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Teacher support enhances self-efficacy and learning outcomes in the age of AI

Shan Xia

With the increasing acceptance and adoption of generative AI in higher education, it remains unclear how this integration can improve the learning outcomes of college students. This study aims to gather empirical evidence on the impact of teacher support and student academic self-efficacy on learning outcomes in EFL (English as a Foreign Language) learning, utilizing generative AI. This quantitative study is based on the Social Cognitive Theory to assess students' attitudes, intentions, and behaviors toward employing generative AI in EFL learning. A questionnaire measuring teachers' affective support, teachers' capacity support, teachers' behavior support, students' academic self-efficacy, and learning outcomes was completed by 906 EFL students in a Chinese higher vocational college. A structural equation modelling study reveals that teachers' capacity support and behavior support can directly predict learners' academic self-efficacy and indirectly affect the students' learning outcomes. Meanwhile, higher levels of students' academic self-efficacy are associated with better academic learning outcomes. This study demonstrates the effectiveness of generative AI as a language-learning tool for EFL learners. Theoretically, it proves that the supportive environment and learners' positive internal psychological factors combine to produce improved learning achievement. Practically, students can make improvements in their English learning with more support from teachers and enhancement of their academic self-efficacy. Consequently, there should be teacher training guiding how to support students emotionally, skillfully, and practically in their English learning, whereas AI-specific pedagogy needs to be further explored to help students enhance their self-efficacy to achieve better learning outcomes.

Keywords Teacher support, Self-efficacy, Learning outcomes, Generative AI

Artificial Intelligence technology, as an important force driving digital transformation and developmental change in education, is increasingly used in language teaching because of its powerful natural language understanding and generation capabilities, providing educators with teaching resources, tailoring learning content to students' individual needs and learning situations, and increasing students' interest in learning. Its capacity to generate human-like, coherent, and contextually appropriate language opens up new avenues for language learning and provides students with never-before-seen chances to receive personalized instruction[1]. However, the rapid development of big language modelling has also brought concerns to educators around the world: The use of human-computer dialogue may lead to a lack of interpersonal interaction opportunities for students; students may use the technology to write assignments on their behalf; writing and essays as a form of assessment have been challenged; and the misuse of big language modelling in the field of science and research has led to academic malpractice[2]. In September 2023, UNESCO released guidelines for applying generative AI in education and research and called on governments to introduce policies regulating the use of AI-generating technologies in schools as soon as possible[3].

Despite the potential problem with AI use in learning, there are two main reasons why incorporating generative AI into studying foreign languages, including English as a foreign language (EFL), is so important and timely. Firstly, learners can quickly apply vocabulary and grammatical structures in a dialogic setting with the help of generative AI tools like ChatGPT, which provide instant and interactive conversational practice that is essential for improving fluency[4]. Secondly, because generative AI tools function as big language models that provide personalized and interactive language practice, they become an invaluable asset with English's sustained role as the world's official language[5,6]. Consequently, generative AI may help students complete complex tasks and projects with personalized guidance, enhancing their academic self-efficacy.

Chengdu Polytechnic, Chengdu, People's Republic of China. email: xiashan@cdp.edu.cn

To explore how the integration of AI in EFL learning enhances college students' learning outcomes, the research gathered empirical data regarding how teacher support and student academic self-efficacy affect learning results in EFL learning with generative AI.

Teachers' roles in the classroom have shifted from the traditional model of lecturers, knowledge holders, or controllers to coaches or counsellors who design tasks and help students complete them[7]. Teachers' affective, capacity, and behavioral support for higher education students' English language learning still had an important place in traditional classrooms. In the context of generative AI, teacher support can still be pivotal, guiding students to use AI in a correct and effective way while driving them to improve their learning outcomes. With the increasing integration of AI in language learning, the model of how teacher support and students' self-efficacy, these kinds of human factors, influence English learning outcomes remains underexplored and needs to be supported by empirical research.

Based on the above background, the following research question is posed:

How do teachers support and academic self-efficacy affect students' learning outcomes in EFL learning with generative AI in higher vocational colleges in China?

Literature review

Social cognitive theory

Bandura's landmark study on self-efficacy served as the foundation for the social cognitive theory, also called social learning theory. He thoroughly examined his social cognitive theory in his 1986 book Social Foundations of Thought and Action: A Social Cognitive Theory[8]. This idea holds that people's motivation and behavior are greatly impacted by the actions they anticipate. This expectation of action indicates a concept of self-efficacy. According to the Social Cognitive Theory, self-efficacy is an important variable that predicts how people learn.

It is hypothesized that self-efficacy beliefs will decide whether a person will take an action, how much effort they will put in, and how long they will sustain themselves in facing difficulties. Self-efficacy is predicted by a range of factors connected to learners' psychological worlds, including emotional arousal, verbal persuasion, vicarious experience, and personal accomplishment. In addition, other elements that affect learning behavior include goal, outcome anticipation, and social-structural factors[9]. Learners with strong self-efficacy can use their limited knowledge to overcome coursework obstacles, manage their time, and study more efficiently[10]. Overall, Self-efficacy influences learning outcomes and performance.

Ways to apply generative AI in EFL learning

The various ways that generative AI can be used in the classroom were highlighted, and it is assumed that it can help students improve their vocabulary, writing, storytelling, reading comprehension, and language translation[11]. Generative AI can also foster students' creativity, provide individualized coaching, and improve their preparedness for future interactions with AI systems[4]. Generative AI can meet students' learning needs, which will increase productivity and academic achievement[12].

A previous study recommends that teachers use the ICE model[13] to assess the work generated by ChatGPT in applying generative AI to EFL learning. The first step would be for teachers to engage students in fact-checking the key ideas in the sample output. This fact-checking will involve the development of research skills as students gather information from multiple sources to confirm a "fact." The second step is to discuss and revise the content of the AI output to make it more consistent with natural language expressions. The third step is an extension approach, where students are instructed to elaborate on the AI output content in the context of their practice, encouraging deeper learning; another extension approach is to invite students to demonstrate their learning through other forms or more authentic tasks, such as oral presentation assignments, artistic expressions, or community projects[14].

Variable definition and relations

In terms of variables, this study selected "teacher support" "self-efficacy" and "learning outcomes" as the main dimensions to explore how generative AI can enhance the quality of the learning experience[15]. The research found that students were more likely to use technologies that teachers had used in the classroom based on their exposure to participatory learning experiences and environments[16]. Previous studies differentiated between different ways of teacher support to promote students' self-directed language learning: raising awareness of the use of technology, helping students discover useful resources, and activating students' interest in technology by organizing various technological activities[17]. Teacher support can be classified as emotional, capacity, and behavior support and is measured by classical scales[18]. Teachers can provide effective support by explaining the benefits of using technology for language acquisition and encouraging students to explore it themselves[18].

Multiple studies have used SEM to demonstrate that teacher support directly and positively affects students' self-efficacy, often with self-efficacy acting as a mediator between teacher support and outcomes like academic engagement, well-being, and performance. These models are validated across diverse contexts and populations[19–22]. The three dimensions of teacher support directly influence students' self-efficacy in language learning with technology[15]. Capacity support and behavior support influence computer self-efficacy through the mediator of facilitation in language learning with self-efficacy[18]. Teacher capacity support involves recommending technological tools and providing cognitive instruction on how to use them successfully[23,24]. Teacher behavior support consists of engaging students in technologically based activities and tasks[18,24]. As English teaching is emotionally demanding[25], past studies show that affective support from teachers correlates and significantly influences self-efficacy in EFL learning[26]. The three dimensions of teacher support, namely affective support, capacity support, and behavior support, correlate significantly in language learning with technology[15,18,27]. However, in the context of artificial intelligence in education, the strong information creation and interactive features of AI technology may challenge the position of the teacher's role. Empirical research is needed to determine how well teacher support affects EFL students' learning outcomes in an AI context[28].

Self-efficacy is the judgment of an individual's ability to engage in certain activities, determining the extent to which a person will persist and strive[29]. Academic self-efficacy refers to a learner's confidence in completing difficult activities[30]. Academic self-efficacy is sometimes described as students' perceptions of their ability to achieve educational goals[31]. As a result, this study particularly used self-efficacy to assess learning and performance. Self-efficacy was measured using the English Self-Efficacy Questionnaire (ESEQ), which is a 6-item scale adapted from the self-efficacy subscale of the MSLQ developed by Pintrich et al.[29,32].

Academic self-efficacy has been seen as an important factor influencing the learning outcome[33]. It is discovered to be a predictor of individual performance[34], and previous study findings demonstrate a favorable relationship between self-efficacy and learning outcomes[35]. In the context of foreign language acquisition, self-efficacy has been shown to influence learning outcomes and specific foreign language skills favorably[36,37]. Students' positive emotion can predict their learning profiles in terms of engagement and willingness to communicate[25].

Learning outcomes refer to the cognitive and practical integration of acquired knowledge and the learner's ideas into the larger society[38,39]. It is related to whether a set of learning objectives is achieved. Learning outcomes in past studies have been evaluated primarily through test scores, achievement measures, students' perceptions of their learning experiences, and expectations of future career prospects. Some researchers have also used questionnaires to judge students' learning experiences[40].

Research gap
Grounded in Social Cognitive Theory, the present study extended the model to AI-mediated EFL settings by examining whether two social-cognitive constructs, teacher support and academic self-efficacy, can predict learning outcomes. Teacher support as a whole or its sub-dimensions can significantly predict the learning behaviors, such as English learning empathy or boredom, willingness to communication, and motivation[28,41], but the efficacy of teacher support to learning outcomes with AI tools urgently requires empirical exploration. AI learning self-efficacy was confirmed to predict willingness to communicate[42], but academic self-efficacy, perceived as students' perceptions of their ability to achieve educational goals[31], can be further discussed.

Methods
Research framework
The conceptual framework was developed from social cognitive theory. Teacher support, especially through feedback and encouragement, acts as a form of social persuasion and vicarious experience, directly enhancing students' self-efficacy[19]. Also, self-efficacy has been recognized as a significant determinant of learning outcomes. Figure 1 illustrates the conceptual framework for this study.

This study aims to investigate the factors that significantly influence learning outcomes (LO) for EFL learning with generative AI among students studying in higher vocational colleges. These factors include academic self-efficacy (SE), teachers' affective support (AS), teachers' capacity support (CS), and teachers' behavior support (BS). It also examines the factors' direct, indirect, and mediating effects. The following are the alternate theories that need to be tested:

Figure 1 Conceptual framework

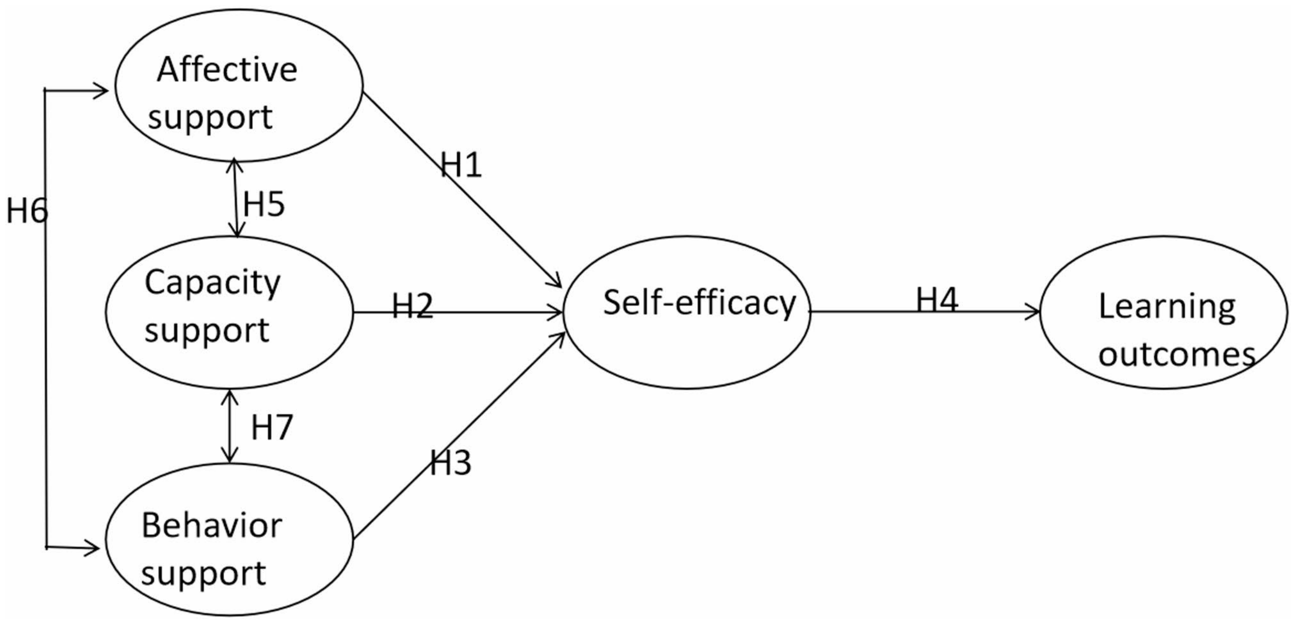

Fig. 1. Conceptual framework.

H1 Affective support has a significant impact on self-efficacy.

H2 Capacity support has a significant impact on self-efficacy.

H3 Behavior support has a significant impact on self-efficacy.

H4 Self-efficacy has a significant impact on learning outcomes.

H5 Affective support and capacity support correlate significantly.

H6 Affective support and behavior support correlate significantly.

H7 Capacity support and behavior support correlate significantly.

Methodology
The researcher employed non-probabilistic sampling and a quantitative technique with an online questionnaire for the study. To identify the key predictors of higher vocational college students' English language learning outcomes and the more complex relationship among the variables, structural equation modelling was chosen, and data were analyzed using statistical software such as Jamovi 2.3.28 and Amos 21.

There are two sections to the questionnaire. Students' demographic data, including gender, grade, disciplinary areas, and years of English study, is included in the first section. The other sections use a 5-point Likert scale, with each question item ranging from (1) strongly disagree to (5) strongly agree, to measure students' opinions or behavior regarding AI-assisted language acquisition. The scales were adapted from the previous classical research and have been used repeatedly in many articles published in international core journals[18,32,40]. The three experts evaluated the content validity of the questions using the index of item-objective congruence (IOC), and all of the question items received scores greater than 0.6[43], indicating that the content validity was passed. A pilot test with sixty respondents assessed the internal consistency reliability; Cronbach's Alpha for each variable was above 0.7, showing acceptable reliability.

After the validity and reliability of the survey were confirmed, Questionnaire Star, a reputable survey website, was used to send the questionnaires to the intended respondents. The sample's demographic features were reflected through the application of descriptive statistics. To determine if a proposed factor structure matches the collection of observed data, confirmatory factor analysis (CFA) was employed. The model fit measurement was calculated using the supplied data to confirm the model's validity and reliability. Finally, the researcher assessed the hypotheses using the Structural Equation Model (SEM).

Population and sample size
The study's participants are Chinese students in higher vocational colleges studying English as a foreign language. Vocational college students typically exhibit low English proficiency and correspondingly low confidence in using the language. When the statistical power is set to 0.95, the Structural Equation Model Sample Size Calculator suggests a minimum sample size of 223.

Sampling technique
Purposive sampling, a non-probabilistic sampling, was used to select the study's sample from the population. For this study, 950 college English students from a higher vocational college in Chengdu were chosen as good representatives of college students enrolled in an English as a foreign language (EFL) course. They were volunteer participants from engineering and liberal arts grade 1 or grade 2 students who mirrored the key demographic and academic profile of EFL students in college.

The information was gathered in May 2025 using the Questionnaire Star website. Students were instructed to complete the survey in around fifteen minutes, either during class or during their free time, and their English teachers delivered it to them directly.

Since the study received official permission from the college's Ethical Approval Committee, all procedures were conducted in compliance with relevant rules and guidance. Before the data-collecting process, the study also used informed consent to ensure that the participants participated voluntarily. Specifically, the 950 students who participated in the survey were made aware that their names would remain anonymous and that it was completely voluntary for them to participate. The survey's introduction made it clear that students might choose to participate, and they verbally agreed. Consequently, 906 interested students collaborated with the researchers, and the students who declined to participate in the study did not reply to their questionnaires.

Results
Demographic information
Only 906 students completed the survey, and their responses were retained for data analysis. Table 1 lists the 906 participants' demographic profiles. In the group, female respondents comprised 68.7%, while male respondents comprised 31.3%. Of those present, 70.2% were in grade 1, while 28.9% were from grade 2. 67.2% of students majored in the liberal arts, whereas 32.8% studied engineering. In terms of years of study for English, 17.9% of students reported having learned English for about four years, 30.8% for around seven years, 33.5% for ten years, and 18.1% for 13 years.

Variables	Category	Frequency	Percentage (%)
Gender	Male	284	31.3
	Female	622	68.7
	Total	906	100
Grade	Grade 1	636	70.2
	Grade 2	262	28.9
	Grade 3	8	0.9
	Total	906	100
Discipline area	Engineering	297	32.8
	Liberal arts	609	67.2
	Total	906	100
Years of study for English (choose the closest number of years)	4 years	162	17.9
	7 years	279	30.8
	10 years	301	33.2
	13 years	164	18.1
	Total	906	100

Table 1. Demographic profile.

Variable	Source of questionnaire (measurement indicator)	Number of items	Cronbach's Alpha	Factor loading	CR	AVE
Affective support	Lai[18]	4	0.900	0.782–0.864	0.902	0.697
Capacity support	Lai[18]	4	0.901	0.720–0.877	0.902	0.697
Behavior support	Lai[18]	4	0.894	0.717–0.892	0.899	0.691
Self-efficacy	Pintrich[29]	8	0.958	0.814–0.880	0.957	0.736
Learning outcomes	Dahleez et al.[40]	8	0.962	0.854–0.885	0.962	0.758

Table 2. Confirmatory factor analysis result, composite reliability (CR) and average variance extracted (AVE). CR, Composite reliability; AVE, Average variance extracted.

	AS	CS	BS	SE	LO
AS	**0.835**				
CS	0.786	**0.835**			
BS	0.744	0.789	**0.831**		
SE	0.657	0.703	0.693	**0.858**	
LO	0.71	0.734	0.747	0.786	**0.871**

Table 3. Discriminant validity. The diagonally listed value is the AVE square roots of the variables AS, Affective support; CS, Capacity support; BS, Behavior support; SE, Self-efficacy; LO, Learning outcomes

Confirmatory factor analysis (CFA)

This study's statistical analysis used confirmatory Factor Analysis (CFA). The measurement model's fit and the item correlations in the latent variables were assessed using confirmatory factor analysis, or CFA. Furthermore, CFA can verify the convergent and discriminant validity of the measurement model[44]. A relationship or interaction between a construct and other constructs in the conceptual framework is confirmed by construct validity[45]. Convergent and discriminant validity are widely used statistical techniques for evaluating concept validity[46].

The following methods were used to evaluate convergent validity: factor loading, average variance extracted, composite reliability, and Cronbach's Alpha reliability. A summary of the results is given in Table 2. Every variable in Table 2 has more than three items, each of which independently demonstrates factor loading in the test of discriminant validity. A p-value of less than 0.05 and a value greater than 0.50 for factor loadings show that the study's factor loadings were suitable for CFA analysis. Values of 0.7 or higher for CR and 0.4 or higher for AVE were deemed appropriate. This study's AVE values and CR scores were above the threshold levels. [47]. Regarding composite reliability, the dimension with the highest internal consistency was learning outcomes.

Table 3 shows that, in terms of discriminant validity, the square root of AVE for each diagonal structure had values of 0.835, 0.835, 0.831, 0.858, and 0.871, respectively, greater than the inter-scale correlations. Consequently, discriminant validity was ensured.

The model fit was estimated to use the acceptable fit index value in Table 4. The statistical outcomes of each index were contrasted with the acceptable limits. After the model was adjusted, the seven indexes achieved

Index	Acceptable values	Statistical values
CMIN/DF	< 5.00[48,49]	4.871
GFI	≥ 0.85[50]	0.878
AGFI	≥ 0.80[50]	0.853
NFI	≥ 0.80[51]	0.941
CFI	≥ 0.80 [52]	0.952
TLI	≥ 0.80[53]	0.947
RMSEA	< 0.08[54]	0.065
Model summary		Acceptable model fit

Table 4. Goodness of fit for confirmatory factor analysis (CFA). CMIN/DF, The ratio of the chi-square value to the degree of freedom; GFI, Goodness-of-fit index; AGFI, Adjusted goodness-of-fit index; NFI, Normalized fit index; IFI, Incremental fit indices; CFI, Comparative fit index; TLI, Tucker Lewis index; RMSEA, Root mean square error of approximation.

Index	Acceptable values	Statistical values after adjustment
CMIN/DF	< 5.00[48,49]	4.858
GFI	≥ 0.85[50]	0.877
AGFI	≥ 0.80[50]	0.854
NFI	≥ 0.80[51]	0.940
CFI	≥ 0.80[52]	0.952
TLI	≥ 0.80[53]	0.947
RMSEA	< 0.08[54]	0.065
Model summary		Acceptable model fit

Table 5. Goodness of fit for structural model after adjustment (SEM).

Hypothesis	Paths	Standardized path coefficient (β)	S.E.	t-value	Testing result
H1	SE<---AS	0.147	0.102	1.560	Not supported
H2	SE<---CS	0.386	0.125	3.853*	Supported
H3	SE<---BS	0.368	0.068	6.946*	Supported
H4	LO<---SE	0.940	0.029	32.498*	Supported
H5	CS<--> AS	0.943	0.021	15.397*	Supported
H6	BS<--> AS	0.864	0.019	14.834*	Supported
H7	BS<--> CS	0.878	0.019	13.542*	Supported

Table 6. Hypotheses testing result of the structural Model. AS, Affective support; CS, Capacity support; BS, Behavior support; SE, Self-efficacy; LO , Learning outcomes *$p < 0.05$.

acceptable model fit: CMIN/DF = 4.871, GFI = 0.878, AGFI = 0.853, NFI = 0.941, CFI = 0.952, TLI = 0.947, RMSEA = 0.065.

Structural equation model (SEM)

To verify model fitness, the predictable connections between variables and factors impacting the learning outcomes of generative AI in EFL learning, the structural model was evaluated using structural equation modeling. To ensure model fitness, the modified structural model is shown in Table 5. Structural models depict the relationship—which may be direct or indirect—between latent variables[55].

By comparing the statistical value from the indices to the acceptable goodness-of-fit values in Table 5, the model fit was assessed. CMIN/DF = 4.858, GFI = 0.877, AGFI = 0.854, NFI = 0.940, CFI = 0.952, TLI = 0.947, and RMSEA = 0.065 were the statistical values for the indices. The CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA indexes were deemed appropriate based on the data. Thus, the fitness of the structural model has been verified.

Research hypothesis testing result

The hypothesis presents the degree of correlation between the independent and dependent variables, which is measured using standardized path coefficients. As seen in Table 6, six of the seven presented hypotheses received support.

Learning outcomes of generative AI in EFL learning were affected strongly by self-efficacy, with the route coefficient(β = 0.940). Self-efficacy was influenced by capacity support (β = 0.386) and behavior support

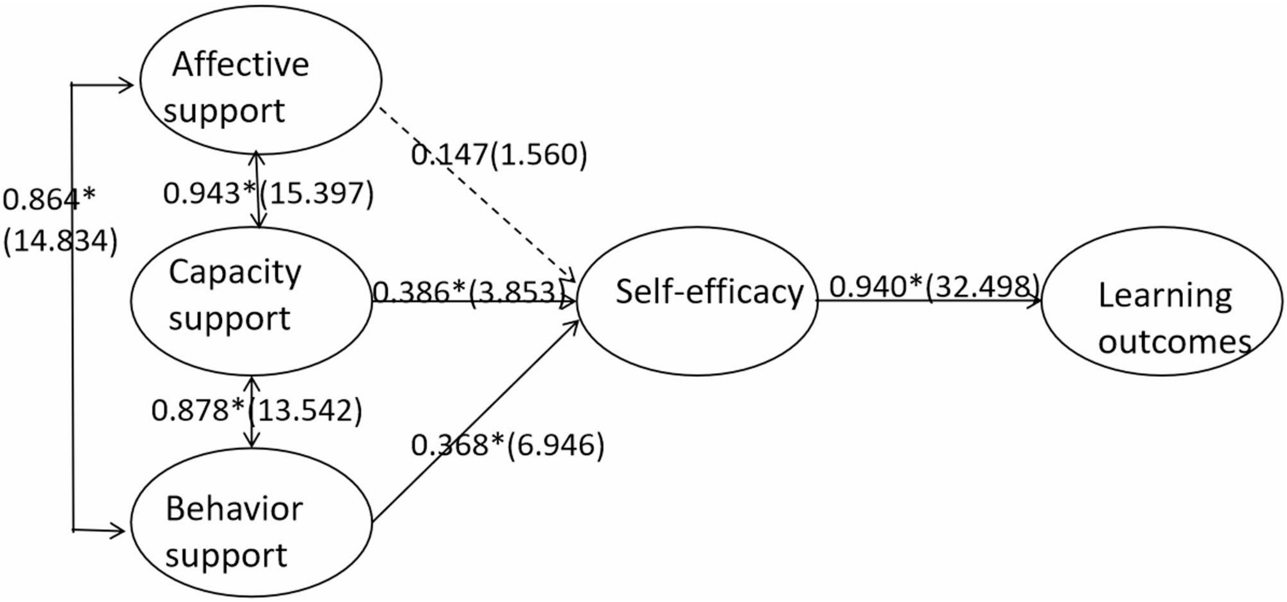

Fig. 2. Result of the structural model. The solid line reports the standardized coefficient with * indicating $p < 0.05$ and the t-value in parentheses; the dotted line reports a non-significant result.

	Dependent variables							
	Self-efficacy (SE)				**Learning outcomes (LO)**			
Independent variables	**Direct effect**	**Indirect effect**	**Total effect**	R^2	**Direct effect**	**Indirect effect**	**Total effect**	R^2
Affective support (AS)	0.147	–	0.147	0.756	–	0.138	0.138	0.884
Capacity support (CS)	0.386	–	0.386		–	0.363	0.363	
Behavior support (BS)	0.368	–	0.368		–	0.346	0.346	
Self-efficacy (SE)	–	–	–		0.840	–	0.840	

Table 7. Direct, Indirect, and total effects of relationships.

(β = 0.368). The paired standardized path coefficients for affective support to capacity support, affective support to behavior support, and capacity support to behavior support were 0.943, 0.864, and 0.878, respectively.

Figure 2 shows the relationship between these factors visually. Solid lines indicate a significant relationship with an asterisk, whereas dotted lines indicate an insignificant relationship. The t-value and the two variables' standardized path coefficients are displayed by the numbers on the arrow lines.

Direct, indirect, and total effects of relationship

With the use of AMOS software, both direct and indirect impacts on the relationship between the variables can be computed. A direct effect (DE) relationship exists when two variables are related without the involvement of a mediating variable. An indirect effect (IE) relationship is one in which the relationship between variables only arises because of at least one mediating variable. The total impact (TE) of a relationship path is the total of its direct and indirect impacts[56]. The R-squared (R2) value indicates the dependent variable's amount of variance[47]. The R square value shows the extent to which other factors can explain the variance in a given variable[57]. The lowest acceptable threshold is an R^2 value of 0.1[58]. The findings demonstrate that two R^2 values—0.756 and 0.884—were higher than the lowest requirement. Based on the given theories, Table 7 shows the direct, indirect, and total implications of the relationship.

From the table, it is shown that 88.4% of the variance in students' learning outcomes with generative AI in EFL learning is explained by the four independent variables, namely self-efficacy, affective support, capacity support, and behavior support. 75.6% of the difference in self-efficacy is explained by its three independent variables, namely affective support, capacity support, and behavior support.

The indirect effects of learning outcomes were influenced by three independent variables, which include affective support (0.138), capacity support (0.363), and behavior support (0.346). The total effects of learning outcomes were impacted by four variables, namely affective support (0.138), capacity support (0.363), behavior support (0.346), and self-efficacy (0.840). The total effects of self-efficacy were affected by the three independent variables: affective support (0.147), capacity support (0.386), and behavior support (0.368).

Discussion

Overall, statistical analysis has supported the majority of the conceptual framework hypotheses tested, apart from H1. This contradicts the previous research, which found that affective support from teachers significantly predicts the students' self-efficacy in EFL learning with new technology[15,26]. This is probably because the generative AI to be applied to EFL teaching is at its infant stage. Some Chinese college English teachers do not use it very proficiently, and some even have negative opinions on students' adoption of AI use. Meanwhile, examination culture and teacher authority remain dominant in the Chinese educational system, so emotional encouragement is discounted unless accompanied by concrete, AI-specific pedagogical guidance. Moreover, AI tools may lead to less interpersonal communication, which involves emotion, thereby diminishing the affective richness of the learning experience. Thus, affective support to self-efficacy was not supported in this study for students with their AI-assisted English learning.

Among all relation hypotheses, the strongest route is from self-efficacy to learning outcomes, with a standardized path coefficient of 0.940, indicating that students' learning outcomes with generative AI are well predicted by academic self-efficacy. This is in line with earlier research[36,37].

It shows that when students have better academic self-efficacy with generative AI in EFL learning, they achieve better learning outcomes in English[36]. This strong link may be magnified among Chinese vocational students, whose lower English proficiency makes self-confidence in learning with AI tools especially decisive for learning achievement.

For the other predictable relation hypothesis, the path from capacity support to self-efficacy came to be the second strongest, with a standardized coefficient of 0.386. This correlates with past research, which stated that teachers' capacity to support significantly influenced the learning outcome in EFL learning with new technology[15]. Behavior support from teachers determines the students' academic self-efficacy significantly, with a standardized path coefficient of 0.368. Previous research also supports this[15]. Capacity support equips students with better skills in AI technology adoption in English learning, while behavior support drives students to take action[18].

For the correlation hypothesis, the standardized path correlation between affective support to capacity support, affective support to behavior support, and capacity support to behavior support is 0.943, 0.864, and 0.878, respectively. This shows that the three dimensions of teacher support have a strong correlation with each other.

Overall, teacher support provides a good, supportive learning environment, which can significantly predict students' academic self-efficacy in learning English; students' self-efficacy can influence learning outcomes significantly. Consequently, a supportive learning environment and students' high self-efficacy lead to better learning outcomes in English learning with generative AI. Practically, these findings urge EFL educators to cultivate a supportive learning environment with AI tools by offering clear guidance, encouragement, and feedback to bolster students' academic self-efficacy. Doing so will translate teacher support and student self-efficacy into measurable gains in English proficiency.

Conclusion

Findings

Resuming the study's topic, "How do teacher support and academic self-efficacy affect students' learning outcomes in EFL learning with generative AI in higher vocational colleges in China?" This study employed quantitative approaches to demonstrate that teachers' affective support, capacity support, behavioral support, and students' self-efficacy work together to influence the dependent variable—learning outcomes. Statistical analysis of the collected data supported the revised research framework based on Social Cognitive Theory[8] In that self-efficacy is an important predictor of learning behavior, and social factors such as AI tools and teacher support can predict the learning outcomes. Thus, Social Cognitive Theory's explanatory power is empirically validated and further extended to EFL learning mediated by generative AI tools.

This study created a model with statistical evidence and discovered that teachers' capacity support and behavior support influenced students' academic self-efficacy positively, indicating teacher support for enhancing student self-confidence in English learning with generative AI. Meanwhile, students' academic self-efficacy strongly predicted the learning outcomes in EFL learning, which provided empirical evidence for social learning theory[8]. Additionally, teachers' capacity support and behavioral support affected the students' learning outcomes by mediating students' academic self-efficacy, which restated the importance of teachers' support for students' academic study in colleges.

Consequently, it can be inferred from the proposed research framework that students make improvements in their English learning outcomes with increasing support from teachers and enhancement of their academic self-efficacy. In other words, the supportive environment and learners' positive internal psychological factors combine to produce better learning achievement.

Based on the above discussion, there should be teacher training guiding how to support students emotionally, skillfully, and practically in their English learning. AI-specific pedagogy needs to be further explored to help students enhance their self-efficacy to achieve better learning outcomes.

Limitation

The sampling method was purposive sampling and was only undertaken in a higher vocational college in Chengdu, so the sampling limits representativeness of the research result. Furthermore, generative AI was employed with EFL learning, but students' acceptance of innovative technologies takes time. Future research should include a longitudinal study to monitor the long-term trend of students' learning outcomes while using generative AI in EFL learning. Additionally, studies could explore how AI-assisted learning influences learner engagement and subsequent career growth.

Data availability
Data is provided within the manuscript.

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Additional information
Correspondence and requests for materials should be addressed to S.X.