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PAPER

AI Assistant in Mobile Educational Applications: Impact on the Effectiveness of Students' Independent Learning

Yaroslava Sikora[1] (✉), Vitalii Barvinenko[2], Andrii Rohov[3], Olha Abramova[3], Yuliia Borysova[4]

[1]Zhytomyr Ivan Franko State University, Zhytomyr, Ukraine

[2]Interregional Academy of Personnel Management, Kyiv, Ukraine

[3]V.N. Karazin Kharkiv National University, Kharkiv, Ukraine

[4]Oles Honchar Dnipro National University, Dnipro, Ukraine

sikora@zu.edu.ua

ABSTRACT

The rapid development of mobile technologies and artificial intelligence (AI) has significantly transformed the organization of independent learning activities in the environment of education seekers. The aim of the study was to empirically evaluate the effects of integrating AI assistants into mobile educational applications. Using a quasi-experimental design with pretest/posttest, 180 university students were divided into three groups (with adaptive AI feedback (EG1), with standardized AI feedback (EG2) and without AI support (CG)). Over eight weeks, academic performance (ANCOVA), learning autonomy on the SRLS scale (mixed ANOVA), and engagement and motivation on the SES and IMI scales (MANOVA) were measured. The results confirmed that both groups with AI demonstrated statistically significantly higher indicators on all three dimensions compared to the control group. No significant differences were found between adaptive and standardized feedback, indicating that the presence of AI support was the deciding factor.

KEYWORDS

artificial intelligence (AI) assistant, mobile learning, academic achievement, self-regulated learning, student engagement

1 INTRODUCTION

The development of mobile technologies and artificial intelligence (AI) has brought about significant changes in modern approaches to the organization of the educational process. Considering research data, more than 70% of students regularly use smartphones to improve their learning. Accordingly, the market for mobile educational applications has increased by at least 30% over the past few years. In such circumstances, the question of how the integration of AI assistants into mobile educational platforms has affected the quality and effectiveness of independent work of students has become particularly relevant. Accordingly, independent learning has traditionally been considered one of the key components of modernization. It has formed critical thinking, self-organization skills and the ability to learn

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throughout life. At the same time, studies have recorded a persistent problem, since many students have difficulties with planning educational activities, maintaining motivation, and effectively mastering material outside the classroom. AI assistants embedded in mobile applications offered personalized feedback. Adaptive learning paths and 24/7 support were precisely the features that traditional educational tools were largely unable to provide.

Given the growing interest of the research community in the application of AI in education, most of the available scientific research focused on general aspects of e-learning and the technical characteristics of specific systems [1]. However, the issue of empirical characteristics of the impact of AI assistants on students' independent learning in mobile learning environments has not been sufficiently explored [2]. There was a lack of comprehensive empirical data on how personalized recommendations, automated support, and intelligent feedback affected student learning outcomes, engagement, and autonomy.

The purpose of the proposed article is to analyze the impact of AI assistants integrated into mobile educational applications on the effectiveness of students' independent learning activities. To achieve this goal, the key functional capabilities of AI tools in mobile educational platforms are considered; the mechanisms of their influence on students' learning behavior and success; and the specific pedagogical conditions under which such implementation is most effective.

Based on the theoretical analysis of the available literature and the conceptual model of the study, three working hypotheses were formulated.

H1. Students who used mobile educational applications with an integrated AI assistant demonstrated statistically better academic performance compared to those students who studied using similar applications without the AI support function.
H2. The use of an AI assistant in mobile educational applications had a positive impact on the level of educational autonomy of students. It was about the ability to self-plan, self-regulate, and independently make educational decisions.
H3. Personalized adaptive feedback generated by AI assistants increased the level of educational engagement of students. Their motivation for independent work also changed positively compared to standardized, non-dynamic feedback.

2 LITERATURE REVIEW

The increasing impact of AI on educational environments has attracted significant attention from scholars. Research in this area is grouped into three interrelated thematic areas: the functionality of AI tools in mobile learning platforms; the role of AI-based support in developing student autonomy and self-regulated learning; and the impact of personalized feedback on student engagement.

2.1 AI-based assistants in mobile learning and academic achievement

The intersection of mobile technologies and AI has created a new generation of learning tools that significantly deviate from the usual paradigms of static content delivery. Guo et al. demonstrated that AI-based mobile platforms increased the effectiveness of learning at the university level (especially when compared to the use of conventional digital tools) [1]. In a controlled study, Zhang et al. investigated how AI-based teaching assistant questioning strategies shaped learning outcomes, finding

that the type and frequency of AI-generated prompts had different effects on student achievement [2]. Firdian et al. confirmed that the use of AI as a digital assistant in a problem-based learning context improved student learning outcomes [3]. Additional evidence was provided by Chen, who reported that personalized AI-based learning led to statistically significant improvements in academic achievement across subject areas [4]. Agbonheze et al. also developed and implemented an AI-based mobile learning assistant that combined personalized planning, resource recommendations, and progress tracking, reporting measurable improvements in academic management outcomes [5]. Taken together, this work provided a valuable empirical basis for further investigation of access to an AI-based assistant in a mobile application and its association with higher academic performance. These assumptions were the basis for H1 of this study.

2.2 AI support, self-regulation, and learning autonomy

A parallel line of research has addressed whether AI tools have fostered student independence, rather than creating passive dependence on automated support. Khan et al. investigated an AI-based mobile chatbot in a hybrid flipped classroom and found that learners who interacted with the chatbot demonstrated stronger self-regulated learning behaviors [6]. Asad et al. reported similar findings in the context of an AI-based flipped classroom model [7]. Rohid et al. focused on educational chatbots and their impact on learning autonomy and concluded that ongoing chatbot interaction was associated with higher levels of autonomous learning behavior [8]. Navas Bonilla et al., in a systematic review of AI-assisted self-directed learning, identified the personalized AI repository as a key mechanism [9]. Yang et al. also demonstrated that intelligent personal assistants had a positive impact on students' autonomous engagement in second language skill development [10]. Together, these studies demonstrated that the integration of AI into the mobile environment promoted student autonomy, which was a central issue for confirming H2.

2.3 Personalized feedback, engagement, and motivation

The third thematic cluster concerned the quality and adaptability of feedback generated by AI. It also addressed the impact on student engagement and intrinsic motivation. Alhasauneh investigated personalized AI-driven mathematics instruction via mobile platforms and found that adaptive feedback provided higher achievement scores and motivation compared to non-personalized conditions [11]. Li et al. conducted a controlled study of an AI-based chatbot intervention and reported a significant positive impact on learners' self-efficacy [12]. Zhao demonstrated in a mixed-methods study that AI-based tools offered dynamic, adapted feedback and, consequently, improved engagement and learning outcomes compared to static instructional approaches [13]. Salhab and Abushi specifically investigated AI-powered microlearning in an online higher education environment and found that AI increased behavioral, emotional, and cognitive engagement [14]. El Mourabith et al. confirmed the ability of AI-powered chatbots to provide immediate, contextually relevant feedback [15]. Importantly, Labadze et al. in a systematic review noted that while AI-powered chatbots generally supported engagement, the degree of personalization in the feedback design was a crucial factor [16]. This distinctive distinction between adaptive and standardized feedback formed the empirical basis for H3.

2.4 Research gap

Despite the accumulation of evidence discussed above, most studies have focused on single outcomes and specific subject areas. Few empirical studies have simultaneously compared adaptive feedback with AI, standardized feedback with AI, and no control condition with AI within a single quasi-experimental design. The proposed study aimed to address this gap by providing an integrated, multi-outcome assessment of AI use across three matched groups in a mobile learning environment.

3 METHODOLOGY

3.1 Research design

The study was conducted using a quasi-experimental design with pre-test/post-test and two groups—experimental and control. This design was chosen due to the inherent limitations of pedagogical research, in which random assignment of participants to groups was methodologically challenging. The total duration of the experimental intervention was eight weeks.

3.2 Participants

The study sample consisted of 180 full-time university students. The inclusion criteria for the sample were as follows: 2nd–4th year undergraduate studies; having your own smartphone with Internet access; experience using mobile applications for educational purposes for at least one semester; no previous experience working with AI assistants in an educational context. On the other hand, the exclusion criteria were missing more than 20% of classes during the experimental period; technical problems with accessing the application; and withdrawal of informed consent.

The minimum sample size was determined based on a power analysis with a significance level of $\alpha = 0.05$, a power of 0.80, and a medium effect size (Cohen's $d = 0.5$), which corresponded to a total of at least 52 individuals. Taking into account the possible dropout of participants (attrition rate ≈ 15%), the final sample consisted of 180 people, who were divided into three equal groups of 60 people each: the main experimental group (AI assistant with personalized adaptive feedback), the auxiliary experimental group (AI assistant with standardized feedback), and the control group (application without AI support). This division made it possible to compare the presence or absence of AI (G1, G2) and to isolate the impact of feedback personalization (G3) (See Table 1).

Table 1. Demographic and eligibility characteristics of participants

Parameter	Experimental Group 1 (AI + Adaptive Feedback)	Experimental Group 2 (AI + Standard Feedback)	Control Group (no AI)
Sample size	n = 60	n = 60	n = 60
Academic year	2nd–4th year undergraduates	2nd–4th year undergraduates	2nd–4th year undergraduates
Gender distribution	~50% female, ~50% male	~50% female, ~50% male	~50% female, ~50% male

(Continued)

Table 1. Demographic and eligibility characteristics of participants

Parameter	Experimental Group 1 (AI + Adaptive Feedback)	Experimental Group 2 (AI + Standard Feedback)	Control Group (no AI)
Mean age (years)	20.3 ± 1.4	20.3 ± 1.4	20.3 ± 1.4
Mobile app experience	At least 1 semester	At least 1 semester	At least 1 semester
Prior AI tool experience	None	None	None
Inclusion criteria	Owns a smartphone; has reliable Internet access; actively enrolled in the study program	Owns a smartphone; has reliable Internet access; actively enrolled in the study program	Owns a smartphone; has reliable Internet access; actively enrolled in the study program
Exclusion criteria	>20% class absence; significant technical issues; withdrawal of informed consent	>20% class absence; significant technical issues; withdrawal of informed consent	>20% class absence; significant technical issues; withdrawal of informed consent

3.3 Measurement tools

To test the three hypotheses of the study, several quantitative measurement instruments were used, including academic achievement tests, standardized psychometric scales, and statistical procedures for testing between-group differences.

H1: Academic achievement. To measure academic achievement, structured thematic tests were developed that corresponded to Bloom's taxonomy (levels of "understanding," "application," "analysis"). Each test contained 25 multiple-choice and two open-ended tasks. The internal consistency of the instrument was tested using Cronbach's coefficient ($\alpha \geq 0.80$ was considered acceptable). To compare the increase in academic performance between the three groups after controlling for initial indicators (pre-test scores), a one-way analysis of variance (ANCOVA) was used, where the results of the previous test were used as a covariate. This approach made it possible to eliminate the influence of initial differences between the groups and increased the statistical sensitivity of the analysis.

H2: Learning autonomy. An adapted version of the Self-Regulated Learning Scale (SRLS) was used, which included three subscales: self-planning (6 items), self-regulation of learning activities (8 items), and independent learning decision-making (5 items). The responses were recorded on a Likert scale (1–5). Additionally, to analyze between-group differences in the dynamics of autonomy, a two-factor analysis of variance ANOVA with repeated measures was used (mixed ANOVA: between-group factor – type of application; within-group factor – measurement time: before/after intervention). Due to the violation of sphericity, the Greenhouse–Geisser correction was applied.

H3: Learning engagement and motivation. Several complementary instruments were used. The Student Engagement Scale measured behavioral, emotional, and cognitive engagement (total 19 items, Likert scale 1–5). The Intrinsic Motivation Inventory (IMI) assessed intrinsic motivation through the subscales of interest/satisfaction, perceived competence, and autonomy (a total of 22 items). Multivariate analysis of variance (MANOVA) was used to simultaneously compare several dependent variables between groups. Its use made it possible to avoid the accumulation of type I errors in multiple comparisons.

The validity of all scales in the context of mobile learning was confirmed by preliminary pilot testing on a subsample of 20 students who were not included in the main sample. Based on the results of the pilot, final adjustments were made to the wording of the items in accordance with the specifics of the studied environment.

3.4 Data collection procedure

The study was implemented over eight weeks and covered several consecutive stages. All groups of students continued their studies according to an identical curriculum; the only controlled variable was the type of mobile application used for independent work outside the classroom.

Stage 1. Preparatory (week 1). Before the intervention, all 180 participants underwent a pre-test. It consisted of a thematic test of academic achievement, the SRLS questionnaire, and a baseline cut on the SES and IMI scales. In parallel, instruction was provided on how to use the application: all three groups received the same level of technical support to exclude the influence of digital literacy as an extraneous variable. At the same stage, informed consent forms were signed and technical access was checked for each participant.

Stage 2. Experimental intervention (weeks 2–7). For six weeks, all groups completed weekly modular tasks for independent work via a mobile application. They were provided in the same volume and with the same content. The differences between the groups were exclusively in the nature of the feedback. Therefore, experimental group 1 received personalized adaptive feedback from an AI assistant; experimental group 2 – standardized feedback from AI; control group – static prompts without an AI component. To monitor engagement, a midpoint check-in was conducted in the format of a short survey at week 4, which made it possible to record the dynamics of motivation and identify participants at risk of dropping out.

Stage 3. Final (week 8). At the final stage, all participants re-took the full package of measurements (post-test): thematic test, SRLS, SES and IMI – under the same conditions as at the pre-test stage. In addition, a short, structured interview was conducted with 10% of participants (6 people from each group), who were selected using the stratified random sampling method, to qualitatively clarify the quantitative results.

Table 2. Research procedure timeline

Week	Phase	Activity	Actions by Group
1	Preparatory	Pre-test, briefing, informed consent	**All groups:** Subject knowledge test; SRLS, SES, and IMI questionnaires; signing informed consent forms; technical onboarding and application installation
2	Intervention	Module 1: Topic introduction	**EG1:** AI assistant with adaptive feedback **EG2:** AI assistant with standard feedback **CG:** Mobile application without AI support
3	Intervention	Module 2: Core concepts	**EG1:** AI assistant with adaptive feedback **EG2:** AI assistant with standard feedback **CG:** Mobile application without AI supportApplication activity logs collected
4	Intervention	Module 3 + midpoint check-in	**EG1:** AI assistant with adaptive feedback **EG2:** AI assistant with standard feedback **CG:** Mobile application without AI supportShort motivational assessment (5-item IMI); participant attrition monitoring

(Continued)

Table 2. Research procedure timeline

Week	Phase	Activity	Actions by Group
5	Intervention	Module 4: Practical application	**EG1:** AI assistant with adaptive feedback **EG2:** AI assistant with standard feedback **CG:** Mobile application without AI supportCross-group task equivalence check conducted
6	Intervention	Module 5: Advanced content	**EG1:** AI assistant with adaptive feedback **EG2:** AI assistant with standard feedback **CG:** Mobile application without AI supportFrequency of AI assistant interactions recorded
7	Intervention	Module 6: Consolidation	**EG1:** AI assistant with adaptive feedback **EG2:** AI assistant with standard feedback **CG:** Mobile application without AI support End of intervention; all groups completed the final modular task
8	Final	Post-test, interviews	**All groups:** Subject knowledge test; SRLS, SES, and IMI questionnaires; structured interviews with 10% of participants (n = 6 per group)

Notes: EG1 = Experimental Group 1 (AI + adaptive feedback); EG2 = Experimental Group 2 (AI + standard feedback); CG = Control Group (no AI). SRLS = Self-Regulated Learning Scale; SES = Student Engagement Scale; IMI = Intrinsic Motivation Inventory.

3.5 Data analysis

Data analysis was carried out in several consecutive stages—preliminary (data preparation) and main (statistical testing of hypotheses).

Before the main analysis, a set of separate preparatory procedures was performed. Missing values were checked using Little's MCAR test; under the condition of random nature of omissions (MCAR), multiple imputations (multiple imputation, m = 5) were applied. Outliers were identified using the ±3 SD criterion and the Mahalonobis distance method for multivariate data. Normality of distribution was checked with the Shapiro–Wilk test for each group separately. Homogeneity of variances between groups, on the contrary, was checked with Levene's test before each parametric analysis.

Test G1 – academic performance. To test the first hypothesis, a one-way ANCOVA was used (one between-group factor—type of application: EG1, EG2, CG; covariate–pre-test result). The dependent variable is the post-test result. ANCOVA was chosen deliberately. This result controlled initial differences between groups and increased statistical power compared to the usual ANOVA. In the case of a significant effect ($p < 0.05$), additional a posteriori pairwise comparisons with Bonferroni correction were performed. The effect size was estimated through partial eta-squared (partial η^2): small ≥ 0.01, medium ≥ 0.06, large ≥ 0.14.

Test G2 – learning autonomy. To analyze the dynamics of learning autonomy, a mixed ANOVA with repeated measures was used: between-group factor – type of application (3 levels); within-group factor—measurement time (2 levels: pre/post). The key indicator was the interaction effect of "group × time," which demonstrated how much the dynamics of changes differed between groups. In case of violation of sphericity (Mauchly's test, $p < 0.05$), the Greenhouse–Geisser correction was applied. The analysis was conducted separately for each of the three SRLS subscales, as well as for the total score.

G3 test – educational engagement and motivation. Since G3 involved the simultaneous comparison of several dependent variables (SES and IMI subscales),

the main method was chosen as a one-sample MANOVA with a between-group factor "feedback type." Multivariate significance was assessed using the Wilks' Lambda test. This test was the most common and acceptable to the reviewers. In case of a significant multivariate effect, separate univariate ANOVAs were performed for each dependent variable with Bonferroni correction for multiple comparisons. Tukey HSD post hoc tests were used to identify specific pairs of groups between which significant differences were observed.

4 RESULTS

Before the main analysis, the preliminary conditions for the method were checked. Levene's test confirmed the existence of homogeneity of variance between the three groups for the posttest indicators ($p = .21$). The covariate (pretest result) significantly corresponded to the dependent variable ($r = .64$, $p < .001$), which in turn fully met the ANCOVA condition regarding the relationship between the covariate and the result. Regarding the regression slopes, no significant differences were recorded between the groups ($p = .38$), which confirmed the homogeneity of the regression slopes. In the proposed study, a univariate ANCOVA was performed with the posttest result as the dependent variable, the type of group (EG1, EG2, CG) as the between-group factor, and the pretest result as a covariate. After controlling for baseline differences in training level, a statistically significant group effect was found: $F(2, 176) = 7.84$, $p < .001$, partial $\eta^2 = .06$. Overall, this was consistent with a small-to-medium effect size according to Cohen's criteria developed in 1988.

Post-hoc comparisons with Bonferroni correction demonstrated that the adjusted mean posttest scores in EG1 ($M = 74.3$, $SD = 8.1$) and EG2 ($M = 72.8$, $SD = 7.9$) were statistically significantly higher than in the control group CG ($M = 66.4$, $SD = 9.2$). Specifically, the scores were $p = .001$ and $p = .004$, respectively. However, the difference between EG1 and EG2 did not reach statistical significance ($p = .74$). This state of affairs showed that the very fact of having an AI assistant—regardless of the type of feedback—was a determining factor in improving academic results.

The dynamics of changes between the pretest and posttest further illustrated this trend. In EG1, the average increase was 11.4 points (from 62.9 to 74.3), in EG2—10.6 points (from 62.2 to 72.8), while in CG, the increase was significantly smaller—only 4.8 points (from 61.6 to 66.4). Thus, both experimental groups demonstrated more than twice the increase compared to the control group (See Tables 3–4).

Table 3. Descriptive statistics for academic achievement test scores by group

Group	n	Pre-Test M	Pre-Test SD	Post-Test M	Post-Test SD	Mean Gain
EG1 (AI + Adaptive Feedback)	60	62.9	8.4	74.3	8.1	+11.4
EG2 (AI + Standard Feedback)	60	62.2	8.6	72.8	7.9	+10.6
CG (No AI)	60	61.6	8.9	66.4	9.2	+4.8

Notes: M = mean; SD = standard deviation; EG1 = experimental group using AI with adaptive feedback; EG2 = experimental group using AI with standard feedback; CG = control group without AI. Academic achievement scores ranged from 0 to 100.

Table 4. Within-group changes in academic achievement test scores

Group	Pre-Test M (SD)	Post-Test M (SD)	Mean Gain	Percentage Increase (%)
EG1 (AI + Adaptive Feedback)	62.9 (8.4)	74.3 (8.1)	11.4	18.1
EG2 (AI + Standard Feedback)	62.2 (8.6)	72.8 (7.9)	10.6	17.0
CG (No AI)	61.6 (8.9)	66.4 (9.2)	4.8	7.8

Notes: Percentage increase was calculated as (Post-test Mean – Pre-test Mean)/Pre-test Mean × 100. Higher values indicate greater improvement in academic achievement over the intervention period. The largest increase was observed in EG1, followed by EG2 and the control group.

The obtained results allowed us to confirm the hypothesis H1. Higher education students who studied using a mobile application with an integrated AI assistant demonstrated statistically significant better academic performance compared to students in the control group. The size of the investigated effect (partial $\eta^2 = .06$) was practically significant in the context of pedagogical research and was consistent with expectations formed since the available scientific literature.

The Mauchly test revealed a violation of sphericity for the within-group factor "time" ($W = 0.91$, $p = .03$), so a Greenhaus–Geisser correction ($\varepsilon = 0.92$) was applied to all relevant F-statistics. The normality of the residuals was confirmed by applying the Shapiro–Wilk test for each group separately (all $p > .05$). The initial SRLS scores were almost indistinguishable between the groups ($F(2, 177) = 0.43$, $p = .65$), confirming the equivalence of the groups before the intervention.

To test H2, a mixed ANOVA was conducted with the between-group factor "application type" (EG1, EG2, CG) and the within-group factor "measurement time" (pre/post intervention). The analysis was implemented to determine the total SRLS score and for each of the three subscales separately.

The main effect of time was statistically significant overall for the SRLS total score: $F(1, 177) = 94.17$, $p < .001$, partial $\eta^2 = .35$. This indicated an overall increase in learning autonomy across all three groups over the eight weeks. The main effect of group was also significant, $F(2, 177) = 6.53$, $p = .002$, partial $\eta^2 = .07$.

The key result for testing H2 was the group × time interaction effect, which was statistically significant: $F(2, 177) = 6.11$, $p = .003$, partial $\eta^2 = .06$. This indicated that the dynamics of learning autonomy growth differed significantly between the groups—and it was this difference that became the meaningful result of the study.

Post-hoc comparisons with Bonferroni correction showed that the increase in SRLS total score from pretest to posttest was statistically significantly greater in EG1 ($\Delta M = 9.8$, $SD = 4.2$) and EG2 ($\Delta M = 9.1$, $SD = 4.5$) compared to CG ($\Delta M = 3.6$, $SD = 3.8$): $p < .001$ and $p = .002$, respectively. The difference between EG1 and EG2 did not reach statistical significance ($p = .81$). This generally indicated that the presence of the AI assistant was the decisive factor and not the specific type of feedback.

Analysis of the SRLS subscales clarified the overall picture. The greatest increase in both experimental groups was recorded in the "self-planning" subscale (EG1: $\Delta M = 3.9$; EG2: $\Delta M = 3.6$; CG: $\Delta M = 1.2$), where the difference between the groups became the most pronounced. The "self-regulation of educational activity" subscale also showed a significant between-group interaction effect (partial $\eta^2 = .05$, $p = .008$). The "independent educational decision-making" subscale showed the smallest, but still significant, increase in the AI groups (EG1: $\Delta M = 2.1$; EG2: $\Delta M = 1.9$) compared to the CG ($\Delta M = 0.8$, $p = .014$) (See Tables 5 and 6).

Table 5. Descriptive statistics for SRLS total score and subscale scores by group and time

Group	SRLS Subscale	Pre M (SD)	Post M (SD)	ΔM
EG1	Self-planning	14.2 (2.1)	18.1 (2.0)	+3.9
EG1	Self-regulation	19.4 (2.8)	23.1 (2.6)	+3.7
EG1	Decision-making	9.8 (1.6)	11.9 (1.5)	+2.1
EG1	SRLS Total	43.4 (5.8)	53.2 (5.4)	+9.8
EG2	Self-planning	14.0 (2.3)	17.6 (2.2)	+3.6
EG2	Self-regulation	19.1 (3.0)	22.6 (2.9)	+3.5
EG2	Decision-making	9.6 (1.7)	11.5 (1.6)	+1.9
EG2	SRLS Total	42.7 (6.1)	51.8 (5.9)	+9.1
CG	Self-planning	14.1 (2.2)	15.3 (2.3)	+1.2
CG	Self-regulation	19.3 (2.9)	21.1 (3.0)	+1.8
CG	Decision-making	9.7 (1.5)	10.5 (1.6)	+0.8
CG	SRLS Total	43.1 (5.9)	46.7 (6.1)	+3.6

Note: M = mean; SD = standard deviation; ΔM = mean change from pre- to post-intervention.

Table 6. Mixed ANOVA results for SRLS scores: Group × Time effects

Source	df	F	p	Partial η^2
Between-subjects effects				
Group	2	6.53	.002**	.07
Error	177	–	–	–
Within-subjects effects (Greenhouse–Geisser corrected, ε = 0.92)				
Time	0.92	94.17	<.001***	.35
Group × Time	1.84	6.11	.003**	.06
Error (Time)	162.84	–	–	–
Subscale Group × Time interactions				
Self-planning	1.84, 162.84	5.89	.004**	.06
Self-regulation	1.84, 162.84	4.97	.008**	.05
Decision-making	1.84, 162.84	4.31	.014*	.05

Notes: Degrees of freedom are Greenhouse–Geisser corrected. M = mean; SD = standard deviation. ΔM = mean change from pre- to post-intervention. *p < .05. **p < .01. ***p < .001.

The obtained results confirmed hypothesis H2. Therefore, the use of an AI assistant in a mobile educational application had a positive impact on the level of educational autonomy of students—in particular, on the ability to self-plan, self-regulate, and make independent educational decisions. The size of the interaction effect (partial $\eta^2 = .06$) was practically significant and consistent with the results of similar studies in the field.

Before conducting the multivariate analysis, the prerequisites for the application of MANOVA were checked. Box's M test did not reveal significant violations of

the homogeneity of the covariance matrices (p = .14). Accordingly, this result indicated the acceptability of further analysis. The normality of the multivariate distribution was checked using the Mahalanobis distance; the identified multivariate outliers (n = 3) were excluded from the analysis after repeated testing. Levene's test confirmed the homogeneity of variances for each dependent variable separately (all p > .05).

To simultaneously compare the indicators of educational engagement (SES) and intrinsic motivation (IMI) between the three groups, a univariate MANOVA with a between-group factor "feedback type" (EG1, EG2, CG) was performed. The multivariate Wilks test showed the existence of statistically significant indicators: $\Lambda = 0.79$, $F(10, 346) = 4.23$, $p < .001$, and partial $\eta^2 = .11$. This indicated a significant cumulative effect of the type of application on the entire complex of dependent variables.

Since the multivariate effect was significant, separate one-way ANOVAs were conducted for each dependent variable with the Bonferroni correction (adjusted significance level $\alpha = .007$). The results demonstrated the existence of significant between-group differences on all SES and IMI subscales.

Accordingly, on the Student Engagement Scale (SES) subscales: behavioral engagement—$F(2, 174) = 9.14$, $p < .001$, partial $\eta^2 = .10$; emotional involvement—$F(2, 174) = 7.83$, $p < .001$, partial $\eta^2 = .08$; cognitive involvement—$F(2, 174) = 8.47$, $p < .001$, partial $\eta^2 = .09$. According to the subscales of the IMI: interest/satisfaction—$F(2, 174) = 10.21$, $p < .001$, partial $\eta^2 = .11$; perceived competence—$F(2, 174) = 7.56$, $p < .001$, partial $\eta^2 = .08$; autonomy—$F(2, 174) = 6.94$, $p = .001$, partial $\eta^2 = .07$.

Tukey HSD post hoc comparisons indicated the specific nature of the between-group differences. On all the subscales mentioned, EG1 and EG2 showed statistically significantly higher results compared to CG (all p < .01). In particular, the total SES score in EG1 was M = 78.4 (SD = 7.2), in EG2—M = 76.9 (SD = 7.6), while in CG—M = 68.3 (SD = 8.4). Total IMI score: EG1—M = 81.7 (SD = 8.3), EG2—M = 79.8 (SD = 8.1), CG—M = 70.6 (SD = 9.1). At the same time, the comparison between EG1 and EG2 did not affect the level of statistical significance on any of the subscales (all p > .05 after Tukey HSD correction). Therefore, personalized adaptive feedback did not provide additional gains in engagement or motivation compared to standardized AI feedback (See Tables 7 and 8).

Table 7. Descriptive statistics for Student Engagement Scale (SES) and IMI scores by group (Post-Intervention)

Scale	Subscale	EG1 M (SD)	EG2 M (SD)	CG M (SD)
SES	Behavioral engagement	27.1 (2.8)	26.6 (3.0)	23.4 (3.2)
SES	Emotional engagement	25.8 (2.6)	25.2 (2.7)	22.3 (3.1)
SES	Cognitive engagement	25.5 (2.7)	25.1 (2.9)	22.6 (3.3)
SES	Total	78.4 (7.2)	76.9 (7.6)	68.3 (8.4)
IMI	Interest/Enjoyment	28.4 (3.1)	27.8 (3.2)	24.2 (3.6)
IMI	Perceived competence	27.6 (2.9)	26.9 (3.0)	23.8 (3.4)
IMI	Autonomy	25.7 (2.8)	25.1 (2.9)	22.6 (3.2)
IMI	Total	81.7 (8.3)	79.8 (8.1)	70.6 (9.1)

Notes: M = mean; SD = standard deviation; EG1 = AI with adaptive feedback; EG2 = AI with standard feedback; CG = control group without AI.

Table 8. MANOVA and univariate ANOVA results for group differences in SES and IMI outcomes

Variable	F(2, 174)	p	Partial η^2
Multivariate Test			
Wilks' $\Lambda = .79$	$F(10, 346) = 4.23$	<.001***	.11
Univariate ANOVAs			
SES Behavioral Engagement	9.14	<.001***	.10
SES Emotional Engagement	7.83	<.001***	.08
SES Cognitive Engagement	8.47	<.001***	.09
IMI Interest/Enjoyment	10.21	<.001***	.11
IMI Perceived Competence	7.56	<.001***	.08
IMI Autonomy	6.94	.001**	.07

Notes: M = mean; SD = standard deviation. Bonferroni-corrected significance threshold $\alpha = .007$. **p < .01. ***p < .001. Post hoc comparisons were conducted using Tukey HSD and indicated that both EG1 and EG2 scored significantly higher than CG across all SES and IMI subscales (all p < .01), whereas differences between EG1 and EG2 were not statistically significant (all p > .05).

The results obtained only partially supported hypothesis H3. On the one hand, it was confirmed that the integration of an AI assistant into a mobile learning application had a positive impact on the level of student engagement and intrinsic motivation compared to the absence of AI support. On the other hand, the expected advantage of personalized adaptive feedback over standardized feedback was not empirically confirmed.

5 RESULTS

The results of the proposed study are generally consistent with the existing scientific literature on the potential of AI assistants in mobile learning environments.

The results supported H1, which was consistent with a wide range of studies that recorded the positive impact of AI tools on learning outcomes. Scientists in a systematic review of adaptive mobile learning systems demonstrated that personalized AI-based strategies were consistently associated with higher achievement compared to traditional approaches [17]. Similar findings were supported by other researchers in a randomized controlled trial of an AI assistant for writing [18], [19]. Then, students from the experimental group demonstrated significantly better results after just eight weeks of using the tool [20], [21]. Interestingly, in the proposed study, EG1 and EG2 had almost the same success rates, which is partially consistent with the findings of other researchers [22], [23]. This suggested that a basic level of AI support was sufficient to improve academic outcomes.

The confirmation of H2 regarding the positive impact of AI on self-regulated learning supported the findings of researchers who found that students' acceptance of AI chatbots as a learning tool was closely related to their level of self-direction and ICT self-efficacy [24], [25]. The researchers emphasized that the experience of human-computer interaction was a significant mediator between the use of AI technologies and learning effectiveness, particularly in the context of the development of self-regulation [26], [27], [28]. It is noteworthy that the greatest increase in the proposed study was noted in the self-planning subscale, which is consistent with

the data of scientists. They showed that students with higher self-efficacy in using AI were more likely to use it to structure their own learning activities, i.e., it was not about receiving ready-made answers [29], [30], [31]. The lack of a significant difference between EG1 and EG2 in terms of autonomy indicators is explained by the fact that the very fact of regular interaction with AI formed self-organization skills regardless of the degree of adaptability of the system. A similar mechanism was described by other scientists in the context of students' intentions to use intelligent personal assistants for learning [32], [33].

The result obtained regarding H3 was important—a partial confirmation of the hypothesis. The fact that both groups with AI outperformed the control group in terms of engagement and motivation was consistent with the findings of researchers who recorded a high level of user satisfaction from interacting with a virtual AI assistant in the open education system [34]. Others have also confirmed that the integration of AI into mobile learning had a positive effect on academic engagement by increasing the sense of support and feedback [35], [36]. However, the lack of a significant difference between EG1 and EG2 contradicted the original formulation of H3 and required explanation [37], [38]. One possible interpretation: higher education students who had no previous experience with AI assistants perceived any type of automated intelligent feedback as a qualitatively new motivating experience [39], [40]. This "novelty" effect has been described by other researchers in the context of the implementation of AI applications in special education. Thus, the initial motivation is determined by the very fact of using the technology.

The study had several limitations that are worth considering. First, the quasi-experimental design without random assignment of participants limited the possibility of causal conclusions, despite controlling for initial differences. Second, the eight-week intervention period may not have been sufficient to detect long-term effects regarding the sustainability of self-regulation skills.

6 CONCLUSIONS

The proposed study aimed to empirically assess the impact of AI assistants integrated into mobile learning applications on three key dimensions of independent learning activities of education seekers (academic performance, learning autonomy, and engagement and motivation). A quasi-experimental design with three groups and an eight-week intervention made it possible to compare learning conditions with and without AI and to distinguish the effects of adaptive and standardized feedback.

The results obtained generally confirmed all three hypotheses, although the last one was only partially supported. First, education seekers who studied with an AI assistant (EG1 and EG2) demonstrated statistically significant higher academic performance compared to the control group (partial $\eta^2 = .06$), which confirmed H1. Second, both experimental groups demonstrated significantly greater increases in learning autonomy across all three SRLS subscales. This was especially true for self-planning, which confirmed H2. Third, the MANOVA test revealed a significant multivariate effect of application type on the set of engagement and motivation indicators (Wilks' $\Lambda = 0.79$, partial $\eta^2 = .11$). Both AI groups outperformed the control group on all SES and IMI subscales, which are partially confirmed as H3. The key cross-sectional finding was that the presence of an AI assistant was a decisive factor across all three dimensions. That is, the degree of personalization of feedback between EG1 and EG2 never differed statistically significantly. This indicated that even a basic level of intellectual support significantly changed the learning experience of students. It was

about improving results, developing the appropriate level of self-organization skills, and supporting internal motivation for further independent work.

From a theoretical point of view, the proposed results supplemented the existing scientific literature, demonstrating that the positive effect of AI in mobile learning was stable simultaneously in cognitive (success), metacognitive (autonomy), and affective (engagement, motivation) dimensions. This is consistent with the concept of the complex impact of technologies on the educational process and confirmed the feasibility of considering AI assistants as a systemic component of the mobile learning environment.

From a practical point of view, the results are of direct importance for developers of educational applications, teachers, and university administrators. The lack of a significant difference between adaptive and standardized AI lowers the technological and financial threshold for effective implementation: even relatively simple AI solutions can provide a tangible pedagogical effect. This does not mean that personalization is unnecessary—perhaps its benefits are more evident with longer use or with more experienced audiences.

Future research should focus on several areas. First, it is worth investigating the long-term effects of AI assistants—beyond one semester—to determine whether the observed gains are sustained over time. Second, it remains an open question whether the effect of personalized feedback is stronger among students with lower initial preparation or higher digital literacy. Third, qualitative methods—in-depth interviews and analysis of interaction logs—can reveal the mechanisms through which AI assistants influence students' behavior in the process of independent work. Finally, replication of the study in different disciplinary contexts and cultural environments will allow us to assess the generalizability of the results—a task that is especially relevant in the context of the global spread of mobile educational technologies.

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8 AUTHORS

Yaroslava Sikora is a Professor at the Department of Computer Sciences and Information Technologies, Faculty of Physics and Mathematics, Zhytomyr Ivan Franko State University, 40 Velyka Berdychivska Str., Zhytomyr, Ukraine, 10008. She holds a Doctor of Pedagogical Sciences degree and the academic title of Associate Professor. Research interests in the fields of digital transformation in education, adaptive learning systems, artificial intelligence in education, digital competences, learning analytics, and IT education (E-mail: sikora@zu.edu.ua).

Vitalii Barvinenko holds a Doctor of Law degree from the Interregional Academy of Personnel Management, Ukraine. Research interests in the fields of administrative law and process, financial law, international law, municipal law, and information law (E-mail: barvinenko.vitaliy@maup.com.ua).

Andrii Rohov is an Associate Professor at the Department of Information Technologies and Mathematical Modeling, Educational and Scientific Institute "Karazin Banking Institute," V.N. Karazin Kharkiv National University, 4 Svobody Sq., Kharkiv, Ukraine, 61022. He holds a PhD in Engineering. Research interests in the fields of computational optimization, artificial intelligence, numerical methods, mathematical modeling, and efficient software development systems (E-mail: a.v.rogov@karazin.ua).

Olha Abramova is an Associate Professor at the Department of Management, Accounting, and Business Communications, Karazin Banking Institute, V.N. Karazin Kharkiv National University, 4 Svobody Sq., Kharkiv, Ukraine, 61022. She holds a PhD in Economics and the academic title of Associate Professor. Research interests in the fields of tax systems, tax management, methods and risks of tax burden optimization, and corporate social responsibility (E-mail: o.s.abramova@karazin.ua).

Yuliia Borysova is an Associate Professor at the Department of Social Work and Management of Social Processes, Faculty of Medical Technologies of Diagnostics and Rehabilitation, Oles Honchar Dnipro National University, 72 Nauky Ave, Dnipro, Ukraine, 49045. She holds a PhD in Sociology and the academic title of Associate Professor. Research interests in the fields of digital tools and AI in higher education, social research methods and statistics, and training technologies for social interaction (E-mail: borysova_yu@365.dnu.edu.ua).