

Artificial intelligence and English learner remotivation: A quasi-experimental study of student perceptions

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Abstract. This quasi-experimental study investigated the primary factors contributing to English-language demotivation among first-year Saudi undergraduates. It evaluated the longitudinal impact of a structured Gemini intervention on student perceptions of remotivation. Baseline metrics identified perceived instructional distance and evaluation-related classroom anxieties, specifically fear of negative peer judgment, as the most severe demotivators. Following a 12-week intervention, a parametric Two-Way Mixed ANOVA revealed a monumental, highly significant longitudinal interaction effect in motivational recovery, with an independent Exploratory Factor analysis confirming excellent psychometric construct validity for the AI remotivation subscale. Qualitative interviews triangulated these findings, demonstrating that participants perceived Gemini's intervention as a primary restorative catalyst for functional, individualistic remotivation. It established a private, zero-anxiety digital sandbox that unblocked finite cognitive processing resources and elevated perceived autonomy and competence. However, the results revealed a critical "efficiency-relatedness paradox": the automated intervention strained perceptions of social relatedness and instructional delivery. The study concludes that for generative AI to serve as a sustainable motivational driver, institutions should move beyond technological substitution models in favor of a blended, human-in-the-loop framework in which instructors leverage automated interfaces for technical feedback while intentionally repurposing saved classroom hours to deepen human mentorship, socio-affective rapport, and empathetic interpersonal validation.

Keywords: *artificial intelligence, affective filter, demotivation, Gemini, remotivation, self-determination theory.*

Аль-Софі Бакр Баґаш Мансур Ахмед. Штучний інтелект та відновлення мотивації у тих, хто вивчає англійську мову: квазіекспериментальне дослідження сприйняття студентів.

Анотація. У цьому квазіекспериментальному дослідженні вивчалися основні чинники, що сприяють втраті мотивації до вивчення англійської мови серед саудівських студентів першого курсу. У ньому оцінювався довгостроковий вплив структурованої інтервенції інструментом III Gemini на сприйняття студентами відновлення мотивації.

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Базові показники визначили сприйняту дистанційність навчання та пов'язані з оцінюванням тривоги в аудиторії, зокрема страх перед негативним судженням однокурсників, як найсерйозніші демотиватори. Після 12-тижневої інтервенції параметричний дворакторний змішаний ANOVA виявив значний, високозначущий довготривалий ефект взаємодії у відновленні мотивації, а незалежний експлораторний факторний аналіз підтвердив відмінну психометричну валідність конструкту для субшкали «Ремотивація за допомогою ІІІ». Якісні інтерв'ю підтвердили ці висновки, продемонструвавши, що учасники сприймали втручання Gemini як основний відновлювальний каталізатор функціональної, індивідуалістичної ремотивації. Воно створило приватну цифрову «пісочницю» без тривоги, яка розблокувала обмежені когнітивні ресурси обробки інформації та підвищила відчуття автономії та компетентності. Однак результати виявили критичний «парадокс ефективності та соціальної пов'язаності»: автоматизоване втручання негативно вплинуло на сприйняття соціальної пов'язаності та способу подання навчального матеріалу. У дослідженні зроблено висновок, що для того, щоб генеративний ІІІ слугував стійким мотиваційним чинником, навчальні заклади повинні відійти від моделей технологічної заміни на користь змішаної моделі з участю людини, в якій викладачі використовують автоматизовані інтерфейси для надання технічного зворотного зв'язку, водночас цілеспрямовано перерозподіляючи заощаджені години аудиторних занять на поглиблення людського наставництва, соціально-афективного взаєморозуміння та емпатичного міжособистісного визнання.

Ключові слова: штучний інтелект, афективний фільтр, демотивація, Gemini, ремотивація, теорія самовизначення.

Introduction

Psycholinguistics recognizes motivation as a fundamental mechanism driving language acquisition, functioning as a critical affective filter and a prerequisite for language learning across multiple theoretical frameworks (Dörnyei, 2005, 2009; Gardner, 1985; Krashen, 1985; Ryan & Deci, 2020). The intersection of psychology and language learning, broadly conceptualized as psycholinguistics, explores how learners' internal mental states, cognitive processes, and affective frameworks shape the efficiency and pace of second language acquisition (SLA) (Dörnyei, 2005).

Motivation is the process that initiates and directs behavior toward achieving learning goals and sustains effort over time (Dörnyei, 2005). To clarify the distinction among the three psychological constructs of motivation, demotivation, and remotivation, the latter is the process through which students regain motivation after experiencing demotivation. These constructs refer to internal mental processes, attitudes, and states that influence learners' behavior, engagement, and achievement. Motivation drives and sustains the long journey of language learning (Bessa et al., 2024; Dörnyei, 2005). For English as a Foreign Language (EFL) students, mastering English is a transformative asset that enables global research, academic excellence, and competitiveness in a multilingual job market. Despite these advantages, many students enter

university lacking motivation and engagement (Albalawi & Al-Hoorie, 2021; Alharbi & Saaty, 2022). This demotivation hinders students from attaining the specialized proficiency required in their disciplines, often leading to poor academic performance and higher dropout rates (Fang, 2025; Ma, Y., 2025).

To address this, Albalawi and Al-Hoorie (2021) argued that research on remotivation must identify the specific catalysts of motivational decline and evaluate the efficacy of intervention. Research attributes this decline to the perceived complexity of the curriculum, the strain of learner-centered instruction, language anxiety, and a disconnect between classroom tasks and real-world application (Dörnyei & Ushioda, 2011; Falout, 2012).

The present study views motivation as a dynamic psychological process subject to both negative shifts (demotivation) and positive reconstruction (remotivation) (Kikuchi, 2017; Ma, Y., 2025). At the University of Bisha, the first year is a critical window for intervention. During this period, students complete an intensive curriculum of three 8-credit-hour courses: General English 1, General English 2, and English for Specific Purposes.

Scholars highlighted the importance of employing effective strategies to enhance learners' motivation in foreign language learning while simultaneously preventing demotivation (Dmitrenko et al., 2021; Dörnyei, 2005). Recently, one of the most influential developments has been the integration of generative AI, which is increasingly reshaping higher education and transitioning from a supplementary technology to an essential academic resource (Abdelaal & Al Sawy, 2024; Khalaf et al., 2025). AI counters traditional demotivation by offering personalized learning, instantaneous feedback, and immersive interactivity. This study explores potential demotivators and students' perceptions of Google Gemini's efficacy as a catalyst for remotivation. Google Gemini was selected because of Google's initiative providing Saudi students with a free year of Gemini Advanced. This premium access provides a robust suite of features, including the Gemini 1.5 Pro model and Deep Research capabilities, that foster an interactive environment through continuous feedback, personalized quizzes, and multimodal analysis.

Although remotivation is underexplored (Albalawi & Al-Hoorie, 2021), this study presents a novel, action-oriented model grounded in the premise that remotivation is most effective when addressing the root psychological causes of demotivation. Furthermore, it examines whether remotivation levels differ significantly between students integrating Gemini and those in traditional learning environments. This study aligns with Kim and Kim's (2017) conceptual link between demotivation and remotivation, addresses Dörnyei's (2005) call for solution-oriented research, and centers on student perceptions to understand AI's potential as a primary motivational catalyst. Consequently, the following questions guide this study:

RQ1. What are the primary factors contributing to first-year Saudi undergraduate students' demotivation in English learning?

RQ2. How do students perceive using Gemini for English learning?

RQ3. Is there a statistically significant difference in motivation levels between students who use AI-powered tools and those following a traditional learning path?

Literature Review

Motivation, Demotivation, and Remotivation: An SDT Perspective

Motivation, demotivation, and remotivation are interconnected psychological constructs that influence learners' engagement and persistence in SLA and educational psychology. Motivation refers to the initial, proactive psychological drive or affective state that prompts a student to engage with course material. Remotivation, on the other hand, is a specialized, restorative psychological process. It is the systematic reclamation and rebuilding of the lost drive to learn following a distinct period of academic demotivation. Motivation primarily drives SLA, often outweighing aptitude or instructional quality (Bessa et al., 2024; Cho & Chung, 2014; Dörnyei, 2005; Falout, 2012; Shurovi et al., 2025; Zhou, 2024). Rather than a static trait, motivation exists on a continuum between demotivation and remotivation (Akay, 2017; Dörnyei & Ushioda, 2011; Falout, 2012; Ma, Y., 2025; Wang & Littlewood, 2021). This study applies Self-Determination Theory (SDT) to this continuum, positing that re-engagement hinges on satisfying three innate psychological needs: autonomy, competence, and relatedness (Ryan & Deci, 2000). While traditional EFL settings often struggle to sustain these pillars, AI-enhanced environments offer a new pathway for their restoration.

Multi-Dimensional Nature of Demotivation

Psychological factors play a significant role in learners' success in acquiring and using a second language (Dörnyei, 2005; Gardner, 1985). The literature establishes a dichotomy between external catalysts and internal psychological states. Systemic external forces, including rigid pedagogy, excessive course difficulty, and inadequate facilities, consistently trigger a decline in motivation (Akay, 2017; Cho & Chung, 2014; Ma, Y., 2025; Ma & Cho, 2014; Wang & Littlewood, 2021). In Middle Eastern contexts, local factors like gender-based perceptions of teacher competence and institutional resource limitations further nuance these triggers (Shoeib, 2022).

However, internal states, such as diminished self-confidence and negative attitudes toward the target culture, ultimately govern the depth of demotivation (Cho & Chung, 2014; Dörnyei & Ushioda, 2011). While external environments trigger the initial decline, a lack of perceived competence (an SDT pillar) often makes demotivation more permanent. Consequently, effective interventions should go beyond surface-level instructional changes to address learners' underlying psychological needs (Bessa et al., 2024).

Shift Toward Remotivation and Growth Mindsets

Remotivation differs from demotivation because it relies on internal psychological shifts rather than purely external changes. It acts as a cognitive filter that directly affects language processing speed and working memory. External triggers, such as inspiring instructors or engaging media, can spark initial interest (Daif-Allah & Alsamani, 2014; Jung, 2011). However, sustained re-engagement requires realizing a language's utility and restoring self-confidence (Cho & Chung, 2014; Jung, 2011; Trang & Baldauf, 2007).

Central to this internal realignment is the Language Learning Mindset. Research suggests a clear correlation between a "fixed mindset", the belief that linguistic ability is innate, and chronic demotivation (Albalawi & Al-Hoorie, 2021). Such beliefs erode the "Ideal L2 Self," making academic setbacks appear insurmountable. Conversely, fostering a "growth mindset" allows learners to view challenges as opportunities for mastery, thereby directly satisfying the SDT need for competence and enabling intentional self-determination (Ma & Cho, 2014).

AI as a Multidimensional Catalyst for Remotivation

AI is revolutionizing language education by dismantling traditional pedagogical barriers and psychologically catalyzing student re-engagement (Abdelaal & Al Sawy, 2024; Ahmed et al., 2025). Rather than serving as a digital substitute, AI tools address core motivational tenets by providing continuous, non-judgmental feedback and personalized learning environments (Amanullah, 2025; Fang, 2025; Mosaku et al., 2026). Empirical evidence from global EFL contexts, ranging from China and Korea to the Middle East, demonstrates that platforms such as Duolingo and various LLMs significantly boost intrinsic motivation and self-efficacy by fostering self-regulated learning (Anuradha et al., 2023; Kim, 2025; Wei, 2023). These tools allow learners to rebuild their "Ideal L2 Self" through interactive experiences that sustain interest more effectively than conventional methods (Ali et al., 2023; Ma, H., 2025).

Enhancing learner autonomy and providing immediate, actionable feedback are central to this shift. AI-driven tools, such as ChatGPT and AI-powered animations, empower students to control their learning pace, a critical factor in undergraduate remotivation (Ali et al., 2023; Behforouz & Al Ghaithi, 2025; Zhou, 2024). In high-anxiety assessment contexts, real-time AI feedback provides a "safe" space for skill development, allowing learners to perceive tangible growth in proficiency (Moybeka et al., 2023; Song & Song, 2023). This perceived mastery improves achievement and fosters a positive disposition toward the learning process (Dzulwantiana, 2024; Mohamed et al., 2025).

However, AI's efficacy is not universal; external infrastructure and internal digital literacy heavily moderate the remotivation process. AI's motivational benefits depend on the student's ability to navigate these tools effectively (Yang, 2024; Yaşar & Karagücük, 2024). Without adequate technical support, the potential for increased engagement remains limited (Banun, 2025). Furthermore, the learner's perception of the tool's usefulness acts as a vital mediator; students re-engage more readily when they view AI as an accessible, practical companion (Khalaf et al., 2025).

Integrating AI requires a balanced approach to address emerging ethical and pedagogical concerns. Over-reliance can lead to diminished independent thinking, anxiety, and dependency (Jayaputri, 2024; Syifauddin & Yuliansyah, 2023). Consequently, AI enhances rather than replaces the teacher's role as a facilitator (Ahmed et al., 2025; Akintunde & Abdallah, 2024). Maintaining the "essential human element" is crucial to ensuring that instruction remains ethical while preserving the socio-affective connections vital to motivation (Dewi et al., 2021; Moybeka et al., 2023).

Despite the recent surge in AI-related research, several critical gaps remain in the literature. Most existing studies have focused on learners' general motivation, with limited attention given to the more nuanced process of remotivation among previously demotivated students. Furthermore, although generative AI tools such as ChatGPT have received considerable scholarly attention, the effectiveness of Google Gemini in fostering learner remotivation remains underexplored, particularly among first-year Saudi university students enrolled in non-English majors, a population that often faces distinctive motivational challenges in language learning. Addressing these gaps, the present study offers a comprehensive and empirically validated examination of how Google Gemini contributes to the transformation of academic demotivation into socio-affective remotivation. Guided by SDT and employing a mixed-methods design, the study investigates the extent to which Gemini supports learners' psychological needs for autonomy, competence, and relatedness, thereby facilitating the remotivation process. By integrating

quantitative and qualitative evidence, the study provides robust empirical insights into learner psychology. It contributes to the emerging literature through its longitudinal examination of the socio-affective transition from demotivation to sustained remotivation.

Methodology

Design and Context

This quasi-experimental study employed a mixed-methods design, employing psychometric survey scales and semi-structured qualitative interviews to evaluate shifts in learner motivation following a 12-week Gemini-mediated intervention (see Figure 1). The metrics used were motivational and survey-based, designed to capture student perceptions and attitudinal changes regarding motivational recovery across the 12-week Gemini intervention period. The study was conducted within a digitally advanced Saudi Arabian higher education setting, namely the University of Bisha. Participants used a robust technological ecosystem including high-speed Wi-Fi, language laboratories, and institutional access to Google Gemini Advanced. Students' high digital literacy and device proficiency complemented this infrastructure, ensuring they could effectively navigate the AI tools for academic tasks.

Participants

This study followed purposive sampling to select two comparable, pre-existing groups with identical baseline motivation levels. The sample consisted of 60 Saudi undergraduates drawn from a population of 102 students enrolled in the same mandatory "*General English-1*" course at the University of Bisha's Applied College (Table 1). These first-year diploma students were selected due to their transitional status; because their lower secondary school Grade Point Averages (GPAs) precluded admission to bachelor's degree programs, they were considered highly susceptible to academic demotivation.

The control group ($n = 30$) followed the standard curriculum through traditional, teacher-led instruction and feedback. Conversely, the experimental group ($n = 30$) received an AI-based intervention that supplemented their regular coursework activities. Of the six weekly hours allocated to coursebook instruction, this intervention utilized Google Gemini Advanced for 30 minutes during each two-hour class, three times a week over 12 weeks. Rather than using Gemini as an open-ended chatbot, students in the experimental group were required to complete a rigid, mandatory 30-minute capstone task at the end of each session. This task instructed them to use Gemini to replicate the

instructional framework explained in that class, mapped explicitly across 14 distinct curriculum units targeting grammar, writing, reading, and everyday English.

Table 1
Characteristics of the Respondents

Items	Category	Frequency	Percent
Age	18–20	43	71.70 %
	21–23	5	8.30 %
	More than 23	12	20.00 %
Major	Human Resources management	10	16.67 %
	Occupational health and safety	10	16.66 %
	Cybersecurity	15	25.0 %
	Programming and applications	13	21.67 %
	Health Records management	12	20.00 %
Frequency of Using AI Tools	Always	19	31.67 %
	Often	13	21.67 %
	Sometimes	18	30.00 %
	Rarely	10	16.66 %
	Never	0	.00 %

Instruments

Quantitative Instrument: Questionnaire Structure

The primary data collection instrument was a researcher-developed psychometric questionnaire administered via Google Forms, theoretically anchored in SDT to track the psychological dimensions of learner autonomy, competence, and relatedness. The instrument was structured into three distinct parts. The first part, demographic and baseline assessment, gathered student profile data and evaluated baseline variables to verify pre-intervention homogeneity between the experimental and control cohorts (see Table 1). A 12-item scale on demotivating factors was administered pre- and post-intervention to track baseline instructional anxieties and perceived demotivators for learning English (see Table 4). Another 12-item section was appended to the post-intervention questionnaire to evaluate students' perceptions of the Gemini's intervention as a socio-affective and cognitive catalyst for restoring their motivation (see Table 5).

Psychometric Validation and Reliability Testing

To establish structural validity and linguistic equivalence, the instrument underwent a rigorous back-translation into Arabic, followed by a review of an expert panel of two survey-design specialists to ensure content validity. A subsequent pilot study ($n = 12$) verified clarity and functionality.

To empirically evaluate construct validity, an Exploratory Factor Analysis (EFA) was performed using Principal Axis Factoring with a Direct Oblimin rotation. The data demonstrated high suitability for factor analysis, yielding an excellent Kaiser-Meyer-Olkin (KMO) measure of .817 and a highly significant Bartlett's Test of Sphericity ($X^2 = 1854.51$, $df = 276$, $p < .001$). Based on Kaiser's criterion (Eigenvalues > 1.0) and scree plot inspection, a robust four-factor solution was extracted that accounted for an exceptionally high 77.83 % of the cumulative variance. The items clustered cleanly into four distinct, conceptually sound subscales. Factor 1 (*AI-Mediated Learning Empowerment*, 12 items, loadings between .857 and .967), Factor 2 (*Curricular Demotivation*, 6 items, loadings between .460 and .711), Factor 3 (*Social Isolation and Academic Anxiety*, 4 items, loadings between -.769 and -.568), and Factor 4 (*Perceived Evaluation*, 2 items, loadings up to .621). Despite minor cross-loadings from two items due to the natural conceptual overlap between student anxiety and demotivation, the overall high magnitude of these loadings confirms robust construct validity and the instrument's reliability.

Internal consistency was evaluated globally and across the primary thematic subscales using Cronbach's alpha (α). As displayed in Table 2, the comprehensive 24-item instrument demonstrated excellent overall reliability ($\alpha = .937$). When evaluated independently, the 12-item primary demotivators subscale exhibited strong cohesion ($\alpha = .887$), indicating that its items successfully capture the overarching construct of academic demotivation despite measuring distinct facets of learner struggle (e.g., rigid methods, irrelevant materials, social anxiety). Concurrently, the 12-item Gemini-mediated remotivation subscale yielded an exemplary reliability coefficient ($\alpha = .987$), mirroring the EFA pattern where all Gemini-related items loaded powerfully onto Factor 1. This indicates that the items tracking AI-mediated empowerment, autonomy, and confidence are tightly unified and measured with virtually zero statistical noise.

Table 2
Reliability Statistics for the Questionnaire Subscales

Questionnaire Subscales	Cronbach's Alpha
Primary demotivators	.887
Gemini-mediated remotivation	.987
Comprehensive questionnaire	.937

Qualitative and Achievement Measures

To provide qualitative depth and triangulate findings, semi-structured interviews were conducted with a purposive sub-sample of 10 experimental-group students, selected for their performance and engagement. These interviews explored the mechanisms of student remotivation and their lived experiences within the AI-mediated environment, capturing nuanced attitudinal shifts beyond the scope of numerical data. Finally, the researcher tracked students' final course grades to examine the correlation between Gemini-enhanced motivation and academic achievement of the two groups.

Data Collection Procedures

Data collection proceeded in three sequential phases during the first semester of the 2025/2026 academic year (see Table 3). The researcher taught two separate cohorts at different times, delivering the same course curriculum and standardized exams to both cohorts. To ensure baseline equivalence and rule out pre-existing differences, a baseline pre-test measure was administered to both cohorts prior to the 12-week intervention, followed by an equivalent post-test tracking measure at the end of the treatment. The experimental group used Google Gemini for course-related tasks, whereas the control group received traditional instruction exclusively. The English course comprised three 2-hour classes per week, covering 14 instructional units. The 30-minute Gemini interaction was integrated as a mandatory capstone activity at the end of each session, totaling 90 minutes per week. Rather than utilizing Gemini for open-ended generation, students were systematically tasked with leveraging the tool to reinforce, expand, and personalize the specific linguistic content covered in that week's unit.

Depending on the core objectives of each unit, students' 30-minute class interactions were strategically channeled into specific language-learning dimensions. For units prioritizing grammar and vocabulary use, students inputted targeted prompts to generate contextualized examples of the week's grammatical structures or queried Gemini for synonymous collocations to expand their lexical range. In writing-focused sessions, students submitted their own initial drafts to receive formative, step-by-step feedback on grammar, structural coherence, and mechanical precision. Finally, because each unit naturally concludes with an everyday English section, students used Gemini to generate interactive, contextual dialogues that mimic real-world scenarios directly related to that unit's theme, thereby reinforcing communicative competence in a safe, zero-anxiety sandbox. After this process, both groups retook the questionnaire to measure motivational shifts and record learning reflections.

Second, the researcher conducted semi-structured interviews with 10 purposively selected participants from the experimental group who exhibited significant fluctuations in motivation.

Table 3
Summary of the Data Collection Procedures

Phase	Control Group	Experimental Group
Phase 1: Pre-intervention	Questionnaire (baseline)	Questionnaire (baseline)
Phase 2: Intervention	Traditional learning	Traditional learning with Gemini AI usage
Phase 3: Post-intervention	Questionnaire (final)	Questionnaire (final)
Semi-structured interviews	None	Yes, with 10 participants
Respondents' performance data	Yes	Yes

Finally, the researcher analyzed end-of-semester academic grades to correlate engagement and motivational shifts with objective performance. This analysis encompassed the full cohort (N=102), providing institutional context for the sampled participants (n=60).

Ethical protocols ensured participant protection. Students provided digital informed consent after a full briefing on study objectives. To maintain anonymity during longitudinal matching, participants used the last three digits of their academic IDs as unique identifiers. Participation was voluntary, with guaranteed confidentiality and the right to withdraw without penalty. Secure data storage and semester-long monitoring ensured privacy and procedural fidelity.

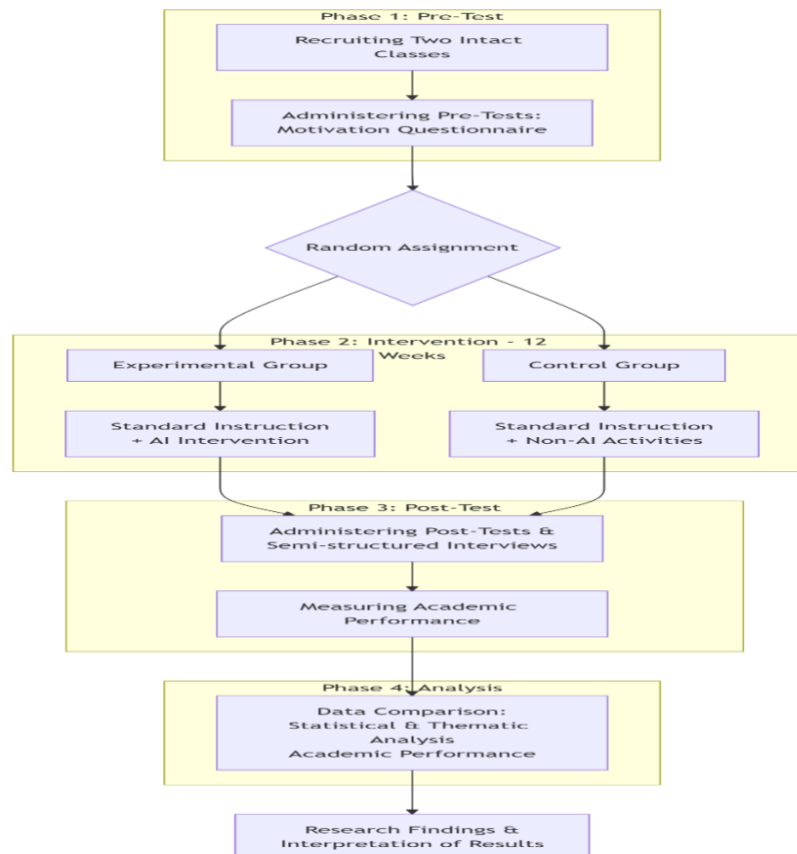
Data Analysis Procedures

Quantitative Data Analysis

Questionnaire data were processed and analyzed using SPSS (Version 26). Initial descriptive statistics were calculated to map overall distribution patterns across all questionnaire items. To evaluate the overall efficacy of the Gemini's AI intervention, a parametric Two-Way Mixed ANOVA (Split-Plot ANOVA) was utilized as the primary inferential statistical technique. A quasi-experimental pretest-posttest design involving a control group and an experimental group yields two distinct levels of variance: between-subjects variance (comparing the separate cohorts to establish baseline equivalence and isolate post-intervention

divergence) and within-subjects variance (tracking individual longitudinal shifts across the 12-week timeline (pre-test vs post-test)).

Figure 1
Methodological Framework for the Study



The Mixed ANOVA evaluates these dimensions concurrently by calculating a single, sophisticated Time X Grouping interaction effect. This interaction is methodologically vital, as it empirically establishes whether Gemini's intervention significantly altered the trajectory of learner psychology and performance over time compared to the traditional curriculum. The linear modeling verified a clear, significant interaction effect in which $F(1,58) = 88.372$, $p < .001$, $\eta_p^2 = .604$. This Partial Eta Squared (η_p^2) indicates that 60.4% of the total longitudinal variance in student trajectories is directly attributable to the structured Gemini intervention. Regarding statistical assumptions, while minor deviations from normality were identified in isolated subsamples, the general linear model is robust to localized normality violations when cell sizes are perfectly balanced ($n = 30$ per group, $n = 60$). This strict equivalence protects the model's statistical power ($1-\beta > .99$) without inflating the risk of Type I errors.

Qualitative and Achievement Analysis

Qualitative data from the semi-structured interviews were thematically analyzed to identify recurring perceptions and experiences. Following a verbatim transcription, the text was thoroughly reviewed and coded using an abductive approach, categorizing responses according to the core pillars of the SDT, autonomy, competence, and relatedness, alongside emerging inductive themes regarding the efficiency-relatedness paradox.

Finally, the cohorts' academic performance outcomes were quantitatively analyzed using tracking data from course grades. This stage investigated whether the significant socio-affective and psychological remotivation curves isolated in the experimental group translated directly into objective, measurable differences in final learning achievement.

Results and Discussion

Primary Factors Contributing to Student Demotivation

The baseline descriptive metrics presented in Table 4 indicate that the primary demotivators among first-year Saudi undergraduates are strongly tied to perceived instructional distance and interpersonal classroom dynamics, such as social evaluation anxiety and fear of negative peer judgment. Both groups recorded their highest baseline mean scores for Item 7 (Control: 4.27; Experimental: 4.63). Interpersonal classroom dynamics and peer influence also significantly shaped learners' psychology; students reported high baseline vulnerability to peer evaluation, as seen in Item 11 (Control: 4.00; Experimental: 4.07).

Table 4

Primary Factors Contributing to Students' Demotivation

Items	Control Group		Experimental Group		Types of Demotivation	Underlying Factors
	Mean	SD	Mean	SD		
1. My control was limited over the content and method of learning English language.	2.73	1.172	2.53	1.074	Extrinsic	Lack of autonomy
2. I felt that the English materials	3.70	.877	3.33	1.124		Learning materials

were irrelevant to my personal interests.						
3. I felt the teaching methods were unengaging.	3.93	.868	3.33	1.093		Instructional style
4. I felt English courses failed to support my unique learning style.	3.77	1.073	3.63	.850		Curriculum/pedagogy
5. The feedback was reaching me late, which prevented benefiting from it.	3.70	.794	3.17	1.206		Teacher support
6. I felt a lack of connection with my professors and peers in the learning process.	3.67	.959	3.40	1.329		Relatedness / environment
7. I felt the teacher didn't care about me as a student.	4.27	.691	4.63	.718		Teacher attitude
8. I found it difficult to see my own progress in English.	3.33	.922	2.83	1.341		Perceived competence
9. I felt anxious about my English abilities in class.	3.13	1.196	3.03	1.402		Learning anxiety
10. I often felt incapable of meeting the course requirements.	3.83	.874	3.27	1.363	Intrinsic	Self-efficacy
11. I felt embarrassed because of peer judgment when making mistakes.	4.00	.871	4.07	1.230		Social anxiety
12. I felt anxious for my lack of	3.60	1.192	3.40	1.404		Social anxiety

integration into
class discussions.

These results contrast with the findings of Ghelichli et al. (2022), who observed that teacher behavior, student personality, and parental influence were the primary drivers of active engagement among Iranian learners. Other substantial baseline demotivators among the control group include unengaging instructional styles in Item 3 ($M = 3.93$, $SD = .868$) and a compromised sense of learner self-efficacy in Item 10, where students often felt incapable of meeting standard course requirements ($M = 3.83$, $SD = .874$). Conversely, a perceived lack of individual control over learning content (Item 1) emerged as the least impactful demotivating factor for both the control ($M = 2.73$, $SD = 1.172$) and experimental ($M = 2.53$, $SD = 1.074$) groups.

From a psycholinguistic perspective, these baseline results suggest that for first-year Saudi undergraduates, the socio-affective and psychological climate of the instructional environment heavily outweighs syllabus or curriculum design as a primary source of academic demotivation. The high scores observed for perceived instructional distance indicate a subjective strain in the teacher-student pedagogical relationship, a critical cornerstone of successful SLA. This finding differs from Shoeib (2022), in which both genders ranked teacher competence as the least significant demotivating factor.

When tracking these results through an affective-cognitive loop, the prominent fear of peer judgment and perceived distance from the teacher points to a highly sensitive "face-saving" classroom culture. In this environment, learners often opt for communicative silence or cognitive withdrawal rather than risk social stigma or exposure to public error during traditional sessions.

In terms of cognitive resource allocation models, this continuous baseline anxiety functions as a severe affective filter. This heightened emotional block acts as an ongoing cognitive drag, consuming a large portion of the learner's finite working memory capacity. Instead of dedicating available attentional resources to online structural parsing, syntactic encoding, and fluid language processing, the student's cognitive energy is diverted toward managing evaluation anxiety. Consequently, while structural instructional factors such as unengaging materials (Item 2: $M = 3.70$) and delayed feedback loops (Item 5: $M = 3.70$) clearly compound the problem, these baseline metrics indicate that pedagogical interventions should prioritize creating a low-anxiety, highly private sandbox to systematically unblock these cognitive processing channels.

When evaluated through the framework of SDT, these findings lay the empirical groundwork for what this study conceptualizes as the "efficiency-relatedness paradox" in generative AI-enhanced instruction. By using Two-Way

Mixed ANOVA alongside EFA, the 12-week structured Gemini capstone framework can be systematically broken down to reveal how it interacts directly with the three pillars of the SDT. Regarding the autonomy and competence pillars, the control group struggled to track their individual progress (Item 8: $M = 3.33$) and exhibited low self-efficacy (Item 10: $M = 3.83$). The integration of Gemini directly resolves this by providing an immediate, highly personalized scaffolding. Because items tracking AI-mediated learning empowerment loaded cleanly into a highly stable, independent subscale ($\alpha = .987$), the results demonstrate that Gemini's instant, step-by-step formatting loops allow students to perceive immediate gains in their language capability. This private environment directly fulfills the learner's psychological need for competence and autonomy without exposing them to classroom embarrassment.

However, regarding the relatedness deficit (the core paradox), a critical tension arises when examining the exceptionally high baseline scores of the experimental group on perceived teacher distance (Item 7: $M = 4.63$). If an AI tool is used as an unguided replacement for human teaching, the technical aspects of language acquisition are effectively outsourced to software. This risk can inadvertently weaken the sense of relatedness, the socio-affective human validation that remains essential for sustaining long-term intrinsic motivation. The results suggest that computational speed alone cannot substitute for the reassuring presence of an educator.

The 12-week quasi-experimental design successfully resolved this tension by implementing a highly structured, 30-minute-per-session capstone framework immediately following a standard, human-led 2-hour lecture. This hybrid model successfully balanced the paradox: Gemini provided a safe, low-anxiety space for building individual competence and autonomy, while the instructor remained the vital anchor for social relatedness, classroom community, and empathetic human validation. This pedagogical balancing act provides a robust theoretical explanation for the notable longitudinal interaction effect isolated in the inferential modeling ($F(1,58) = 88.372, p < .001, \eta_p^2 = .604$). The steep, positive remotivation growth curve seen exclusively in the experimental cohort demonstrates that statistical gains in instructional efficiency can be systematically coupled with strategies that preserve and reinforce the social bond between the instructor and the students. This necessity for a balanced integration of human-driven pedagogy and generative technology aligns with recent consensus in the wider literature (Ahmed et al., 2025; Akintunde & Abdallah, 2024; Dewi et al., 2021; Fang, 2025; Ma, H., 2025).

Students' Perceptions of Gemini's Effectiveness for Remotivation

To gain a granular understanding of the specific dimensions driving the intervention's success, a descriptive analysis was conducted on the specialized

12-item subscale assessing students' perceptions of Gemini's effectiveness as a primary longitudinal catalyst for psychological remotivation (see Table 5). The descriptive metrics reveal a profound, systematic divergence between the experimental and control cohorts across all measured dimensions. Within this subscale, the experimental group demonstrated a remarkably high and homogeneous endorsement of the AI framework, with item mean scores consistently ranging from 4.53 to 4.70. In contrast, the control group's evaluations consistently remained in the negative tier of the scale ($M \leq 2.43$). This baseline deficit underscores a critical socio-affective and structural gap within the traditional classroom setting, supporting the conclusion that Gemini's AI intervention served as an explicit catalyst for the experimental group's heightened psychological empowerment.

The experimental cohort reported that Gemini granted them substantial autonomy over the content and methodology of their learning ($M = 4.63$, $SD = .490$) and accommodated their unique, individual learning styles ($M = 4.60$, $SD = .563$). By providing an immediate, adaptive scaffolding tool that helped students realize their writing progress clearly ($M = 4.67$, $SD = .479$) and fix linguistic mistakes instantly ($M = 4.60$, $SD = .621$), the students perceived that the structured Gemini sessions directly satisfied their psychological needs for autonomy and competence as outlined by SDT.

Beyond purely cognitive and curricular benefits, the descriptive results highlight a powerful socio-affective transformation in student perceptions. The experimental group indicated that using Gemini significantly mitigated academic anxiety while bolstering individual confidence in capability ($M = 4.53$, $SD = .730$). Furthermore, the participants expressed a profound sense of psychological safety regarding peer evaluation. Because Gemini allowed them to process, evaluate, and rectify linguistic errors privately ($M = 4.57$, $SD = .817$), the localized reduction in evaluation anxiety subsequently enhanced their perceived confidence in actively participating within the broader peer group ($M = 4.70$, $SD = .466$).

Furthermore, the results in Table 5 address the "efficiency-relatedness paradox" by showing that students perceived the instructor as supportive of their individual needs through their active encouragement to utilize Gemini ($M = 4.70$, $SD = .466$). This high score confirms that when generative AI is integrated systematically as a targeted capstone rather than an unguided replacement for human instruction, it does not induce student isolation. Instead, the teacher's active endorsement of the technology bridges the socio-affective gap, allowing students to experience heightened instructional efficiency while feeling structurally supported by their instructor. These findings provide compelling support for contemporary research showing that generative AI tools

significantly bolster student motivation (Ebadi & Amini, 2022; Mohamed et al., 2025), while explicitly demonstrating how a blended pedagogical architecture mitigates the potential risks of digital isolation.

Table 5

Students' Perceptions of Gemini's Effectiveness for Remotivation

Questionnaire Items of Section 3	Control Group		Experimental Group	
	Mean	SD	Mean	SD
1. Gemini granted me the freedom of choosing the content and method of my learning.	1.73	.907	4.63	.490
2. Gemini helped me create materials that were directly relevant to my interests.	1.93	.868	4.63	.490
3. I felt more engaged because Gemini allowed me to customize the tasks to my interests.	2.03	.765	4.63	.490
4. Gemini enabled me to learn in a way that fits my unique style.	2.00	.830	4.60	.563
5. Gemini helped me realize my progress clearly by demonstrating how to develop my drafts.	2.17	.834	4.67	.479
6. Gemini provided immediate feedback that helped me fix my mistakes instantly.	2.13	.900	4.60	.621
7. Using Gemini helped me reduce anxiety and granted me greater confidence in my abilities.	2.43	.774	4.53	.730
8. Gemini made me feel capable of accomplishing difficult course tasks.	1.93	.980	4.70	.466
9. Using Gemini gave me greater confidence when sharing my ideas with my colleagues.	2.27	1.143	4.70	.466
10. I became less worried about colleagues' judgments because Gemini helped me fix my errors privately.	2.20	.997	4.57	.817
11. Gemini granted me the	2.37	1.189	4.70	.466

confidence for participation and the feeling of belonging to the group.

12. I felt the instructor supported my individual needs through his encouragement to use Gemini. 2.20 1.126 4.70 .466

Statistical Variations in Remotivation: Google Gemini vs Traditional Instruction

To evaluate the long-term psychological efficacy of the Google Gemini integration compared to traditional instruction over the 12-week timeline, a parametric Two-Way Mixed ANOVA was conducted. The statistical model specified *Time* (Pre-test vs Post-test) as the within-subjects factor and *Grouping* (experimental group vs control group) as the between-subjects factor.

As shown in Table 6, the descriptive baseline metrics indicate that the control group ($M = 3.39$, $SD = .81$) and the experimental group ($M = 3.64$, $SD = .63$) demonstrated comparable motivation scores during the pre-intervention phase. This baseline proximity confirms satisfactory comparability between the pre-test group within the quasi-experimental design. By the post-test phase, however, their psychological trajectories diverged substantially, with the control cohort's scores declining ($M = 2.12$, $SD = .71$) and the Gemini-assisted cohort displaying a pronounced upward shift ($M = 4.64$, $SD = .40$).

Table 6
Descriptive Statistics

	Group	Mean	SD
Pretest	Control group	3.39	.81
	Experimental group	3.64	.63
Posttest	Control group	2.12	.71
	Experimental group	4.64	.40

Because the within-subjects factor contained only two levels, the assumption of sphericity was inherently satisfied. This analysis evaluates the Time X Grouping interaction effect to determine if the longitudinal rate of psychological change differed significantly as a function of the instructional condition. It reveals a highly significant, robust interaction effect, $F(1, 58) = 88.37$, $p < .001$. The magnitude of this effect was exceptionally pronounced, yielding a Partial Eta Squared (η_p^2) of .604. This indicates that 60.4% of the variance in students'

longitudinal score shifts is directly attributable to the AI intervention's interaction over time.

Table 7
Tests of Within-Subjects Effects

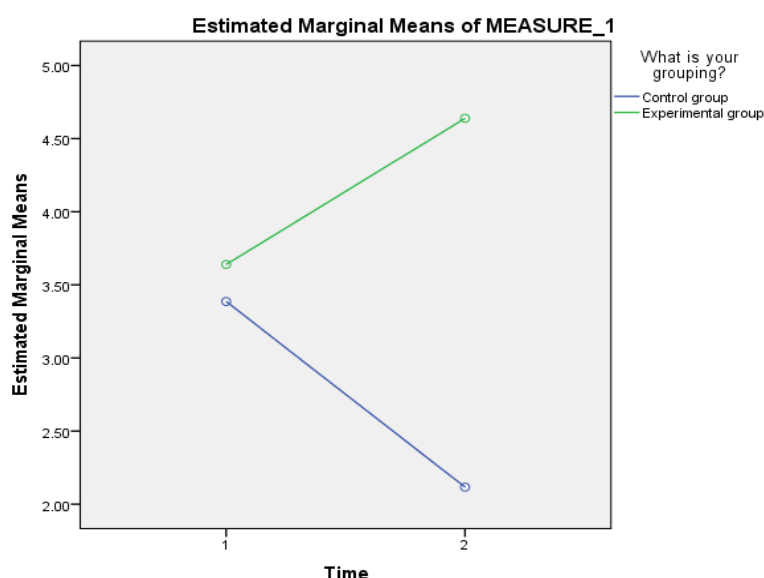
Measure: MEASURE_1		Type III	df	Mean	F	Sig.	Partial
Source		Sum of Squares		Square			Eta Squared
Time	Sphericity Assumed	.545	1	.545	1.246	.269	.021
	Greenhouse-Geisser	.545	1.000	.545	1.246	.269	.021
	Huynh-Feldt	.545	1.000	.545	1.246	.269	.021
	Lower-bound	.545	1.000	.545	1.246	.269	.021
	Sphericity Assumed	38.628	1	38.628	88.372	.000	.604
Time * Grouping	*Greenhouse-Geisser	38.628	1.000	38.628	88.372	.000	.604
	Huynh-Feldt	38.628	1.000	38.628	88.372	.000	.604
	Lower-bound	38.628	1.000	38.628	88.372	.000	.604
	Sphericity Assumed	25.352	58	.437			
	Greenhouse-Geisser	25.352	58.000	.437			
Error (Time)	Huynh-Feldt	25.352	58.000	.437			
	Lower-bound	25.352	58.000	.437			

Conversely, the isolated main effect of time did not achieve statistical significance, $F(1, 58) = 1.246$, $p = .269$, $\eta_p^2 = .021$, confirming that psychological erosion or recovery did not occur globally across the student sample. Instead, the shifts were explicitly driven by the contrasting treatments of the separate groups. This highly divergent interaction path is visually displayed in the estimated marginal means profile plot in Figure 2, providing definitive evidence that a structured, 30-minute-per-class capstone framework across 14 units can systematically reverse a downward psychological trajectory into a steep growth curve in the experimental group. These findings offer clear support for integrating conversational AI to rebuild learner self-efficacy, provided the

technology is deployed as a targeted pedagogical catalyst rather than an unguided instructional replacement.

Figure 2

Profile Plot of the Time X Grouping Interaction Effect



Semi-Structured Interview Results

Consistent with the quantitative metrics presented in Tables 4 and 5, the thematic analysis of the semi-structured interviews revealed a nuanced, dual reality. Participants expressed high satisfaction regarding Gemini's data-driven efficacy in fostering autonomy and competence, alongside critical subjective concerns regarding the perceived distance in instructional delivery. Student 441 highlighted the cognitive benefits of Gemini's immediate feedback loops:

I loved using Gemini because the feedback was instant. In normal classes, I wait days for a mark, but the AI evaluated me... immediately. It made me feel like I was actually making progress.

Participants closely linked this immediate structural scaffolding to heightened feelings of personal capability. Student 397 likened Gemini to *"a 24/7 tutor that helps me build my own learning path."*

However, this rapid outsourcing of technical feedback loops inadvertently exposed the delicate socio-affective boundaries of the classroom. Student 497 noted that while they *"felt safer talking to the AI than to my classmates"* due to deep-seated embarrassment over making public linguistic errors, the physical classroom environment felt neglected:

The teacher was just watching us... and didn't really care about our personal struggles.

Student 534 explicitly echoed this sentiment, capturing the core of the efficiency-relatedness paradox:

The materials the AI gave me were interesting... but the classroom felt 'cold.' It felt like the teacher replaced themselves with a machine.

Triangulating these narratives with the questionnaire data suggests that within this undergraduate student culture, learners closely equate instructor investment with direct, visible pedagogical involvement. When teachers step back to let an AI tool handle formative feedback, students can perceive this shift as an emotional withdrawal or a breakdown in the instructor-student bond. This systemic perception explains the study's central paradox: while the experimental cohort achieved substantial statistical growth in perceived competence, their qualitative responses revealed a vulnerability regarding relatedness. To maximize the utility of generative AI, the time saved by automated error correction should be intentionally repurposed by the instructor for intensive human mentoring and active rapport-building.

The interview data clarify that the restorative mechanics of learner remotivation are highly functional, individualistic, and directly tied to how the technology solves traditional classroom pain points: slow feedback loops, standardized topics, and the fear of public failure. Student 464 explicitly detailed this psychological transition:

Before Gemini, I felt incapable of meeting course requirements because I didn't know where to start. Gemini acted like a personal tutor that gave me a starting point without judging me. Being able to see my progress instantly made me want to keep going instead of giving up or dropping the course.

By establishing a private practice environment, the tool neutralized the social anxiety that typically blocks active language processing. Student 427 demonstrated this shift:

Gemini remotivated me because I could practice my English privately. It removed the 'fear' of the classroom, allowing me to focus on learning rather than worrying about peer judgment.

Student 375 corroborated this psycholinguistic unblocking:

I used to stay silent in class because I was embarrassed to make mistakes and Gemini doesn't laugh or judge; it corrected me privately, which gave me the confidence to start trying again.

Furthermore, the conversational nature successfully satisfied the psychological need for autonomy by allowing students to break away from rigid, unengaging curricular paths. Student 400 remarked:

Gemini allowed me to submit questions about the things I care about. This made the lessons feel more 'real' and less like a chore, which was the main reason I felt remotivated to study.

Student 610 validated this personal relevance:

I asked Gemini to teach me English through my favorite video games. This made the lesson interesting and actually fun, which I haven't felt in an English class before.

In sum, the qualitative findings confirm that the Gemini integration moved students toward active engagement by systematically supporting the competence and autonomy pillars of the SDT. From a psycholinguistic perspective, the tool served as a safe digital sandbox that reduced participants' social-evaluation anxiety, thereby freeing up finite cognitive processing and attentional resources.

Crucially, however, the results reveal that this functional remotivation is primarily tied to the tool itself rather than to the academic institution or the instructor. While Gemini excels at sparking immediate, efficiency-driven remotivation, sustaining long-term, intrinsic motivation requires a collaborative partnership rather than an instructional replacement. To prevent digital isolation, generative AI tools are most effective when framed as a cooperative baseline: the technology manages computational speed and linguistic error-correction, while the human mentor remains the primary source of empathy, social relatedness, and cultural validation.

Results of the Students' Academic Performance

The final administrative tracking dataset reveals a profound divergence in behavioral persistence and achievement quality. In the control group, clear patterns of suboptimal motivation and academic "satisficing" were observed. This patch experienced a considerable 29.41% official withdrawal rate, resulting in nearly one-third of its students failing to meet basic course completion requirements due to non-attendance or incomplete statuses. Furthermore, among the control students who completed the course, the grade distribution was notably skewed toward the lowest passing intervals, peaking at the minimum-effort D+ range (13.73 %) and only a marginal 5.88 % reaching an A or A+. This indicates that traditional classroom barriers and evaluation anxieties

led disengaged students to opt for early attrition, while those who remained exerted only the minimum effort required to pass an institutional hurdle.

Conversely, the experimental group demonstrated a remarkable shift toward active language engagement and sustained motivation. Official student attrition was virtually eradicated, dropping to a minimal 1.96 % withdrawal rate and yielding a robust 92.16 % overall pass rate. The positive shift in academic performance within this cohort also reflects an explicit drive for remotivation and engagement: nearly one-third of the experimental group (31.91 %) achieved an A or A+ grade, while the typical performance peak migrated up to the above-average B range (21.28 %).

Table 8
Distribution of the Grades of the Two Groups

Groups	Grades										Status Distributions						
	Grades	A+	A	B+	B	C+	C	D+	D	F	Denied Entry	In Progress	Incomplete	Pass	Fail	Withdrawn	Total
Control group	Frequency	2	1	4	3	6	4	7	5	0	2	0	2	32	0	15	51
	%	3.92 %	1.96 %	7.84 %	5.88 %	11.76 %	7.84 %	13.73 %	9.80 %	0.00 %	3.92 %	0.00 %	3.92 %	62.75 %	0.00 %	29.41 %	100 %
Experimental group	Frequency	8	7	8	10	8	5	0	1	0	0	0	3	47	0	1	51
	%	17.02 %	14.89 %	17.02 %	21.28 %	17.02 %	10.64 %	0.00 %	2.13 %	0.00 %	0.00 %	0.00 %	5.88 %	92.16 %	0.00 %	1.96 %	100 %

In contrast, low passing grades (D+/D) were almost eliminated. Triangulating these outcomes with the study's inferential data indicates that Gemini's private, low-anxiety error-correction loops successfully lowered learners' affective filters,

thereby redirecting student behavior away from passive course survival and toward high-level academic engagement and task persistence.

Table 9

Specific Differences in Motivation between the two Groups

Motivational Indicator	Control Group	Experimental Group	Comparison Insight
Retention (Withdrawal Rate)	29.41 %	1.96 %	The experimental group showed significantly higher persistence.
Completion (Pass Rate)	62.75 %	92.16 %	Nearly all experimental students successfully completed the course.
High Achievement (A+/A)	5.88 %	31.91 %	Experimental students were over 5 times more likely to reach the highest marks.
Low Passing Grades (D+/D)	23.53 %	2.13 %	The control group was primarily concentrated within the lower passing intervals.
Performance Peak (Mode Grade)	D+ (13.73 %)	B (21.28 %)	The experimental group's typical performance shifted from "just passing" to "above average."
Lack of Entry/ Compliance	3.92 %	0.00 %	The experimental group showed perfect attendance/initial compliance.

Conclusion

The findings of this 12-week quasi-experimental study demonstrate that while the structured integration of Gemini facilitates a powerful, statistically significant shift from academic demotivation to active psychological remotivation, it introduces a highly complex motivational trade-off within the SDT framework. Baseline pre-intervention metrics indicated that the primary demotivators among first-year Saudi undergraduates are linked to perceived instructional distance and interpersonal classroom anxieties, particularly the fear of public error exposure and peer judgment. Following the intervention, the parametric Two-Way Mixed ANOVA isolated a monumental longitudinal interaction effect, $F(1,58) = 88.372, p < .001, \eta_p^2 = .604$), empirically confirming

that Gemini served as a transformative longitudinal catalyst for altering student trajectories.

Participants in the experimental cohort exhibited substantial gains across the SDT pillars of autonomy and competence, demonstrating near-perfect psychometric consensus regarding the tool's ability to build writing confidence ($\alpha = .987$) and eliminate the logistical pain of delayed feedback. Conversely, however, their perceptions of social relatedness were strained, tracking high baseline demotivation scores regarding perceived teacher distance ($M = 4.63$, $SD = .718$). This empirical divergence indicates that while Gemini's AI tool effectively neutralizes technical and structural demotivators, it does not serve as a direct substitute for the human teacher-student relationship. Within the Saudi undergraduate context, this interpersonal bond remains a foundational cornerstone of student engagement, requiring a blended pedagogical strategy that systematically leverages technological efficiency to augment, rather than displace, human-centric support.

Implications for Further Research

These results offer vital theoretical and practical implications for the rapidly evolving field of AI tools. This study introduces a novel techno-motivational framework by operationalizing the "efficiency-relatedness paradox." This paradox demonstrates that while Gemini can rapidly build a learner's sense of autonomy and competence by establishing a private, immediate error-correction loop, an unguided reliance on the technology risks triggering feelings of instructional abandonment. Gemini's AI tool functions as an invaluable cognitive restorative mechanism: by serving as a low-stakes, zero-anxiety testing sandbox, it lowers the learner's affective filter, thereby freeing up finite working memory and attentional resources for more efficient structural language processing. These findings imply that the long-term educational sustainability of generative AI does not depend on software complexity but on curriculum architecture. To prevent digital isolation, software-driven efficiency should be coupled with intentional social scaffolding to ensure that technology enhances the human instructor's interpersonal mentoring capacity.

Limitations of the Study

Despite the clear empirical and behavioral gains observed in the final tracking sample ($n = 60$), several strict design constraints limit the generalizability of these findings. First, the cultural specificity of the Saudi educational context, in which socio-affective rapport and face-saving dynamics heavily influence SLA, may limit the immediate transferability of these outcomes to other regional

settings. Second, the bounded 12-week intervention schedule introduces the potential inflation of a technological "novelty effect," in which initial student enthusiasm for a cutting-edge generative AI tool may temporarily drive engagement rather than reflect a permanent, internalized motivational shift. Third, the reliance on self-reported survey data for the psychological constructs introduces a layer of subjective bias. Finally, because academic achievement outcomes were evaluated using localized final course grades rather than external, standardized proficiency indicators, the grade gains should be interpreted with caution as reflecting heightened task persistence, retention, and course-specific performance rather than an unmediated expansion in raw language proficiency.

Recommendations

To maximize the educational potential of generative AI while mitigating the risks of digital isolation, educational institutions should adopt a blended, "human-in-the-loop" instructional architecture. Within this framework, conversational tools like Google Gemini should be structured as a personalized "practice shield" for handling highly repetitive, technical tasks, such as baseline grammar feedback, vocabulary collocations, and immediate syntax formatting. Crucially, the instructional time saved by this automation should be aggressively repurposed by curriculum developers into intensive, high-density human interaction. Instructors should use these freed classroom hours for targeted interpersonal mentoring, small-group dialogues, and empathetic human validation, effectively transforming faculty into motivational mentors who directly alleviate student anxieties and bridge the relatedness gap. Additionally, universities should model proactive early-intervention systems on the experimental cohort's robust retention rates to systematically guide struggling learners away from minimum-effort "satisficing" and toward active mastery.

Methodologically, future research can expand upon these findings by employing long-term longitudinal research designs with larger, multi-institutional samples to determine whether these socio-affective gains persist beyond the initial period of technological novelty. Subsequent studies should also move beyond purely subjective, self-reported survey data by pairing student psychometric tracking with objective, externally validated standardized language proficiency tests, such as IELTS, TOEFL, or the Standardized Test of English Proficiency (STEP), which is widely recognized in Saudi Arabia. Finally, future research can incorporate ethnographic or direct classroom observation methods to document actual teacher behavior and instructor-student dynamics during AI-mediated sessions.

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The author declared no conflicts of interest.

Generative AI Statement

During the preparation of this work, the author used Gemini 3.1 Pro and Grammarly to refine language and improve clarity. The author critically reviewed and edited all AI-generated suggestions and remains fully responsible for the integrity, accuracy, and original contributions of the final manuscript.

References

- Abdelaal, N. M., & Al Sawy, I. (2024). Perceptions, challenges, and prospects: University professors' use of artificial intelligence in education. *Australian Journal of Applied Linguistics*, 7(1), 1–24. <https://doi.org/10.29140/ajal.v7n1.1309>
- Ahmed, I., Ghafoor, A., Liliuara, D., & Akyuningrum, V. Q. (2025). The impact of AI learning tools on ESL learners' motivation and success: A systematic literature review. *English Learning Innovation (englie)*, 6(1), 134–142. <https://doi.org/10.22219/englie.v6i1.38961>
- Akay, C. (2017). Turkish high school students' English demotivation and their seeking for remotivation: A mixed method research. *English Language Teaching*, 10(8), 107–118. <https://doi.org/10.5539/elt.v10n8p107>
- Akintunde, A. F., & Abdallah, F. S. (2024). Exploring artificial intelligence applications for motivating learners in English as a second language classroom. *European Journal of Contemporary Education and E-Learning*, 2(6), 187–199. [https://doi.org/10.59324/ejceel.2024.2\(6\).11](https://doi.org/10.59324/ejceel.2024.2(6).11)
- Albalawi, F. H., & Al-Hoorie, A. H. (2021). From demotivation to remotivation: A mixed-methods investigation. *SAGE Open*, 11(3), 1–14. <https://doi.org/10.1177/21582440211041101>
- Alharbi, A., & Saaty, N. (2022). Demotivating teaching practices in EFL classrooms in Saudi secondary schools. *Journal of Language Teaching and Research*, 13(6), 1324–1331. <https://doi.org/10.17507/jltr.1306.21>

- Ali, J. K. M., Shamsan, M. A. A., Hezam, T. A., & Mohammed, A. A. (2023). Impact of ChatGPT on learning motivation: Teachers and students' voices. *Journal of English Studies in Arabia Felix*, 2(1), 41–49. <https://doi.org/10.56540/jesaf.v2i1.51>
- Al-Qahtani, M. (2016). The importance of English language in Saudi Arabia from the students' perspective of PY at KSU. *Journal of Education and Practice*, 7(8), 114–119.
- Amanullah, A. (2025). Enhancing student learning motivation: An artificial intelligence framework grounded in motivational theory. *SiRad: Pelita Wawasan*, 1(3), 319–336. <https://doi.org/10.64728/sirad.vii3.art11>
- Anuradha, S, Shanmugathai, M, Mini Stanley, Geetha, A., & Maya, P. R. (2023). Analyzing the effect of artificial intelligence technology on learning English language. *Intelligent Computing and Control for Engineering and Business Systems (ICCEBS)*, Chennai, India, 1–7. <https://doi.org/10.1109/ICCEBS58601.2023.10449071>
- Banun, F. F. (2025). The use of AI in increasing motivation to learn English for university students. *Educational Praxis Journal*, 1(1), 1–7. <https://doi.org/10.32529/epj.viii.3782>
- Behforouz, B., & Al Ghaithi, A. (2025). Visual language learning: Exploring the effects of artificial intelligence-generated animations on vocabulary and motivational growth. *Technology in Language Teaching & Learning*, 7(4), 1–19. <https://doi.org/10.29140/tltl.v7n4.103077>
- Bessa, L. C. P., Silva, E. M., Meirinhos, G., & Silva, R. (2024). Are Portuguese higher education students motivated to study English as a second/foreign language? *Theory and Practice of Second Language Acquisition*, 10(2), 1–18. <https://doi.org/10.31261/TAPSLA.15257>
- Cho, Y. A., & Chung, J. H. (2014). Demotivation and remotivation affecting L2 English learning of Korean college students. *Journal of English Language and Literature*, 27(2), 387–408. <https://doi.org/10.35771/engdoi.2014.27.2.018>
- Daif-Allah, A. S., & Alsamani, A. S. (2014). Motivators for demotivators affecting English language acquisition of Saudi preparatory year program students. *English Language Teaching*, 7(1), 128–138. <https://doi.org/10.5539/elt.v7n1p128>
- Dewi, H. K., Rahim, N. A., Putri, R. E., Wardani, T. I., & Pandin, M. G. R. (2021). The use of AI (artificial intelligence) in English learning among university student: Case study in English department, Universitas Airlangga. *Journal of English Language Teaching*, 12(4), 515–528. <https://doi.org/10.31219/osf.io/sdntr>
- Dmitrenko, N., Budas, I., Koliadych, Y., & Poliarush, N. (2021). Impact of formative assessment on students' motivation in foreign language acquisition. *East European Journal of Psycholinguistics*, 8(2), 36–50. <https://doi.org/10.29038/eejpl.2021.8.2.dmi>
- Dörnyei, Z. (2005). *The psychology of the language learner: Individual differences in second language acquisition*. Lawrence Erlbaum Associates.
- Dörnyei, Z. (2009). The L2 motivational self system. In Z. Dörnyei & E. Ushioda (Eds.), *Motivation, language identity and the L2 self* (pp. 9–42). Multilingual Matters.
- Dörnyei, Z., & Ushioda, E. (2011). *Teaching and researching motivation* (2nd ed.). Pearson Education Limited.
- Dzulwantiana, A. (2024). *The impact of AI use on students' English learning motivation in the Philippines* [Unpublished undergraduate thesis, Sriwijaya University].
- Ebadi, S., & Amini, A. (2022). Examining the roles of social presence and human-likeness on Iranian EFL learners' motivation using artificial intelligence technology: A case of CSIEC chatbot. *Interactive Learning Environments*, 32(2), 655–673. <https://doi.org/10.1080/10494820.2022.2096638>

- Falout, J. (2012). Coping with demotivation: EFL learners' remotivation processes. *TESL-EJ: The Electronic Journal for English as a Second Language*, 16(3), 1–29. <https://tesl-ej.org/pdf/ej63/a3.pdf>
- Fang, L. (2025). The impact of AI tools on ESL learners' engagement and language learning motivation. *Journal of Education and Educational Research*, 12(3), 111–114. <https://doi.org/10.54097/hvm6wo44>
- Gardner, R. C. (1985). *Social psychology and second language learning: The role of attitudes and motivation*. Edward Arnold.
- Ghelichli, Y., Seyyedrezaei, S. H., & Seyyedrezaei, Z. S. (2022). Improving student engagement and motivation: Perspectives of Iranian EFL learners. *Theory and Practice of Second Language Acquisition*, 8(2), 1–19. <https://doi.org/10.31261/TAPSLA.11768>
- Jayaputri, H. E. (2024). ChatGPT in action: Unraveling its impact on student motivation in English language learning. *SCOPE: Journal of English Language Teaching*, 8(2), 448–456. <https://doi.org/10.30998/scope.v8i2.22375>
- Jung, S. K. (2011). Demotivating and remotivating factors in learning English: A case of low level college students. *English Teaching*, 66(2), 47–72.
- Khalaf, B. K., Mahmood, I. M., Al-Abbas, L. S., & Khudhur, S. A. (2025). Necessity for artificial intelligence in higher education: Learners' motivation for continuous use of AI-powered tools. *International Journal of Innovative Research and Scientific Studies*, 8(2), 1123–1137. <https://doi.org/10.53894/ijirss.v8i2.5413>
- Kikuchi, K. (2017). Reexamining demotivators and motivators: A longitudinal study of Japanese freshmen's dynamic system in an EFL context. *Innovation in Language Learning and Teaching*, 11(2), 128–145. <https://doi.org/10.1080/17501229.2015.1076427>
- Kim, H.-I. (2025). Exploring the relationship between AI tool language learning awareness and motivation to learn English: Focusing on the mediating role of adaptability. *Theory and Practice of Second Language Acquisition*, 11(2), 1–25. <https://doi.org/10.31261/TAPSLA.17139>
- Kim, S. (2015). Demotivation and L2 motivational self of Korean college students. *English Teaching*, 70(1), 29–55. <http://dx.doi.org/10.15858/engtea.70.1.201503.29>
- Kim, T. Y., & Kim, M. (2017). Demotivators and remotivation strategies in L2 learning: A case study of Korean EFL students. *Foreign Languages Education*, 24(2), 45–74. <http://dx.doi.org/10.15334/FLE.2017.24.2.45>
- Krashen, S. D. (1985). *The input hypothesis: Issues and implications*. Longman.
- Ma, H. (2025). Effectiveness evaluation on the application of artificial intelligence in personalized English learning. *Scientific Journal of Humanities and Social Sciences*, 7(6), 28–31. <http://dx.doi.org/10.54691/rwgh4r11>
- Ma, J. H., & Cho, Y. A. (2014). The analysis of demotivators and remotivators for Korean L2 English learners. *Studies in English Language & Literature*, 40(2), 137–161. <https://doi.org/10.21559/AELLK.2014.40.2.008>
- Ma, Y. (2025). The dynamics of demotivation and remotivation among Chinese students in learning English: Insights from a Q methodology study. *SAGE Open*, 15(2), 1–15. <https://doi.org/10.1177/21582440251324987>
- Mohamed, A. M., Shaaban, T. S., Bakry, S. H., Guillén-Gámez, F. D., & Strzelecki, A. (2025). Empowering the faculty of education students: Applying AI's potential for motivating and enhancing learning. *Innovative Higher Education*, 50, 587–609. <https://doi.org/10.1007/s10755-024-09747-z>
- Moybeka, A. M. S., Syariat, N., Tatipang, D. P., Mushthoza, D. A., Dewi, N. P. J. L., & Tineh, S. (2023). Artificial intelligence and English classroom: the implications of AI toward EFL

- students' motivation. *Edumaspul: Jurnal Pendidikan*, 7(2), 2444–2454. <https://doi.org/10.33487/edumaspul.v7i2.6669>
- Mosaku, I. J., Ndidi, O. M., Rane, N. L., & Rane, J. (2026). Artificial intelligence for enhancing learning and motivation among education faculty students. *International Journal of Applied Resilience and Sustainability*, 2(2), 223–242. <https://doi.org/10.70593/deepsci.0202009>
- Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1), 68–78. <https://doi.org/10.1037/0003-066X.55.1.68>
- Ryan, R. M., & Deci, E. L. (2020). *Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions*. *Contemporary Educational Psychology*, 61. <https://doi.org/10.1016/j.cedpsych.2020.101860>
- Shoeib, A. F. (2022). Exploration of EFL male and female university students stand points on demotivation: A case study of Albaha University, KSA. *Shanlax International Journal of Education*, 11(1), 24–46. <https://doi.org/10.34293/education.viii.5851>
- Shurovi, M., Hasan, M. K., & Ounissi, A. (2025). Modelling the nexus between tertiary learners' socioeconomic background, social cognitive motivation and achievement-oriented behaviour. *Australian Journal of Applied Linguistics*, 8(5), 102727. <https://doi.org/10.29140/ajal.v8n5.102727>
- Song, B., & Kim, T. Y. (2017). The dynamics of demotivation and remotivation among Korean high school EFL students, *System*, 65, 90–103. <https://doi.org/10.1016/j.system.2016.12.010>
- Song, C., & Song, Y. (2023). Enhancing academic writing skills and motivation: assessing the efficacy of ChatGPT in AI-assisted language learning for EFL students. *Frontiers in Psychology*, 14, 1–14. <https://doi.org/10.3389/fpsyg.2023.1260843>
- Syifauddin, M., & Yuliansyah, A. R. (2023). The effect of using AI on students' motivation and anxiety in learning English. *Transformational Language, Literature, And Technology Overview in Learning*, 2(2), 9–15. <https://doi.org/10.55047/transtool.v2i2.1354>
- Trang, T. T. T., & Baldauf Jr, R. B. (2007). Demotivation: Understanding resistance to English language learning – the case of Vietnamese students. *The Journal of Asia TEFL*, 4(1), 79–105.
- Wang, S., & Littlewood, W. (2021). Exploring students' demotivation and remotivation in learning English, *System*, 103, 102617. <https://doi.org/10.1016/j.system.2021.102617>
- Wei, L. (2023). Artificial intelligence in language instruction: Impact on English learning achievement, L2 motivation, and self-regulated learning. *Frontiers in Psychology*, 14, 1–14. <https://doi.org/10.3389/fpsyg.2023.1261955>
- Yang, T. (2024). Impact of artificial intelligence software on English learning motivation and achievement. *SHS Web of Conferences*, 193, 1–7. <https://doi.org/10.1051/shsconf/202419302011>
- Yaşar, H., & Karagucuk, V. (2024). Exploring the relationship between artificial intelligence literacy and English language learning motivation. *International Journal of Languages Education and Teaching*, 12(4), 107–124. <https://doi.org/10.71084/ijlet.1561914>
- Zhou, W. (2024). The impact of ChatGPT on undergraduate student's English learning motivation. *Journal of Education, Humanities and Social Sciences*, 30, 33–39. <https://doi.org/10.54097/ghyk2039>