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The Impact of Generative Artificial Intelligence Applications on the Development of Self-efficacy

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Abstract: *The swift advancement of generative artificial intelligence (GenAI), illustrated by tools such as ChatGPT, has garnered substantial interest regarding its potential applications across diverse fields. This research investigates the influence of GenAI on self-efficacy, employing transactional stress theory as a framework. Conceptualizing GenAI as a potential stressor, the research examines how challenge appraisals mediate its effects on self-efficacy. The empirical data show that perceiving GenAI as a learning and problem-solving tool boosts confidence in their academic capabilities. Conversely, negative attitudes toward GenAI can reduce its positive effects. These findings extend the application of transactional stress theory to modern technologies, offering insights for policymakers on promoting positive engagement with GenAI.*

Keywords: *Generative artificial intelligence, Appraisal, Self-efficacy*

1. Introduction

Generative artificial intelligence (GenAI) denotes a category of AI technologies tasked with producing content that appears original, spanning texts, visuals, and other media types[1]. Following the introduction of ChatGPT, there has been a worldwide spike in enthusiasm for these technologies. Early analysis by McKinsey estimated that GenAI might add as much as $4.4 trillion per year to the global economy[1]. This rapid rise in GenAI, with ChatGPT at the forefront, has sparked significant exploration into its transformative potential across multiple industries.

The emergence of ChatGPT highlights the transformative potential of GenAI in higher education[2]. Educational institutions can harness GenAI to develop critical thinking skills [3], enhance writing proficiency[4], and advance innovative teaching, learning, and assessment practices [5]. Firat emphasizes that AI enriches education by delivering personalized and interactive learning experiences, including tailored progress tracking, support, feedback, and guidance, which foster student independence and engagement[6]. Additionally, AI-driven systems are expected to revolutionize the evaluation of student assignments by providing more detailed and timely feedback for both formative and summative assessments, surpassing traditional methods. Given the burgeoning applications of GenAI in higher education, this study focuses on examining the impact of GenAI on individuals within the context of higher education. This perspective allows for a nuanced exploration of how GenAI contributes to personal development, autonomy, and engagement in learning processes, ultimately informing strategies for effective implementation and integration of AI technologies in practices.

Self-efficacy is broadly acknowledged as a key predictor of academic success and decision-making in diverse fields, such as mathematics, science, and language arts[7]. For example, a meta-analysis by Valentine demonstrated a consistently positive, albeit modest, impact of self-efficacy on achievement outcomes across various disciplines, even after accounting for prior performance[8].

A Gen AI-based learning environment has the potential to positively influence students' learning experiences by fostering enhanced interactions, such as active participation, timely feedback, and ongoing personalized conversations [9]. With GenAI, students may address study-related issues more efficiently, without the need to wait for extended periods to consult teachers or peers. Furthermore, GenAI has been shown to boost learners' confidence, motivation, engagement, and self-efficacy[10].

Current research largely focuses on the perspectives of academic staff and researchers regarding ChatGPT and its future potential. However, students, as primary stakeholders in higher education, remain

[1] What's the future of generative AI? An early view in 15 charts | McKinsey

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underrepresented in studies addressing their acceptance of this emerging technology and its impact on them[5]. While GenAI is driving substantial changes in higher education, little is known about its effects on students' self-efficacy. The rapid evolution of GenAI offers both disruptive and transformative potential, creating opportunities to innovate and enhance educational practices, from workforce preparation to learning methodologies. Understanding student responses to GenAI is crucial for anticipating its future role in learning, teaching, assessment, and administration within higher education.

To address this gap, this study introduces a conceptual model (see Figure 1) grounded in transactional stress theory, aiming to explore how GenAI applications influence students' self-efficacy. This research offers several theoretical contributions. First, by linking the technological characteristics of GenAI with the processes of self-efficacy development in higher education students, it opens a new avenue in technology and education research. Second, by creating an impact assessment model for GenAI's role in education, this study not only offers practical guidance for educational strategies and policymaking but also expands the theoretical foundations of related domains. Lastly, its exploration of GenAI's potential to support diverse and personalized learning pathways suggests novel strategies for advancing educational equity and individualized learning experiences.

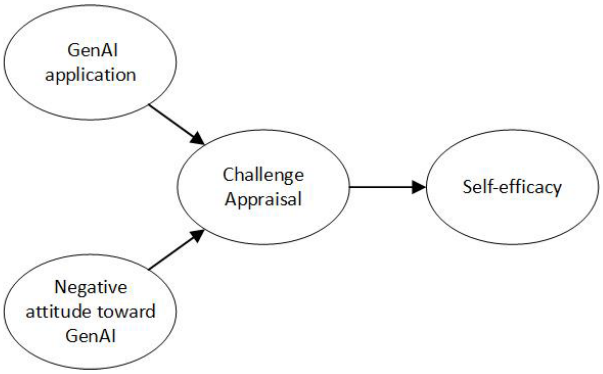

Figure 1: Conceptual model

2. Theoretical Development and Hypotheses

2.1. The Applications of GenAI

GenAI has become a pivotal technology with broad ramifications across the educational sector [11]. In the context of teaching and learning, this technology is increasingly recognized for its capability to revolutionize educational methodologies and enhance learning outcomes across various disciplines such as the social sciences, mathematics, and engineering[12]. To tackle the challenges and opportunities presented by GenAI in educational settings, both local educational bodies and international organizations are actively participating in dialogues concerning the optimal uses of GenAI in education[13]. The consensus among most educators and scholars is that GenAI serves as a double-edged sword; while it offers significant advantages for educators and learners, it simultaneously poses new challenges and risks of misuse [14], [15].

The application of GenAI in education spans four critical domains: learning, teaching, assessment, and administration, each presenting unique roles and challenges[16]. In learning, AI personalizes tasks, enables human-machine interactions, and enhances adaptability in digital environments, though challenges include limited resources, interaction constraints, and evaluation difficulties[17], [18]. In teaching, AI supports adaptive strategies, simplifies classroom management, and aids in professional development, yet teachers face limitations in evaluation methods and trust in AI tools[19], [20]. In assessment, AI facilitates automatic grading and performance prediction, though these applications remain limited to certain disciplines and lack robust predictive data models [21], [22]. In administration, AI improves platform performance, provides personalized services, and aids decision-making through big data insights, though development and research gaps persist [23], [24]. The emergence of GenAI presents potential advancements across these domains by offering new content, facilitating communication, and enhancing assessment roles, but it also requires new student competencies in prompt skills, AI literacy, and ethical knowledge.

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2.2. GenAI Application and Self-efficacy

Transactional stress theory suggests that when individuals face a stressor, they assess its relevance to their well-being. If deemed significant, they evaluate its implications. A challenge appraisal views the stressor as an opportunity for growth and happiness, whereas a hindrance appraisal sees it as an obstacle to personal development and well-being[25]. These appraisals, while distinct and independent, are not mutually exclusive; stressors can be simultaneously perceived as both challenges and hindrances[26]. As GenAI reshapes the educational landscape, questions emerge: will its use in higher education cause unease among students? Will they see it as a challenge or a hindrance to their learning and lives, and how will they adapt? Exploring this interaction is critical for advancing AI research in education and understanding student responses to GenAI's role.

Self-efficacy, as defined by Bandura, is an individual's belief in their ability to achieve specific goals in various situations [27]. This construct is pivotal in fostering resilience, with individuals possessing higher self-efficacy demonstrating greater persistence in the face of challenges compared to those with lower self-efficacy [27]. In education, students with strong self-efficacy set higher goals and persevere more in achieving them. In contrast, students with low self-efficacy often view challenges as signs of inadequacy, leading to task abandonment and reduced persistence [7].

The digital revolution has enhanced students' creativity, technology use, and other comprehensive skills, with support from AI [28]. AI-based teaching methods have been found to positively impact students' information literacy, which in turn bolsters their self-efficacy[29]. AI systems have the capacity to elevate both human self-efficacy and creativity. In educational settings, AI can boost students' self-efficacy by enabling virtual learning environments and improving academic performance[30].

H1: GenAI application positively relates to challenge appraisals.

H2: Challenge appraisals positively mediate the relationship between GenAI application and self-efficacy.

Students' attitudes towards GenAI technologies influence their sustainable use in education. A positive attitude may foster the acceptance and application of this technology in the future, while a negative attitude could hinder its effective integration into educational practices[31].

According to Transactional Stress Theory, challenge appraisal occurs when individuals believe they have sufficient resources to handle stressors and can identify opportunities for growth or benefit in the challenges they face[25]. However, when students harbor negative attitudes towards GenAI—such as concerns about privacy, job risks, or uncertainty regarding technological control—these attitudes shape their primary appraisal, leading them to perceive AI technologies as threats rather than challenges. Negative attitudes also affect the secondary appraisal, where individuals evaluate whether they have adequate resources to address these threats. Students with such attitudes may feel lacking in technological knowledge, financial support, or other resources needed to manage AI-related challenges, further reinforcing the perception of AI as a threat. This appraisal process, shaped by negative emotions, results in reduced challenge appraisals and heightened threat appraisals. Ultimately, these negative attitudes not only hinder students from recognizing the opportunities GenAI offers but also impair their ability to adopt proactive strategies for addressing technological challenges.

H3: Negative attitude toward GenAI negatively relates to challenge appraisals.

H4: Challenge appraisals negatively mediate the relationship between Negative attitude toward GenAI and self-efficacy.

3. Method

3.1. Sample and Procedure

To test the hypotheses, data were collected from undergraduate and graduate students across various countries. Adopting the approach of Podsakoff, a three-stage data collection process was employed to reduce potential common method bias (CMB)[32]. Data from China were collected via the Chinese online survey platform 'Wenjuanxing', frequently used in prior research, while data from other countries were obtained through 'Prolific', a multi-national data collection platform. To ensure data quality, this study adhered to rigorous online data collection protocols, following best practices outlined in recent research[33], [34]. The survey included attention-check questions, and participants who completed it

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successfully and passed these checks were provided with a small financial incentive. Overall, we gathered 95 samples from China and 108 from other countries.

3.2. Measures

We adopted scales previously validated in related studies, making minor adjustments to suit the specific context of this research. All items, unless stated otherwise, were evaluated using a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

The questionnaire, initially created in English, was translated into Chinese for respondents in China to ensure clear understanding. To preserve linguistic accuracy and equivalence, we utilized the back-translation method as suggested by Bhalla and Lin[35]. This process involved translating the Chinese questionnaire back into English and comparing it to the original, with any discrepancies reviewed by a professor specializing in information systems and two PhD students. Their feedback led to minor modifications, ensuring both the accuracy and clarity of the final questionnaire content.

GenAI application. GenAI application was measured with a with a three-item scale adapted from Chatterjee and Bhattacharjee[36]. A sample item is "Using generative AI in higher education is good for student."

Challenge appraisals. Challenge appraisals was measured with a with a three-item scale adapted from Searle and Auton[37]. A sample item is "Using generative AI will help me to learn a lot."

Negative attitude toward GenAI. Negative attitude toward GenAI was measured with a with a three-item scale adapted from Schepman and Rodway[38]. A sample item is "I think generative AI is dangerous."

Self-efficacy. Self-efficacy was measured with a with a seven-item scale adapted from Chen, Gully, and Eden[39]. A sample item is "I will be able to achieve most of the goals that I have set for myself."

Control variables. Control variables included the respondents' gender, age, education background.

3.3. Data Analysis and Results

Table 1: Finalized results of confirmatory factor analysis

Model construct	Item	Factor loading	Cronbach's alpha	AVE
Challenge appraisal	CA1	0.922	0.882	0.742
	CA2	0.912		
	CA3	0.845		
	CA4	0.756		
GenAI application in Higher education	GAHE1	0.847	0.837	0.672
	GAHE2	0.861		
	GAHE3	0.739		
	GAHE4	0.828		
Negative attitude toward GenAI	NA1	0.826	0.828	0.66
	NA2	0.839		
	NA3	0.836		
	NA4	0.743		
Self-efficacy	SE1	0.826	0.936	0.721
	SE2	0.836		
	SE3	0.873		
	SE4	0.846		
	SE5	0.85		
	SE6	0.855		
	SE7	0.856		

To evaluate convergent validity, we applied the method proposed by Anderson[40], assessing the significance of factor loadings for each construct. Convergent validity is confirmed when items significantly load onto their respective latent variables. In our analysis, we performed a confirmatory factor analysis (CFA) using a four-construct model in SmartPLS 4.0, incorporating constructs such as GenAI Application (GA), Challenge Appraisals (CA), Negative Attitude toward GenAI (NA), and Self-

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Efficacy (SE). Table 1 presents detailed findings from our analysis, providing evidence of convergent validity.

Table 1 displays the internal consistency evaluation for each construct using Cronbach's alpha (α). All constructs attained an alpha score above 0.80, exceeding the recommended reliability benchmark of 0.70 [41]. These results validate the constructs' reliability, affirming their suitability for further analysis.

Discriminant Validity: Discriminant validity was evaluated using the approach recommended by Gefen [42], which involves comparing factor correlations with the average variance extracted (AVE) for each construct. Table 2 demonstrates that the square root of each construct's AVE consistently surpassed its correlations with other constructs, offering robust evidence of discriminant validity.

Table 2: Descriptive statistics

Variables	Mean	SD	1	2	3	4	5	6
1.CA	3.76	0.82	0.91					
2.GA	3.69	0.83	0.80	0.87				
3.NA	2.68	0.92	0.27	0.17	0.86			
4.SE	3.85	0.68	0.42	0.32	0.05	0.85		
5.Age	25.85	5.07	0.03	0.20	0.05	0.05	N/A	
6.Education background	1.56	0.61	0.11	0.01	0.12	0.05	0.37	N/A

Notes: Diagonal elements represent the square root of the average variance extracted (AVE).

Common method variance: To address concerns of common method variance, given that data for GA, CA, NA, and SE were sourced from the same respondents, we implemented procedural and statistical techniques as recommended by Podsakoff[32]. To minimize potential biases associated with evaluation apprehension and social desirability, participants were first assured of anonymity and confidentiality. A time-lagged data collection approach was also employed. Additionally, we conducted Harman's single-factor test through a principal factor analysis with Varimax rotation to assess whether a single factor accounted for a substantial portion of the variance. The results showed multiple factors with eigenvalues above one, and the primary factor explained only 39.58% of the total variance. Consequently, common method variance was not a significant concern in this study.

Testing of hypotheses: Hierarchical regression analysis was used to accurately estimate the strength of interaction effects in the moderating relationships[43]. Several models were developed in Partial Least Squares (PLS), starting with control variables, to examine direct, mediating, and moderating effects.

In Model 1, the influence of control variables on CA is clarified. Models 2a and 2b separately describe the effects of GA and NA on CA. Model 3 highlights the combined influence of GA and NA on CA. Following this, six additional models were developed to evaluate mediation effects. Model 4 outlines the regression equation for SE, incorporating control variables. Models 5a and 5b respectively add GA and NA alongside the control variables. Model 6 presents the effect of CA on SE, while in Models 7a and 7b, CA is added separately.

Table 3 presents the results of the regression analysis, detailing the standardized path coefficients, variance explained by independent variables (R^2), incremental variance change (ΔR^2), effect size (f^2), and model fit, indicated by the SRMR. Given the model's complexity, an additional analysis with a hypothetical sequence was performed for further interpretation.

In Model 1, age negatively influences CA, while educational background positively influences CA; however, neither effect is statistically significant (β = -0.085, $p > 0.05$ and β = 0.139, $p > 0.05$). Additionally, the model's explanatory power is not statistically significant ($R^2 = 0.018$, $p > 0.05$). In contrast, Model 2a indicates a significant positive effect of GA on CA (β = 0.72, $p < 0.001$), with the model's explanatory power also reaching statistical significance (β = -0.227, $p < 0.05$). Similarly, Model 2b shows a significant negative effect of NA on CA (β = 0.72, $p < 0.001$), with significant explanatory power (β = -0.227, $p < 0.05$). Thus, H1 and H3 are supported.

Model 4 assesses the effects of age and educational background on SE, but neither effect is statistically significant (β = -0.085, $p > 0.05$ and β = 0.139, $p > 0.05$), and the model's explanatory power is also insignificant ($R^2 = 0.018$, $p > 0.05$). In Model 5a, GA has a significant positive effect on SE (β =

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0.312, $p < 0.001$), with notable explanatory power ($R^2 = 0.096$, $p < 0.001$). Model 7a shows CA has a strong positive influence on SE ($\beta = 0.363$, $p < 0.001$) with high explanatory power ($R^2 = 0.5$, $p < 0.001$). Similarly, Model 7b demonstrates that CA positively impacts SE ($\beta = 0.413$, $p < 0.001$) with substantial explanatory power ($R^2 = 0.161$, $p < 0.001$). To explore mediation relationships, we applied the bootstrapping method with 5,000 samples in SmartPLS 4.0[44]. When controlling for CA, the direct effect of GA on SE is not statistically significant ($\beta = 0.046$, $p > 0.05$), while the 95% confidence interval for the indirect effect ($\beta = 0.257$) does not include zero (0.122, 0.412). Similarly, the direct effect of NA on SE is insignificant ($\beta = 0.074$, $p > 0.05$), while the 95% confidence interval for the indirect effect ($\beta = -0.098$) excludes zero (-0.189, -0.021). These findings suggest that CA mediates the relationships between GA/NA and SE, thus supporting hypotheses H2 and H4.

In this study, aside from the regression model that included only control variables for the dependent variable, the main fit index, the standardized root mean square residual (SRMR), remained below 0.08, indicating satisfactory model fit. Figure 2 illustrates the structural equation modeling results, showing the path estimates between GA, NA, CA, and SE. This figure includes path coefficients (β values), t-values, p-values, and the relationships between exogenous and endogenous constructs.

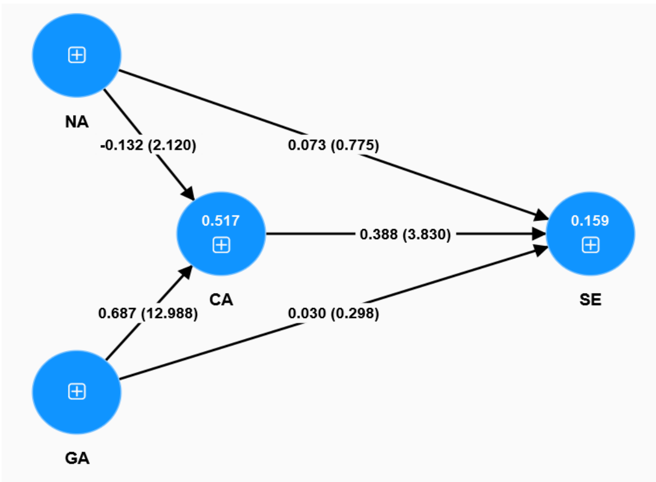

Figure 2: Structural equation modeling for the study model

Table 3: Results of the regression analyses

	CA				SE					
	1	2a	2b	3	4	5a	5b	6	7a	7b
Control										
Age	-0.085	0.07	-0.072	0.07	-0.071	0.084	0.007	0.047	0.054	0.046
Education background	0.139	0.077	0.111	0.065	0.15	0.009	0.042	-0.022	-0.021	-0.015
Independent										
GA		0.72***		0.702***		0.312***			0.046	
NA			-0.227*	-0.122*			-0.065			0.074
CA								0.397***	0.363***	0.413***
R^2	0.018	0.516	0.068	0.531	0.02	0.096	0.007	0.157	0.5	0.161
$\triangle R^2$						0.076	-0.013	0.137	0.343	0.004
f^2		0.031	0.055	0.986		0.104	0.004	0.184	0.076	0.19
SRMR	0.042	0.055	0.054	0.063	0.151	0.052	0.052	0.049	0.052	0.049

Notes: Tabled values are standardized regression weights. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$ (two-tailed).

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4. Conclusion

4.1. Theoretical Implications

This study, through the lens of transactional stress theory, reveals how the application of GenAI impacts individuals' self-efficacy, thereby enriching existing theoretical frameworks. Firstly, this research extends the applicability of transactional stress theory. The findings suggest that individuals frequently view GenAI as a challenge-based stressor, which in turn boosts their self-efficacy. This not only provides a new theoretical perspective on the psychological effects of technology in personal growth but also highlights the crucial mediating role of challenge appraisal between technology use and psychological efficacy.

Secondly, this research deepens the theoretical connection between technology and self-efficacy. By analyzing how GenAI influences individuals' challenge appraisals, it is found that when individuals perceive GenAI as a tool that facilitates personal growth and problem-solving, their self-efficacy significantly improves. This suggests that in technology-assisted environments, challenge appraisal can effectively bridge the application of technology and psychological efficacy, offering a theoretical basis for future exploration of other technological tools in personal development.

4.2. Practical Implications

This study offers several practical suggestions to promote the effective use of GenAI to enhance individuals' self-efficacy. The findings indicate that the application of GenAI can trigger a challenge appraisal in users, which in turn boosts their self-efficacy. Therefore, individuals are encouraged to actively explore GenAI functions within a positive technological environment. Specifically, activities can be designed to include tasks that require users to utilize GenAI for creative problem-solving and project research, motivating them to leverage technological tools to improve their personal development and outcomes.

Secondly, to mitigate individuals' negative perceptions of GenAI, organizations and communities should implement comprehensive training programs to help people understand and alleviate their concerns about GenAI. By organizing workshops on the advantages of AI technology, data privacy, and practical applications, these programs can effectively address personal apprehensions, thereby fostering positive acceptance and effective use of GenAI.

Furthermore, given that challenge appraisal can enhance individuals' self-efficacy, organizations and support programs can leverage GenAI to design personalized development pathways. Mentors and trainers can utilize GenAI to tailor content and feedback for individuals at different skill levels, enabling them to gain a sense of accomplishment through incremental challenges, thereby boosting their confidence and autonomy in their personal growth.

4.3. Limitations and Future Research

While this study provides valuable insights, several theoretical limitations warrant acknowledgment, also pointing to directions for future research. Firstly, the study relies heavily on self-reported data, which may be prone to biases like social desirability and self-assessment inaccuracies. Future research could address this by incorporating varied data sources, such as behavioral data, external observations, and performance metrics, to yield a more comprehensive view of GenAI’s influence on self-efficacy.

Secondly, this study primarily utilizes transactional stress theory to explain the impact of individuals' interactions with GenAI on self-efficacy, centering on challenge appraisals as the primary mediating factor. However, this theoretical approach may not encompass the full spectrum of psychological mechanisms involved. Factors such as cognitive load, motivation, and intrinsic engagement when interacting with GenAI may also play a crucial role in shaping self-efficacy. Integrating psychological frameworks like self-determination theory or cognitive load theory in future studies may yield a more comprehensive understanding of GenAI's effects on personal development behaviors and outcomes.

Lastly, while this study primarily examines the positive aspects of GenAI, such as enhancing self-efficacy through challenge appraisals, it does not fully address potential negative effects, such as dependency on technology or ethical concerns related to data privacy and intellectual property. Future research should explore these darker sides of GenAI integration, investigating how to balance the benefits of technology with its potential drawbacks to create an ethically responsible and effective environment for personal growth and development.

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