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The Mediating Role of Achievement Goal Motivation in the Relationship between Self-Regulated Learning Ability and Academic Achievement in Generative AI-Supported High School Mathematics

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Abstract: This study investigates whether achievement goal motivation helps to explain the relationship between self-regulated learning ability and academic achievement when generative artificial intelligence tools are applied to high school students' mathematics course learning. Examined via descriptive analysis, reliability appraisals, Pearson correlation tests, regression methods, and bootstrap mediation assessments were the responses from 849 Chinese students. The set of three scales showed outstanding internal reliability, having Cronbachs alpha values of 0.904, 0.900, and 0.881.The self-regulated learning ability was linked to both achievement goal motivation and academic achievement. The calculated indirect impact was 0.127 (with a 95% bootstrap confidence interval of [0.091, 0.165]), which made up 21.8% of the total linkage. Consequently, the drive associated with achievement goal motivation accounted for part, but not the whole, of the link between students' self-regulated learning ability and academic achievement. The results suggest that generative artificial intelligence is most advantageous in the field of education when students set goals for its use, assess its reasoning, and improve their own work rather than simply accepting its answers.

Keywords: Generative AI; High School Mathematics; Self-regulated Learning Ability; Achievement Goal Motivation; Academic Achievement

1. Introduction

Generative AI presents high school students with a quick response, including detailed and standardized problem-solving process, thinking tips, summary and promotion, and various solutions. However, in the field of mathematics, this seamless and direct response does not always guarantee the accuracy of its answers. Lack of conditions, rapid transition of reasoning or unexplained changes may make seemingly reasonable and rigorous reasoning processes or solutions unusable. Research on large scale language models in the field of education has pointed out both potential advantages and difficulties [1,2]. Evaluations centered on mathematics instruction in schools yield comparable results: immediate help turns out to be advantageous, but the efficacy of learning depends on the way in which the resource is employed and checked [3]. Therefore, the core problem of mathematics course learning is not whether students can use generative artificial intelligence tools, but whether they can decide the content of questions independently, identify the information that needs to be verified, and link the results given by artificial intelligence tools with mathematical reasoning.

This study focuses on the role of autonomous learning ability in the educational environment empowered by artificial intelligence. Zimmerman's point of view regards "adjustment" as a circular process: in this process, individuals set goals, take actions, evaluate the results, and adjust their next action plan accordingly [4]. For high school students who are solving a math problem, the problem-solving process may involve reasonable planning of time, selection of appropriate problem-solving methods, identification of uncertainties in the problem, backtracking of

previous calculation steps, or seeking help for specific problems. Artificial intelligence offers an extra instrument to the process and at the same time presents novel options. Learners need to design practical hints, distinguish explanations from assertions, and evaluate whether the answers meet the requirements of the questions. Recent research on artificial intelligence driven educational methods also shows that although the planning and supervision links can be supported by auxiliary support, students are still responsible for carrying out these operations [5].

Achievement goal theory provides another perspective for problem interpretation. When performing the same task, students adopt different success criteria: they may understand a certain method, focus on improving their own ability, show their actual performance, or avoid making mistakes [6]. These standards impact resilience and the understanding of mistakes. With the help of generative artificial intelligence, students who pay attention to mastering knowledge can compare two proof methods or explore why a step is established. Students who focus on completing tasks quickly may stop exploring after getting the first feasible answer. Mathematics research studies that use ChatGPT have pointed out differences in self-directed learning according to different usage patterns of the tool; nevertheless, the association with performance results is still uncertain in different contexts [7]. This study examines the interaction among self-regulated learning ability, achievement goal motivation, and academic achievement within a mediated structure.

The framework addresses an actual world issue that often goes unnoticed by technology centered methods. Students in one classroom may interact with the same app, but they acquire knowledge in notably different ways. Stressing supervision and goals enables examining the learners procedures that cause the variation, instead of simply connecting the outcomes to the presence of AI.

2. Literature Review and Hypotheses

2.1 Self-Regulated Learning Ability and Academic Achievement

Self-directed learning refers to the procedure where individuals formulate plans, make adjustments, and exercise control over their endeavors during a task. Although models differ in terminology, they commonly include preparation, strategic action, monitoring, and reflection [8]. Generative AI can offer support at each stage. It could help a student comprehend a question prior to initiating, assess a concept while solving problems, or examine methods after making a mistake. Chius classification of activities leveraging ChatGPT emphasizes these prospects and stresses the significance of continuous educator participation [9]. Experimental work on AI enabled mathematics environments also suggests that carefully structured interaction can support problem solving [10]. Based on this assumption, H1 states that self-regulated learning ability positively predicts academic achievement in high school mathematics.

2.2 Self-Regulated Learning Ability and Achievement Goal Motivation

The implementation of strategies alone cannot completely explain the reason why a person starts, persists with, or returns to a demanding activity. The selections made are related to the goal the person intends to reach. A student who can identify what a problem demands and monitor partial progress has a clearer basis for setting a realistic achievement goal. By contrast, inadequate supervision might shift the emphasis to simply finishing the worksheet or avoiding an incorrect answer. Social-cognitive models also connect goals, perceived capabilities, and self-regulation behaviors [11]. In an AI-supported environment, the link could become notably evident as learners constantly determine whether to get more clarification, address a distinct question, or end their session.

Generative AI brings up a problem of excess, rapidly creating several possible solutions within just a few moments. A well-defined learning goal helps students figure out which answer deserves attention and if further questions are worthwhile. When there is no distinct standard, the flow of suggestions may distract rather than assist. H2 therefore states that self-regulated learning ability positively predicts achievement goal motivation.

2.3 The Mediating Role of Achievement Goal Motivation

The 2 by 2 framework categorizes objectives into four kinds: mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance categories [6]. These

viewpoints lead students to view feedback in a distinct manner. A learner aiming for proficiency could make use of errors to enhance their comprehension, while a person centered on avoiding failure may choose the quickest method to finish the task. Research on feedback has shown that information gains value when learners are able to link it to the task, the process, and their following steps [12]. Evidence on explicit self-regulation instruction similarly indicates that strategies can be developed rather than treated as fixed traits [13]. When independent learning helps students set significant goals, and these goals direct their efforts, achievement goal motivation should transmit part of the association with performance. H3 predicts a positive relationship between achievement goal motivation and academic achievement. H4 predicts a mediating role for achievement goal motivation.

3. Method

3.1 Participants

Table 1.Participant Characteristics

Variable	Category	n	%
Gender	Boys	402	47.3
	Girls	447	52.7
Grade	10	261	30.7
	11	270	31.8
	12	318	37.5
Background	Urban	416	49.0
	Rural	433	51.0

Data was gathered from 849 pupils enrolled in regular high-schools throughout China. The set consisted of 402 males (47.3%) and 447 females (52.7%). There were 261 pupils in Grade 10 (30.7%), 270 registered in Grade 11 (31.8%), and 318 studying in Grade 12 (37.5%). There were 416 pupils from urban regions, accounting for 49.0%, whereas rural pupils numbered 433, constituting 51.0%. No particular personal information was requested, and the assessment depended only on aggregated data.

Table 1 shows the traits of the sample. Gender and living surroundings were nearly evenly balanced, encompassing all senior-high school grades; the 12th grade constituted the largest proportion.

3.2 Measures

The ability of self-regulated learning was measured with 15 items covering self-efficacy, learning motivation, metacognitive strategies, cognitive strategies, and management of learning resources. Twelve assessments evaluated goal-oriented motivation in connection with mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance inclinations. Academic achievement was evaluated from nine perspectives concentrating on dedication to studies, educational results, and students descriptions of quantifiable achievements. Responses used a five-point scale, and higher averages denoted more of the measured construct. Internal consistency was 0.904 for self-regulated learning ability, 0.900 for achievement goal motivation, and 0.881 for academic achievement. In the process of single-factor analysis, the initial factor made up 30.42% of the variance, which did not reach the 40% threshold set for this study. Academic achievement remained a self-report measure and was not treated as equivalent to a standardized examination score.

From the wider survey structure, just the three elements crucial for the present model were retained. The answers to the items were aggregated and averaged to compute the score for each scale. The obtained scores, having reliability ratings that all went beyond 0.80, were regarded as appropriate for utilization in the subsequent analyses.

3.3 Data Analysis

After conducting an assessment of the item records to ensure accuracy, scale scores were recalculated from the initial responses. The analysis then moved from description to model testing. Initial calculations involved computing arithmetic means, standard deviations, distribution indicators, reliability metrics, and Pearsons correlation coefficients. Regression coefficients were estimated for the proposed paths. The indirect impact was evaluated by means of 5,000 bootstrap repetitions together with a 95% confidence interval; a range that did not contain zero was regarded as suggestive of an indirect association. As the survey was carried out at a specific moment, the framework depicts statistical prediction instead of established cause-effect sequencing.

The sequence of examinations advanced as described. The characteristics of the sample and the spread of variables were examined; following steps included evaluating bivariate associations; total effects, a-path, b-path, and

direct routes were computed; finally, bootstrapping was utilized to assess the indirect impact. Results are reported at $p < 0.05$, with $p < 0.001$ shown where applicable.

4. Results

4.1 Descriptive Statistics and Correlations

The mean scores showed a close alignment: 3.653 for self-regulated learning ability, 3.632 for achievement goal motivation, and 3.633 for academic achievement. The individual standard deviations were 0.535, 0.574, and 0.588. The absolute value of skewness did not exceed 0.18, and the kurtosis remained below an absolute value of 0.24.In every case, the relationships indicated positive correlations. The ability for Self-regulated learning had a correlation of r = 0.448 with achievement goal motivation and r = 0.529 with academic achievement; furthermore, achievement goal motivation was related to academic achievement at r = 0.443 (all $p < 0.001$).

Table 2. Descriptive Statistics and Correlations

Variable	M	SD	1	2	3
1 SRL ability	3.653	0.535	1		
2 Goal motivation	3.632	0.574	0.448***	1	
3 Achievement	3.633	0.588	0.529***	0.443***	1

*Note. N = 849. ***p < 0.001.*

The complete matrix is presented in Table 2. In it, the most notable coefficient links self-regulation abilities with academic achievement. No associations were strong enough to suggest that the three scales evaluated the exact same concept.

4.2 Regression Analysis

In the preliminary analysis, the ability for self-regulated learning predicted educational achievement (B = 0.582, SE = 0.032, β = 0.529, t = 18.162, $p < 0.001$), resulting in an R^2 value of 0.280. Moreover, it predicted achievement goal motivation within the second framework (B = 0.481, SE = 0.033, β = 0.448, t = 14.576, $p < 0.001$; $R^2 = 0.201$). In Model 3, the two predictors each independently demonstrated significant connections to achievement: B = 0.455 (SE = 0.035, β = 0.414, t = 13.190, $p < 0.001$) for self-regulated learning ability and B = 0.264 (SE = 0.032, β = 0.257, t = 8.201, $p < 0.001$) for achievement goal motivation. Their combined R^2 was 0.333. H1, H2, and H3 were therefore supported.

As shown in Table 3, integrating achievement goal motivation reduced the influence of self-regulated learning ability yet did not entirely nullify its coefficient. This model corresponds to the idea of partial mediation.

Table 3. Regression Results

Model	Outcome	Predictor	B	SE	β	R?
1	Achievement	SRL ability	0.582	0.032	0.529***	0.280
2	Goal motivation	SRL ability	0.481	0.033	0.448***	0.201
3	Achievement	SRL ability	0.455	0.035	0.414***	0.333
	Achievement	Goal motivation	0.264	0.032	0.257***	

*Note. Model 3 included both predictors. ***p < 0.001*

4.3 Mediation Analysis

By employing bootstrapping, the indirect effect was computed to be 0.127, having a 95% confidence interval ranging from 0.091 to 0.165. The relevant direct approximation equaled 0.455 (95% CI [0.385, 0.523]), whereas the overall computation attained 0.582 (95% CI [0.519, 0.644]). As zero was beyond the range of the indirect route, Hypothesis 4 (H4) was confirmed. The non-direct part made up 21.8% of the entire total, leading to a remarkable direct section.

Table 4 concurrently presents the set of three effect estimates. The results indicate that achievement-goal motivation acts as a partial intermediary instead of a complete one.

Table 4. Bootstrap Mediation Effects

Effect	Estimate	Boot LL	Boot UL	%
Direct	0.455	0.385	0.523	78.2
Indirect	0.127	0.091	0.165	21.8
Total	0.582	0.519	0.644	100.0

Note. Number of Bootstrap repetitions = 5,000; LL stands for the lower limit; UL denotes the upper limit.

5. Discussion and Conclusion

The most notable observed tendency was the association between self-regulated learning

ability and academic achievement in mathematics. The presence of an AI system did not remove the need to formulate a strategy, oversee progress during the process, or decide on subsequent steps after an error. Surely, such requirements could seem more obvious when a reply is generated right away. Students who take charge of their own learning process can engage with the system in a strategic way: they may first attempt to solve the problem on their own, ask for help at a specific stage, and assess the given solution based on their own thinking process. A learner who has difficulties in study management could accept the early results and miss the opportunity to examine the effectiveness of the method. In classroom undertakings, this suggests that teaching the composition of prompts ought to be incorporated instead of being regarded as an independent technical proficiency. It should be linked to assessing situations, elaborating on alterations, and recording the modifications done to the initial proposal.

The notion of achievement goal motivation offered understanding regarding a part of this link. Individuals who monitor their own progress are better prepared to evaluate whether they are moving towards understanding, improvement, or a particular performance objective. The capacity to assess can sustain motivation after an incorrect response and determine the kind of assistance obtained from artificial intelligence. The proportion of mediation was 21.8%, which showed that motivation carried importance even without taking into account the whole relationship. Extra factors, like self-confidence, stress states, teaching support, and AI-related experience, may also affect how rules get put into practice and result in success.

Three findings can be drawn from the model. Self-regulated learning ability was associated with academic achievement and with achievement goal motivation. Achievement goal motivation, in turn, contributed to achievement after self-regulated learning ability was considered. Its mediating role was partial. The tangible outcome is evident: a mathematics class augmented by AI ought to cultivate students capability to oversee their learning and their drive to keep working on a task.

The results do not match a performance model mainly propelled by technology. Generative artificial intelligence boosts the support available to a learner. However, it is still up to the learner to decide how to incorporate that help into the problem-solving method. One approach to sustaining steady academic commitment appears to be achievement-focused goal motivation.

6. Limitations and Recommendations

A variety of constraints determine these results. The examination fails to ascertain the succession of alterations among variables as the data were collected at a single moment in time. The evaluation of performance relied on submissions from students instead of a test that was standardized. Furthermore, generative artificial intelligence influenced the educational structure yet was not assessed as a standalone component. The poll cannot distinguish among frequent and occasional utilization, queries intended for comprehension as opposed to those for answers, or comprehensive verification as against random acceptance.

The instance further confines wide-ranging applicability. The research encompassed Chinese high-school pupils. There were differences among schools in terms of their rules, admission requirements, and views on acceptable AI assistance. Subsequent research could combine different educational establishments, numerous assessments, standardized mathematics tests, teacher evaluations, and recorded cases of AI involvement. Observing the dynamics in the classroom can offer useful insights into the instances when students interact with AI, their behaviors upon getting insufficient feedback, and whether validation occurs before or after educator participation. Differentiating between approach and avoidance objectives might assist in clarifying whether the four forms of goal-orientations operate distinctively in an AI-assisted setting.

For guidance, the outcomes back a distinct sequence of tasks. Before asking for AI help, learners are able to record the specifics of the problem and sketch out a basic strategy. After getting an answer, they can choose to mark the phase that addressed their question, verify the calculations independently, and clear up any differences in comparison to their initial attempt. Brief assessments of errors or improvements can make this process quantifiable. Activities ought to stress the significance of offering reasoning in mathematics, instead of merely concentrating on

the answer. Educational establishments need clearly-specified standards about confidentiality, source attribution, verification, and allowable assistance. These approaches guarantee that students maintain control of the mathematical reasoning procedure, whereas AI offers assistance via feedback and presenting diverse methods.

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