

High School Students' Generative AI Over-reliance and Learning Goal Orientation

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Abstract

This study examines the relationship between high school students' reliance on GenAI and potential predictors: student demographic characteristics, academic background, and learning goal orientation. The findings highlight the importance of guiding students to use GenAI appropriately, preventing over-reliance on AI, and fostering mastery goal orientations in the AI age.

1 Introduction

1.1 Background

ChatGPT was launched in November 2022, followed by the release of several other generative artificial intelligence (GenAI) tools, such as Gemini, Claude, Copilot, and DeepSeek. As these tools became more widely available, high school students rapidly adopted GenAI for school-related tasks. According to a College Board study, the percentage of high school students who reported using GenAI tools for schoolwork increased from 79% to 84% between January and May 2025 (College Board, 2025). Despite this growth, students remain divided on whether GenAI benefits their own learning. At the same time, educators are still exploring how to appropriately regulate and guide students' use of GenAI, and most schools have yet to establish formal policies governing its use. GenAI has the potential to enhance student learning by offering personalized content, immediate feedback, and support with problem-solving (Delello et al., 2025; Hu et al., 2025; Ma and Zhong, 2025). However, it may also negatively impact learning through issues such as plagiarism, misinformation, reduced creativity,

diminished critical thinking, lower motivation, and increased dependence on technology (Delello et al., 2025).

1.2 Over-reliance

Among the concerns about GenAI's negative impact, over-reliance is one of the most significant and troubling risks. Over-reliance on GenAI occurs when users accept AI-generated content without critical evaluation, thereby increasing the tendency to default to GenAI for everyday tasks (Abubakar et al., 2025; Zhai et al., 2024). Hou et al. (2025) reported that past research identified over-reliance as accepting AI-generated suggestions without sufficient consideration, particularly when users fail to double-check for information inaccuracies. As GenAI continues to advance daily, academic tasks become easier to complete through GenAI applications, which may exacerbate students' overdependence on GenAI tools and contribute to over-reliance (Elshafey, 2025). Based on a latent profile analysis of 490 university students, Stojanov et al. (2024) found that 23.1% of participants relied on ChatGPT to draft assignments and write homework.

As GenAI tools become more accessible and user-friendly, this reliance pattern has become a growing concern in academic settings. Over-reliance on GenAI may undermine students' ability to learn independently and develop essential cognitive skills. Pitts et al. (2025) found that persistent use of GenAI may lead students to depend on it rather than engage in independent thinking. In their review of over-reliance, Zhai et al. (2024) suggested that over-reliance on GenAI can negatively affect decision-making and critical and analytical thinking by fostering dependence and diminishing individual judgment.

1.3 Goal Orientation

Goal orientations can explain why learners engage in learning activities and respond to achievement situations differently (Ames and Archer, 1988; Meece et al., 2006). Mastery and performance goal orientations are two fundamental types. A mastery goal orientation emphasizes learning, skill development, and competence improvement. Learners with mastery goal orientations define success as improvement and learning. In contrast, a performance goal orientation focuses on comparing one's own performance with others (Dweck and Leggett, 1988). Researchers further classified performance goal orientations into performance-approach and performance-avoidance goals (Elliot and Harackiewicz, 1996). Learners with performance-approach goals are motivated to outperform others, while learners with performance-avoidance goal orientation are motivated to avoid appearing inferior to others.

Students with strong mastery or learning goals tend to adopt more effective learning strategies and prefer challenging tasks (Dweck and Leggett, 1988). In contrast, performance-avoidance goals are associated with negative learning outcomes, including decreased task interest, reduced deep processing and feedback seeking, and increased reliance on surface-level processing (Świątkowski and Dompnier, 2021). For performance-approach goals, the data show mixed outcomes. For example, Linnenbrink (2005) found that personal performance-approach goals were detrimental to achievement and test anxiety but unrelated to help-seeking, interest, and self-efficacy.

With the widespread use of GenAI, researchers have begun to examine the role of goal orientation in GenAI use and its impact on learning. For example, Kwan and Hung (2025) found that undergraduate students' habitual adoption of GenAI tools is negatively correlated with learning goal orientation, but not with performance goal orientation. Stojanov et al. (2024) found that a mastery-approach orientation was associated with a lower reliance on ChatGPT. A study of Slovenian vocational high school students found that mastery goal orientation is positively correlated with AI literacy. Students with performance-oriented learning are likely to avoid complex topics to appear more capable (Avsec and Rupnik, 2025).

1.4 Research Gap and Questions

Most existing studies on GenAI goal orientation and/or over-reliance have been primarily conducted among undergraduate students. But few studies have examined high school students' GenAI goal orientation, over-reliance, and its consequences. Given that high school students are younger and may require more self-discipline and guidance, it is urgent to fill this gap. This study aims to examine the relationship between high school students' over-reliance, goal orientation, and other demographic and academic background, aiming to answer the following questions:

1. How is high school students' reliance on GenAI?
2. How do demographic and academic background predict students' reliance on GenAI?
3. How do students' goal orientations predict their reliance on GenAI?
4. How does students' GenAI reliance associate with the GenAI impact on their learning outcomes?

2 Method

2.1 Procedure

We invited 103 high school students in the United States to participate in this study over two weeks of school days. To be eligible, students must meet three criteria: (a) They must have used GenAI for their schoolwork; (b) Their parents must have signed a consent form if they are under 18; and (c) Students must provide their own signed consent form. After submitting all required consent forms, participants completed the survey at home. Each participant received \$5 in compensation for their time and participation.

2.2 Participants

From the original pool of invited students, 49 students met the study criteria and completed the survey via Qualtrics. Among the invited students, nine reported not using GenAI at all for their homework, and four disclosed using GenAI but chose not to participate in this study. The remaining invited students did not submit consent forms or complete the survey.

Table 1 shows demographic information of the participants. Because the school is in a college town, many students' parents hold advanced degrees, such as master's or doctoral degrees. The

data indicated relatively high levels of parental educational attainment.

Table 1: Demographic information ($N = 49$)

Demographic	Category	n	Percentage
Gender	Female	25	51.0
	Male	24	49.0
Grade	Freshmen	5	10.5
	Sophomore	15	30.6
	Junior	12	24.5
	Senior	17	34.7
Ethnicity	Asian	22	44.9
	Black/African American	2	4.1
	Latino/Latina	1	2.0
	Middle Eastern/North African	2	4.1
	White/Caucasian	20	40.8
	2+ races	2	4.1
Father	unknown	5	10.2
Highest Education	elementary school	1	2.0
	High school	4	8.2
	bachelor's degree	4	8.2
	Master's degree	10	20.4
	Doctoral degree	25	51.0
Mother	unknown	2	4.1
Highest Education	elementary school	1	2.0
	High school	3	6.1
	bachelor's degree	9	18.4
	Master's degree	17	34.7
	Doctoral degree	17	34.7

Students' academic performance is summarized as follows: (a) GPA ranges from 3.00 to 4.00 ($M = 3.77$, $SD = 0.29$); (b) Number of honors classes ranges from 0 to 7 ($M = 1.33$, $SD = 1.40$); and (c) number of AP classes ranges from 0 to 5 ($M = 1.92$, $SD = 1.62$).

2.3 Instruments

In addition to students' demographic and academic information, the survey primarily measures students' frequency of GenAI use, GenAI overreliance, goal orientation, and the perceived impact of GenAI use.

GenAI Use Frequency: Students rate the frequency of their GenAI use across 16 school-related activities using a 5-point scale: Rarely/Never (1), Monthly (2), Weekly (3), Several times a week (4), Almost daily (5). The activities include Completing my homework problems; Helping me with challenging

homework problems; Checking the correctness the homework assignments I have completed; Providing detailed feedback for improving the work I have completed; Explaining the contents that I need help with; Learning more and in greater depth; Writing practice test problems for me; Writing computer coding for me; Debugging my programming; Making a study plan; Helping me find information sources; Summarizing reading; Brainstorming ideas for writing or projects; Drafting writing; Editing/proofreading/improving my writing; and Translating languages. We sum up frequency ratings across the 16 activities to create a total GenAI usage score.

GenAI Over-reliance: We developed 10 items to measure GenAI over-reliance by asking students to indicate their level of agreement with statements that assess GenAI's role in their learning, using a 5-point Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree). The 10-item GenAI over-reliance scale has an internal consistency alpha coefficient = .86. We calculated a composite GenAI over-reliance score by averaging the 10 items for further analysis ($M = 2.32$, $SD = 0.69$).

Table 2: Goal orientation scales, internal consistency, and descriptive statistics

Statement	α	$M (SD)$
Learning Goal Orientation	.77	3.54 (0.63)
I like schoolwork the most when I learn from it.		
I do my schoolwork because I like to learn new things.		
An important reason I do my schoolwork is that I enjoy learning.		
My goal in school is to learn as much as possible.		
Performance Approach Goal Orientation	.86	3.30 (0.96)
Doing better than other students in school is important to me.		
I would feel successful in school if I did better than most of the other students.		
I enjoy schoolwork the most when I do better than my classmates		
My goal in school is to perform better than other students.		
Performance Avoidance Goal Orientation	.83	2.90 (0.98)
It's very important to me that I don't look less knowledgeable than my peers in my classes		

I do my schoolwork to avoid doing worse than other students
The reason I do my work is so others won't think I lack ability
One of my main goals is to avoid looking like I can't do my work.

Goal Orientation: We developed the scale to measure three goal orientations by modifying existing scales to facilitate interpretation and make the measures more relevant to high school students (Midgley et al., 1998; Elliot and Murayama, 2008). Students are asked to indicate the extent to which they agree or disagree with 12 statements that assess their learning goals, using a 5-point Likert scale. Based on the literature, four items are developed for each goal orientation (Table 2). Reliability analyses showed that the alpha coefficient exceeded .70 for all goal orientations, so we created composite scores by averaging item scores for future analysis.

GenAI Impact: Students indicate to what extent they agree or disagree with statements regarding GenAI's impact on their learning using a 5-point Likert scale. The items are grouped into two subscales: Positive Impact on Learning and Negative Impact on Learning. The internal consistency for the positive impact on learning is .85, while the negative impact on learning is .67. Composite scores are calculated for both subscales for further analysis.

3 Results

3.1 GenAI Over-reliance

As shown in Table 3, one third of the students reported that "I turn to AI quickly when schoolwork feels difficult" and "Using AI for schoolwork has become a habit for me." A quarter of the students reported that "When I use AI, I often stop trying to solve the problem on my own." Even though most students disagree with those statements, a fairly large proportion of students have shown a tendency toward overreliance on AI.

Table 3: GenAI over-reliance scale and the number and percentage of students who agree or strongly agree. ($N = 49$)

Statement	<i>n</i>	Percentage
I rely on AI to do my homework assignments.	5	10
Without AI, I struggle to generate ideas.	2	4

When I use AI, I often stop trying to solve the problem on my own.	12	25
I feel less confident completing schoolwork without AI.	14	29
I use AI even when I can figure things out myself.	9	18
I try less hard on assignments because I know AI can help.	10	20
I turn to AI quickly when schoolwork feels difficult.	16	33
I give up on a problem if AI can do it faster.	7	14
I use AI to complete tasks instead of learning how to do them.	9	18
Using AI for schoolwork has become a habit for me.	16	33

3.2 GenAI Over-reliance and Student Background Information

Analyses show that over-reliance on GenAI did not differ significantly by gender, grade level, or parents' highest educational degree. Although the means appear to differ, the differences were not statistically significant, which may be caused by small sample sizes in some groups, e.g., only three fathers' highest degrees are high school, four fathers' highest degrees are bachelor's, and only five students are freshmen.

Table 4 shows the correlation coefficients between GenAI over-reliance and other factors. GenAI over-reliance is significantly negatively correlated with students' GPA ($r = -.29, p < .05$). That is, the higher the academic performance, the less likely students are to have GenAI over-reliance. While the total GenAI usage is positively related to GenAI over-reliance ($r = .52, p < .01$), it is not significantly associated with GPA. Together, these results suggest that GPA is linked to how students use GenAI (i.e., over-reliance) rather than how much they use it.

Table 4: Correlation between GenAI over-reliance and other factors.

	1	2	3	4	5	6	7
1 GenAI Over-reliance							
2 GPA	-.29*						
3 Total GenAI Usage	.52**	.05					
4 Learning Goal Orientation	-.31*	.22	.04				
5 Performance Approach Orientation	-.10	.18	.04	.23			

6 Performance Avoidance Orientation	-	-	.05	.05	.02	.10	.55**
7 Positive Impact on Learning	-	-	-.09	.05	.01	.17	.18 .09
8 Negative Impact on Learning	-	-	.37**	.13	.27	.27	-.03 .05 .30*

*. Correlation is significant at the .05 level (2-tailed).

**. Correlation is significant at the .01 level (2-tailed).

3.3 GenAI Over-reliance and Goal Orientation

As shown in Table 4, over-reliance on GenAI is also negatively correlated with learning goal orientation ($r = -.31, p < .05$). That is, students with a strong learning goal orientation are less likely to overly rely on GenAI. However, the relationship between GenAI over-reliance and performance goal orientation is not significant.

To examine the additional value of goal orientation, we conducted sequential regression with GenAI over-reliance as the dependent variable, GPA as the first predictor, and learning goal orientation as the second predictor. We found that learning goal orientation increased R^2 from .085 to .146, $F(1, 46) = 3.32, p = .075$. Although it is not significant at the $p < .05$ level, the magnitude of the change ΔR^2 is fairly large, suggesting that after controlling for GPA, students with higher learning goal orientation are less likely to over-rely on GenAI.

3.4 GenAI Over-reliance and GenAI Impact

Table 5 shows the number and percentage of students who agree or strongly agree with each statement on the GenAI impact scale. Most students perceive a positive impact of GenAI on their learning. For example, 67% of students agree or strongly agree that GenAI helps their learning, and only 4% think using GenAI hurts their learning. Ninety percent of students reported using GenAI to learn difficult material.

Table 5: GenAI impact scales and the number and percentage of students who agree or strongly agree. ($N = 49$)

Statement	<i>n</i>	Percentage
Positive Impact on Learning ($M = 3.95, SD = 0.66$)		
AI helps me understand difficult contents.	44	90
AI helps me learn more.	36	73
AI helps me learn efficiently.	34	69
AI helps me teach myself.	39	80

Overall, using AI helps my learning.	33	67
Negative Impact on Learning ($M = 2.36, SD = 0.69$)		
AI makes me less motivated to learn.	6	12
AI hinders my creativity.	10	20
AI hurt my independence in learning.	9	18
Overall, using AI hurts my learning.	2	4

As shown in Table 4, the positive correlation between GenAI over-reliance and students' perceived negative impact of GenAI is statistically significant ($r = .37, p < .01$). That is, those who over-rely on GenAI are more likely to perceive negative impacts on learning, e.g., reduced motivation to learn, reduced creativity, and reduced independence.

4 Conclusion and Limitations

This study yielded the following major findings. First, this study found that a fairly large proportion of students have shown a tendency toward overreliance on AI in the studied sample. Second, the over-reliance did not differ significantly by gender, grade level, or parental education. The insignificant differences might be due to the small sample size, particularly the small subgroup sizes. Third, students' academic performance was associated with GenAI use. Specifically, academic performance was negatively related to over-reliance, but not to the extent of their GenAI use; total GenAI usage was not significantly correlated with academic performance. Fourth, learning goal orientation was negatively correlated with over-reliance on GenAI. That is, students with stronger learning goal orientations were less likely to over-rely on GenAI, whereas other goal orientations showed no significant relationship with over-reliance. This finding is consistent with results reported for undergraduate students (Stojanov et al., 2024; Kwan and Hung, 2025). Moreover, learning goal orientation remained a strong predictor of GenAI overreliance even after controlling for academic performance. This pattern indicates that, regardless of achievement level, students with learning goal orientations are less likely to over-rely on AI. Finally, although most students reported a positive impact of AI on their learning, students with high levels of GenAI over-reliance were more likely to report negative impacts. The

amount of GenAI use, however, was not significantly correlated with perceived learning impact.

This research advances our understanding of GenAI overreliance among high school students, including their background characteristics, goal orientation, and perceived impacts on learning. The findings provide guidance for schools, teachers, parents, and students in supporting appropriate GenAI use in high school settings. Importantly, the results suggest that the use of GenAI per se does not necessarily lead to positive or negative learning outcomes; rather, overreliance on GenAI is associated with negative impacts on learning.

The findings also underscore the importance of learning goal orientation. When students adopt a learning-goal orientation by focusing on improving their understanding and developing competence rather than comparing themselves with others, they are less likely to over-rely on GenAI. Although the use of GenAI for schoolwork is relatively new, the role of goal orientation in shaping its use aligns with established goal-orientation theory. Prior research shows that students with learning goal orientations are more likely to adopt effective learning strategies and engage in deeper information processing (Ames and Archer, 1988). Accordingly, when students use GenAI to improve learning, they are less likely to over-rely on it.

These results highlight the importance of fostering a mastery-learning goal orientation rather than a performance-goal orientation. Research on motivation has shown that when schools emphasize mastery, understanding, and skill and knowledge improvement, students are more likely to develop positive motivation (Meece et al., 2006). Schools may intentionally foster a mastery-learning goal orientation so that students are more likely to use AI to improve their learning rather than their performance.

These results also highlight the importance of guiding students toward appropriate use of GenAI for schoolwork. Because students with lower academic performance are more likely to over-rely on GenAI, schools should pay particular attention to these students to prevent performance gaps from widening due to inappropriate GenAI use. Schools may also consider developing policies to regulate and guide the use of GenAI in ways that support learning. Professional development could be provided to teachers to guide students' use of GenAI.

This study has several limitations. First, data were collected from a single high school in a college town, where many parents hold advanced degrees; consequently, the student sample was relatively homogeneous, limiting the generalizability of the conclusions. Future studies should include students from more diverse demographic backgrounds. Second, the sample size in this study is relatively small, which poses several challenges for data analysis and interpretation of results. For example, the instrument underwent only expert review, and its psychometric properties could not be examined using advanced statistical methods such as Exploratory Factor Analysis and Confirmatory Factor Analysis. The small sample size could also result in low power to detect the effects of students' demographic information; thus, the insignificant difference among subgroups should be interpreted with caution and examined with larger sample sizes. Third, the conclusions were based on students who voluntarily participated in the study rather than on a randomized sample, which may introduce self-selection bias. For example, some students did not participate in the study because they forgot to obtain parental consent or complete the survey on time. In addition, those who completed the survey may be more familiar with or more positive about GenAI than those who did not. Future research could adopt random sampling or improve recruitment strategies to increase participation and minimize self-selection bias. Finally, self-reported responses may be subject to social desirability bias; for example, students may be less likely to admit to inappropriate use of AI. Future studies may address this issue by emphasizing anonymity and using objective measures, such as processing data and artifacts.

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