SiRad: Pelita Wawasan
E-ISSN: 3090-5591| DOI: 10.64728/sirad.v2i3.art7 pp. 455-472

What Happens When Generative AI Enters College Data Analysis Education? Evaluating Changes in Students' Academic Self-Efficacy, Self-Regulated Learning, and Engagement

Yundong Wu

Higher Education, Psychology, and Policy Analysis Laboratory, South Korea

Abstract

Generative artificial intelligence (AI) is increasingly used to support learning in higher education, but evidence regarding changes in students' academic self-efficacy, self-regulated learning, and academic engagement remains limited. This study examined changes associated with a six-week generative AI-based data analysis education program among students at a three-year college in Wuhan, Hubei Province, China. A one-group pretest-posttest design was employed. Of 210 questionnaires distributed, 202 valid paired responses were analyzed. Academic self-efficacy, self-regulated learning, and academic engagement were measured using five-point Likert scales, with adapted items informed by established instruments. Descriptive statistics, reliability analysis, Pearson correlations, and paired-samples t tests were conducted. All three outcomes increased significantly: academic self-efficacy from 3.21 to 3.48 (dz = 0.38), self-regulated learning from 3.18 to 3.52 (dz = 0.51), and academic engagement from 3.35 to 3.66 (dz = 0.44). Posttest correlations among the outcomes were positive (r = 0.56-0.65, all p < .001). These findings suggest that structured AI-supported data analysis instruction may accompany improvements in students' confidence, learning regulation, and engagement. However, the one-group design cannot isolate the causal contribution of generative AI from other elements of the instructional program.

Keywords: Analysis; Efficacy; Engagement; Generative; Learning; Regulation; Students; Technology

Apa yang Terjadi Ketika AI Generatif Digunakan dalam Pembelajaran Analisis Data di Perguruan Tinggi? Evaluasi Perubahan Efikasi Diri Akademik, Regulasi Diri dalam Belajar, dan Keterlibatan Mahasiswa

Abstrak

Kecerdasan buatan (AI) generatif semakin banyak digunakan untuk mendukung pembelajaran di perguruan tinggi, tetapi bukti mengenai perubahan efikasi diri akademik, regulasi diri dalam belajar, dan keterlibatan akademik mahasiswa masih terbatas. Penelitian ini mengkaji perubahan yang berkaitan dengan program pembelajaran analisis data berbantuan AI generatif selama enam minggu pada mahasiswa perguruan tinggi vokasional tiga tahun di Wuhan, Provinsi Hubei, Tiongkok. Penelitian menggunakan desain satu kelompok dengan prates dan pascates. Dari 210 kuesioner yang dibagikan, sebanyak 202 respons berpasangan yang valid dianalisis. Ketiga konstruk diukur menggunakan skala Likert lima poin dengan butir adaptasi yang mengacu pada instrumen yang telah dikembangkan sebelumnya. Analisis meliputi statistik deskriptif, reliabilitas, korelasi Pearson, dan uji t berpasangan. Seluruh konstruk mengalami peningkatan yang signifikan: efikasi diri akademik dari 3,21 menjadi 3,48 (dz = 0,38), regulasi diri dalam belajar dari 3,18 menjadi 3,52 (dz = 0,51), serta keterlibatan akademik dari 3,35 menjadi 3,66 (dz = 0,44). Korelasi antarkonstruk pada pascates bersifat positif (r = 0,56-0,65; seluruh p < 0,001). Temuan ini menunjukkan bahwa pembelajaran analisis data terstruktur yang didukung AI dapat berkaitan dengan peningkatan keyakinan akademik, regulasi belajar, dan keterlibatan mahasiswa. Namun, desain satu kelompok tidak dapat mengisolasi pengaruh kausal AI generatif dari komponen pembelajaran lainnya.

Kata kunci: Analisis; Efikasi; Generatif; Keterlibatan; Mahasiswa; Pembelajaran; Regulasi; Teknologi

Submitted: September 19, 2026	Accepted: October 6, 2026	Published: October 19, 2026

Contact: Yundong Wu | ethanwu0525@gmail.com

This is an Open Access article distributed under the terms of the Creative Commons Attribution-ShareAlike 4.0 International **(CCBY-SA 4.0)** License (https://creativecommons.org/licenses/by-sa/4.0/).

INTRODUCTION

Generative artificial intelligence has quickly entered higher education. Tools based on large language models can answer questions, explain concepts, generate examples, summarize information, and support coding and data analysis. These functions have created new possibilities for teaching and learning. At the same time, the educational value of generative AI depends on how students use it and how teachers design learning tasks. Recent reviews show that higher education research on ChatGPT and related tools has grown rapidly, with attention to learning support, student engagement, academic integrity, and the quality of AI-generated information (Bhullar et al., 2024; Tlili et al., 2023)

Generative AI can be especially useful in data analysis education because data analysis often requires students to understand a problem, select a method, prepare data, interpret results, and communicate findings. Students may have difficulty with software procedures, statistical concepts, and error checking. An AI system can provide explanations and examples during these steps. However, direct use of generated answers may also reduce the need for students to think through a problem. Systematic reviews have therefore emphasized both the learning opportunities and the risks of generative AI, including incorrect information, dependence on the tool, privacy concerns, and academic dishonesty (Albadarin et al., 2024; Farrokhnia et al., 2024).

A related concern is whether AI-supported learning changes students' beliefs about their own academic ability. Academic self-efficacy refers to students' judgments about whether they can successfully perform academic tasks. Bandura (1997) argued that self-efficacy affects the choices students make, the effort they invest, and their persistence when difficulties appear. In an AI-supported learning environment, students may receive rapid feedback and examples that help them complete difficult tasks. These experiences may create successful learning experiences and increase confidence. However, confidence may not increase if students simply copy AI answers without understanding the process.

Self-regulated learning is also important in AI-supported education. Self-regulated learners set goals, select strategies, monitor their progress, and change their actions when a strategy does not work. Zimmerman (2002) described self-regulation as an active process in which learners manage cognition, motivation, behavior, and learning conditions. The MSLQ was developed to assess college students' motivation and use of learning strategies, including metacognitive self-regulation and resource management (Pintrich et al., 1991). These ideas are highly relevant to generative AI because students need to decide when to ask AI for help, how to evaluate an answer, and when to solve a problem independently.

Academic engagement provides a third important outcome. Engagement includes the energy and attention that students bring to learning activities. Fredricks et al. (2004) described engagement as a multidimensional construct that can include behavioral, emotional, and cognitive aspects. The Utrecht Work Engagement Scale for Students provides another approach by focusing on vigor, dedication, and absorption (Schaufeli et al., 2002). When students use AI as a learning partner, immediate feedback may reduce frustration and help them remain active. Yet engagement may also be weakened if the technology makes students passive receivers of answers.

Research on educational technology has shown that student engagement is closely connected with the design of learning environments rather than technology alone. Bond et al. (2020) found that educational technology research in higher education has examined engagement through several types of interaction and learning activity. Kahu (2013) also explained that student engagement is shaped by both institutional and psychosocial factors. Therefore, a generative AI intervention should not be treated simply as a new software tool. It should be embedded in a clear teaching process.

Recent work by Wu (2026b) also suggests that generative AI should be used as a mediated learning resource rather than as a replacement for learner judgment. This idea is important for data

analysis education because students must understand the logic behind data cleaning, method selection, interpretation, and reporting. Wu and Lin (2026) further showed that learning outcomes can be related to persistence and goal-related learning processes. Although their study focused on high school mathematics, the finding supports the broader view that learning behaviors and motivational processes should be considered together.

Recent empirical studies in practice-oriented courses provide a more specific comparison point for the present study. Sun et al. (2024) found that ChatGPT-supported programming changed students' programming behaviors and perceptions, while the evidence for performance differences was more limited. Huang et al. (2025) reported that structured GenAI coding support improved coding performance and several self-regulated learning outcomes in an SRL-based Python course. These studies suggest that the learning design surrounding GenAI may be as important as access to the tool itself. However, empirical evidence remains limited for structured GenAI-supported data analysis courses that examine academic self-efficacy, self-regulated learning, and engagement together, especially in practice-oriented three-year college settings. The present study addresses this gap by examining these three outcomes within one six-week data analysis learning process.

The current study therefore asks three questions. First, does generative AI-based data analysis education improve college students' academic self-efficacy? Second, does the education improve students' self-regulated learning? Third, does it improve academic engagement? Based on social cognitive theory and self-regulated learning theory, the study expected positive pretest to posttest changes in all three outcomes. The study also examined correlations among the posttest variables to understand whether confidence, learning regulation, and engagement were related after the intervention.

Literature Review

Generative AI in Higher Education

Artificial intelligence in higher education has developed from prediction and recommendation systems to interactive tools that can communicate with students. Earlier reviews of AI in higher education identified applications in assessment, prediction, tutoring, and student support (Zawacki-Richter et al., 2019). The arrival of generative AI has expanded these uses because students can interact with the system using ordinary language.

AI chatbots may provide explanations, examples, feedback, and support for learning tasks. Labadze et al. (2023) reported that AI chatbots can provide immediate academic support and may help students with personalized learning. Mohebi (2024) and Lo et al. (2024) similarly found that research on ChatGPT in higher education has emphasized personalized learning and collaborative learning, while also identifying concerns about pedagogical integration and student engagement.

Recent empirical work in practice-oriented courses also shows that outcomes depend on how GenAI is integrated into learning activities. Sun et al. (2024) compared ChatGPT-facilitated and self-directed programming among college students and found differences in programming behaviors and perceptions, while the performance advantage was not statistically significant. Huang et al. (2025) used an SRL-based Python course and reported improved coding performance and several SRL-related outcomes when GenAI support was provided through structured hints. These findings are closer to the present study than general surveys of AI use because they examine GenAI inside specific learning tasks. At the same time, they focus mainly on programming rather than data analysis and do not jointly examine academic self-efficacy, self-regulated learning, and academic engagement.

However, generative AI does not always produce correct or appropriate information. It may produce confident but incorrect statements, and students may have difficulty identifying these errors.

Kasneci et al. (2023) noted that large language models offer educational opportunities but also raise concerns about reliability, bias, privacy, and academic integrity. Cotton et al. (2024) also discussed the challenge of academic integrity in the context of ChatGPT. These concerns mean that AI literacy should be part of the learning design.

Data analysis education creates a useful setting for responsible AI use. A student can ask an AI system to explain a statistical method, suggest a code structure, identify a possible error, or provide an example. The student can then test the suggestion, compare it with course materials, and explain the result in their own words. This process is different from asking AI to complete the whole assignment. Zastudil et al. (2023) emphasized that AI use in computing education can support higher-level work but may also create dependence if students do not develop conceptual understanding.

Responsible use also requires attention to privacy. Data analysis tasks often contain real or sensitive information. Students should not place personal identifiers or confidential institutional data into public AI systems. Wu (2026b) highlighted privacy, assessment validity, learner dependence, and teacher readiness as important issues in responsible generative AI use. In the present intervention, students were instructed to use de-identified learning datasets and to check AI-generated information before accepting it.

Academic Self-Efficacy

Academic self-efficacy is grounded in social cognitive theory. Bandura (1986) explained that people develop judgments about their ability through experience, observation, social persuasion, and interpretations of their own psychological states. In academic settings, self-efficacy affects the goals students select and the amount of effort they are willing to invest.

Students with stronger academic self-efficacy are more likely to approach difficult tasks as manageable learning problems. Schunk (1991) and Bandura (1993) argued that self-efficacy has an important role in academic motivation because students' beliefs about their ability influence persistence and performance. The College Academic Self-Efficacy Scale was also developed to measure students' confidence in routine academic behaviors and showed encouraging initial measurement properties (Owen & Froman, 1988).

In a generative AI-supported data analysis class, students may receive immediate assistance when they encounter a difficult step. A successful experience can reduce uncertainty and help students believe that they can complete similar tasks. This process is consistent with Bandura's (1997) view that mastery experiences are an important source of self-efficacy. At the same time, if students depend on AI without understanding the task, their confidence may not transfer to independent work.

The present study therefore treated academic self-efficacy as a learning-related belief rather than simple satisfaction with AI. Items focused on students' confidence in understanding data analysis concepts, selecting appropriate methods, completing analysis tasks, interpreting outputs, and solving problems when difficulties occurred.

Self-Regulated Learning

Self-regulated learning describes how students actively manage their learning. Zimmerman (2002) as well as Winne and Hadwin (1998) described self-regulation as a cognitive and metacognitive process where learners monitor, control, and evaluate their own studying strategies. Students set goals before a task, use strategies during the task, monitor their progress, and reflect on the results after the task.

Pintrich et al. (1991) developed the MSLQ to measure motivation and learning strategies among college students. The learning strategy section includes metacognitive self-regulation and resource

management. In this study, three areas were selected because they fit data analysis education particularly well: metacognitive self-regulation, effort regulation, and time and study environment management.

Metacognitive self-regulation is important because students must plan an analysis, monitor whether the selected method is suitable, and revise the process when results are unclear. Effort regulation concerns persistence when a task is difficult. Time and study environment management concerns the ability to organize learning conditions and study time. These components can be supported by structured AI tasks, but only when students remain responsible for decisions.

Research has shown that self-regulated learning strategies are related to academic outcomes. Panadero (2017) reviewed major models of self-regulated learning and noted the importance of planning, monitoring, and reflection. Dignath and Büttner (2008) also found evidence that self-regulation can be supported through instruction. Broadbent and Poon (2015) reported relationships between self-regulated learning strategies and academic achievement in online higher education. These findings provide a basis for expecting changes in SRL after a structured AI learning program.

Academic Engagement

Academic engagement concerns students' active involvement in learning. Fredricks et al. (2004) emphasized that engagement is multidimensional and can include behavior, emotion, and cognition, with later studies also highlighting agentic aspects of student engagement during learning activities (Reeve & Tseng, 2011). In higher education, engagement is affected by the learning environment, student motivation, relationships, and learning activities.

Schaufeli et al. (2002) developed the student version of the Utrecht Work Engagement Scale and identified vigor, dedication, and absorption as core dimensions. Vigor refers to energy and persistence. Dedication refers to a sense of significance and involvement. Absorption refers to being deeply focused on an activity. These dimensions are suitable for examining whether students remain actively involved during data analysis learning.

Educational technology can influence engagement when it changes the way students interact with tasks. Bond et al. (2020) showed that technology-supported engagement research includes active participation, interaction, and learning processes. Kahu and Nelson (2018) further proposed that educational engagement is an interface between student and institution, with psychosocial processes linking educational conditions to learning outcomes.

Generative AI may increase engagement by lowering the time needed to overcome small technical barriers. For example, a student who cannot understand a software error may receive a short explanation and continue the task. However, AI may also decrease engagement if students simply request complete answers. Therefore, the intervention in this study required students to write prompts, inspect responses, test suggestions, and explain final decisions.

Research Model and Hypotheses

The conceptual model was based on the idea that structured generative AI use can provide learning support while requiring students to remain active in planning, monitoring, and reflection. Figure 1 presents the model. The intervention was expected to influence academic self-efficacy, self-regulated learning, and academic engagement.

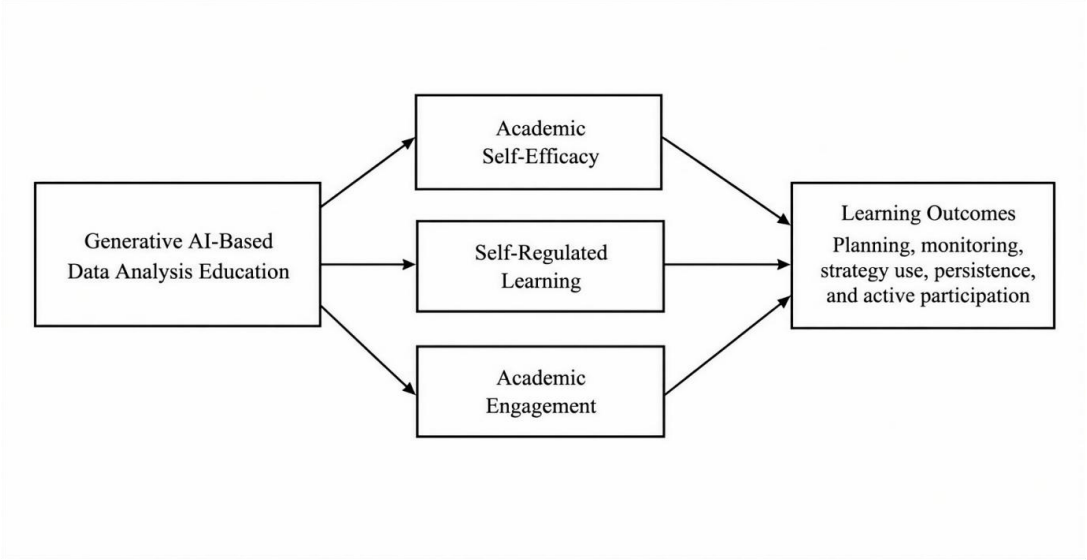


Figure 1. Conceptual framework of generative AI-based data analysis education and the three learning outcomes.

H1: Students will report higher academic self-efficacy after the generative AI-based data analysis education than before the education.

H2: Students will report higher self-regulated learning after the education than before the education.

H3: Students will report higher academic engagement after the education than before the education.

H4: Academic self-efficacy, self-regulated learning, and academic engagement will show positive correlations at posttest.

METHODS

Research Design

A one-group pretest and posttest design was used. The present study extended that approach by including self-regulated learning and academic engagement.

The intervention lasted six weeks. Students completed a pretest during the first class and a posttest during the final class. Between the two assessments, students completed a structured data analysis learning program that integrated generative AI into explanation, planning, data preparation, analysis support, error checking, interpretation, and reflection.

AI was not used as a replacement for students' own work. Students identified the problem, used AI when needed, and checked responses against course materials and the dataset, consistent with the responsible learning approach discussed by Wu (2026b).

Participants

Participants were students enrolled at a three-year college in Wuhan, Hubei Province, China. The college provides practice-oriented higher education programs. Students came from several academic programs and were enrolled in a data analysis related course. A total of 210 questionnaires were distributed. After screening, eight questionnaires were removed because the responses were incomplete or showed clearly abnormal response patterns. Therefore, 202 valid questionnaires were included in the final analysis. The valid response rate was 96.19%.

Table 1. Demographic characteristics of the participants (N = 202).

Characteristic	Category	n	%
Gender	Male	91	45.0
	Female	111	55.0
Age	18-19	63	31.2
	20-21	104	51.5
	22 or above	35	17.3
Year	First year	78	38.6
	Second year	72	35.6
	Third year	52	25.7
Previous AI use	Regularly	69	34.2
	Occasionally	98	48.5
	Rarely or never	35	17.3

Instructional Intervention

The six-week program was organized around a repeated learning cycle: understand the task, plan the analysis, use generative AI when needed, test the response, interpret the result, and reflect on the learning process. This structure was designed to connect AI use with self-regulated learning rather than with simple answer production.

Table 2. Six-week structure of the generative AI-based data analysis education.

Week	Main content	AI-supported activity	Student responsibility
1	AI literacy and data analysis basics	Prompt design, question refinement, explanation of basic concepts	Check AI explanations and identify errors
2	Data cleaning	Suggestions for cleaning steps and code examples	Decide which cleaning actions are justified
3	Descriptive analysis	Interpretation examples and code support	Select indicators and explain results
4	Statistical analysis	Method comparison and troubleshooting	Choose methods and test assumptions
5	Data interpretation	Alternative interpretations and report structure	Compare explanations with evidence
6	Integrated project	Revision, feedback, and reflection	Complete analysis and explain final decisions

During Week 1, students learned basic principles of responsible generative AI use. They were asked not to enter personal or confidential data. They also learned that an AI response should be treated as a suggestion that requires checking. This was important because AI-generated content may contain errors (Kasneci et al., 2023).

During Weeks 2 and 3, students worked with data cleaning and descriptive analysis. AI was used to explain procedures, generate simple code examples, and suggest ways to inspect data. Students had to identify whether the suggestion was suitable for the dataset. The teacher emphasized that an AI response was not accepted until students could explain why it was appropriate.

During Weeks 4 and 5, students worked with statistical analysis and interpretation. They used AI to compare possible methods and to explain output. Students were required to state the purpose of a method before using it. They also checked the generated interpretation against statistical output and course materials.

During Week 6, students completed an integrated data analysis task. They submitted a short report that included the research question, data preparation steps, analysis method, main results,

interpretation, and a reflection on AI use. The reflection asked students to identify one useful AI contribution, one AI limitation, and one decision they made without relying on the AI response.

Measures

The items were adapted from the cited source measures to fit data analysis learning tasks and were translated into Chinese for administration. The wording was checked for semantic clarity and relevance to the course context before the main survey. Because the study used adapted items rather than an established Chinese-language version of each full instrument, the reliability results are interpreted as evidence of internal consistency in this sample rather than as a full validation of the adapted measures.

All measures used a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The questionnaire was administered in Chinese. Items were checked for clear wording before the main administration. Higher scores indicated higher levels of the measured construct.

Academic self-efficacy. Academic self-efficacy was measured with eight items adapted from the college academic self-efficacy approach developed by Owen and Froman (1988) and informed by social cognitive theory (Bandura, 1997). The items focused on confidence in understanding data analysis concepts, completing analysis tasks, selecting methods, interpreting results, and dealing with difficulties. Example content included confidence in completing a difficult data analysis task and confidence in learning a new analysis procedure.

Self-regulated learning. Self-regulated learning was measured using 15 items based on the learning strategy framework of the MSLQ (Pintrich et al., 1991). Five items assessed metacognitive self-regulation, five assessed effort regulation, and five assessed time and study environment management. The three dimensions were selected because they directly matched the intervention process. The measure focused on planning, monitoring, persistence, time use, and organization of learning conditions.

Academic engagement. Academic engagement was measured using 12 items based on the student version of the Utrecht Work Engagement Scale (Schaufeli et al., 2002). Four items assessed vigor, four assessed dedication, and four assessed absorption. The wording was adapted to the learning context while keeping the original conceptual meaning. The measure examined energy during study, interest and involvement in learning, and concentration during data analysis tasks.

Table 3. Item composition and reliability of the study measures.

Construct	Subscale	Items	Cronbach's α
Academic self-efficacy	Overall	8	.89
Self-regulated learning	Metacognitive self-regulation	5	.86
Self-regulated learning	Effort regulation	5	.82
Self-regulated learning	Time & study environment management	5	.84
Self-regulated learning	Overall	15	.91
Academic engagement	Vigor	4	.84
Academic engagement	Dedication	4	.87
Academic engagement	Absorption	4	.85
Academic engagement	Overall	12	.92

The reliability values were acceptable for all measures. The overall alpha values were .89 for academic self-efficacy, .91 for self-regulated learning, and .92 for academic engagement. These values indicate that the items within each construct showed good internal consistency.

Data Collection Procedure

Before the intervention, students received an explanation of the study purpose and the voluntary nature of participation. The pretest was completed before the first instructional activity. The six-week program

then proceeded during normal class time. At the end of Week 6, students completed the same outcome measures as the posttest.

Questionnaires were matched using anonymous codes rather than student names. Eight cases were excluded during screening when substantial missing responses prevented complete scoring or when the response pattern was clearly abnormal, such as selecting the same response across nearly all items together with failure on an attention check. The remaining 202 paired cases were used in the analysis.

Students were reminded that AI-generated answers could be wrong. They also had to explain their decisions and check outputs before using them in reports. This approach keeps AI in a supporting role (Cotton et al., 2024).

Data Analysis

IBM SPSS Statistics 29.0 was used for quantitative analysis. First, descriptive statistics were calculated for the main variables. Second, Cronbach's alpha was used to examine internal consistency. Third, Pearson correlation coefficients were calculated to examine the relationships among the posttest variables. Fourth, paired-samples t tests were conducted to compare pretest and posttest scores. For the three primary pretest-posttest comparisons, 95% confidence intervals for the mean changes were calculated from the paired mean difference and its standard error, using the paired-samples t statistic with 201 degrees of freedom.

The analysis used Pearson correlation analysis and paired-samples t tests to examine relationships and pretest-posttest changes during the generative AI-based data analysis program. Statistical significance was evaluated at the .05 level. Effect sizes for the paired comparisons were also calculated using Cohen's dz, defined as the mean change divided by the standard deviation of the paired difference. Given the one-group design, these statistics describe changes associated with the program rather than an isolated causal effect of generative AI.

RESULTS AND DISCUSSION

Table 4 presents the descriptive statistics and correlations for the posttest measures. Academic self-efficacy, self-regulated learning, and academic engagement were positively related. The correlation between academic self-efficacy and self-regulated learning was moderate to strong, while the correlations involving academic engagement were also positive. These results are consistent with the view that students' beliefs, learning strategies, and engagement can operate together in the learning process.

Table 4. Posttest descriptive statistics and Pearson correlations (N = 202).

Variable	M	SD	1	2	3
1. Academic self-efficacy	3.48	0.64	1		
2. Self-regulated learning	3.52	0.59	.62***	1	
3. Academic engagement	3.66	0.60	.56***	.65***	1

Note. ***p < .001.

Academic self-efficacy increased from a pretest mean of 3.21 (SD = 0.61) to a posttest mean of 3.48 (SD = 0.64). The paired-samples t test showed a significant difference, $t(201) = -5.41$, $p < .001$, with a medium effect size, $dz = 0.38$. The result is consistent with H1. The mean change was 0.27 (95% CI [0.17, 0.37]).

The increase suggests that students felt more able to complete data analysis tasks after the intervention. The instructional sequence may have contributed to this change because students were able to receive immediate explanations when they encountered difficulty while still being required to check and explain the response. This combination may have provided successful experiences without removing the need for student decision making.

The result should not be interpreted as evidence that AI alone increased self-efficacy. The intervention included teacher explanation, repeated practice, structured tasks, and reflection. These elements could also contribute to the change. Social cognitive theory suggests that successful task experiences are an important source of self-efficacy (Bandura, 1997). Therefore, the observed increase is better understood as a result associated with the complete learning design.

Self-regulated learning increased from a pretest mean of 3.18 (SD = 0.55) to a posttest mean of 3.52 (SD = 0.59). The difference was statistically significant, $t(201) = -7.18$, $p < .001$, with $dz = 0.51$. The result is consistent with H2. The mean change was 0.34 (95% CI [0.25, 0.43]).

Table 5. Pretest and posttest results for self-regulated learning.

SRL component	Pre M	Pre SD	Post M	Post SD	t	p	dz
Metacognitive self-regulation	3.12	0.62	3.49	0.64	-6.72	<.001	.47
Effort regulation	3.26	0.63	3.53	0.65	-5.02	<.001	.35
Time and study environment management	3.17	0.61	3.54	0.63	-6.31	<.001	.44
Overall SRL	3.18	0.55	3.52	0.59	-7.18	<.001	.51

All three SRL components increased significantly. The largest mean gain was observed in metacognitive self-regulation. This result is important because the intervention required students to plan analysis steps, monitor AI responses, and reflect on whether the selected method was appropriate. The process gave students repeated opportunities to practice the basic actions of self-regulated learning.

The result is consistent with the theoretical view that self-regulation can be developed through direct instruction and practice (Dignath & Büttner, 2008). It also fits the MSLQ framework, which treats metacognitive regulation and resource management as learnable strategies (Pintrich et al., 1991). In online and technology-supported learning, self-regulated strategies have also been linked to academic outcomes (Broadbent & Poon, 2015).

The finding may also be explained by the fact that generative AI creates a new need for monitoring. Students cannot simply know whether an AI answer is correct. They must compare the response with the task, inspect the data, and decide whether the suggested method is suitable. In this sense, AI may create additional opportunities for metacognitive activity when the teacher makes checking a required part of the task.

Academic engagement increased from a pretest mean of 3.35 (SD = 0.57) to a posttest mean of 3.66 (SD = 0.60). The paired-samples t test was significant, $t(201) = -6.31$, $p < .001$, with $dz = 0.44$. The result is consistent with H3. The mean change was 0.31 (95% CI [0.21, 0.41]).

Table 6. Pretest and posttest results for academic engagement.

Engagement component	Pre M	Pre SD	Post M	Post SD	t	p	dz
Vigor	3.28	0.64	3.61	0.66	-5.82	<.001	.41
Dedication	3.39	0.62	3.72	0.64	-6.01	<.001	.42
Absorption	3.38	0.63	3.65	0.66	-5.18	<.001	.36
Overall engagement	3.35	0.57	3.66	0.60	-6.31	<.001	.44

The largest posttest mean was found for dedication, followed by absorption and vigor. This pattern suggests that students reported greater involvement in the data analysis learning activities after the program. The result is consistent with the student engagement framework in which engagement is shaped by the learning environment and by students' active involvement in tasks (Fredricks et al., 2004).

The result also supports the view that educational technology can influence engagement when it is integrated into meaningful learning activities. Kahu and Nelson (2018) argued that engagement is connected with the interaction between students and their educational environment. In the present

intervention, AI was not a separate activity. It was part of the data analysis process, so students could use it to continue working when they faced a problem.

Table 7. Paired-samples t test results for the three main outcomes.

Outcome	Pre (SD)	MPost (SD)	Mt(201)	p	Cohen's dz	Mean Diff.	95% CI for MD
Academic self-efficacy	3.21 (0.61)	3.48 (0.64)	-5.41	< .001	.38	0.27	[0.17, 0.37]
Self-regulated learning	3.18 (0.55)	3.52 (0.59)	-7.18	< .001	.51	0.34	[0.25, 0.43]
Academic engagement	3.35 (0.57)	3.66 (0.60)	-6.31	< .001	.44	0.31	[0.21, 0.41]

Note. Mean difference = posttest minus pretest; 95% confidence intervals are based on paired differences.

Figure 2 presents the pretest and posttest means for the three main outcomes. The visual pattern is consistent with the statistical results, with higher posttest means for all three variables.

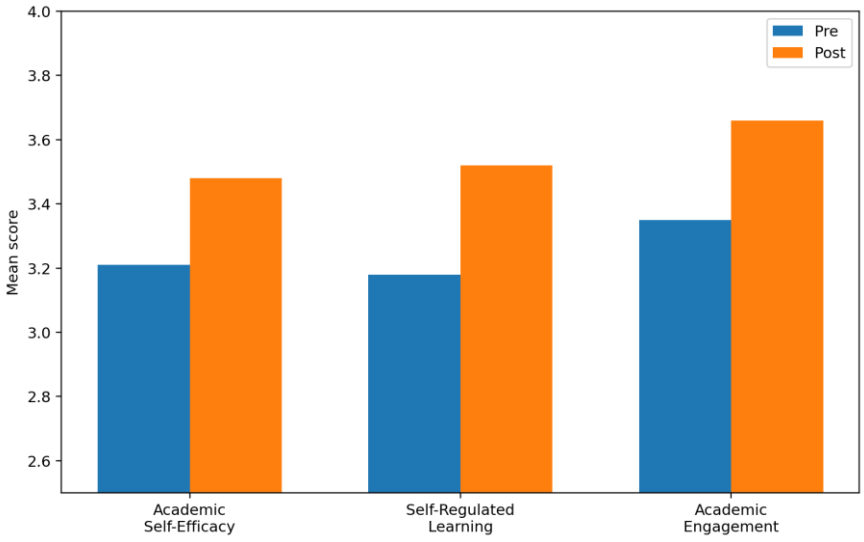


Figure 2. Pretest and posttest means for academic self-efficacy, self-regulated learning, and academic engagement.

The correlation analysis showed that academic self-efficacy was positively related to self-regulated learning, r = .62, p < .001. Academic self-efficacy was also positively related to academic engagement, r = .56, p < .001. Self-regulated learning showed the strongest relationship with academic engagement, r = .65, p < .001. These results support H4. These are cross-sectional posttest associations and should not be interpreted as evidence that one outcome caused another.

The strongest relationship between self-regulated learning and academic engagement is also reasonable from a learning process perspective. Students who plan their work, manage time, persist when tasks are difficult, and monitor their progress may be more likely to stay involved in learning activities. The result is consistent with research that treats self-regulation as an important part of active learning (Zimmerman, 2002).

Discussion

The purpose of this study was to examine whether a structured generative AI-based data analysis education program was associated with changes in academic self-efficacy, self-regulated learning, and academic engagement among students at a three-year college in Wuhan. All three outcomes showed significant pretest-to-posttest increases during the program. The findings provide support for the use of generative AI as a learning support when it is integrated with planning, checking, reflection, and active task

completion. Because there was no control group, these changes should be understood as associations with the structured learning program rather than evidence of a unique causal effect of generative AI.

The increase in academic self-efficacy is consistent with the idea that successful learning experiences can strengthen students' judgments about their ability. Students completed small data analysis tasks before moving to more complex tasks, while AI support was available for technical or conceptual barriers. The teacher still required students to explain important decisions, which connected task completion with understanding.

Recent empirical studies provide useful comparisons. Sun et al. (2024) found that ChatGPT-facilitated programming changed students' programming behaviors and perceptions, but the difference in programming performance was not statistically significant. Huang et al. (2025) reported stronger coding performance and improvements in several SRL-related outcomes when GenAI was provided through structured scaffolding. The present findings extend this line of work to data analysis education and combine self-efficacy, self-regulated learning, and engagement within the same intervention. However, the one-group design means that the observed changes cannot be attributed to GenAI alone.

Their study found improvement in some academic self-efficacy components after generative AI-based data analysis practice. The similarity is useful because both studies place generative AI inside a data analysis learning process rather than examining general AI use. At the same time, the present study used a larger sample and focused on a three-year college context.

The improvement in self-regulated learning may be the most important result. Generative AI changes the learning process because students can ask questions at almost any time. This convenience can reduce independent effort if students use the tool as an answer machine. The intervention addressed this problem by making students responsible for prompt design, response checking, method choice, and reflection. In this way, AI became an object of monitoring as well as a source of support.

The findings are consistent with the MSLQ approach, which treats metacognitive regulation and resource management as important parts of learning strategy use (Pintrich et al., 1991). The strongest change was in metacognitive self-regulation. Students were asked to think about what they were trying to do before asking AI for help and to check the response after receiving it. This repeated cycle may have strengthened planning and monitoring habits.

The improvement in academic engagement is also important. Technical problems can interrupt data analysis learning, especially for beginners. AI support can provide a quick explanation and help students continue, which may explain the increases in vigor and absorption. Dedication also increased, suggesting greater involvement in the course tasks.

The relationship among the three outcomes provides another useful finding. Self-regulated learning had the strongest correlation with academic engagement. This result suggests that engagement may not be supported only by making learning easier. Students may also need skills for managing their own learning process. Kahu (2013) and Kahu and Nelson (2018) emphasized that engagement develops through the interaction between students and their learning environment. The present findings fit this view because the intervention changed both the technology environment and the learning process.

The study also has implications for responsible AI education. Generative AI should be used within clear learning tasks that require students to evaluate outputs and explain their decisions. Recent evidence also shows that GenAI outcomes vary across tasks and learning designs. Experimental syntheses report positive effects on several learning outcomes but more limited evidence for metacognition, while course-based studies show that structured scaffolding can shape how students use AI (Chen & Cheung, 2025; Huang et al., 2025). The present study suggests that task design can reduce some risks by requiring students to explain and verify their work rather than copy generated responses.

The result also does not show whether students would maintain the gains after the course. Self-regulated learning may increase during a structured program and decrease when the structure is removed. Longitudinal research should therefore examine whether students continue to plan, monitor, and reflect when they use generative AI independently.

Educational Implications

Teachers should design AI activities around learning goals rather than around the tool itself. Students should know what they are expected to understand before they use generative AI. For data analysis, this means defining the research question and selecting the general analysis plan before requesting detailed AI assistance. For three-year colleges and other practice-oriented programs, this means connecting AI activities directly to practical data tasks, workplace-oriented problem solving, and students' gradual development of independent analysis skills.

Second, teachers should require verification. Students should compare AI suggestions with course materials, statistical output, and the actual dataset. This is especially important because AI systems can generate plausible but incorrect explanations (Kasneci et al., 2023). Verification can also strengthen metacognitive monitoring.

Third, teachers should use reflection tasks. A short reflection can ask students what the AI helped with, what it got wrong, and what decision the student made independently. This keeps students active and may support self-regulated learning.

Fourth, teachers should protect data privacy. Students should use de-identified datasets and should understand what information should not be entered into an external AI system. This point is especially important in health, education, business, and other fields where datasets may contain personal information.

Fifth, assessment should include process evidence. If an assignment only evaluates the final answer, students may have little reason to understand the process. Teachers can instead assess the research question, analysis plan, prompt strategy, verification steps, interpretation, and reflection. This approach makes responsible AI use visible.

Finally, institutions should provide teacher development. Teachers need to understand both the strengths and limits of generative AI. They also need simple classroom rules that students can follow. As generative AI becomes more common, the focus should move from whether students use AI to how they use it for learning. These recommendations are teaching implications rather than causal conclusions from the present design; they should be tested further with comparison groups and objective performance measures.

Limitations and Future Research

This study has several limitations. First, the participants came from one three-year college in Wuhan. The findings may not generalize to universities with different student populations, academic programs, or institutional conditions. Future studies should include several colleges and compare students from different majors.

Second, the study used a one-group pretest and posttest design. A control group was not included. Therefore, the results show pretest-posttest changes during the intervention but cannot provide a strong causal estimate of the unique contribution of generative AI. Future studies should use randomized controlled designs or matched comparison groups.

Third, the outcomes were measured by self-report questionnaires. Students may report higher confidence or engagement because they enjoyed the new learning format. Future research should combine

questionnaires with learning records, performance tasks, prompt logs, and independent assessments of data analysis skills.

Fourth, the intervention lasted six weeks. Longer programs are needed to determine whether the changes remain after students stop receiving structured classroom support. Future research should include follow-up measures several weeks or months after the course.

Fifth, the study did not compare different patterns of AI use. Some students may use AI mainly for explanations, while others may use it for coding or error checking. Future studies could compare these use patterns and examine which forms of AI support are most strongly related to self-regulated learning and engagement.

CONCLUSION

This study examined changes associated with a six-week generative AI-based data analysis education program on academic self-efficacy, self-regulated learning, and academic engagement among 202 students at a three-year college in Wuhan, China. Significant pretest to posttest increases were found for all three outcomes. Self-regulated learning showed the largest overall effect, followed by academic engagement and academic self-efficacy. The mean change in academic self-efficacy was 0.27 (95% CI [0.17, 0.37]), the mean change in self-regulated learning was 0.34 (95% CI [0.25, 0.43]), and the mean change in academic engagement was 0.31 (95% CI [0.21, 0.41]).

The findings suggest that a structured learning program involving generative AI can be useful in data analysis education when it is used as part of a structured learning process. The key feature was not simply access to AI. Students were required to plan tasks, ask targeted questions, check AI responses, make their own decisions, and reflect on the learning process. This design may help students gain confidence while also strengthening self-regulated learning and engagement. The present results do not isolate the contribution of generative AI from teacher guidance, repeated practice, and reflection.

The study also supports a cautious view of generative AI in higher education, particularly when interpreting changes from a one-group design. AI can reduce some barriers to learning, but it does not remove the need for student judgment. Teachers remain important in setting learning goals, checking understanding, designing assessments, and guiding responsible use. Future research with control groups, multiple institutions, objective performance measures, and longer follow-up periods is needed to test the durability and generalizability of these findings.

Acknowledgment

The author expresses sincere appreciation to the 202 students from a three-year college in Wuhan, Hubei Province, China, who participated in the six-week generative AI-based data analysis education program. Their participation in the learning activities and completion of the pretest and posttest questionnaires provided the data necessary for this study. The author also acknowledges the contributions of previous researchers whose work on academic self-efficacy, self-regulated learning, student engagement, and artificial intelligence in education informed the theoretical and methodological foundations of this research.

Conflict of Interest Statement

The author declares no financial, professional, or personal conflicts of interest that could have influenced the research design, data collection, analysis, interpretation, or conclusions presented in this article.

Funding Statement

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

Albadarin, Y., Saqr, M., Pope, N., & Tukiainen, M. (2024). A systematic literature review of empirical research on ChatGPT in education. *Discover Education*, *3*, 60. https://doi.org/10.1007/s44217-024-00138-2

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational Psychologist*, *28*(2), 117–148.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman.

Bhullar, P. S., Joshi, M., & Chugh, R. (2024). ChatGPT in higher education: A synthesis of the literature and a future research agenda. *Education and Information Technologies*, *29*, 21501–21522. https://doi.org/10.1007/s10639-024-12723-x

Bond, M., Buntins, K., Bedenlier, S., Zawacki-Richter, O., & Kerres, M. (2020). Mapping research in student engagement and educational technology in higher education: A systematic evidence map. *International Journal of Educational Technology in Higher Education*, *17*, 2. https://doi.org/10.1186/s41239-019-0176-8

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies and academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education*, *27*, 1–13. https://doi.org/10.1016/j.iheduc.2015.04.007

Chen, S., & Cheung, A. C. K. (2025). Effect of generative artificial intelligence on university students learning outcomes: A systematic review and meta-analysis. *Educational Research Review*, *49*, 100737. https://doi.org/10.1016/j.edurev.2025.100737

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating? Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, *61*(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148

Dignath, C., & Büttner, G. (2008). Components of fostering self-regulated learning among students: A meta-analysis on intervention studies at primary and secondary school level. *Metacognition and Learning*, *3*, 231–264. https://doi.org/10.1007/s11409-008-9029-x

Farrokhnia, M., Banihashem, S. K., Noroozi, O., & Wals, A. E. J. (2024). A SWOT analysis of ChatGPT: Implications for educational practice and research. *Innovations in Education and Teaching International*, *61*(3), 460–474.

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, *74*(1), 59–109. https://doi.org/10.3102/00346543074001059

Huang, A. Y. Q., Lin, C.-Y., Su, S.-Y., & Yang, S. J. H. (2025). The impact of GenAI-enabled coding hints on students' programming performance and cognitive load in an SRL-based Python course. *British Journal of Educational Technology*, *56*, 1942–1972. https://doi.org/10.1111/bjet.13589

Kahu, E. R. (2013). Framing student engagement in higher education. *Studies in Higher Education*, *38*(5), 758–773. https://doi.org/10.1080/03075079.2011.598505

Kahu, E. R., & Nelson, K. (2018). Student engagement in the educational interface: Understanding the mechanisms of student success. *Higher Education Research & Development*, *37*(1), 58–71. https://doi.org/10.1080/07294360.2017.1344197

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeiffer, F., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., Stadler, M., & Kasneci, G. (2023). ChatGPT

for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Labadze, L., Grigolia, M., & Machaidze, L. (2023). Role of AI chatbots in education: Systematic literature review. *International Journal of Educational Technology in Higher Education*, *20*, 56. https://doi.org/10.1186/s41239-023-00426-1

Lo, C. K., Yu, P. L. H., Xu, S., Ng, D. T. K., & Jong, M. S. Y. (2024). Exploring the application of ChatGPT in ESL/EFL education and related research issues: A systematic review of empirical studies. *Smart Learning Environments*, *11*, 50. https://doi.org/10.1186/s40561-024-00342-5

Mohebi, L. (2024). Empowering learners with ChatGPT: Insights from a systematic literature exploration. *Discover Education*, *3*, 36. https://doi.org/10.1007/s44217-024-00120-y

Owen, S. V., & Froman, R. D. (1988). Development of a college academic self-efficacy scale. [Conference presentation]. Annual Meeting of the National Council on Measurement in Education, New Orleans, LA, United States.

Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology*, *8*, 422. https://doi.org/10.3389/fpsyg.2017.00422

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1991). *A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ)*. National Center for Research to Improve Postsecondary Teaching and Learning.

Reeve, J., & Tseng, C.-M. (2011). Agency as a fourth aspect of students' engagement during learning activities. *Contemporary Educational Psychology*, *36*(4), 257–267. https://doi.org/10.1016/j.cedpsych.2011.05.002

Schaufeli, W. B., Martínez, I. M., Pinto, A. M., Salanova, M., & Bakker, A. B. (2002). Burnout and engagement in university students: A cross-national study. *Journal of Cross-Cultural Psychology*, *33*(5), 464–481. https://doi.org/10.1177/0022022102033005003

Schaufeli, W. B., Salanova, M., González-Romá, V., & Bakker, A. B. (2002). The measurement of engagement and burnout: A two sample confirmatory factor analytic approach. *Journal of Happiness Studies*, *3*, 71–92. https://doi.org/10.1023/A:1015630930326

Schunk, D. H. (1991). Self-efficacy and academic motivation. *Educational Psychologist*, *26*(3–4), 207–231.

Sun, D., Boudouaia, A., Zhu, C., & Li, Y. (2024). Would ChatGPT-facilitated programming mode impact college students' programming behaviors, performances, and perceptions? An empirical study. *International Journal of Educational Technology in Higher Education*, *21*, 14. https://doi.org/10.1186/s41239-024-00446-5

Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments*, *10*, 15. https://doi.org/10.1186/s40561-023-00237-x

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), Metacognition in educational theory and practice (pp. 277–304). Erlbaum.

Wu, Y. (2026a). Predicting the well-being of private university students in Quanzhou, Fujian Province, China: The critical roles of self-awareness and responsible decision-making. *Academos Journal*, *2*(3), 67–75.

Wu, Y. (2026b). The role of generative artificial intelligence in Korean language learning: Applications, challenges, and instructional strategies. *Review of Resp AI*, *1*(2), 54–65. https://doi.org/10.17613/tmqt8-ajh44

Wu, Y., & Lin, R. (2026). Understanding high school mathematics learning through grit and achievement goals: An empirical study. *Journal of Advances in Social Sciences*, *2*(4), 22–32. https://doi.org/10.65192/25zrdd11

Zastudil, C., Rogalska, M., Kapp, C., Vaughn, J., & MacNeil, S. (2023). Generative AI in computing education: Perspectives of students and instructors. In 2023 IEEE Frontiers in Education Conference (FIE). IEEE. https://doi.org/10.1109/FIE58773.2023.10343467

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? International Journal of Educational Technology in Higher Education, 16, 39. https://doi.org/10.1186/s41239-019-0171-0

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice*, *41*(2), 64–70. https://doi.org/10.1207/S15430421TIP4102_2

This page intentionally left blank.