

Tailored to Thrive: How Customized Generative Artificial Intelligence Appropriation Shapes Academic Achievement in Higher Education

Junsheng Wang

Student Career Guidance Office, Harbin Normal University <https://orcid.org/0009-0008-0389-7227>

Xiyue Hong

School of Economics and Management, Harbin University of Science and Technology

<https://orcid.org/0009-0008-9908-5804>

Shan Liu

liushan0907@foxmail.com

School of Business Administration, South China University of Technology <https://orcid.org/0009-0005-9446-5603>

Research Article

Keywords: customized GAIA, academic resilience, academic self-efficacy, academic achievement, college students

Posted Date: October 21st, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11443453/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: The authors declare no competing interests.

Tailored to Thrive: How Customized Generative Artificial Intelligence Appropriation Shapes Academic Achievement in Higher Education

Abstract

Generative artificial intelligence (GAI) has become increasingly common in higher education, helping students with a wide range of academic tasks. Yet its implications for academic achievement remain mixed. Understanding how students can use tools such as ChatGPT effectively is therefore an important question. We argue that how students use GAI helps explain whether they benefit from it. Drawing on social cognitive theory, we examine the relationship between customized generative artificial intelligence appropriation (customized GAIA) and academic achievement. We also examine the mediating role of academic self-efficacy and the moderating role of academic resilience. We tested our hypotheses using three-wave survey data from 420 university students at a Chinese university. Customized GAIA was positively associated with academic achievement through academic self-efficacy. Moreover, the positive relationship between customized GAIA and academic self-efficacy was stronger among students with higher academic resilience. By adopting a technology appropriation perspective, this study extends research on GAI and learning outcomes in higher education. It identifies a psychological pathway and an individual-level boundary condition linking personalized human-AI interaction to academic achievement. It also offers practical insights into how universities can guide students toward more effective GAI use.

Keywords: customized GAIA, academic resilience, academic self-efficacy, academic achievement, college students

Introduction

As generative artificial intelligence (GAI) continues to advance, its role in higher education is expanding. University students increasingly use GAI to support their academic work (Al-Abri, 2025). This widespread adoption has prompted growing interest in its implications for academic achievement (Sun & Zhou, 2024). Some studies suggest that GAI helps students find learning resources and identify suitable learning strategies more efficiently, thereby improving academic outcomes (Chen & Cheung, 2025; Dong et al., 2025). Others raise concerns that students may become overly reliant on AI to complete assignments without engaging in essential learning processes (Galindo-Domínguez et al., 2026). Such dependence may limit the development of independent learning skills and creative

thinking (An et al., 2026). Thus, the evidence on the relationship between GAI use and academic achievement remains mixed.

Much of the existing literature focuses on whether students use GAI and how frequently they use it. Less attention has been paid to how students adapt these tools to their needs. Yet the way GAI is used may be central to its educational value (Fang & Cai, 2025). For example, GAI can support higher-order thinking and students' learning experiences when it serves as a cognitive scaffold (Ding & Song, 2026). By contrast, it may undermine learning when it substitutes for students' own cognitive efforts (Abbas et al., 2025). The manner in which students engage with GAI may therefore help explain differences in their learning outcomes. Generative artificial intelligence appropriation (GAIA) captures the extent to which users adapt, reconfigure, and extend a technology as they make it their own (Dourish, 2003; Hussenot, 2008; Khatri et al., 2026). In higher education, customized GAIA may involve choosing AI models to suit specific learning tasks, developing prompts that reflect individual goals, and exercising judgment when using AI-generated content. Such customization can shift students from passive recipients of AI output to active participants who evaluate and integrate the information they receive (Luther et al., 2026). More cognitively engaged forms of GAI use may foster learning engagement and outcomes (Fang & Feng, 2026). Academic achievement also depends on the effective use of learning resources, self-regulation, and active participation in learning (Liang et al., 2023; Stadler et al., 2021). Customized GAIA may help students adapt general-purpose AI tools to their particular learning needs and preferences. This, in turn, may give them greater control over their learning. We therefore expect customized GAIA to be positively associated with academic achievement.

Social cognitive theory holds that personal beliefs and states shape behavior, while the outcomes of behavior can, in turn, influence those beliefs (Bandura, 1986; Schunk & DiBenedetto, 2020). Self-efficacy refers to individuals' beliefs in their ability to perform the actions needed to achieve a particular goal. These beliefs are important determinants of behavioral choices and persistence (Talsma et al., 2018). In higher education, academic self-efficacy reflects students' confidence in their ability to complete academic tasks, manage learning challenges, and achieve academic goals (Honicke & Broadbent, 2016; Putwain et al., 2013; Yilmaz et al., 2007). These judgments are informed by perceived competence, existing knowledge, and a sense of control over learning. Interaction with AI may provide timely feedback and encouragement that strengthen students' beliefs in their learning capabilities (Liang et al., 2023; Ren et al., 2026). Customized GAIA may enable students to adjust the content, pace, and feedback of AI interactions to suit their needs (Dourish, 2003; Hussenot, 2008; Khatri et al., 2026). This may help them complete appropriately challenging tasks and build successful

learning experiences. Academic self-efficacy may then encourage students to set more ambitious goals and persist when difficulties arise (Cassidy, 2016). We therefore propose that academic self-efficacy helps explain the relationship between customized GAIA and academic achievement.

The value students derive from customized GAIA may also depend on their academic resilience. Students with greater resilience tend to remain engaged and maintain adaptive judgments when they encounter academic challenges (Cassidy, 2016; King et al., 2026). Academic resilience is the capacity to sustain effort, adjust one's approach, and seek appropriate support in the face of academic pressure, setbacks, and adversity (Sever & Aliyev, 2025; Tan et al., 2024). Customized GAI use often involves revising prompts, evaluating imperfect output, and adjusting one's approach in response to feedback. These activities can introduce uncertainty and require sustained effort. Resilient students may be better able to interpret errors and setbacks constructively and to persist through repeated attempts (Martin & Marsh, 2006; Cassidy, 2016; King et al., 2026). They may consequently be more likely to turn challenging AI interactions into experiences that strengthen their beliefs in their own abilities (Afzali et al., 2024; King et al., 2026). We therefore expect students with higher academic resilience to benefit more from customized GAIA.

We tested the proposed model in a three-wave survey of students at a university in China. This study makes three contributions. First, it shifts attention from the frequency of GAI use to the ways students appropriate the technology. In doing so, it extends research on GAI and learning outcomes through a technology appropriation perspective and offers insight into the mixed evidence concerning GAI and academic achievement. Second, by examining academic resilience, it identifies an individual characteristic that may shape the benefits students derive from customized GAIA. Finally, it offers insights into effective GAI use and suggests ways in which university administrators and instructors can support students' academic development.

Theoretical Overview and Hypotheses

Generative Artificial Intelligence Appropriation

GAIA refers to the extent to which users adapt, modify, extend, and reinvent generative AI as they integrate it into their work and everyday lives (Khatri et al., 2026). The concept shifts attention from whether people use AI to how they make the technology their own. Technology appropriation theory suggests that the value of technology is not determined solely by its built-in features. It also depends on how users interpret, adapt, and reconstruct those features in practice (Dourish, 2003; Hussenot, 2008). Likewise, GAIA views users as active agents rather than passive recipients of technological capabilities (Khatri et al., 2026). Through ongoing interaction, users adjust the fit between their needs and AI capabilities and develop distinctive patterns of use. This perspective is consistent with research

on human–AI collaboration, which locates value in the ongoing interaction between people and AI rather than in the technology alone (Jarrahi, 2018; Faraj et al., 2018).

Among the forms of GAIA, customized appropriation is particularly relevant to higher education. Customized GAIA refers to the extent to which individuals actively adjust and personalize GAI according to their goals, preferences, and task requirements (Khatri et al., 2026). Customization is not simply a matter of using AI more frequently, nor does it imply uncritical acceptance of AI-generated content. Rather, its defining feature is the active adaptation of technology use to task demands. This view is consistent with the distinction between AI as a cognitive scaffold and AI as a substitute for students' own thinking (Ding & Song, 2026; Nasr et al., 2025). For example, students may select AI models for particular tasks, design tailored prompts, evaluate and revise generated content, and refine their prompting strategies through repeated interaction. In this way, GAI can become a personalized learning aid rather than merely a source of generic answers (Luckin et al., 2016).

Higher education provides a particularly relevant setting for customized GAIA. Academic tasks vary in their complexity and requirements, and students differ in their prior knowledge, learning preferences, and academic goals (Pintrich, 2004; Broadbent & Poon, 2015). Generic AI output may therefore fail to meet individual learning needs. Students may need to adapt their interactions with AI to obtain more relevant support. Compared with simply requesting answers, customized appropriation involves greater initiative and control over how the tool is used (Azevedo & Cromley, 2004; Zimmerman, 2008). It also differs from passive AI use. Students who engage in customization may assess output quality, revise prompts, compare alternatives, and connect AI-generated information with their existing knowledge. These activities demand cognitive effort and may encourage evaluation and reconstruction of information. Research on human–AI collaboration suggests that active interaction can support deeper processing, self-regulated learning, and knowledge construction (Nasr et al., 2025; Luther et al., 2026; Du et al., 2025). Repeated cycles of prompting, feedback, and revision may also help students monitor their understanding and adapt their learning strategies (Panadero, 2017). Over time, they may develop ways of using AI that better match their learning needs.

Social cognitive theory suggests that development depends not only on environmental conditions but also on how individuals use available resources (Bandura, 1986). From this perspective, customized GAIA may provide personalized learning support that shapes students' judgments and subsequent academic progress (Schunk & DiBenedetto, 2020; Wang & Li, 2026). Customization can make feedback more relevant to students' needs and create opportunities to complete challenging tasks successfully (Jia & Tu, 2024; Liang et al., 2023). Such interactions may improve learning efficiency

while also shaping students' beliefs about their own academic capabilities. Customized GAIA thus offers a useful perspective for understanding the role of GAI in students' academic development.

Customized GAIA, Academic Self-Efficacy, and Academic Achievement

According to social cognitive theory, personal beliefs shape behavior and contribute to subsequent outcomes (Bandura, 2000; Schunk & DiBenedetto, 2020). In higher education, academic self-efficacy refers to students' beliefs in their ability to complete academic tasks and attain learning goals. These beliefs reflect their perceived knowledge, competence, and control over learning (Macakova & Wood, 2022). Judgments of academic self-efficacy are shaped in part by information students obtain from their learning experiences. Customized GAI use allows students to tailor questions and support to their current level of understanding. It may therefore provide a more personalized learning experience (Luo et al., 2025) and shape beliefs about academic task completion (Zhi & Han, 2026). For example, personalized AI support may help students work through problems they would otherwise find difficult and manage cognitive demands at an appropriate level (Nasr et al., 2025). It may also create opportunities for useful feedback and successful task experiences. By observing how AI approaches a problem, students may acquire strategies that they can apply themselves (Du et al., 2025). Tailored support may also help manage learning-related anxiety, allowing students to concentrate on the task (Karaoglan Yilmaz et al., 2025). Importantly, success with AI is more likely to support lasting efficacy beliefs when students actively analyze the problem, verify the answer, and transfer what they have learned to new tasks (Bandura, 1986; Nasr et al., 2025; Galindo-Domínguez et al., 2026).

Students with higher customized GAIA may also engage more actively in their interactions with AI. They can revise their questions, evaluate the accuracy of generated content, and seek further feedback (Ji et al., 2025). These interactions may provide relevant information and successful experiences that strengthen confidence in their academic abilities (Huyen et al., 2026; Yang et al., 2026). By contrast, students with lower levels of customized GAIA may be less likely to obtain feedback tailored to their needs or to accumulate successful experiences at an appropriate level of difficulty. Their academic self-efficacy may consequently benefit less. The critical issue is therefore not simply how much AI feedback students receive, but whether they actively evaluate, revise, and internalize it (Liang et al., 2023; Schunk & DiBenedetto, 2020). Accordingly, we propose:

Hypothesis 1: Customized GAIA is positively associated with academic self-efficacy.

Social cognitive theory suggests that individuals are more likely to initiate and sustain goal-directed behavior when they believe their actions can produce the desired outcomes (Cook & Artino, 2016). Academic self-efficacy is therefore more than a judgment of competence; it is also an important

motivational resource for learning and coping with academic challenges. Students with higher academic self-efficacy are more willing to pursue challenging goals and persist when they encounter difficulties, failure, or negative feedback (Honicke & Broadbent, 2016; Putwain et al., 2013). They may interpret setbacks as signs that their knowledge or strategies need improvement rather than as evidence of limited ability. Such beliefs can support sustained effort, deeper processing, self-monitoring, and adaptive strategy use while reducing avoidance associated with anxiety, procrastination, and anticipated failure (Yilmaz et al., 2007). Prior research provides consistent evidence of a positive association between academic self-efficacy and academic performance (Honicke & Broadbent, 2016; Meng & Zhang, 2023). These adaptive learning behaviors may increase engagement, persistence, and the effectiveness of learning strategies. We therefore propose:

Hypothesis 2: Academic self-efficacy is positively associated with academic achievement.

GAI may influence not only students' external learning environment but also their internal psychological processes. We propose that academic self-efficacy helps explain the relationship between customized GAIA and academic achievement. Academic self-efficacy reflects students' beliefs in their ability to complete academic tasks, manage challenges, and attain their goals (Richardson et al., 2012). These beliefs are closely related to motivation and perceived academic capability (Huyen et al., 2026). Customized GAI use may not translate directly into higher achievement (Thüs et al., 2024). Instead, personalized feedback and successful experiences with appropriately challenging tasks may strengthen students' academic self-efficacy (Jia & Tu, 2024). Students with stronger efficacy beliefs may then be better able to turn external support into sustained motivation and productive learning behavior (Liang et al., 2023). They are also more likely to use deeper learning strategies, set challenging goals, and persist through difficulties (Honicke & Broadbent, 2016; Putwain et al., 2013). Taken together, these arguments suggest the following mediating relationship:

Hypothesis 3: Academic self-efficacy mediates the positive relationship between customized GAIA and academic achievement.

The Moderating Effects of Academic Resilience

Social cognitive theory suggests that the extent to which external support is translated into efficacy beliefs may depend on students' capacity to persist and recover in the face of academic difficulties (Chen & Cheung, 2025; Wu & Lu, 2026). We therefore expect academic resilience to strengthen the positive relationship between customized GAIA and academic self-efficacy. Academic resilience refers to students' capacity to maintain engagement, adapt their strategies, and seek appropriate support when facing academic pressure or setbacks (Karimova & Tu, 2026). Customized GAI use

requires students to revise prompts, evaluate outputs, and adjust their approach in response to feedback. These activities demand persistence and flexibility. Students with greater academic resilience may be more willing to approach these interactions as opportunities for exploration and learning (Martin & Marsh, 2006). They may interpret challenging experiences constructively and persist until they can make effective use of the feedback (Gao & Wang, 2026; King et al., 2026). As a result, they may be better able to convert customized AI support into stronger academic self-efficacy. By contrast, students with lower resilience may become discouraged by imperfect outputs and repeated revisions. They may find it harder to sustain engagement and derive positive efficacy information from AI-assisted learning. We therefore propose:

Hypothesis 4: Academic Resilience positively moderates the positive relationship between customized GAIA and academic self-efficacy, such that the relationship is stronger when academic resilience is higher.

The theoretical model of this study is shown in Figure 1.

[Insert Figure 1]

Methods

Sample and Procedure

We conducted a three-wave, time-lagged survey at a university in Harbin, China. Separating the measurement of key variables over time was intended to reduce some risks of common method bias, although it does not establish causality (Podsakoff et al., 2003, 2024). Before data collection, the study was reviewed and approved by the researchers' institutional ethics committee. All procedures followed the ethical principles of the Declaration of Helsinki and its subsequent amendments. Participants received information about the study's purpose, content, and duration through an online survey platform. They were informed that participation was voluntary, that the data would be used only for research, and that their information would be kept confidential. The questionnaires did not collect names, student identification numbers, or other directly identifying information. Responses across the three waves were matched using the last four digits of participants' mobile phone numbers. This information was used solely for matching and was stored separately from the survey responses after the data had been linked.

At Time 1 (T1), we invited 557 university students to complete an online survey assessing customized GAIA, academic resilience, frequency of GAI use, and demographic characteristics. We obtained 520 valid responses, yielding a valid response rate of 93.4%. Two weeks later, at Time 2 (T2), the 520 T1 respondents were invited to complete a second survey measuring academic self-efficacy. We received 462 valid responses. At Time 3 (T3), two weeks after T2, the 462 T2 respondents were

invited to complete a third survey assessing subjective academic achievement. With their consent, participants also reported their average grade point average (GPA) for the academic year. We received 433 valid T3 responses.

After excluding incomplete responses and responses that did not meet the survey's quality criteria, the final sample comprised 420 students (21.2% men and 78.8% women). Their fields of study included the humanities and social sciences (37.6%), science and engineering (31.6%), arts and sports (14.5%), interdisciplinary programs (2.3%), and other fields (13.8%).

Measures

All constructs were assessed using previously published scales. We used a standard translation and back-translation procedure (Brislin, 1970). Unless otherwise specified, all items were rated on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Higher scores indicated higher levels of the corresponding construct.

Customized GAIA (T1). We used the six-item customized appropriation subscale from the GAIA measure developed by Khatri et al. (2026). The subscale assesses the extent to which users adapt, reconfigure, or reinvent GAI as they make the technology their own. Sample items include "I have modified Generative AI to leverage its potential," "I can't wait to invent new uses of Generative AI," and "I proactively seek updates to ensure optimal usage of Generative AI" ($\alpha = .95$).

Academic resilience (T1). We used the six-item, unidimensional academic resilience scale developed by Martin and Marsh (2006). It measures students' ability to cope with academic setbacks, challenges, adversity, and stress. Sample items include "I believe I'm mentally tough when it comes to exams," "I don't let study stress get on top of me," and "I'm good at bouncing back from a poor mark in my schoolwork" ($\alpha = .96$).

Academic self-efficacy (T2). We used the seven-item academic self-efficacy scale adapted by Yılmaz et al. (2007) from a general self-efficacy measure for use in academic settings. Sample items include "I can always manage to solve difficult problems if I try hard enough," "If someone opposes me, I can find the means and ways to get what I want," and "It is easy for me to stick to my aims and accomplish my goals" ($\alpha = .97$).

Academic achievement (T3). We assessed academic achievement using subjective and grade-based indicators. Subjective academic achievement was measured with the five-item scale developed by Stadler et al. (2021). This scale captures students' evaluations of their academic success. Sample items include "I am satisfied with my grades at university," "I am successful in my studies," and "My grades are appropriate for my effort" ($\alpha = .87$). Participants also self-reported their average GPA for the academic year as a grade-based indicator of academic achievement.

Control variables. We controlled for gender, field of study, and frequency of GAI use. Gender may be associated with differences in technology acceptance, self-efficacy, and academic performance. Previous work has suggested that men may report greater confidence and engagement in some technology-related contexts (González-Calatayud et al., 2021). Academic disciplines also differ in their learning demands and opportunities for AI use. For example, students in science and engineering may use AI for coding tasks, whereas students in the humanities and social sciences may use it for drafting and literature searches (Chan & Hu, 2023). Such differences could shape students' initial patterns of customized GAIA. Finally, frequency of GAI use does not necessarily translate into learning benefits; excessive reliance on AI may even reduce deep cognitive processing. We therefore included these three variables as controls.

Results

Cronbach's alpha coefficients ranged from .87 to .97, and composite reliability values ranged from .96 to .97. All exceeded the commonly used threshold of .70. Average variance extracted (AVE) values ranged from .79 to .87, above the recommended threshold of .50. The square root of each construct's AVE exceeded its correlations with the other constructs, providing further support for discriminant validity. Table 1 reports item-level descriptive statistics, factor loadings, reliability estimates, and AVE values.

[Insert Table 1]

Table 2 presents the confirmatory factor analysis results. The hypothesized four-factor model, comprising customized GAIA, academic resilience, academic self-efficacy, and academic achievement, showed acceptable fit: $\chi^2(246) = 1008.53$, $\chi^2/df = 4.10$, RMSEA = .08, CFI = .94, TLI = .93, and SRMR = .04. Chi-square difference tests indicated that the four-factor model fit significantly better than all alternative models (all $ps < .001$). These findings provide support for the distinctiveness of the four constructs.

[Insert Table 2]

Table 3 reports the means, standard deviations, and correlations. Customized GAIA was positively correlated with academic self-efficacy ($r = .52$, $p < .01$) and subjective academic achievement ($r = .48$, $p < .01$). Academic self-efficacy was also positively correlated with subjective academic achievement ($r = .75$, $p < .01$). These associations provide preliminary support for the hypothesized relationships.

[Insert Table 3]

We tested the hypothesized paths using structural equation modeling in Mplus. Table 4 presents the results. After controlling for gender, field of study, and frequency of GAI use, customized GAIA

positively predicted academic self-efficacy ($b = .07$, $SE = .03$, $p < .05$), supporting Hypothesis 1. Academic self-efficacy positively predicted academic achievement ($b = .63$, $SE = .03$, $p < .01$), supporting Hypothesis 2. The interaction between customized GAIA and academic resilience was also positively associated with academic self-efficacy ($b = .05$, $SE = .02$, $p < .01$). Thus, academic resilience positively moderated the relationship between customized GAIA and academic self-efficacy. We conducted a simple slopes analysis to clarify the interaction. As illustrated in Figure 2, the positive relationship between customized GAIA and academic self-efficacy was stronger at higher levels of academic resilience (+1 SD), supporting Hypothesis 4.

[Insert Table 4]

[Insert Figure 2]

We tested the mediating role of academic self-efficacy using bias-corrected bootstrapping with 5,000 resamples. As shown in Table 5, the indirect effect of customized GAIA on subjective academic achievement through academic self-efficacy was .27 ($SE = .03$, 95% CI [.22, .33]). Because the confidence interval excluded zero, the indirect effect was statistically significant. The direct effect of customized GAIA on subjective academic achievement remained significant after accounting for academic self-efficacy (effect = .08, $SE = .03$, 95% CI [.03, .14]). The total effect was .35 ($SE = .03$, 95% CI [.29, .41]). These results are consistent with partial mediation and support Hypothesis 3.

[Insert Table 5]

Discussion

Theoretical Implications

First, this study extends research on the relationship between GAI and academic achievement from a technology appropriation perspective. Previous studies have examined the frequency of GAI use, its perceived usefulness, and its overall learning outcomes (Chan & Hu, 2023; Chen & Cheung, 2025). Yet the same technology may lead to different learning experiences depending on how it is used. We introduce the concept of customized GAIA proposed by Khatri et al. (2026) into higher education and focus on how students actively adapt, reconfigure, and extend AI use to meet their learning goals. This perspective is consistent with the view that technological value emerges through situated use (Dourish, 2003; Hussenot, 2008). It also echoes the distinction between passive AI use and human–AI collaboration (Nasr et al., 2025). The potential benefits of GAI and the cognitive risks associated with dependence are not necessarily mutually exclusive, because students with similar levels of use may interact with AI in different ways. Our findings show that customized GAIA remains positively related to academic self-efficacy and subjective academic achievement after controlling for the frequency of GAI use. The study thus provides evidence that students' active shaping of technology use matters and

offers a further perspective on variation in GAI-related learning outcomes.

Second, this study draws on social cognitive theory to examine the psychological process linking customized GAIA to academic achievement. In particular, it identifies academic self-efficacy as a mediator. Social cognitive theory emphasizes that beliefs about one's capabilities shape goal setting, effort, and performance (Bandura, 1986; Schunk & DiBenedetto, 2020). We found that customized GAIA was associated with higher academic self-efficacy, which was, in turn, associated with higher subjective academic achievement. Personalized feedback and successful task experiences are important not only because they may increase efficiency, but also because students' interpretations of these experiences can shape their beliefs about their capabilities (Bandura, 1986; Schunk & DiBenedetto, 2020). We extend this argument to customized GAIA: when students actively adapt AI interactions to their learning goals, they may receive more relevant feedback and develop more positive judgments of their academic abilities. At the same time, the significant direct and indirect effects suggest that academic self-efficacy is an important but not exhaustive explanatory pathway. Future research should separately measure and test other possible mechanisms, including cognitive engagement, knowledge integration, and self-regulated learning (Panadero, 2017; Broadbent & Poon, 2015).

Third, by examining the moderating role of academic resilience, this study adds an individual-difference perspective to research on customized GAIA. Rather than treating students as a homogeneous group of technology users, we show that the positive relationship between customized GAIA and academic self-efficacy is stronger among more resilient students. This finding is consistent with research on academic resilience and psychological resources (Martin & Marsh, 2006; Cassidy, 2016; King et al., 2026). It also provides a basis for considering how technology-related support and students' existing psychological resources may jointly relate to learning. Customized appropriation can involve repeated prompt revisions, identifying inaccurate output, and changing strategies in response to feedback (Dourish, 2003; Hussenot, 2008; Khatri et al., 2026). Thus, customizing technology is not always a frictionless process. More resilient students may be more willing to persist when feedback is unsatisfactory and to view revision as an opportunity to improve. Our findings provide correlational evidence consistent with this account and suggest that the value of AI support may depend, in part, on students' psychological resources.

Practical Implications

First, universities should move beyond rules that address only whether students may use GAI and offer guidance on how to use it effectively. Instructors can demonstrate how to break complex assignments into manageable questions, tailor prompts to prior knowledge, and verify and critically assess AI-generated information. Assessment should consider students' problem formulation, reasoning, and

independent understanding rather than the final AI-assisted answer alone. These recommendations are consistent with customized appropriation and active knowledge construction (Khatri et al., 2026; Panadero, 2017; Nasr et al., 2025). For example, instructors could ask students to document their initial questions, revised prompts, evidence used to verify the output, and the reasoning and revisions they completed independently. Such practices make customization an observable part of learning rather than merely a way to generate answers more quickly.

Second, instructors can use progressively challenging tasks and timely feedback to help students form realistic beliefs about their academic capabilities. After students use GAI for explanations, hints, or feedback, instructors could assign independent practice, transfer tasks, or reflective activities without AI assistance. These activities would allow students to determine what they have genuinely learned. They may reinforce academic self-efficacy while reducing the risk of mistaking AI-supported task completion for independent competence. This approach distinguishes external support from genuine mastery experiences and is consistent with a cautious application of social cognitive theory (Bandura, 1986; Schunk & DiBenedetto, 2020). Completing a task with AI does not necessarily mean that students can perform it independently. AI-supported practice should therefore help students develop an accurate understanding of their own capabilities rather than simply increase confidence in the tool's performance.

Third, universities should recognize that students may differ in the support they need according to their academic resilience. Students who tend to disengage after setbacks may benefit from scaffolded tasks, learning-strategy instruction, peer support, and targeted instructor feedback. These resources may help them become more comfortable with inaccurate AI output and repeated revisions. Students with higher academic resilience may benefit from open-ended problems and activities that require iterative verification and independent exploration. These recommendations are practical possibilities based on the present findings; their effectiveness should be evaluated through instructional interventions. Universities should also establish course-appropriate policies on academic integrity, source verification, data privacy, and disclosure of AI use. Encouraging customized GAIA should not mean encouraging unrestricted dependence on AI. Students remain responsible for the accuracy and originality of their submissions and for their own learning processes.

Limitations and Future Research

First, although the three-wave design separated the measurement of the predictor, mediator, and outcome, it cannot rule out reverse causality or omitted-variable explanations. Customized GAIA and academic resilience were both measured at T1, and we did not control for baseline academic self-

efficacy or academic achievement. Temporal ordering alone therefore cannot establish change or causality. Meta-analytic evidence suggests that self-efficacy and academic performance may influence each other. Students with stronger academic capabilities or higher self-efficacy may also be more willing to experiment with sophisticated forms of AI customization (Talsma et al., 2018). Future research could use cross-lagged designs, repeatedly measure the key constructs, or randomly assign students to different GAI-use training conditions to strengthen causal inference.

Second, the key variables were primarily self-reported, including participants' GPA. The results may therefore be affected by common method bias, social desirability, and recall error. Separating surveys over time may reduce some same-occasion measurement effects, but it cannot eliminate common method bias (Podsakoff et al., 2003, 2024). GPA was reported by participants rather than obtained directly from institutional records. Although GPA is a grade-based indicator, self-reporting introduces measurement error. It is also influenced by differences in grading standards and course difficulty across disciplines. Future studies should combine subjective assessments with authorized academic records and performance on standardized learning tasks (Stadler et al., 2021).

Third, the sample was drawn from a single university in Harbin, China, and women made up a relatively large proportion of participants. The generalizability of the findings across institutions, disciplines, year levels, and cultural contexts remains uncertain. Research on self-regulated learning suggests that task characteristics and learning environments can shape students' strategy use, underscoring the value of replication across courses and universities (Pintrich, 2004; Broadbent & Poon, 2015). Technology appropriation also depends on learning goals, task demands, and available technological resources (Dourish, 2003; Khatri et al., 2026). Universities may differ in their AI-use policies, disciplines in their approaches to verifying knowledge, and students in their access to paid AI models. Future studies could use stratified samples and multi-institutional designs. They should also report field of study, year level, and access to AI tools to clarify the boundary conditions of the present findings.

Finally, we examined academic self-efficacy as a psychological mediator and academic resilience as a moderator. Other processes and boundary conditions remain to be explored. Future research could examine cognitive engagement, self-regulated learning, and knowledge integration as parallel mediators. It could also investigate whether AI output quality, task difficulty, instructor guidance, and students' prior knowledge moderate the relationships identified here. These possibilities are consistent with research on human–AI collaboration and self-regulated learning that emphasizes active cognitive processing (Luther et al., 2026; Panadero, 2017; Du et al., 2025). Examining psychological processes, learning behaviors, and contextual conditions together would provide a more comprehensive account

of how and when customized GAIA is associated with academic achievement.

Ethics Considerations

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Consent Statements

Informed consent was obtained from all individual participants included in this study.

Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

References

- Abbas, M., Khan, T. I., & Jam, F. A. (2025). Avoid excessive usage: Examining the motivations and outcomes of generative artificial intelligence usage among students. *Journal of Academic Ethics*, 23(4), 2423-2442. <https://doi.org/10.1007/s10805-025-09659-3>
- Afzali, L., Hosseini, S., & Nooripour, R. (2024). Mediating role of academic competence in the relationship between perceived teaching style and academic resilience among adolescents. *BMC Psychology*, 12(1), 553. <https://doi.org/10.1186/s40359-024-02011-1>
- Al-Abri, A. (2025). Exploring ChatGPT as a virtual tutor: A multi-dimensional analysis of large language models in academic support. *Education and Information Technologies*, 30(12), 17447-17482. <https://doi.org/10.1007/s10639-025-13484-x>
- An, C., Lu, K., & Yang, J. (2026). The dependency trap: A systematic review of the contributing factors and consequences of student over-reliance on generative AI in higher education. *Humanities and Social Sciences Communications*, 13(1), 1604. <https://doi.org/10.1057/s41599-026-08959-2>

459 Azevedo, R., & Cromley, J. G. (2004). Does training on self-regulated learning facilitate students'
 460 learning with hypermedia?. *Journal of Educational Psychology*, 96(3), 523-535.
 461 <https://doi.org/10.1037/0022-0663.96.3.523>

462 Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Englewood
 463 Cliffs, N.J.: Prentice-Hall.

464 Bandura, A. (2000). Exercise of human agency through collective efficacy. *Current Directions in*
 465 *Psychological Science*, 9(3), 75-78. <https://doi.org/10.1111/1467-8721.00064>

466 Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of Cross-Cultural*
 467 *Psychology*, 1(3), 185-216. <https://doi.org/10.1177/135910457000100301>

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

471 Cassidy, S. (2016). The academic resilience scale (ARS-30): A new multidimensional construct
 472 measure. *Frontiers in Psychology*, 7, 1787. <https://doi.org/10.3389/fpsyg.2016.01787>

473 Chan, C. K. Y., & Hu, W. (2023). Students voices on generative AI: Perceptions, benefits, and
 474 challenges in higher education. *International Journal of Educational Technology in Higher*
 475 *Education*, 20(1), 43. <https://doi.org/10.1186/s41239-023-00411-8>

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

479 Cook, D. A., & Artino Jr, A. R. (2016). Motivation to learn: An overview of contemporary theories.
 480 *Medical Education*, 50(10), 997-1014. <https://doi.org/10.1111/medu.13074>

481 Ding J., & Song Y. (2026). Descriptive writing using generative AI as a cognitive scaffold in the
 482 metaverse environment: University students' perceptions, learning engagement, and
 483 performance. *Educational Psychology*, 46(1), 183.
 484 <https://doi.org/10.1080/01443410.2025.2568189>

485 Dong, L., Tang, X., & Wang, X. (2025). Examining the effect of artificial intelligence in relation to
 486 students' academic achievement: A meta-analysis. *Computers and Education: Artificial*
 487 *Intelligence*, 8, 100400. <https://doi.org/10.1016/j.caeai.2025.100400>

488 Dourish, P. (2003). The appropriation of interactive technologies: Some lessons from placeless
 489 documents. *Computer Supported Cooperative Work (CSCW)*, 12(4), 465-490.
 490 <https://doi.org/10.1023/A:1026149119426>

- Du, X., Du, M., Zhou, Z., & Bai, Y. (2025). Facilitator or hindrance? The impact of AI on university students' higher-order thinking skills in complex problem solving. *International Journal of Educational Technology in Higher Education*, 22(1), 39. <https://doi.org/10.1186/s41239-025-00534-0>
- Fang, X., & Cai, Y. (2025). Research of ethical adoption of college students' learning applications of generative artificial intelligence. *Journal of Computer Assisted Learning*, 41(6), e70146. <https://doi.org/10.1111/jcal.70146>
- Fang, X., & Feng, J. (2026). Research on the application behavior of generative artificial intelligence learning of college students based on self-determination theory. *Frontiers in Psychology*, 17, 1805498. <https://doi.org/10.3389/fpsyg.2026.1805498>
- Faraj, S., Pachidi, S., & Sayegh, K. (2018). Working and organizing in the age of the learning algorithm. *Information and Organization*, 28(1), 62-70. <https://doi.org/10.1016/j.infoandorg.2018.02.005>
- Galindo-Domínguez, H., Delgado, N., Sainz-de-la-Maza, M., & Etxabe, J.-M. (2026). Self-regulation and overreliance on artificial intelligence: Unpacking a paradox through a mixed-methods study in higher education. *Computers in Human Behavior*, 181, 108985. <https://doi.org/10.1016/j.chb.2026.108985>
- Gao, L., & Wang, W. (2026). The relationship between self-efficacy and perceived academic achievement among college students: The chain mediation roles of time management and psychological resilience. *Frontiers in Psychology*, 17. <https://doi.org/10.3389/fpsyg.2026.1852212>
- González-Calatayud, V., Prendes-Espinosa, P., & Roig-Vila, R. (2021). Artificial intelligence for student assessment: A systematic review. *Applied Sciences*, 11(12), 5467. <https://doi.org/10.3390/app11125467>
- Honicke, T., & Broadbent, J. (2016). The influence of academic self-efficacy on academic performance: A systematic review. *Educational Research Review*, 17, 63-84. <https://doi.org/10.1016/j.edurev.2015.11.002>
- Hussenot, A. (2008). Between structuration and translation: An approach of ICT appropriation. *Journal of Organizational Change Management*, 21(3), 335-347. <https://doi.org/10.1108/09534810810874813>
- Huyen, N. T., Chi, N. Y., Lam, P. X., & Hoc, L. H. (2026). Students' perceptions of metaverse-enhanced self-regulated learning: An AI virtual assistant can be key. *The Internet and Higher Education*, 69, 101060. <https://doi.org/10.1016/j.iheduc.2025.101060>

- Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577-586.
<https://doi.org/10.1016/j.bushor.2018.03.007>
- Ji, Y., Zhong, M., Lyu, S., Li, T., Niu, S., & Zhan, Z. (2025). How does AI literacy affect individual innovative behavior: The mediating role of psychological need satisfaction, creative self-efficacy, and self-regulated learning. *Education and Information Technologies*, 30(11), 16133-16162. <https://doi.org/10.1007/s10639-025-13437-4>
- Jia, X.-H., & Tu, J.-C. (2024). Towards a new conceptual model of ai-enhanced learning for college students: The roles of artificial intelligence capabilities, general self-efficacy, learning motivation, and critical thinking awareness. *Systems*, 12(3), 74.
<https://doi.org/10.3390/systems12030074>
- Karaoglan Yilmaz, F. G., Yilmaz, R., Ustun, A. B., & Uzun, H. (2025). Exploring the role of cognitive flexibility, digital competencies, and self-regulation skills on students' generative artificial intelligence anxiety. *Computers in Human Behavior: Artificial Humans*, 5, 100187.
<https://doi.org/10.1016/j.chbah.2025.100187>
- Karimova, K., & Tu, H.-F. (2026). Dimensionality, reliability, and validity of academic resilience scales: A systematic review and meta-analysis. *Educational Psychology Review*, 38(1), 112.
<https://doi.org/10.1007/s10648-026-10207-7>
- Khatri, P., Duggal, H. K., Thomas, A., Corvello, V., Prafat, E., & Shiva, A. (2026). Development and validation of the generative artificial intelligence appropriation (GAIA) scale: A comprehensive measurement tool for assessing user engagement and utilisation. *Technovation*, 150, 103379.
<https://doi.org/10.1016/j.technovation.2025.103379>
- King, R. B., Li, J., & Wang, Y. (2026). Both individual and peer growth mindsets matter for academic resilience. *Npj Science of Learning*, 11(1), 17. <https://doi.org/10.1038/s41539-026-00403-z>
- Liang, J., Wang, L., Luo, J., Yan, Y., & Fan, C. (2023). The relationship between student interaction with generative artificial intelligence and learning achievement: Serial mediating roles of self-efficacy and cognitive engagement. *Frontiers in Psychology*, 14, 1285392.
<https://doi.org/10.3389/fpsyg.2023.1285392>
- Luckin, R., & Holmes, W. (2016). Intelligence unleashed: An argument for AI in education. Pearson Education.

555 Luo, L., Hu, J., Zheng, Y., & Li, C. (2025). Human vs. AI: Does AI learning assistant enhance
556 students' innovation behavior? *Education and Information Technologies*, 30(12), 17483-17530.
557 <https://doi.org/10.1007/s10639-025-13474-z>

558 Luther, T., Belcher, K., Kimmerle, J., Meurers, D., & Cress, U. (2026). Collaborative knowledge
559 construction with generative AI: Exploring argumentative co-writing processes through n-gram
560 and cluster analysis. *International Journal of Computer-Supported Collaborative Learning*,
561 21(3), 619-646. <https://doi.org/10.1007/s11412-026-09470-1>

562 Macakova, V., & Wood, C. (2022). The relationship between academic achievement, self-efficacy,
563 implicit theories and basic psychological needs satisfaction among university students. *Studies*
564 *in Higher Education*, 47(2), 259-269. <https://doi.org/10.1080/03075079.2020.1739017>

565 Martin, A. J., & Marsh, H. W. (2006). Academic resilience and its psychological and educational
566 correlates: A construct validity approach. *Psychology in the Schools*, 43(3), 267-281.
567 <https://doi.org/10.1002/pits.20149>

568 Meng, Q., & Zhang, Q. (2023). The influence of academic self-efficacy on university students'
569 academic performance: The mediating effect of academic engagement. *Sustainability*, 15(7),
570 5767. <https://doi.org/10.3390/su15075767>

571 Nasr, N. R., Tu, C.-H., Werner, J., Bauer, T., Yen, C.-J., & Sujo-Montes, L. (2025). Exploring the
572 impact of generative AI chatgpt on critical thinking in higher education: Passive AI-directed use
573 or human-AI supported collaboration? *Education Sciences*, 15(9), 1198.
574 <https://doi.org/10.3390/educsci15091198>

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

577 Pintrich, P. R. (2004). A conceptual framework for assessing motivation and self-regulated learning
578 in college students. *Educational Psychology Review*, 16(4), 385-407.
579 <https://doi.org/10.1007/s10648-004-0006-x>

580 Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases
581 in behavioral research: A critical review of the literature and recommended remedies. *Journal of*
582 *Applied Psychology*, 88(5), 879-903. <https://doi.org/10.1037/0021-9010.88.5.879>

583 Podsakoff, P. M., Podsakoff, N. P., Williams, L. J., Huang, C., & Yang, J. (2024). Common method
584 bias: It's bad, it's complex, it's widespread, and it's not easy to fix. *Annual Review of*
585 *Organizational Psychology and Organizational Behavior*, 11(1), 17-61.
586 <https://doi.org/10.1146/annurev-orgpsych-110721-040030>

Putwain, D., Sander, P., & Larkin, D. (2013). Academic self-efficacy in study-related skills and behaviours: Relations with learning-related emotions and academic success. *British Journal of Educational Psychology*, 83(4), 633-650. <https://doi.org/10.1111/j.2044-8279.2012.02084.x>

Ren, L., Stephens, J. M., & Lee, K. (2026). The impact of AI on learners' self-efficacy: A meta-analysis. *Behavioral Sciences*, 16(1), 158. <https://doi.org/10.3390/bs16010158>

Richardson, M., Abraham, C., & Bond, R. (2012). Psychological correlates of university students' academic performance: A systematic review and meta-analysis. *Psychological Bulletin*, 138(2), 353-387. <https://doi.org/10.1037/a0026838>

Schunk, D. H., & DiBenedetto, M. K. (2020). Motivation and social cognitive theory. *Contemporary Educational Psychology*, 60, 101832. <https://doi.org/10.1016/j.cedpsych.2019.101832>

Sever, G., & Aliyev, R. (2025). Factors shaping academic resilience: A mixed-method exploration of high school students' resilience experiences. *European Journal of Education*, 60(4), e70326. <https://doi.org/10.1111/ejed.70326>

Stadler, M., Kemper, C. J., & Greiff, S. (2021). Assessing subjective university success with the subjective academic achievement scale (SAAS). *The European Educational Researcher*, 4(3), 283-290. <https://doi.org/10.31757/euer.431>

Sun, L., & Zhou, L. (2024). Does generative artificial intelligence improve the academic achievement of college students? A meta-analysis. *Journal of Educational Computing Research*, 62, 1676-1713. <https://doi.org/10.1177/07356331241277937>

Talsma, K., Schüz, B., Schwarzer, R., & Norris, K. (2018). I believe, therefore I achieve (and vice versa): A meta-analytic cross-lagged panel analysis of self-efficacy and academic performance. *Learning and Individual Differences*, 61, 136-150. <https://doi.org/10.1016/j.lindif.2017.11.015>

Tan, W., Chen, J., Lu, S., Liu, C., Luo, Q., Ma, Y., Zhou, Y., Wong, T. K. S., Chen, H., Song, L., Miao, C., Chen, J., & Smith, G. D. (2024). Psychometric evaluation of the Chinese version of the Academic Resilience Scale-30 (C-ARS-30) in college students. *Frontiers in Psychology*, 15. <https://doi.org/10.3389/fpsyg.2024.1276618>

Thüs, D., Malone, S., & Brünken, R. (2024). Exploring generative AI in higher education: A RAG system to enhance student engagement with scientific literature. *Frontiers in Psychology*, 15. <https://doi.org/10.3389/fpsyg.2024.1474892>

Wang, R., & Li, H. (2026). The impact of perceived social support on college students' artificial intelligence literacy: A social cognitive theory perspective. *Sage Open*, 16(3), 21582440261489321. <https://doi.org/10.1177/21582440261489321>

- Wu, Y., & Lu, X. (2026). Scaffolds or crutches? Examining the relationships between artificial intelligence dependency and academic resilience in higher education. *Assessment in Education: Principles, Policy & Practice*, 0(0), 1-18. <https://doi.org/10.1080/0969594X.2026.2736632>
- Yang, X., Liu, X., & Gao, Y. (2026). The impact of generative AI on students' learning: A study of learning satisfaction, self-efficacy and learning outcomes. *Educational Technology Research and Development*, 74(1), 235-248. <https://doi.org/10.1007/s11423-025-10540-8>
- Yilmaz, M., Gürçay, D., & Ekici, G. (2007). Adaptation of the academic self-efficacy scale to Turkish. *Hacettepe Universitesi Egitim Fakultesi Dergisi-Hacettepe University Journal of Education*, (33).
- Zhi, Y., & Han, C. (2026). Structural relationships among academic self-efficacy, academic performance, and career preparation behavior: The roles of value and cost as mediating variables. *Frontiers in Psychology*, 16. <https://doi.org/10.3389/fpsyg.2025.1680088>
- Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal*, 45(1), 166-183. <https://doi.org/10.3102/0002831207312909>

636
637



Figure 1. Hypothesized Conceptual Model.

638

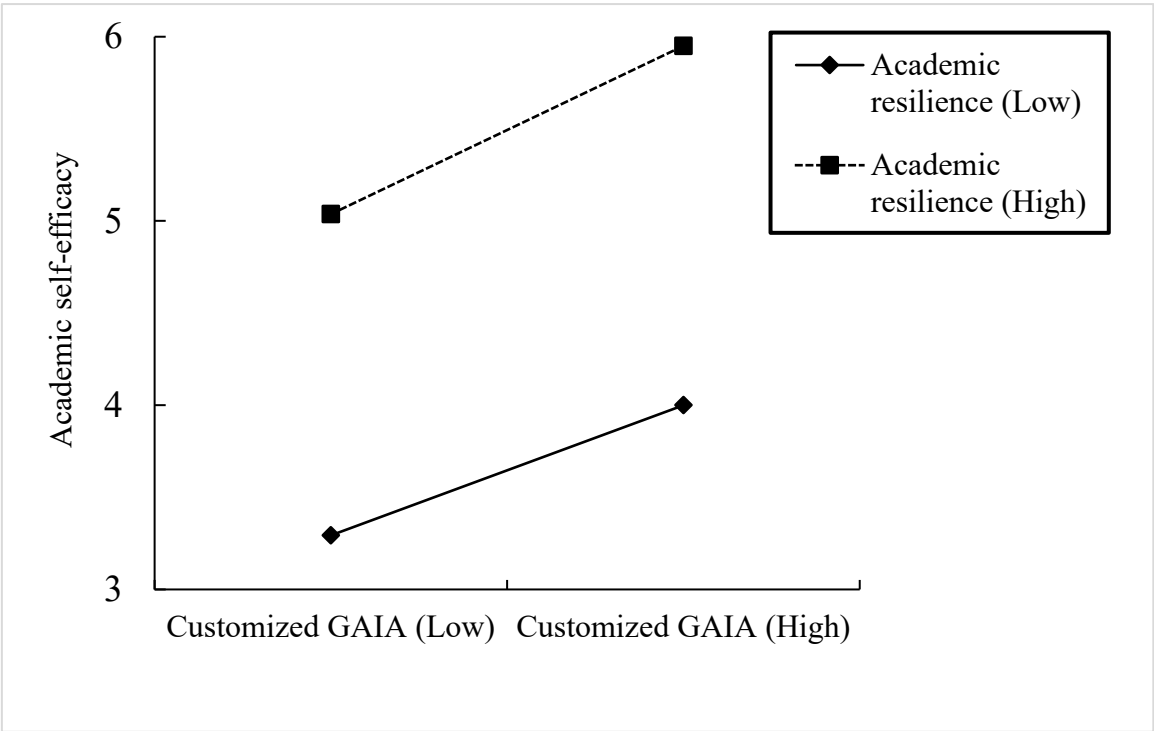


Figure 2. The moderating effect of academic resilience on the relationship between customized GAIA and academic self-efficacy.

641

Table 1. Items' Descriptive Information, Loadings, Reliabilities, and AVEs.

Construct	Item	Mean	SD	Loading	Alpha	CR	AVE
Customized GAIA	C1	5.40	1.27	0.88	0.95	0.96	0.79
	C2	5.33	1.31	0.91			
	C3	5.59	1.16	0.91			
	C4	5.27	1.31	0.87			
	C5	5.66	1.13	0.87			
	C6	5.44	1.27	0.89			
Academic resilience	A1	6.03	0.97	0.91	0.96	0.97	0.85
	A2	5.98	1.00	0.92			
	A3	6.04	0.96	0.92			
	A4	5.96	0.99	0.94			
	A5	5.86	1.11	0.92			
	A6	5.87	1.06	0.92			
Academic self-efficacy	AS1	5.93	0.97	0.93	0.97	0.97	0.85
	AS2	5.95	1.00	0.91			
	AS3	6.04	0.95	0.94			
	AS4	5.98	0.96	0.96			
	AS5	5.98	0.91	0.92			
	AS6	6.00	0.92	0.89			
	AS7	5.94	0.94	0.91			
Academic achievement	AA1	5.75	1.06	0.93	0.87	0.97	0.87
	AA2	5.60	1.13	0.91			
	AA3	5.88	0.96	0.94			
	AA4	5.66	1.08	0.96			
	AA5	5.22	1.31	0.92			

Note: $N = 420$. CR = composite reliability; AVE = average variance extracted.

Table 2. Results of confirmatory factor analysis.

Model	χ^2	df	χ^2/df	RMSEA	CFI	TLI	SRMR
Model 1 (hypothesized four-factor model)	1008.53	246	4.10	0.08	0.94	0.93	0.04
Model 2 (three-factor model: combines CGAIA and AR)	2727.35	249	10.95	0.15	0.80	0.78	0.11
Model 3 (two-factor model: combines CGAIA, AR, and ASE)	3831.328	251	15.26	0.18	0.71	0.68	0.11
Model 4 (single-factor model)	4562.18	252	18.10	0.20	0.65	0.62	0.12

Note: $N = 420$. CGAIA = customized GAIA; AR = academic resilience; ASE = academic self-efficacy.

Table 3. Descriptive statistics and correlations.

Variables	Mean	SD	1	2	3	4	5	6	7
1. Gender	1.79	0.41							
2. GAI-freq	3.56	1.10	0.10*						
3. Major	2.23	1.35	-0.04	0.02					
4. Customized GAIA (T1)	5.45	1.10	-0.04	0.15**	-0.06	(0.95)			
5. Academic resilience (T1)	5.96	0.94	-0.06	0.03	-0.01	0.59**	(0.96)		
6. Academic self-efficacy (T2)	5.97	0.87	-0.04	-0.02	-0.02	0.52**	0.78**	(0.97)	
7. Academic achievement (T3)	5.41	0.80	-0.03	0.04	-0.04	0.48**	0.59**	0.75**	(0.87)

Note: $N = 420$. T1 = Time 1; T2 = Time 2; T3 = Time 3. ** $p < 0.01$, * $p < 0.05$.

Table 4. Results of Hypothesis Testing.

Variable	Academic self-efficacy		Academic achievement	
	<i>b</i>	<i>SE</i>	<i>b</i>	<i>SE</i>
Gender	0.06	0.07	-0.01	0.06
GAI-freq	-0.05	0.02	0.03	0.02
Major	-0.01	0.02	-0.01	0.02
Customized GAIA	0.07*	0.03	0.08**	0.03
Academic self-efficacy			0.63**	0.03
Academic resilience	0.71**	0.04		
Customized GAIA × Academic resilience	0.05**	0.02		
R^2	.28**		.27**	

Note: $N = 420$. *SE* = standard error. * $p < 0.05$, ** $p < 0.01$.

Table 5. Bootstrapping results of mediation effects.

Path	Estimate	<i>SE</i>	95% CI	
			LL	UL
Customized GAIA → Academic self-efficacy	0.43	0.04	0.35	0.50
Academic self-efficacy → Academic achievement	0.63	0.04	0.56	0.70
Direct effect: Customized GAIA → Academic achievement	0.08	0.03	0.03	0.14
Indirect effect: Customized GAIA → Academic self-efficacy → Academic achievement	0.27	0.03	0.22	0.33
Total effect	0.35	0.03	0.29	0.41

Note: $N = 420$. *SE* = standard error; CI = confidence interval; LL = lower limit; UL = upper limit. Bootstrap = 5,000.