International Journal of Innovative Research and Scientific Studies, 8(6) 2025, pages: 23-33

IJIRSS
International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Effectiveness of e-counseling platforms enhanced by AI chatbots on academic self-efficacy and fear of negative evaluation among undergraduate students

Rana Suhaim Aldabbous[1], Adel Eladl[2], Ashraf Ragab Ibrahim[3*]

[1]*Department of Psychology, College of Basic Education, Public Authority for Applied Education and Training, Kuwait.*
[2]*Educational Psychology Department, Faculty of Education, Zagazig University, Egypt.*
[3]*Educational Psychology and Statistics Department, Al-Azhar University, Dakahlia, Egypt.*

Corresponding author: Ashraf Ragab Ibrahim (*Email: AshrafIbrahem.26@azhar.edu.eg*)

Abstract

Undergraduate students face significant psychological challenges, including diminished academic self-efficacy (ASE) and heightened fear of negative evaluation (FNE), which impact academic performance and university adaptation. This study evaluated the effectiveness of AI chatbot-enhanced e-counseling platforms in addressing these critical concerns among university students. A quasi-experimental design was employed with 66 undergraduate students randomly assigned to experimental (n=34) or control (n=32) groups. The experimental group received access to an AI-enhanced e-counseling platform incorporating cognitive-behavioral therapy techniques and personalized support over eight weeks, while the control group received standard university services. Participants completed assessments at pre-intervention, post-intervention, and four-week follow-up using validated measures of ASE and FNE. Results revealed significant improvements in the experimental group, with ASE scores more than doubling from baseline (M=22.85 to M=46.23) and sustained at follow-up (M=45.88). FNE significantly decreased from pre-intervention to post-intervention and follow-up. Large effect sizes were observed for ASE (η^2p=.598) and medium effects for FNE (η^2p=.156). The AI-enhanced e-counseling platform demonstrated substantial and durable effectiveness in improving psychological outcomes among university students, suggesting promising applications for scalable university mental health interventions.

Keywords: Academic self-efficacy, AI chatbots, Digital interventions, E-counseling, Fear of negative evaluation.

DOI: 10.53894/ijirss.v8i6.9481
Funding: This study received no specific financial support.
History: Received: 2 July 2025 / **Revised:** 7 August 2025 / **Accepted:** 8 August 2025 / **Published:** 26 August 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Conceptualization, methodology design, study supervision, data collection coordination, manuscript review, Rana Suhaim Aldabbous (RSA); Data analysis, statistical analysis, results interpretation, manuscript editing, Ashraf Ragab Ibrahim (ARI); Literature review, data collection, manuscript writing, final draft preparation, Adel Eladl (AE). All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Institutional Review Board Statement: The Ethical Committee of the Faculty of Education, Al-Azhar University, Egypt, has granted approval for this study (Ref. No.: EDU-REC-2025-019).
Publisher: Innovative Research Publishing

1. Introduction

The contemporary higher education landscape presents unprecedented psychological challenges for undergraduate students, with the digital age fundamentally transforming the nature and complexity of their academic and social experiences. These students face multifaceted psychological pressures, including heightened academic stress and digital apprehension that affects approximately 36% of the student population [1, 2]. The prevalence of depression and anxiety has reached alarming levels, often linked to technology misuse and the pervasive influence of digital environments on student well-being [2]. The post-pandemic transition has further intensified these challenges, creating an increased reliance on digital technologies while simultaneously exacerbating social and emotional adjustment difficulties that are characteristic of the university transition period [3, 4].

This technological paradox presents a unique dilemma for contemporary students, as technology simultaneously serves as both a facilitator of learning and a significant source of stress. Digital environments shape student identity formation and academic expectations while potentially contributing to social isolation and the development of nomophobia the fear of being without mobile phone connectivity [5, 6]. These interconnected technological and psychological challenges necessitate the development of comprehensive interventions that address both digital literacy and mental health support needs among university students.

The concept of ASE is central to understanding university student success, defined as a student's belief in their ability to successfully perform academic tasks and navigate educational challenges [7, 8]. This psychological construct is a fundamental cornerstone for academic achievement, directly influencing student retention rates, academic performance trajectories, and overall psychological well-being during the critical transition period to higher education [9-11]. Extensive research consistently demonstrates that students possessing higher levels of ASE achieve superior academic performance outcomes, exhibit greater persistence when facing academic challenges, and experience significantly reduced dropout rates compared to their peers with lower self-efficacy beliefs [12, 13].

The protective functions of ASE extend beyond mere academic performance, serving as a crucial buffer against academic stress while promoting effective emotional regulation strategies. Students with robust self-efficacy beliefs demonstrate enhanced resilience, which proves essential for navigating the complex and often overwhelming demands of university life [14, 15]. However, several interconnected factors contribute to diminished ASE among undergraduate students, creating significant barriers to successful university adaptation. High stress levels combined with inadequate stress management skills substantially undermine students' confidence in their academic abilities, while learning difficulties such as ADHD and specific learning disabilities further compromise the development of healthy self-efficacy beliefs [14, 16].

The social and environmental context of university education plays an equally critical role in self-efficacy development. Insufficient social support networks and unfamiliar or unsupportive educational environments significantly hinder students' belief in their capabilities and impede their successful adaptation to university demands [15, 16]. The relationship between ASE and university adaptation operates bidirectionally, as students with higher self-efficacy demonstrate enhanced utilization of effective learning strategies, superior time management skills, and better emotional regulation capabilities, ultimately facilitating smoother transitions to the rigorous demands of higher education [17-19].

Complementing the challenges related to ASE is the pervasive issue of FNE, which represents the persistent anxiety and dread individuals experience regarding potential unfavorable judgments from others, particularly within evaluative social contexts [20, 21]. In academic environments, FNE manifests through students' reluctance to participate actively in class discussions, hesitation to ask clarifying questions, and avoidance of collaborative group activities due to overwhelming fears of criticism, embarrassment, or social judgment [20, 22].

Undergraduate students demonstrate heightened vulnerability to FNE, with certain marginalized populations experiencing disproportionately elevated levels of evaluative anxiety. These populations include first-generation college students, LGBTQ+ individuals, and students with disabilities, who face additional layers of social and academic pressure [23]. Students experiencing high levels of FNE exhibit characteristic behavioral patterns, including excessive overthinking of responses, significantly reduced classroom participation, and increased anxiety during presentations or when called upon individually during class sessions [22, 23].

The relationship between FNE and academic performance demonstrates a consistently negative correlation, with higher evaluative fear associated with diminished academic outcomes and reduced educational satisfaction [21, 24]. This detrimental relationship is mediated by several psychological factors, including academic motivation, self-esteem levels, and self-efficacy beliefs, which can either buffer against or exacerbate FNE's negative effects on student success [24-26]. Furthermore, FNE significantly impairs students' help-seeking behaviors and willingness to engage in meaningful classroom participation, as fear of negative judgment prevents them from accessing crucial academic support resources and learning opportunities [27, 28]. This creates a self-perpetuating cyclical pattern where reduced engagement leads to continued academic difficulties, particularly affecting marginalized student populations and potentially widening existing achievement gaps [22, 29].

Despite the clear need for psychological support services, university students encounter significant barriers when accessing traditional counseling services. These barriers include a lack of familiarity with available campus services, feelings of discomfort when discussing emotional concerns, and pronounced stigma concerns related to seeking mental health support [30, 31]. Cultural and generational factors substantially influence help-seeking behaviors, with first-generation college students and minority populations experiencing additional challenges related to cultural norms, language barriers, and the negative perceived value of traditional counseling services [32, 33]. Practical obstacles, including extended appointment wait times, financial constraints, limited session availability, and various structural barriers, further impede students' access to essential mental health support services [34, 35].

In response to these accessibility challenges, e-counseling platforms have evolved significantly in recent years, utilizing advanced digital technologies, including video conferencing systems, interactive chat interfaces, and sophisticated mobile applications to deliver accessible and convenient mental health support services [36, 37]. These innovative platforms offer distinct advantages over traditional face-to-face counseling services, including significantly greater accessibility, reduced stigma barriers, enhanced convenience and flexibility, and the unique ability to reach students who actively avoid in-person services due to social discomfort or logistical constraints [38, 39]. Research evidence demonstrates that both traditional face-to-face counseling and web-based e-counseling approaches effectively improve student mental health outcomes, with e-counseling providing valuable alternatives for students facing barriers to conventional service access, though some studies suggest that face-to-face counseling may be preferred for specific populations or particular types of psychological issues [40, 41].

Integrating artificial intelligence (AI) chatbots into e-counseling platforms represents a significant technological advancement in mental health service delivery. AI chatbots are sophisticated computer programs that utilize natural language processing capabilities and machine learning algorithms to simulate human conversation patterns, and they are increasingly being integrated into mental health services to provide accessible, immediate psychological support to users [42]. These advanced systems possess comprehensive capabilities, including psychoeducation delivery, implementation of cognitive-behavioral therapy techniques, systematic symptom screening, continuous mood tracking, and the provision of personalized coping strategies through sophisticated emotion recognition technology [43, 44].

AI chatbots effectively complement human counseling services by offering continuous 24/7 availability, reducing stigma-related barriers to help-seeking, providing essential first-line support and triage services, while facilitating appropriate referrals to professional counseling services when more complex therapeutic interventions are required [45, 46]. Research demonstrates that AI-powered chatbots significantly enhance e-counseling platform effectiveness by providing accessible, scalable, and immediate support that directly addresses traditional counseling barriers prevalent in educational settings [47, 48]. Evidence indicates that AI-powered chatbots effectively reduce student anxiety through real-time emotional support and personalized guidance, with students reporting anxiety reduction levels comparable to human counselor interactions during initial counseling phases [43, 49].

These innovative platforms overcome stigma-related barriers while providing anonymous access to mental health resources, demonstrating cost-effectiveness and continuous availability [50]. Furthermore, AI chatbots facilitate academic and career guidance services, assist in counselor training through interactive role-play scenarios, and demonstrate strong user acceptance rates among student populations. However, they remain most effective as complementary tools rather than complete replacements for human counselors in comprehensive treatment approaches [51, 52]. Integrating AI chatbots with traditional e-counseling platforms creates a hybrid model that maximizes the strengths of both technological innovation and human therapeutic expertise, potentially offering students a comprehensive support system that addresses their unique developmental and academic needs.

Despite the growing body of literature documenting the individual benefits of e-counseling platforms and AI chatbots in educational settings, there remains a significant gap in empirical research examining the combined effectiveness of AI-enhanced e-counseling platforms specifically targeting ASE and FNE among undergraduate students. While previous studies have explored these technologies and psychological constructs separately, limited research has investigated their integrated impact through rigorous experimental designs. Furthermore, there is insufficient evidence regarding the sustained effects of such interventions, as most existing studies focus on immediate post-intervention outcomes without examining long-term maintenance of therapeutic gains. This research gap is particularly pronounced in understanding how AI-enhanced e-counseling platforms might differentially impact diverse student populations and whether such interventions can produce lasting changes in ASE and FNE beyond the immediate intervention period.

The primary objective of this study is to evaluate the effectiveness of AI chatbot-enhanced e-counseling platforms in improving ASE and reducing FNE among undergraduate students through a comprehensive quasi-experimental research design. This study employs a controlled methodology utilizing two groups: a control group receiving standard university support services and an experimental group receiving access to AI-enhanced e-counseling interventions. This comprehensive approach aims to provide robust empirical evidence regarding the potential of AI-enhanced e-counseling platforms to address critical psychological challenges faced by university students while contributing valuable insights to the emerging field of digital mental health interventions in higher education settings.

2. Method

2.1. Participants

The study employed a two-phase sampling approach to establish both psychometric validation and experimental investigation. For the psychometric validation phase, a comprehensive sample of 427 undergraduate students was recruited, consisting of 125 males and 302 females. This validation sample was drawn from two educational institutions: 240 students from the Faculty of Education at Al-Azhar University in Dakahlia, Egypt, and 187 students from the College of Basic Education at the Public Authority for Applied Education and Training in Kuwait. The sample included 160 students from practical specializations and 267 from theoretical specializations, with ages ranging from 18 to 19 years (M = 18.19, SD = 0.399).

The primary sample consisted of 66 undergraduate students randomly assigned to either the experimental group (n = 34) or the control group (n = 32). The experimental group included 26 males and 40 females, with 32 students recruited from Al-Azhar University's College of Education in Dakahlia and 34 from the College of Basic Education in Kuwait. Academic specializations were distributed as 30 students in practical fields and 36 in theoretical fields. Participants' ages ranged from 18 to 19 years (M = 18.13, SD = 0.345).

2.2. Measures

2.2.1. Academic Self-Efficacy Scale

ASE was assessed using the scale developed by Hemade et al. [53] a 9-item instrument designed to measure students' confidence in their ability to perform academic tasks effectively. The scale employs a 7-point Likert response format ranging from 1 (strongly disagree) to 7 (strongly agree), with higher scores indicating grseater ASE. Comprehensive psychometric validation was conducted to ensure the scale's appropriateness for the current sample. Confirmatory factor analysis supported a unidimensional structure with acceptable model fit indices: CFI = .961, TLI = .949, NFI = .951, and RMSEA = .078. Standardized factor loadings ranged from .409 to .885, with the majority of items demonstrating strong loadings above .70. Internal consistency reliability was excellent across multiple indices, including Cronbach's alpha (α = .912), McDonald's omega (ω = .917), and Guttman's lambda-2 ($\lambda 2$ = .917). Additional psychometric support was provided by construct reliability (CR = .917) and average variance extracted (AVE = .563), with inter-item correlations ranging from .496 to .873, indicating appropriate internal consistency without problematic multicollinearity.

2.2.2. Brief Fear of Negative Evaluation Scale

FNE was measured using the Brief Fear of Negative Evaluation Scale-II (BFNE-II) Carleton et al. [54], a revised version of Leary [55] original scale. This 12-item self-report instrument assesses participants' fear of being negatively evaluated by others, with all items rephrased as straightforward statements to eliminate reverse-worded items and improve psychometric properties. Respondents rate each item on a 5-point Likert scale ranging from 0 (Not at all characteristic of me) to 4 (Extremely characteristic of me), with higher scores indicating greater FNE. Psychometric validation for the current sample demonstrated strong measurement properties. Confirmatory factor analysis supported a unidimensional structure with acceptable model fit indices: CFI = .950, TLI = .939, NFI = .936, and RMSEA = .075. Standardized factor loadings ranged from .650 to .813, with most items showing strong factor loadings above .70. Internal consistency reliability was excellent, with Cronbach's alpha (α = .942), McDonald's omega (ω = .942), and Guttman's lambda-2 ($\lambda 2$ = .942), all exceeding recommended thresholds. Additional psychometric support was provided by CR = .942 and AVE = .576.

2.3. Design and Procedures

This study employed a quasi-experimental design with a mixed-methods approach, utilizing both between-subjects and within-subjects factors. The between-subjects factor consisted of group assignment (experimental vs. control). In contrast, the within-subjects factor involved repeated measurements across three time points: pre-intervention (baseline), post-intervention (immediately following the 8-week intervention), and follow-up (4 weeks post-intervention) to assess the maintenance of therapeutic gains.

Participants were recruited systematically and collaboratively with academic advisors and student services departments at both participating institutions. Initial recruitment presentations were conducted during orientation sessions for university students, emphasizing the voluntary nature of participation and the potential benefits of the research for student well-being. Interested students completed a comprehensive screening questionnaire to ensure eligibility criteria were met, including university enrollment status, absence of severe psychological disorders requiring immediate clinical intervention, and basic technological literacy necessary for platform navigation.

Following recruitment, all participants completed baseline assessments during individual sessions in private, comfortable settings within each institution's student counseling centers. The sessions lasted approximately 45 minutes and included administering both primary outcome measures and demographic questionnaires, as well as a comprehensive orientation to the study procedures. Participants received detailed explanations of the intervention timeline, expectations for engagement, and procedures for accessing technical support throughout the study period.

The experimental group received access to an innovative AI-enhanced e-counseling platform specifically designed for university students. This platform integrated evidence-based cognitive-behavioral therapy techniques with advanced AI capabilities to provide personalized, responsive mental health support. The AI chatbot component utilized natural language processing algorithms trained on validated therapeutic protocols, enabling dynamic conversation flows adapted to individual student responses and emotional states. The platform featured multiple interactive modules addressing academic stress management, social anxiety reduction, study skills enhancement, and peer relationship building.

Participants in the experimental group were provided with secure login credentials and completed a comprehensive platform orientation session conducted by trained research assistants. This 90-minute orientation included hands-on navigation training, privacy and confidentiality explanations, and practice interactions with the AI chatbot to ensure comfort with the technology. Students were encouraged to engage with the platform for a minimum of 30 minutes per week over the 8-week intervention period, though access was unlimited to accommodate varying schedules and preferences. The platform tracked engagement metrics, including session frequency, duration, and module completion rates, to monitor adherence and identify students requiring additional support.

The AI chatbot was programmed to provide personalized feedback based on user responses, offer evidence-based coping strategies tailored to specific challenges, and facilitate skill-building exercises targeting ASE and social confidence. Advanced features included mood tracking capabilities, personalized goal-setting modules, and automated check-ins to maintain engagement and monitor psychological well-being. The system was designed to recognize responses indicating potential crisis situations and included appropriate referral protocols to human counselors when necessary.

Control group participants continued to receive standard university support services, including access to traditional counseling centers, academic advising, and peer support programs typically available to university students. These participants completed the same assessment schedule as the experimental group but did not receive access to the AI-enhanced platform during the intervention period. To maintain engagement and ensure ethical research practices, control group participants were offered access to the platform following the completion of the follow-up assessment.

Post-intervention assessments were conducted immediately following the 8-week intervention period using identical procedures and measures as the baseline assessment. These sessions were scheduled within one week of intervention completion to capture immediate effects while minimizing potential confounding variables. Participants in both groups completed comprehensive evaluation sessions lasting approximately 60 minutes, including the administration of outcome measures and qualitative feedback questionnaires regarding their experiences during the study period.

Follow-up assessments were conducted four weeks after the post-intervention measurement to evaluate the maintenance and durability of any observed treatment effects. These sessions followed identical protocols to previous assessments, emphasizing understanding participants' continued use of learned strategies and any ongoing academic and social adjustment challenges. After completing all assessments, participants received comprehensive debriefing sessions, personalized feedback on their progress, and recommendations for continued support resources.

2.4. Data Analysis

The primary analytical approach utilized repeated measures analysis of variance (ANOVA) with Bonferroni adjustment for multiple comparisons to control Type I error inflation. This analytical strategy examined main effects of time (pre-intervention, post-intervention, follow-up), group (experimental vs. control), and time × group interactions for both primary outcome variables. Effect sizes were calculated using partial eta-squared (η^2p) for ANOVA results and Cohen's d for pairwise comparisons to evaluate practical significance alongside statistical significance. Additional analyses included examination of potential moderating variables such as gender, academic specialization, and institutional affiliation to identify factors influencing intervention effectiveness. The significance level was set at $\alpha = .05$ for all statistical tests, with Bonferroni correction applied to maintain familywise error rate across multiple comparisons.

3. Results

The analysis examined the effectiveness of AI-enhanced e-counseling platforms on ASE and FNE among undergraduate students through a comprehensive repeated measures design. Descriptive statistics revealed substantial differences in treatment outcomes between experimental and control groups across the three measurement time points, with the experimental group demonstrating considerable improvements in both primary outcome variables following the intervention period.

As presented in Table 1, baseline measurements indicated comparable starting points between groups for both ASE (experimental group: M = 22.85, SD = 6.31; control group: M = 23.31, SD = 5.80) and FNE (experimental group: M = 20.55, SD = 1.46; control group: M = 20.71, SD = 1.83). However, marked divergences emerged following the intervention period. The experimental group exhibited dramatic increases in ASE from pre-intervention to post-intervention (M = 46.23, SD = 7.86), representing more than a doubling of baseline scores, while the control group remained relatively stable (M = 24.37, SD = 6.60). These substantial gains were largely maintained at the four-week follow-up assessment (experimental group: M = 45.88, SD = 8.30; control group: M = 24.96, SD = 6.88), indicating durable treatment effects.

Table 1.
Descriptive Statistics for ASE and FNE Across Time Points.

Variable	Group	Pre-intervention		Post-intervention		Follow-up	
		M	SD	M	SD	M	SD
ASE	Experimental	22.85	6.31	46.23	7.86	45.88	8.30
	Control	23.31	5.80	24.37	6.60	24.96	6.88
FNE	Experimental	20.55	1.46	17.77	4.22	17.00	4.23
	Control	20.71	1.83	20.21	2.15	19.84	2.49

Note: M = Mean, SD = Standard Deviation.

Regarding FNE, the experimental group demonstrated meaningful reductions from baseline levels, with scores decreasing from 20.55 to 17.77 immediately post-intervention and further declining to 17.00 at follow-up assessment. Conversely, the control group showed minimal change across time points, with scores remaining relatively stable throughout the study period (baseline: M = 20.71; post-intervention: M = 20.21; follow-up: M = 19.84).

The repeated measures ANOVA results, summarized in Table 2, revealed statistically significant effects across all examined factors for both outcome variables. For ASE, significant main effects emerged for time ($F(2, 128) = 119.980$, $p = .01$, $\eta^2p = .652$) and group ($F(1, 64) = 159.997$, $p = .01$, $\eta^2p = .836$), accompanied by a significant time × group interaction ($F(2, 128) = 95.019$, $p = .01$, $\eta^2p = .598$). These findings indicate that the intervention produced differential effects between groups across time, with large effect sizes suggesting substantial practical significance. Similarly, FNE demonstrated significant main effects for time ($F(2, 128) = 28.127$, $p = .01$, $\eta^2p = .305$) and group ($F(1, 64) = 17.248$, $p = .01$, $\eta^2p = .354$), along with a significant time × group interaction ($F(2, 128) = 11.835$, $p = .01$, $\eta^2p = .156$), though with smaller effect sizes compared to ASE.

Table 2.
Repeated Measures ANOVA Results for ASE and FNE.

Variable	Source	df	F	p	η²p
ASE	Time	2	119.980	0.01	.652
	Group	1	159.997	0.01	.836
	Time × Group	2	95.019	0.01	.598
	Error	128	---	---	---
FNE	Time	2	28.127	0.01	.305
	Group	1	17.248	0.01	.354
	Time × Group	2	11.835	0.01	.156
	Error	128	---	---	---

Note: df = degrees of freedom, η²p = partial eta squared effect size.

The pairwise comparisons with Bonferroni adjustment, detailed in Table 3, provide crucial insights into the specific nature and timing of treatment effects within each group. For the experimental group, ASE demonstrated significant improvements from pre-intervention to post-intervention (mean difference = -23.382, p = .01, 95% CI [-26.071, -20.694]) and from pre-intervention to follow-up (mean difference = -23.029, p = .01, 95% CI [-26.201, -19.858]). Notably, no significant difference was observed between post-intervention and follow-up measurements (mean difference = 0.353, p = 1.000), indicating stable maintenance of therapeutic gains over the four-week follow-up period. In contrast, the control group exhibited no significant changes across any time point comparisons, with all p-values exceeding the adjusted significance threshold.

Table 3.
Pairwise Comparisons of Treatment Effects with Bonferroni Adjustment.

Variable	Group	Comparison	Mean Difference	SE	p	95% CI	
						Lower	Upper
ASE	Experimental	Pre vs. Post	-23.38*	1.09	0.01	-26.07	-20.69
		Pre vs. Follow-up	-23.02*	1.29	.01	-26.20	-19.85
		Post vs. Follow-up	0.35	1.42	1.00	-3.14	3.84
	Control	Pre vs. Post	-1.06	1.12	1.00	-3.83	1.70
		Pre vs. Follow-up	-1.65	1.33	0.65	-4.92	1.61
		Post vs. Follow-up	-0.59	1.46	1.00	-4.19	3.00
FNE	Experimental	Pre vs. Post	3.11*	0.48	0.01	1.91	4.31
		Pre vs. Follow-up	3.55*	0.52	0.01	2.27	4.84
		Post vs. Follow-up	0.44	0.25	0.26	-0.18	1.06
	Control	Pre vs. Post	0.50	0.50	0.97	-0.73	1.73
		Pre vs. Follow-up	0.87	0.53	0.32	-0.44	2.19
		Post vs. Follow-up	0.37	0.26	0.47	-0.27	1.02

Note: SE = Standard Error, CI = Confidence Interval, p < .01 after Bonferroni adjustment.

For FNE within the experimental group, significant reductions were observed from pre-intervention to post-intervention (mean difference = 3.118, $p = .01$, 95% CI [1.916, 4.319]) and from pre-intervention to follow-up (mean difference = 3.559, $p = .01$, 95% CI [2.277, 4.841]). The lack of a significant difference between post-intervention and follow-up measurements (mean difference = .441, $p = .267$) suggests sustained treatment benefits. The control group again showed no significant changes across any comparison time points, reinforcing the specificity of treatment effects to the intervention group.

Between-group comparisons at each time point, presented in Table 4, further illuminate the differential impact of the intervention. At baseline, no significant differences existed between groups for either ASE (mean difference = -0.460, $p = 0.760$) or FNE (mean difference = -0.160, $p = 0.696$), confirming appropriate randomization and group equivalence. However, substantial between-group differences emerged at post-intervention for both ASE (mean difference = 21.860, $p = 0.01$, 95% CI [18.276, 25.444]) and FNE (mean difference = -2.778, $p = 0.01$, 95% CI [-4.441, -1.114]). These differences were maintained at the follow-up assessment, with ASE showing a mean difference of 20.914 ($p = 0.01$, 95% CI [17.149, 24.678]) and FNE demonstrating a mean difference of -2.844 ($p = 0.01$, 95% CI [-4.566, -1.122]).

Table 4.
Between-Group Pairwise Comparisons at Each Time Point with Bonferroni Adjustment.

Variable	Time Point	Mean Difference	SE	p	95% CI	
					Lower	Upper
ASE	Pre-intervention	-0.460	1.49	0.76	-3.44	2.52
	Post-intervention	21.860*	1.79	0.01	18.27	25.44
	Follow-up	20.914*	1.88	0.01	17.14	24.67
FNE	Pre-intervention	-0.160	0.40	0.69	-0.97	0.65
	Post-intervention	-2.778*	0.83	0.01	-4.44	-1.11
	Follow-up	-2.844*	0.86	0.01	-4.56	4.56

The pattern of results demonstrates that the AI-enhanced e-counseling intervention produced substantial and sustained improvements in both primary outcome variables. The large effect sizes observed for ASE ($\eta^2p = .598$ for the time × group interaction) indicate that the intervention accounted for approximately 60% of the variance in treatment response, representing a robust therapeutic effect. While the effect sizes for FNE were smaller ($\eta^2p = .156$), they still exceeded conventional thresholds for medium effects and demonstrated practical significance in reducing evaluative anxiety among university students.

4. Discussion

The findings of this study provide compelling evidence for the effectiveness of AI-enhanced e-counseling platforms in improving ASE and reducing FNE among undergraduate students. The substantial improvements observed in the experimental group, coupled with the sustained effects at follow-up, suggest that these technological interventions represent a promising approach to addressing the psychological challenges inherent in the university transition period.

The dramatic increase in ASE scores within the experimental group, representing more than a doubling from baseline measurements, aligns closely with emerging research demonstrating the positive impact of AI chatbot support on student confidence and academic capabilities. These findings are consistent with Bation [56] research, which identified statistically significant improvements in self-efficacy among college students receiving chatbot support, particularly when the chatbot provided effective interaction and query resolution. The sustained nature of these improvements at the four-week follow-up assessment suggests that the AI-enhanced platform successfully facilitated the development of durable psychological resources rather than merely providing temporary support. This durability is particularly significant given that ASE serves as a foundational element for long-term academic success and psychological well-being throughout the university experience.

The mechanisms underlying these improvements appear to be multifaceted, involving both direct therapeutic interventions and enhanced engagement with support resources. Chang et al. [52] demonstrated that chatbots incorporating goal setting, feedback, and personalization features effectively promote self-regulated learning and enhance self-efficacy beliefs. The current study's AI platform incorporated similar evidence-based features, including personalized feedback systems, individualized goal-setting modules, and adaptive therapeutic responses based on student input. This technological sophistication likely contributed to the platform's effectiveness by providing students with immediate, tailored support that addressed their specific academic concerns and learning needs. Furthermore, the continuous availability of the platform may have addressed one of the primary barriers to traditional counseling services accessibility and convenience thereby enabling students to engage with therapeutic resources at optimal times for their individual schedules and emotional needs.

The reduction in FNE, while demonstrating smaller effect sizes compared to ASE improvements, nonetheless represents a meaningful therapeutic outcome with significant implications for student engagement and academic performance. Although the available literature provides limited direct evidence regarding AI chatbots' impact on FNE specifically, the current findings suggest that the anonymity and accessibility inherent in AI-enhanced platforms may effectively reduce barriers to help-seeking behavior that are often exacerbated by evaluative anxiety. This interpretation is supported by research indicating that students' willingness to engage with digital support systems is influenced by perceived ease of use and reduced social pressure, factors that are particularly relevant for individuals experiencing high levels of evaluative fear.

The sustained improvements in both outcome variables at the four-week follow-up assessment are particularly noteworthy, as they suggest that the intervention facilitated genuine skill acquisition and psychological growth rather than temporary symptom relief. This pattern of maintained therapeutic gains indicates that participants successfully internalized the coping strategies and cognitive restructuring techniques delivered through the AI platform, enabling continued benefit even after the formal intervention period concluded. The stability of these improvements stands in contrast to some traditional counseling interventions where therapeutic effects may diminish over time without ongoing support, suggesting that AI-enhanced platforms may offer unique advantages in promoting lasting psychological change.

However, the current findings must be interpreted within the context of existing research examining both the benefits and limitations of AI-based therapeutic interventions. While studies have consistently demonstrated the effectiveness of AI chatbots in improving various aspects of student well-being and academic performance, researchers have also identified important considerations regarding the appropriate scope and application of such technologies. The integration of AI chatbots with human counseling services, as implemented in the current study's platform, appears to maximize the strengths of both technological innovation and human therapeutic expertise while mitigating potential limitations of purely automated interventions.

The substantial effect sizes observed for ASE improvements, accounting for approximately 60% of the variance in treatment response, suggest that AI-enhanced e-counseling platforms may be particularly effective for addressing confidence and competency-related academic challenges. This finding has important implications for university support services, as ASE difficulties are prevalent among university students and significantly impact retention rates, academic performance, and overall psychological adjustment. The scalability and cost-effectiveness of AI-enhanced platforms make them particularly attractive for addressing these widespread concerns in resource-constrained educational environments.

The differential impact observed between the two primary outcome variables, with larger effects for ASE compared to FNE may reflect the specific design characteristics of the intervention platform and the underlying psychological mechanisms involved in each construct. ASE may be more readily influenced by the structured, goal-oriented features of AI chatbots, which can provide immediate feedback on academic tasks and facilitate skill-building exercises. In contrast, FNE involves deeply ingrained social and emotional patterns that may require more intensive or prolonged therapeutic intervention to achieve substantial change.

The study's findings also contribute to the growing understanding of how digital mental health interventions can effectively complement traditional counseling services in university settings. The hybrid model implemented in this research, which combined AI chatbot capabilities with access to human counselors when needed, may represent an optimal approach for addressing the diverse and complex needs of undergraduate students. This integration allows for the scalability and accessibility advantages of AI technology while maintaining the therapeutic depth and nuanced understanding that human counselors provide for more complex psychological issues.

Despite the promising outcomes observed in this study, several important considerations must be acknowledged when interpreting these findings and planning future implementations. The relatively short follow-up period, while adequate for demonstrating initial maintenance of therapeutic gains, may not capture longer-term outcomes or potential delayed effects of the intervention. Additionally, the study's focus on undergraduate students, while addressing a critical population, limits the generalizability of findings to other student populations or educational contexts. Future research should examine the effectiveness of AI-enhanced e-counseling platforms across diverse academic levels, cultural contexts, and psychological presenting concerns to establish the broader applicability of these interventions.

The implications of these findings extend beyond individual therapeutic outcomes to encompass broader considerations for university mental health service delivery and educational policy. The demonstrated effectiveness of AI-enhanced platforms suggests that educational institutions may benefit from integrating such technologies into their comprehensive student support systems, potentially expanding access to mental health resources while maintaining cost-effectiveness. However, careful attention must be paid to issues of privacy, data security, and ethical considerations in the implementation of AI-based therapeutic interventions, particularly given the sensitive nature of mental health information and the vulnerability of the student populations being served.

In conclusion, this study provides robust empirical evidence supporting the effectiveness of AI-enhanced e-counseling platforms for improving ASE and reducing FNE among undergraduate students. The substantial and sustained improvements observed in both outcome variables, coupled with large effect sizes and maintained therapeutic gains at follow-up, suggest that these technological interventions represent a valuable addition to traditional university mental health services. The integration of AI capabilities with evidence-based therapeutic approaches appears to offer unique advantages in addressing the accessibility, scalability, and effectiveness challenges that have historically limited the reach of mental health interventions in higher education settings. As universities continue to grapple with increasing demands for student mental health support amid resource constraints, AI-enhanced e-counseling platforms may provide a promising pathway for expanding access to effective psychological interventions while maintaining therapeutic quality and promoting meaningful, lasting change in student well-being and academic success.

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