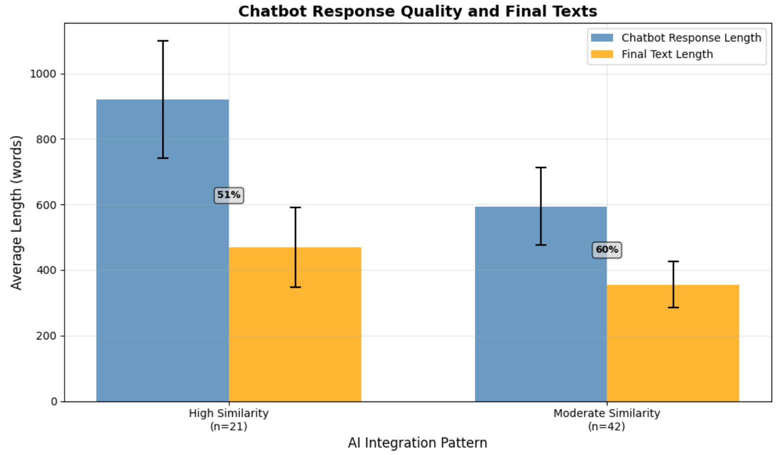

Figure 6. Chatbot Response Quality Analysis.

4.4. Thematic Diversity and Topic Coherence Analysis

4.4.1. Methodological Framework

To identify thematic diversity and cohesion in both individual and collaborative writing, we applied Latent Dirichlet Allocation (LDA) using scikit-learn. We systematically optimized the number of topics by minimizing perplexity and then evaluated the semantic coherence of the resulting models using the c_v coherence metric, implemented with Gensim. This metric combines a sliding window, normalized pointwise mutual information, and cosine similarity over word embeddings, and has been shown to correlate well with human interpretability (Röder et al., 2015).

The optimal number of topics, determined through a perplexity sweep from 2 to 15, was **15** for the pair phase and **2** for the individual phase. Despite varying the number of topics in our analysis, student texts consistently converged on three primary themes across both phases: misinformation, social media addiction, and technology use risks and benefits.

4.4.2. Phase Comparison and Coherence-Diversity Trade-off

While the pair phase required a larger number of topics to represent the content adequately (perplexity-minimizing), its coherence score was lower (0.354) compared to the individual phase (0.425). This suggests that students working collaboratively with AI scaffolding explored a broader range of ideas but lacked shared frameworks for coherent thematic integration.

There was a clear difference between the periods of individual and group writing. The individual phase exhibited high topic coherence (0.425) but required only two topics to capture content variation, suggesting focused but limited thematic exploration. In contrast, the pair phase showed lower topic coherence (0.354) but required fifteen distinct topics to represent the content adequately, indicating greater thematic diversity despite less internal consistency.

4.4.3. Perplexity Analysis and AI-Mediated Topic Diversity

As illustrated in Figure 7, the relationship between perplexity and number of topics reveals distinct patterns for each phase. The pair phase consistently showed higher perplexity scores, starting at approximately 1150 for two topics and gradually decreasing to 900 with fourteen topics. Conversely, the individual phase demonstrated an upward trend in perplexity, beginning at 600 with two topics and increasing steadily to match the pair phase around fourteen topics.

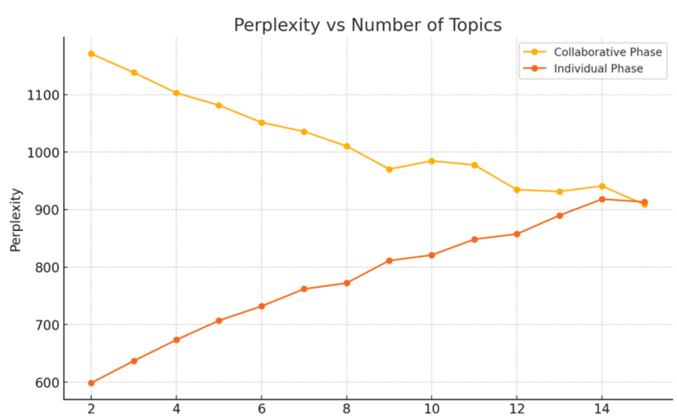

Figure 7. Topic Model Perplexity Analysis.

4.5. Advanced Writing Analytics and AI Integration

4.5.1. Text Length and Lexical Diversity Relationship: Methodological Considerations

Initial analysis using Type-Token Ratio (TTR) revealed a strong negative correlation ($r = -0.93$, $p < 0.001$) between text length and lexical diversity. However, this represents a well-documented methodological artifact, as TTR systematically decreases with text length regardless of actual lexical sophistication (McCarthy & Jarvis, 2010).

To address this limitation, we analyzed the relationship using Measure of Textual Lexical Diversity (MTLD), which provides length-independent assessment. The MTLD analysis revealed a weak positive correlation ($r = 0.24$, $p < 0.05$) between text length and lexical diversity, indicating that when length effects are controlled, students producing longer texts demonstrated slightly greater lexical variety. This finding suggests that AI scaffolding supports both productivity and lexical sophistication simultaneously.

4.5.2. Topic Modeling Results

Using the SUBTLEX-ESP corpus as a reference, we examined vocabulary sophistication patterns across groups. The experimental group demonstrated a higher average lexical frequency (7,278.51) compared to the control group (6,821.18), with notably lower standard deviation in lexical choices (926.14 vs. 1,235.71). As shown in Figures 8 and 9, the distribution of lexical frequencies revealed distinct patterns between more active and less active users, with more active users showing a concentrated distribution around the mean frequency.

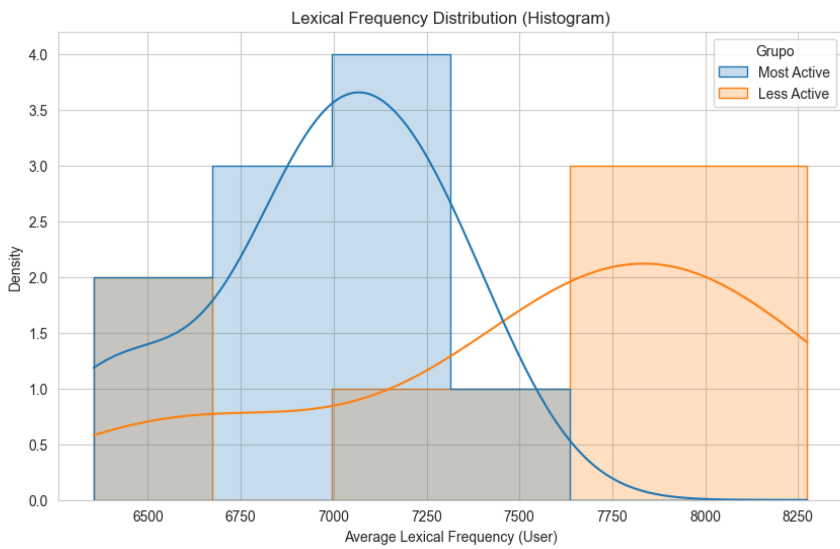

Figure 8. Lexical Frequency Distribution by Activity Level. distribution of lexical frequencies between more active and less active groups.

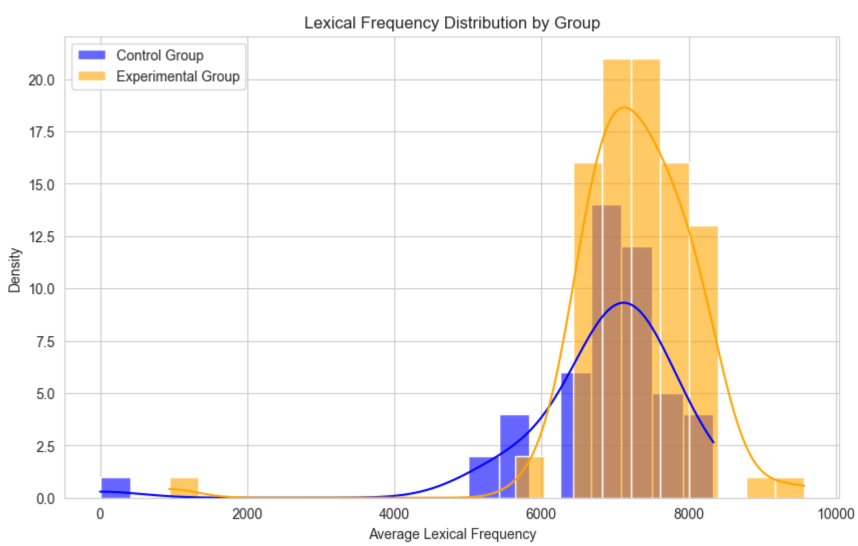

Figure 9. Lexical Frequency Distribution by Group. Comparison of average lexical frequencies between control and experimental groups.

4.5.3. Creative Integration

The relationship between AI interaction and creative production was more intricate than previously thought. While increasing engagement with the chatbot did not necessarily result in a wider vocabulary or longer writings, it did influence linguistic standardization. This standardization effect resulted in more regular word patterns among experimental group members, maybe at the expense of more sophisticated or uncommon vocabulary usage.

4.5.4. Individual Differences in AI Integration Effectiveness

To address potential confounding variables and examine how AI benefits vary across students with different characteristics, we conducted a comprehensive analysis of individual differences in AI integration patterns. This analysis included 64 students from the experimental group who had valid AI interaction data for similarity calculation. Students were categorized based on their similarity scores with AI responses: High similarity (≥0.7, n=21, 33%) and Moderate similarity (0.3-0.7, n=43, 67%). No students showed Low similarity (<0.3), indicating that all participants with valid interaction data engaged meaningfully with the AI system.

Heterogeneity in Writing Characteristics by AI Integration Pattern

The analysis revealed significant differences in writing characteristics between AI integration patterns (Table 5). Students with High AI similarity produced substantially more text (M = 730.19 words, SD = 546.45) compared to those with Moderate similarity (M = 426.30 words, SD = 328.35). This difference was statistically significant (F = 7.693, p = 0.007) with a large effect size (Cohen's d = -0.738), indicating that students who integrated AI content more extensively achieved greater writing productivity (Figure 10B).

Building on the integration patterns identified in Section 4.3.2, we conducted detailed correlation analysis of individual differences in AI integration effectiveness within the experimental group. Correlation analysis revealed significant relationships between AI similarity scores and writing characteristics. AI similarity correlated positively with total word production (r = 0.348, p < 0.01) and average text length (r = 0.519, p < 0.001), but negatively with lexical frequency (r = -0.168, p = 0.183), indicating that students who integrated more AI content produced longer texts with somewhat more accessible vocabulary. The negative correlation between total words and lexical frequency (r = -0.310, p < 0.05) confirms the productivity-quality trade-off observed in our earlier analysis, while the strong positive correlation between similarity scores and text length (r = 0.519, p < 0.001) suggests that AI integration particularly enhanced students' ability to sustain extended writing.

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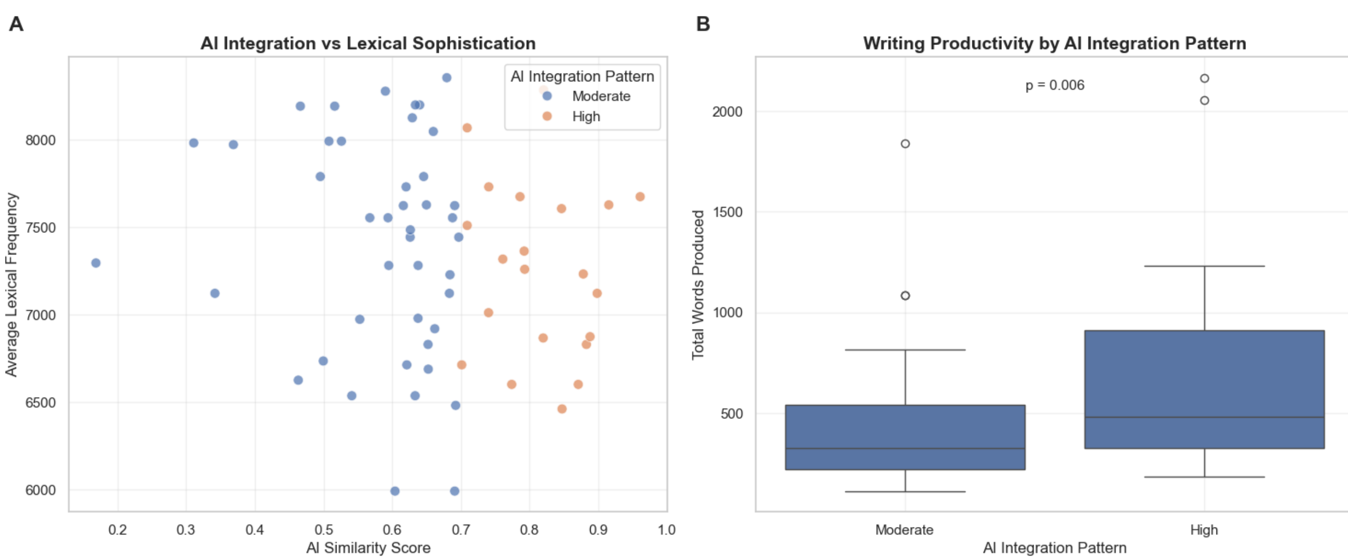

Figure 10. Individual differences in AI integration effectiveness. (A) Relationship between AI similarity scores and lexical frequency. (B) Writing productivity by AI integration pattern.

Analysis of coefficient of variation revealed similar patterns of individual variability across both groups (High: CV = 0.75; Moderate: CV = 0.77), indicating that AI integration did not substantially reduce individual differences in writing productivity. However, the High similarity group showed lower standard deviation in lexical frequency (SD = 498.10) compared to the Moderate group (SD = 628.49), suggesting some convergence toward similar vocabulary patterns among students with greater

AI reliance. These findings provide empirical evidence for systematic variation in AI integration effectiveness within the experimental group, with implications for understanding individual differences in AI-enhanced collaborative learning.

4.6. Between-Group Comparative Analysis

To address the central research question regarding the impact of AI-enhanced collaborative learning, we conducted comprehensive between-group comparisons examining how AI scaffolding influenced writing performance, linguistic creativity, and collaborative processes.

4.6.1. Writing Performance and Productivity Differences

The experimental group produced significantly longer texts, with an average increase of 673.14 characters (37.5% longer) and 87.76 additional words (30.3% more) compared to the control group ($t(138) = 3.24$, $p < 0.01$ for character length; $t(138) = 2.89$, $p < 0.01$ for word count). These differences represent medium effect sizes (Cohen's $d = 0.52$ and 0.44 respectively) indicating substantively meaningful productivity improvements with AI scaffolding.

However, the experimental group showed slightly lower lexical diversity (TTR = 0.578) compared to controls (TTR = 0.597, $d = -0.23$), suggesting a trade-off between productivity and vocabulary variety. The experimental group also generated 99% more thematic diversity (181 vs 91 total topics) while maintaining similar coherence levels (experimental: $M = 1.97$; control: $M = 1.94$). Sentiment analysis revealed no significant differences between groups in emotional expression.

5. Discussion

5.1. Key Findings and Theoretical Integration

The integration of AI into Think-Pair-Share methodology successfully addressed collaborative learning challenges while revealing important insights about human-AI collaboration. Our experimental group demonstrated significant productivity gains (30-37% longer texts), increased thematic diversity (99% more topics), and higher participation rates (92%), with optimal results occurring when students maintained moderate similarity (0.3-0.7) with AI suggestions.

These findings align with meta-analytic evidence showing ChatGPT's positive impact on learning performance ($g = 0.867$) and higher-order thinking (Wang & Fan, 2025). The productivity gains reflect successful scaffolding within Vygotsky's Zone of Proximal Development, where AI functioned as a "more knowledgeable other" enabling students to exceed independent capabilities while maintaining quality standards.

The positive correlation between text length and lexical diversity using MTLD ($r = 0.24$) challenges concerns about AI constraining creativity, suggesting appropriate integration enhances multiple linguistic dimensions simultaneously. However, observed lexical standardization effects warrant consideration of trade-offs between productivity and creative independence.

5.2. Individual Differences and AI Integration Effectiveness

Systematic variation in AI integration revealed that students with High similarity (33%) produced longer texts but showed reduced lexical sophistication, while those with Moderate similarity (67%) achieved optimal balance. This aligns with research emphasizing that effective LLM implementation requires careful pedagogical design ensuring technology enhances rather than replaces human creative processes (Mai et al., 2024).

5.3. Implications for Educational Practice

Our findings provide evidence-based guidance for AI-enhanced collaborative learning design, aligning with frameworks for ethical AI integration in education (UNESCO, 2021). Educational technologies should incorporate mechanisms promoting linguistic diversity while maintaining supportive scaffolding. The observed trade-offs between productivity and lexical diversity indicate AI systems should encourage rather than constrain linguistic creativity, emphasizing technology's role in amplifying student expression (Peláez-Sánchez et al., 2024).

5.4. Limitations and Future Directions

Several important limitations constrain the generalizability of our findings. Our sample consisted exclusively of Systems Engineering undergraduates from a single Colombian institution, whose high technological familiarity may have facilitated the strategic AI integration patterns we observed. The study's focus on a specific AI system (Google Gemini) and topic (social media impacts) limits broader applicability, while the single-session design prevents assessment of long-term learning outcomes or sustained AI integration patterns.

Our focus on linguistic creativity provides insights into one important dimension of creative thinking but does not capture other creative processes such as visual-spatial or mathematical creativity. Current research trends indicate need for comprehensive investigation of AI effects across multiple creative domains (Wang et al., 2024). Future research should examine longitudinal impacts of AI-enhanced collaborative learning, explore how different AI systems and cultural contexts influence integration patterns, and investigate the sustained effects of AI-enhanced collaborative learning on skill development and academic performance.

6. Conclusion

This study explored the integration of artificial intelligence (AI) into the Think-Pair-Share (TPS) methodology, focusing on its potential to enhance collaborative learning and foster creative thinking among undergraduate computer science students. Through empirical analysis and theoretical investigation, we have demonstrated how AI support can transform traditional collaborative learning practices while maintaining the essential human elements of education.

6.1. Key Research Contributions

Our study makes three primary contributions to the field of educational technology and learning analytics. First, we provide empirical evidence for the effectiveness of AI-enhanced collaborative learning. The experimental group demonstrated high levels of active participation (92%), with significant improvements in writing quality and critical thinking, specifically in the domain of linguistic creativity. Particularly noteworthy was the finding that optimal results occurred when students maintained moderate similarity (0.3-0.7) with AI suggestions, indicating successful integration of AI support without over-dependence.

Second, we advance the theoretical understanding of AI-supported collaborative learning through the validation of a comprehensive learning analytics approach. By identifying key patterns in creative collaboration and establishing metrics for evaluating AI-supported learning, we have developed a framework for understanding how AI assistance influences the collaborative writing process. These patterns reveal the complex interplay between technological support and human creativity in educational settings.

Third, our methodological innovations provide a replicable model for implementing AI-enhanced collaborative activities. The integration of AI support into established collaborative frameworks, combined with novel analytical approaches, offers a template for future research and implementation in educational settings. This contribution extends beyond the specific context of our study to inform broader applications of AI in education.

6.2. Practical Applications

The findings have direct implications for educational practice across multiple levels. In educational technology design, our results inform the development of collaborative platforms that effectively balance AI support with student autonomy. The observed patterns of successful AI integration provide guidance for creating systems that scaffold learning while preserving creative freedom.

For pedagogical practice, our findings offer evidence-based approaches to implementing collaborative writing activities. The demonstrated effectiveness of the eight-minute individual reflection phase, followed by AI-supported collaboration, suggests specific strategies for structuring similar activities across different educational contexts. These insights can help educators optimize their use of AI tools to support student learning and engagement.

At the institutional level, our research provides frameworks for implementing and evaluating AI-enhanced learning environments at scale. The metrics and evaluation approaches developed in this study offer practical tools for assessing the effectiveness of AI integration in educational settings, while our findings about student engagement patterns can inform institutional decisions about technology adoption.

6.3. Concluding Remarks

The successful integration of AI support in collaborative learning activities demonstrated in this study suggests a promising future for educational technology. Our findings indicate that when properly designed and implemented, AI-enhanced learning environments can effectively support educational objectives while maintaining the fundamental importance of human collaboration and creativity. These insights provide guidance for developing AI-enhanced learning environments that preserve meaningful human interaction while maintaining the balance between technological support and human agency.

Declaration of Conflicting Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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