

The Effectiveness of AI-Assisted Classroom Guidance Services in Improving Academic Resilience among Junior High School Students

Elin Maulida Rahmawati¹, Andi Kiswanto², Mumu Muzayyin Maq³, Reri Taria Nurhaliza⁴

^{1,2,3,4}Universitas Nahdlatul Ulama Cirebon, Jawa Barat, Indonesia

Article Info

Article history:

Received 2026-09-04

Revised 2026-09-23

Accepted 2026-10-07

Keywords:

Academic Resilience

Artificial Intelligence

AI-Assisted Counseling

Classical Guidance

Junior High School Students

ABSTRACT

Academic resilience is an important psychological capacity that enables students to adapt to academic pressure, difficulties, and failure. This study examined the effectiveness of an AI-assisted 5C-based classical guidance service in improving academic resilience among junior high school students. A quasi-experimental pretest-posttest control group design was conducted involving 62 eighth-grade students at SMP Negeri 15 Kota Cirebon, Indonesia. Participants were selected from two intact classes, with 31 students assigned to the experimental group and 31 students to the control group. The experimental group received five classical guidance sessions based on Martin and Marsh's 5C framework: Confidence, Coordination, Control, Composure, and Commitment, supported by the RESILIA-BK AI-assisted guidance application. Academic resilience was measured using a 32-item scale based on Cassidy's framework. Data were analyzed using descriptive statistics, independent-samples t-test, and ANCOVA with pretest scores as covariates. The experimental group increased from Mean = 95.65 to Mean = 104.74, while the control group increased from Mean = 94.97 to Mean = 98.00. ANCOVA results showed a significant difference in adjusted posttest scores between groups, $F(1,59) = 36.989$, $p < .001$, partial $\eta^2 = .385$. The findings indicate that AI-assisted classical guidance may serve as a complementary approach to strengthen students' academic resilience under counselor supervision.

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Corresponding Author:

Elin Maulida Rahmawati

Guidance and Counseling Education Study Program, Faculty of Teacher Training and Education, Nahdlatul Ulama University of Cirebon, West Java, Indonesia

Email: elin@unucirebon.ac.id

1. INTRODUCTION

Students' success in education is influenced not only by cognitive abilities and mastery of learning materials but also by psychological capacities that enable them to cope with pressure, failure, and various academic demands. At the junior high school (SMP) level,

students experience significant cognitive, emotional, and social developmental changes while simultaneously facing increasingly complex academic expectations. Academic pressure that is not managed adaptively may contribute to anxiety, decreased motivation, difficulty maintaining effort, and negative emotional responses [1]. Therefore, students' ability to persevere, adapt, and re-engage constructively in learning activities represents an important psychological resource for successful academic development.

One psychological capacity closely related to students' ability to cope with academic challenges is academic resilience. Academic resilience refers to an individual's capacity to respond adaptively to academic pressure and adversity. Martin and Marsh [2] explained that students may demonstrate different responses when encountering unfavorable academic conditions; some experience prolonged difficulties, whereas others are able to recover and maintain their academic development. Thus, academic resilience is not merely the ability to endure difficulties but also involves maintaining effort, regulating emotional responses, and adapting effectively when facing academic obstacles. Furthermore, academic resilience has been associated with students' psychological well-being and academic achievement [3].

Martin and Marsh [2] proposed five psychological factors that contribute to students' ability to overcome academic difficulties, including self-efficacy, planning, control, low anxiety, and persistence. In this study, these factors are operationalized through the 5C framework consisting of Confidence, Coordination, Control, Composure, and Commitment. Confidence reflects students' beliefs regarding their academic abilities, which influence persistence and responses toward academic challenges. Coordination refers to students' ability to establish academic goals and organize learning strategies, while control represents their ability to regulate aspects of learning that can be managed. Composure relates to emotional regulation when facing academic pressure, and Commitment reflects students' willingness to maintain effort in achieving academic goals. Recent research highlights that academic self-efficacy contributes significantly to students' engagement, persistence, and adaptive responses during learning processes [4]. Furthermore, these components are closely associated with self-regulated learning processes, where students establish goals, monitor progress, regulate emotions, and adjust learning strategies according to academic demands [5]. Therefore, the 5C framework provides a relevant theoretical foundation for designing interventions aimed at strengthening academic resilience.

Academic resilience develops through interactions between individual characteristics and environmental support. Previous studies have demonstrated that academic resilience is associated with various contextual and psychological factors. Parental support has been identified as an important factor related to junior high school students' academic resilience [6], while learning motivation also contributes significantly to resilience development [7]. Other studies have highlighted the contribution of emotion regulation and family social support [8], as well as self-efficacy and social support among junior high school students [9]. These findings indicate that academic resilience is not a fixed personal attribute but can be strengthened through structured educational experiences that facilitate self-belief, adaptive strategies, emotional regulation, and perseverance.

Within the educational context, guidance and counseling services play an important role in facilitating students' personal, social, academic, and career development. Guidance

and counseling services are not limited to problem-solving but also function as preventive and developmental interventions that support students' optimal growth [10]. One service format that enables counselors to provide systematic interventions for groups of students is classical guidance. Through classical guidance, counselors can facilitate students' self-understanding, learning strategy development, emotional management, and adaptive decision-making. Previous studies have demonstrated that classical guidance services can support improvements in students' self-confidence and learning enthusiasm [11] and enhance learning motivation [12]. Furthermore, comprehensive school counseling programs contribute to students' academic and developmental outcomes [13].

However, the implementation of classical guidance services faces challenges in adapting to students' characteristics within increasingly digital educational environments. Contemporary students are accustomed to interactive digital experiences, creating opportunities for counseling services to adopt more responsive and reflective approaches. Artificial Intelligence (AI) has emerged as a technology with potential applications in education by supporting personalized interaction, immediate feedback, and reflective learning experiences when integrated within appropriate pedagogical frameworks [14]. Large language models, including ChatGPT-based systems, also provide opportunities to support explanation, feedback, and dialogic learning processes, although their implementation requires pedagogical control and ethical considerations [15].

Research on AI in education indicates that AI can support personalization and learning processes; however, its effectiveness depends on pedagogical design, users' technological literacy, and appropriate risk management [16], [17]. Therefore, AI should be positioned as a complementary technology that enhances human decision-making rather than replacing professional expertise [15]. In school counseling contexts, responsible AI implementation requires adequate AI literacy among counselors to ensure ethical, meaningful, and pedagogically appropriate utilization [18].

In the context of classical guidance services, AI may provide additional value through several mechanisms that strengthen counselor-led interventions. First, AI can facilitate personalized reflective interaction by providing structured prompts that encourage students to identify academic difficulties, recognize personal strengths, and evaluate possible coping strategies. Second, AI can support cognitive exploration by assisting students in generating alternative perspectives and problem-solving options when encountering academic challenges. Third, AI can increase students' active engagement during guidance activities by providing immediate responses and opportunities for self-reflection within structured learning scenarios. Through these mechanisms, AI functions as an interactive reflective scaffold that supports students' metacognitive awareness, emotional regulation, and adaptive decision-making. Nevertheless, AI remains a supportive instrument under counselor supervision and does not replace the professional role of counselors in interpreting students' conditions, providing emotional support, and facilitating meaningful change.

The integration of AI into guidance and counseling has received increasing attention in recent years. AI literacy has been identified as an important competency for school counselors in adapting to technological developments [19]. Previous studies have also discussed the potential role of AI in supporting guidance services [20] and emphasized

ethical considerations related to Generative AI implementation in counseling contexts [21]. These studies suggest that AI offers promising opportunities for improving counseling services; however, its implementation must remain aligned with pedagogical objectives, ethical principles, and professional counselor supervision.

Despite increasing interest in AI applications in education and counseling, empirical evidence regarding AI-supported counselor-led interventions remains limited. Previous studies on academic resilience have primarily focused on identifying relationships between resilience and psychological factors or evaluating conventional counseling approaches. For example, academic resilience among junior high school students has been examined during limited face-to-face learning contexts [22]. Intervention studies have also explored self-management strategies in individual counseling [23] and cognitive restructuring techniques in group counseling [24]. Meanwhile, studies related to AI in guidance and counseling have predominantly focused on technology literacy, implementation possibilities, and ethical issues rather than empirical evaluation of AI-assisted interventions. Previous reviews have indicated that empirical studies examining human-centered AI implementation in education remain limited, particularly those integrating AI with structured pedagogical interventions [25]. In mental health-related contexts, AI-based chatbot systems have demonstrated potential to support interaction and psychological support; however, professional supervision remains essential to ensure safe and appropriate implementation [26].

Therefore, further empirical investigation is needed to understand how AI assistants can be integrated into structured classical guidance services to strengthen students' academic resilience. This study addresses this gap by examining an AI-assisted classical guidance intervention based on Martin and Marsh's 5C framework. In this intervention, RESILIA-BK functions as an AI-assisted reflective support tool that facilitates students' exploration of academic challenges, development of alternative solutions, and formulation of adaptive responses under counselor supervision.

The novelty of this study lies in the integration of three components: (1) Martin and Marsh's 5C framework as the theoretical foundation for strengthening academic resilience, (2) classical guidance services as a counselor-led developmental intervention, and (3) AI-assisted reflective support through RESILIA-BK as a complementary mechanism to enhance student engagement and adaptive problem-solving. This integrated approach provides empirical evidence regarding the potential role of AI in supporting school counseling practices while maintaining the essential role of professional counselors.

Based on the background above, this study aims to evaluate the effectiveness of AI-assisted classical guidance services in improving junior high school students' academic resilience. Specifically, this study compares changes in academic resilience between students who received AI-assisted classical guidance and those who participated in classical guidance without AI assistance. It was hypothesized that, after controlling for baseline academic resilience scores, students in the experimental group would demonstrate significantly higher academic resilience outcomes than students in the control group.

2. METHOD

Research Design

This study employed a quantitative approach using a quasi-experimental method with a pretest-posttest control group design. This design was selected because the intervention was conducted in naturally existing classroom settings (*intact classes*), where individual random assignment was not feasible due to school administrative considerations. Quasi-experimental designs are commonly applied in educational research when researchers aim to examine intervention effects but cannot implement full randomization of participants [27].

The experimental design consisted of two groups: an experimental group receiving AI-assisted classical guidance services and a control group receiving classical guidance services without AI assistance. Both groups were measured before and after the intervention to examine changes in academic resilience. The experimental group received five sessions of AI-assisted classical guidance, while the control group received classical guidance with equivalent objectives and duration but without AI support. Academic resilience was measured before the intervention (pretest) and after completion of the intervention (posttest).

Because the study used intact classes rather than individual random assignment, potential differences in classroom characteristics should be considered when interpreting the findings. Therefore, the results are interpreted as the effect of an integrated AI-assisted classical guidance package within the studied classroom context rather than as the isolated effect of AI technology. The research design is presented in Table I.

Table 1. Research Design

Group	Pretest	Treatment	Posttest
Experimental	O ₁	X ₁	O ₂
Control	O ₃	X ₂	O ₄

Note:

O₁ = experimental-group pretest;

O₂ = experimental-group posttest;

O₃ = control-group pretest;

O₄ = control-group posttest;

X₁ = AI-assisted classroom guidance intervention;

X₂ = classroom guidance without AI assistance.

Participants

The population of this study consisted of all eighth-grade students at SMP Negeri 15 Kota Cirebon, Indonesia. Participants were selected using **purposive sampling** with intact classes as the sampling units. The use of purposive sampling was based on the nature of the intervention, which was implemented as a classroom-based guidance service. Therefore, selecting naturally existing classes was considered more appropriate than individually assigning students to different treatment conditions.

Two classes were selected based on several similarity criteria, including: 1) the same grade level; 2) comparable learning environments; 3) similar class size; and 4) comparable baseline academic resilience characteristics.

Class VIII-G, consisting of 31 students, was assigned as the experimental group, while class VIII-E, consisting of 31 students, was assigned as the control group. Thus, the final sample consisted of 62 students. Before analyzing the intervention effect, baseline equivalence between the two groups was examined using pretest academic resilience scores.

Research Instrument

Academic resilience was measured using an instrument developed based on Cassidy's multidimensional framework of academic resilience [28]. The framework conceptualizes academic resilience through three dimensions: 1) perseverance; 2) reflecting and adaptive help-seeking; and 3) negative affect and emotional response.

The final instrument consisted of 32 items representing these three dimensions. The perseverance dimension consisted of 12 items, reflecting and adaptive help-seeking consisted of 10 items, and negative affect and emotional response consisted of 10 items. Each item was rated using a four-point Likert scale ranging from Very Appropriate (4) to Very Inappropriate (1). Favorable items were scored directly, while unfavorable items were reverse-scored. Higher total scores indicated higher levels of academic resilience.

Prior to data collection, the instrument was evaluated through expert validation and empirical testing using the Rasch Model approach with Winsteps software. The analysis examined item quality, measurement consistency, and instrument reliability. The reliability analysis showed acceptable measurement quality with:

Table 2. Reliability Analysis

Reliability Indicator	Value	Interpretation
Cronbach's Alpha	0.81	Good internal consistency
Person Reliability	0.76	Acceptable person consistency
Item Reliability	0.96	Excellent item reliability

The reliability analysis demonstrated acceptable measurement quality. As presented in Table 2, the instrument obtained a Cronbach's alpha coefficient of 0.81, indicating good internal consistency. The person reliability value was 0.76, while item reliability reached 0.96, indicating acceptable respondent consistency and excellent item reliability, respectively. These results indicated that the instrument demonstrated adequate reliability for assessing students' academic resilience.

Intervention Procedure

The intervention was developed based on Martin and Marsh's academic resilience framework, which emphasizes five components: Confidence, Coordination, Control, Composure, and Commitment (5C) [2]. The AI-assisted classical guidance intervention consisted of five sessions, with each session lasting approximately 40 minutes.

Table 3. AI-Assisted Classroom Guidance Intervention

Session	5C Dimension	Service Focus	AI-Assisted Activity
1	Confidence	Academic self-confidence	Reflection on personal strengths and academic beliefs
2	Coordination	Academic planning	Development of learning goals and strategies.
3	Control	Academic control	Identification of controllable academic situations.
4	Composure	Emotional composure	Reflection on academic stress and coping responses.
5	Commitment	Academic Commitment	Development of action plans and commitment strategies.

The experimental group received guidance sessions supported by RESILIA-BK, an AI-assisted guidance application designed to facilitate reflective activities, academic problem exploration, and adaptive response planning. During the intervention, the counselor remained the primary facilitator, while RESILIA-BK functioned as a supporting tool by providing structured reflective prompts; encouraging students to explore academic challenges; supporting alternative problem-solving processes; and assisting students in developing adaptive action plans.

All AI-supported activities were conducted within predetermined guidance scenarios and under counselor supervision. Therefore, AI was positioned as an augmentative reflective tool rather than an autonomous counseling agent or replacement for professional counseling services.

Research Procedure

The research procedure consisted of four stages. First, the researchers prepared intervention materials, validated the research instrument, conducted pilot testing, and coordinated the implementation process with the school. Second, pretest measurements were administered to both experimental and control groups before the intervention. Third, the experimental group participated in five AI-assisted classical guidance sessions, whereas the control group received classical guidance services without AI assistance. Fourth, posttest measurements were administered to both groups after completion of the intervention. The collected data were then coded and prepared for statistical analysis.

Data Analysis

Data analysis was conducted using descriptive and inferential statistical procedures. Descriptive statistics were first performed to summarize students' academic resilience scores, including the mean, standard deviation, minimum and maximum scores, and changes in scores from pretest to posttest. These analyses were used to describe the distribution and development of academic resilience levels in both the experimental and control groups.

Before examining the intervention effect, an independent-samples t-test was conducted to determine whether there were significant baseline differences in academic resilience scores between the experimental and control groups. This analysis was performed to ensure that both groups had comparable initial conditions prior to the intervention.

The effectiveness of the AI-assisted classical guidance intervention was examined using Analysis of Covariance (ANCOVA). In the ANCOVA model, posttest academic resilience scores were treated as the dependent variable, treatment condition (experimental

and control groups) was included as the independent variable, and pretest academic resilience scores were entered as a covariate. ANCOVA was selected because this analysis enables researchers to compare posttest outcomes while statistically controlling for potential initial differences between groups.

Prior to conducting ANCOVA, assumption testing was performed to ensure the validity of the analysis. The assumptions examined included the normality of residuals, homogeneity of variance, and homogeneity of regression slopes. Statistical significance was determined at a significance level of $\alpha = .05$, and the magnitude of the intervention effect was reported using partial eta squared (η^2) as an effect size indicator. All statistical analyses were conducted using IBM SPSS Statistics version 25.

Research Ethics

The study was conducted in accordance with ethical principles for research involving human participants. Ethical approval was obtained from the Research Ethics Committee of Universitas Nahdlatul Ulama Cirebon (Approval No. 188/200.12.1/ADM/VIII/2026, August 14, 2026). Participant identities were kept confidential, and the data were used exclusively for research purposes and reported in aggregate form.

3. RESULTS AND DISCUSSION

RESULT

3.1. Descriptive Profile of Academic Resilience

Descriptive analysis showed that the baseline mean scores of the two groups were relatively similar. The experimental group’s mean score increased from 95.65 at pretest to 104.74 at posttest, whereas the control group’s mean score increased from 94.97 to 98.00. Descriptively, the mean change was 9.10 points in the experimental group and 3.03 points in the control group.

Table 4. Descriptive Statistics of Academic Resilience Scores

Group	Measurement	n	Mean	SD	Minimum	Maximum	Mean Change
Control	Pretest	31	94.97	12.15	70	118	3,03
	Posttest	31	98.00	9.16	73	117	
Experimental	Pretest	31	95.65	8.95	77	113	9.10
	Posttest	31	104.74	5.96	87	120	

At the individual level, all 31 students (100%) in the experimental group showed increased scores from pretest to posttest. In the control group, 22 students (71.0%) showed increased scores, four students (12.9%) obtained the same scores, and five students (16.1%) showed decreases. This pattern indicates more consistent change in the experimental group; however, conclusions regarding effectiveness were based on between-group inferential analysis.

3.2. Changes in Academic Resilience Categories

Table 5. Distribution of Academic Resilience Categories

Group	Category	Pretest f	Pretest %	Posttest f	Posttest %
Control	Low	0	0.0	0	0.0
	Moderate	16	51.6	15	48.4
	High	15	48.4	16	51.6
Experimental	Low	0	0.0	0	0.0
	Moderate	18	58.1	2	6.5
	High	13	41.9	29	93.5

In the experimental group, the proportion of students in the high category increased from 41.9% to 93.5%, with 16 students moving from the moderate to the high category. In the control group, the proportion in the high category increased from 48.4% to 51.6%. Categorization was used as descriptive information and did not constitute the primary basis for determining effectiveness because score changes can occur without a shift in category.

3.3. Baseline Equivalence Between Groups

Table 6. Pretest Score Comparison

Group	n	Mean	SD	t	df	p
Control	31	94.97	12.15	0,250	60	0,803
Experimental	31	95.65	8.95			

The independent-samples t-test showed no significant difference in pretest scores between the experimental and control groups, $t(60) = 0.250$, $p = .803$. This result indicates that the two groups were relatively comparable at baseline on the measured academic resilience variable, although equivalence on other unmeasured variables cannot be assured because individual randomization was not conducted.

3.4. ANCOVA Assumption Tests

Table 7. Results of ANCOVA Assumption Test

Assumption Tested	Test	Statistic	p	Criterion	Decision
Residual normality	Shapiro-Wilk	$W = 0.973$	.180	$p > .05$	Assumption met
Homogeneity of residual variance	Levene's Test	$F(1, 60) = 0.001$	.981	$p > .05$	Assumption met
Homogeneity of regression slopes	Pretest $\times$ Group	$F(1, 58) = 2.451$	.123	$p > .05$	Assumption met

The Shapiro-Wilk test of model residuals yielded $W = 0.973$, $p = .180$, indicating no significant departure from residual normality. Levene's test yielded $F(1, 60) = 0.001$, $p = .981$, indicating homogeneity of residual variances. The interaction between pretest scores and group was not significant, $F(1, 58) = 2.451$, $p = .123$, indicating that the homogeneity of regression slopes assumption was met. Thus, the data satisfied the principal reported assumptions for proceeding with ANCOVA.

3.5. Effectiveness of AI-Assisted Classroom Guidance Services

Table 8. ANCOVA Results for the Effectiveness of the Intervention

Group	Adjusted Posttest Mean	Adjusted Mean Diff.	95% CI	F	df	p	Partial η^2
Control	98.21	6.32	4.24–8.41	36.989	1.59	<0.001	0.385
Experimental	104.53						

After controlling for pretest scores, the adjusted posttest mean was 104.53 for the experimental group and 98.21 for the control group. The adjusted mean difference was 6.32 points, with a 95% confidence interval from 4.24 to 8.41. ANCOVA showed a significant posttest difference between the two groups after controlling for baseline scores, $F(1, 59) = 36.989$, $p < .001$, partial $\eta^2 = .385$. The model including group and pretest scores explained 76.9% of the variance in posttest scores ($R^2 = .769$). Thus, the data supported the hypothesis that AI-assisted classroom guidance produced higher academic resilience outcomes than classroom guidance without AI assistance within the context of this study.

DISCUSSION

This study examined the effectiveness of an AI-assisted 5C-based classical guidance intervention in improving academic resilience among junior high school students. The findings showed that students who participated in the AI-assisted classical guidance program demonstrated higher adjusted posttest academic resilience scores compared with students who received classical guidance without AI assistance after controlling for baseline scores. These findings indicate that integrating AI support within a structured counselor-led intervention may provide additional support for strengthening students' academic resilience within the studied classroom context.

The improvement observed in the experimental group can be interpreted through Martin and Marsh's academic resilience framework, which emphasizes the importance of Confidence, Coordination, Control, Composure, and Commitment (5C) in helping students respond adaptively to academic challenges [2]. The intervention implemented in this study was designed to strengthen students' confidence in academic abilities, learning planning, perceived control, emotional regulation, and persistence. These components represent important psychological resources that enable students to maintain adaptive functioning when facing academic difficulties [2]. Furthermore, the focus on reflection and adaptive responses is consistent with the multidimensional conceptualization of academic resilience, which involves perseverance, adaptive help-seeking, and emotional regulation [28].

The findings also suggest that AI may provide additional value beyond conventional classical guidance services through its role as a reflective support mechanism. In this study, RESILIA-BK did not function as an autonomous counseling agent but as a supportive tool integrated within counselor-led activities. Through structured prompts and interactive responses, AI-assisted activities encouraged students to identify academic challenges, reflect on personal experiences, explore alternative solutions, and formulate adaptive action plans. These processes may support students' metacognitive awareness and self-regulated learning, which are important factors in students' ability to manage academic demands effectively [5].

In addition, students' confidence and persistence in dealing with academic challenges may be strengthened through improved self-efficacy beliefs [4].

Compared with conventional classical guidance, AI-assisted guidance provides opportunities for more interactive and personalized learning experiences. Previous studies have indicated that AI technologies can support educational processes through personalized interaction, feedback provision, and adaptive learning experiences when implemented within appropriate pedagogical frameworks [13]. Large language models also have potential to support dialogue, reflection, and knowledge exploration; however, their implementation requires careful consideration of accuracy, ethical issues, and appropriate human oversight [14]. Therefore, the contribution of AI in this study should be understood as an extension of counselor-led guidance processes rather than a replacement for professional counseling roles.

The present findings extend previous research on AI implementation in education and counseling. Previous studies have predominantly examined AI literacy, technological acceptance, and ethical considerations, while empirical investigations of AI-supported interventions in authentic educational settings remain limited [15]. In school counseling contexts, AI integration requires counselors to possess adequate technological understanding and ethical awareness to ensure meaningful and responsible implementation [16]. Thus, this study contributes by demonstrating an applied model of AI integration within classical guidance services based on an established psychological framework of academic resilience.

Nevertheless, the interpretation of these findings requires consideration of alternative explanations. Because this study employed intact classes with one experimental class and one control class, differences between groups may also be influenced by classroom-specific characteristics, student engagement, counselor-student interactions, or novelty effects associated with the introduction of AI technology. Therefore, the observed differences should be interpreted as the effect of the integrated AI-assisted classical guidance package rather than the isolated effect of AI technology alone.

From an ethical perspective, AI implementation in counseling requires careful supervision and responsible use. Previous studies have emphasized that AI-based systems may provide opportunities for psychological support but should not replace professional judgment and human-centered counseling processes [17]. In this study, AI interactions were conducted within predetermined guidance scenarios and under counselor supervision to minimize risks related to inappropriate responses, excessive dependence on AI, and misinterpretation of AI-generated suggestions. This approach aligns with the principle that AI should function as a complementary tool that enhances professional practice while maintaining counselor responsibility [14], [24].

The findings have practical implications for school counseling practice. AI-assisted classical guidance may serve as an innovative approach to enhance student engagement, reflection, and adaptive problem-solving during developmental counseling activities. However, successful implementation requires counselor readiness, AI literacy, ethical considerations, and appropriate instructional design [16], [24]. Therefore, future research should examine AI-assisted counseling interventions using larger samples, multiple schools, and randomized or longitudinal designs to strengthen evidence regarding their effectiveness.

4. CONCLUSION

This study examined the effectiveness of an AI-assisted 5C-based classical guidance intervention in improving academic resilience among junior high school students. The findings indicated that students who participated in the AI-assisted classical guidance program demonstrated higher adjusted posttest academic resilience scores compared with students who received classical guidance without AI assistance after controlling for baseline academic resilience scores. These findings suggest that integrating AI support into counselor-led classical guidance may provide additional support for strengthening students' academic resilience within the context of the studied classroom settings.

The contribution of this study lies in demonstrating an applied model of AI integration in school counseling by combining Martin and Marsh's 5C academic resilience framework, classical guidance services, and AI-assisted reflective support through RESILIA-BK. In this model, AI functions as a complementary tool that facilitates reflection, exploration of academic challenges, and adaptive problem-solving processes while maintaining the central role of professional counselors.

However, the findings should be interpreted with consideration of several limitations. The use of intact classes and the absence of individual random assignment may limit the ability to attribute changes exclusively to AI assistance. In addition, the study was conducted within a single school context, which may affect the generalizability of the findings to other educational settings.

Future research should examine AI-assisted classical guidance using larger samples, multiple schools, and more rigorous experimental designs, including randomized controlled trials or longitudinal approaches. Further studies may also investigate how specific AI-supported mechanisms, such as personalized feedback, reflective prompts, and student engagement, contribute to the development of academic resilience.

5. ACKNOWLEDGMENTS

The authors gratefully acknowledge Direktorat Penelitian dan Pengabdian kepada Masyarakat (DPPM), Kementerian Pendidikan Tinggi, Sains, dan Teknologi Republik Indonesia, for the research funding support provided through the Penelitian Dosen Pemula (PDP) Program, Fiscal Year 2026.

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