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Self-efficacy as a mediator between ChatGPT usage and research motivation among postgraduate students

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Abstract

This study investigated the mediating role of self-efficacy in the relationship between ChatGPT usage and research motivation among postgraduate students. A cross-sectional design was employed with 324 postgraduate students from Egyptian universities. Participants completed questionnaires to assess their usage of ChatGPT, students' self-efficacy, and student motivation for research. Structural equation modeling revealed a significant partial mediation model where self-efficacy accounted for 34.13% of the total effect of ChatGPT usage on research motivation, while a substantial direct effect (65.86%) remained. ChatGPT usage significantly predicted both self-efficacy ($\beta = .574, p < .001$) and research motivation ($\beta = .372, p < .001$), with self-efficacy significantly predicting research motivation ($\beta = .336, p < .001$). The results suggest that ChatGPT functions as both a technical aid and a psychological tool that enhances students' confidence in their research capabilities, consequently improving their motivation to engage in research activities. The findings show that intentional leveraging of AI tools can positively affect students' research experience, emphasizing the importance of the balance that would help to foster independent skill development.

Keywords: Artificial intelligence, ChatGPT, Mediation analysis, Postgraduate students, Research motivation, Self-efficacy.

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Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Institutional Review Board Statement: The study protocol was approved by the Research Ethics Committee of the Faculty of Education at Al-Azhar University, Dakahlia, Egypt (Ref. No. EDU-REC-2024-0358). All procedures performed in this study involving human participants were in accordance with the ethical standards of the institutional research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

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1. Introduction

The emergence of AI tools like ChatGPT has fundamentally transformed the academic research landscape for postgraduate students, enhancing research efficiency and quality [1, 2]. These technologies accelerate literature reviews and data analysis processes [3] while simultaneously improving academic writing skills through immediate feedback and language refinement [4, 5]. AI integration has shifted supervisory dynamics, fostering greater student autonomy and confidence [1, 6]. Furthermore, AI-powered personalized learning environments have demonstrated positive impacts on student engagement and academic performance [7, 8], though concerns persist regarding ethical implementation and maintaining academic integrity [9]. This technological evolution necessitates thoughtful integration that balances AI assistance with critical thinking development.

Postgraduate students commonly struggle with maintaining research motivation due to challenges in sustaining engagement [1], preserving autonomy [10], overcoming cognitive barriers [11], and navigating routine research obstacles [12]. AI tools, particularly generative platforms like ChatGPT, potentially address these challenges by enhancing engagement through personalized support [13], fostering intellectual partnership [14], improving productivity [15], and providing scaffolding for academic writing [16]. However, concerns persist regarding potential overreliance, ethical considerations, and possible erosion of critical research skills [9].

Self-efficacy serves as a pivotal construct in academic research contexts for postgraduate students, functioning as a significant predictor of research engagement and outcomes. Research demonstrates that self-efficacy directly correlates with academic performance [17, 18], research productivity [19], positive research attitudes [20] and cognitive engagement [21]. This psychological mechanism is influenced by various factors, including computer skills [22], critical thinking abilities [23], academic hardiness [24], supervisor support [25] and institutional academic atmosphere [26]. Research self-efficacy, when high, enhances creativity and adaptability in students; thus, strengthening their resolve to confront and overcome research hurdles.

Previous studies have explored the relationship between technology adoption and research motivation through multiple dimensions, including individual characteristics, psychological needs, and contextual factors [27, 28]. Research indicates that motivation significantly influences technology adoption intentions in higher education [29, 30], with intrinsic motivation particularly affecting students' adoption of mobile technologies [31]. Value beliefs and social influence play critical roles in determining educators' technology adoption decisions [29] while self-enhancement orientations and openness to change predict stronger motivation to adopt e-learning systems [32]. Additionally, task-technology fit explains substantial variance in adoption motivation [33], suggesting that technologies aligned with users' needs enhance engagement and utilization. Recent literature indicates AI tools significantly influence students' academic self-efficacy, with both positive and negative implications. AI integration can enhance self-efficacy and learning performance through improved feedback mechanisms and study habits [34-36]. An inverse relationship exists between academic self-efficacy and AI dependence [37, 38]. Additionally, AI tools can reduce student anxiety [39] increase creativity [40] and improve academic performance through enhanced motivation [41], though excessive reliance may diminish students' confidence in completing tasks independently [42].

Despite growing interest in AI impact on academic environments, the mediating role of self-efficacy between AI usage and research motivation remains insufficiently examined due to research fragmentation across related but distinct constructs. While studies have explored AI self-efficacy [43, 44], research efficacy [45], general motivation [46, 47] and AI attitudes [48] few have integrated these concepts into a comprehensive mediational framework. Most investigations examine isolated relationships between AI usage and performance outcomes [49, 50], overlooking the self-efficacy potential mediating function in enhancing research motivation among postgraduate students.

This study explores the relationship between ChatGPT usage and research motivation among postgraduate students, focusing on personalized support and improved productivity. It investigates how ChatGPT usage influences academic self-efficacy, extending previous findings on AI integration's impact on students' confidence in their academic abilities. Moreover, the study proposes a theoretical mediation model where ChatGPT usage (XC) affects research motivation (YM) both directly and indirectly through self-efficacy (MS) as a mediating variable. Through an integrated lens, the current study can contribute to the recognition of AI's impact on postgraduate research, which can inform the creation of strategies that maximize AI incorporation while preserving research skills and independence. The findings of the study can serve as a basis for institutions to develop balanced guidelines that emphasize the strengths of AI tools without fostering excessive reliance on them.

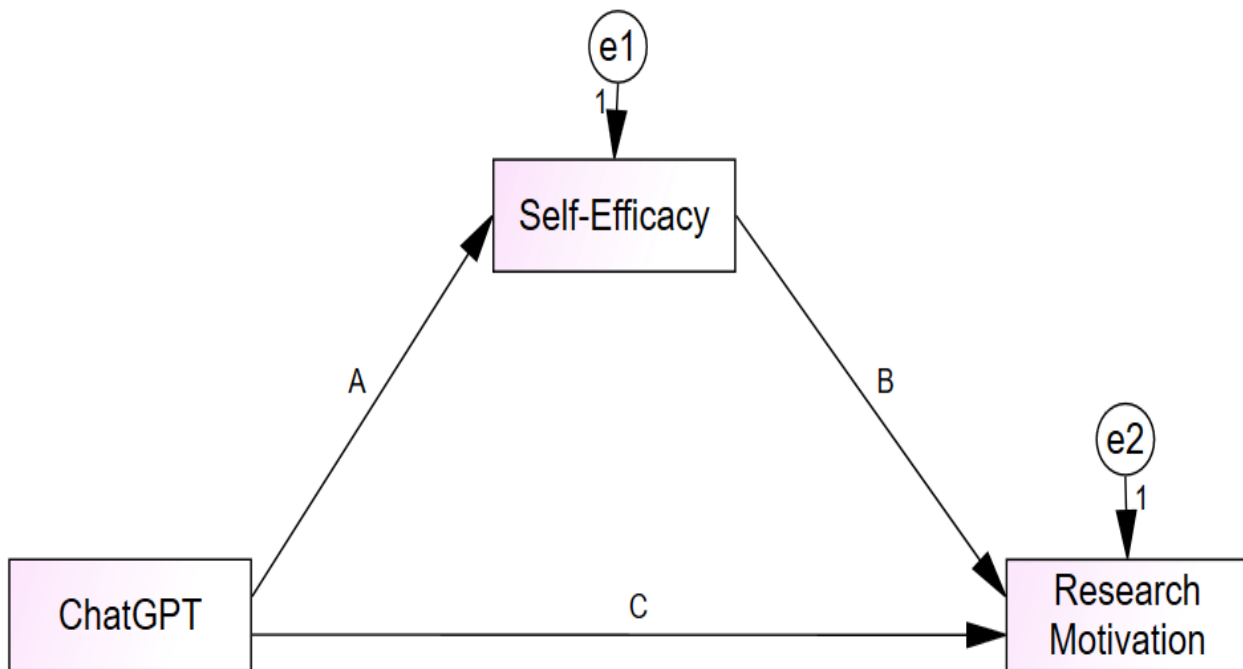


Figure 1.
The theoretical mediation model of ChatGPT usage, self-efficacy and research motivation.

2. Method

2.1. Participants and Procedure

This study employed a cross-sectional design with data collected from 324 postgraduate students enrolled at Zagazig and Al-Azhar Universities, Egypt (see Table 1 for detailed demographic characteristics). Prior to the main study, a separate sample of 220 postgraduate students participated in a preliminary psychometric assessment of the study instruments. The study received approval from the institutional ethics committee, and all participants provided informed consent before data collection.

Table 1.
Demographic Characteristics of the Sample (N = 324).

Characteristic	Category	N	%
Gender	Male	54	16.7
	Female	270	83.3
Age	23-27 years	122	37.7
	28-30 years	52	25.3
	31-35 years	120	37.0
Academic Level	Doctoral	33	10.2
	Master's	50	15.4
	Graduate Diploma	241	74.4
Field of Study	Applied	125	38.6
	Theoretical	199	61.4
Family Residence	Urban	196	60.5
	Rural	288	88.6
ChatGPT Usage	Yes	324	100

2.2. Measures

All measures were translated from English to Arabic using a rigorous back-translation procedure. Three bilingual experts in psychology and educational measurement independently translated the scales, after which consensus meetings were held to resolve discrepancies and ensure conceptual equivalence. The final Arabic versions were then back-translated into English by a fourth independent translator to verify accuracy before being administered to participants.

2.3. New General Self-Efficacy Scale (NGSE)

Self-efficacy was assessed using the NGSE developed by Chen et al. [51]. The scale consists of 8 items measuring individuals' belief in their capability to perform across a variety of achievement situations. Participants responded on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Higher scores indicate greater levels of self-efficacy.

Confirmatory factor analysis supported a unidimensional structure with excellent fit indices ($\chi^2/df = 2.014$, CFI = .986, TLI = .981, GFI = .957, RMSEA = .068, 90% CI [.037, .098]). The scale demonstrated high internal consistency (McDonald's

$\omega = .945$, Cronbach's $\alpha = .944$, Guttman's $\lambda_2 = .945$, Guttman's $\lambda_6 = .942$). Composite reliability (CR = .945) and average variance extracted (AVE = .684) exceeded recommended thresholds (CR > .70, AVE > .50), indicating excellent convergent validity. MaxR(H) value of .954 further supported the scale's reliability. Standardized factor loadings ranged from .723 to .923, all exceeding the recommended .70 threshold, with individual item reliabilities showing strong item-rest correlations ranging from .707 to .890.

2.4. Research Motivation Scale (RMS)

Research motivation was measured using the RMS developed by Deemer et al. [52]. The scale consists of 20 items across three dimensions: Intrinsic Reward (9 items), Failure Avoidance (6 items), and Extrinsic Reward (5 items). Participants rated each item on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

Confirmatory factor analysis supported a hierarchical factor structure with acceptable fit indices ($\chi^2/df = 2.399$, CFI = .932, TLI = .922, GFI = .900, RMSEA = .080, 90% CI [.070, .090]). The scale showed excellent internal consistency for the overall scale (McDonald's $\omega = .933$, Cronbach's $\alpha = .938$, Guttman's $\lambda_2 = .942$, Greatest Lower Bound = .976) and good reliability for all subscales with McDonald's ω values of .842 for Intrinsic Reward, .848 for Failure Avoidance, and .849 for Extrinsic Reward. Composite reliability for the higher-order factor was excellent (CR = .798) with AVE = .581 and MaxR(H) = .871. Standardized factor loadings for the three dimensions on the higher-order factor were .820 (Intrinsic Reward), .902 (Extrinsic Reward), and .507 (Failure Avoidance). Item-level analysis revealed robust item-rest correlations ranging from .319 to .831, with most items exceeding the .50 threshold.

2.5. ChatGPT Usage Scale for Postgraduate Students

ChatGPT usage was assessed using the ChatGPT Usage Scale for Postgraduate Students developed by Nemt-Allah et al. [53]. This 15-item scale measures three dimensions: Academic Writing Aid (7 items), Academic Task Support (4 items), and Reliance and Trust (4 items). Participants responded on a 5-point Likert scale from 1 (strongly disagree) to 5 (strongly agree).

Confirmatory factor analysis confirmed a hierarchical factor structure with good fit indices ($\chi^2/df = 2.245$, CFI = .960, TLI = .952, GFI = .891, RMSEA = .075, 90% CI [.061, .090]). The scale demonstrated excellent reliability for the overall scale (McDonald's $\omega = .960$, Cronbach's $\alpha = .960$, Guttman's $\lambda_2 = .960$, Greatest Lower Bound = .977) with an average inter-item correlation of .617. The subscales showed strong reliability: Academic Writing Aid (McDonald's $\omega = .934$, Cronbach's $\alpha = .933$), Academic Task Support (McDonald's $\omega = .891$, Cronbach's $\alpha = .890$), and Reliance and Trust (McDonald's $\omega = .828$, Cronbach's $\alpha = .819$). Convergent validity was established with excellent com CR = .982, AVE = .947, and MaxR(H) = .986. Standardized factor loadings for the three dimensions on the higher-order factor were notably high at .975 (Academic Writing Aid), .989 (Reliance and Trust), and .955 (Academic Task Support). Item-level analysis revealed substantial item-rest correlations ranging from .610 to .851.

3. Data Analysis

Data were analyzed using SPSS 27.0 and AMOS 23.0. Confirmatory factor analysis was conducted to validate the factor structure of each instrument. Scale reliability was assessed using multiple indices, including McDonald's ω , Cronbach's α , Guttman's λ_2 , CR, and AVE.

To test the mediational model, structural equation modeling (SEM) was employed following the two-step approach recommended by Anderson and Gerbing [54]. First, the measurement model was evaluated to ensure an adequate fit to the data. Second, the structural model was tested to examine the direct and indirect relationships among ChatGPT usage, self-efficacy, and research motivation. Bootstrap analysis with 5000 resamples was used to test the significance of the indirect effect and construct bias-corrected 95% confidence intervals. Model fit was evaluated using multiple indices, including chi-square/df ratio (χ^2/df), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Goodness of Fit Index (GFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR). The significance level was set at $p < .05$ for all analyses.

4. Results

Prior to the main analysis, preliminary tests were conducted to examine common method bias. Harman's single-factor test revealed that the first factor accounted for 38.45% of the variance, which is below the critical threshold of 40% [55], indicating no significant common method bias in the data.

Descriptive statistics and intercorrelations among study variables are presented in Table 2. Analysis revealed that all variables were negatively skewed, indicating that participants generally reported high levels of ChatGPT usage, self-efficacy, and research motivation. The correlation analysis demonstrated significant positive relationships between all main variables, with moderate to strong correlations between ChatGPT usage and self-efficacy ($r = .574$, $p < .01$), ChatGPT usage and research motivation ($r = .564$, $p < .01$), and self-efficacy and research motivation ($r = .549$, $p < .01$).

Table 2.
Descriptive Statistics and Correlations Among Study Variables (N = 324).

Variable	M	SD	Skewness	Kurtosis	1	2	3
1. ChatGPT Usage	54.61	10.98	-1.37	3.74	1		
2. Self-Efficacy	31.11	6.29	-1.74	4.73	0.574**	1	
3. Research Motivation	70.72	13.51	-2.28	6.32	0.564**	0.549**	1

Note: ** $p < .01$.

Further analysis of the subscales in the measurement model revealed strong relationships between the dimensions of each construct. As presented in Table 3, all dimensions of ChatGPT usage were significantly correlated with each other, with coefficients ranging from .841 to .876. Similarly, the dimensions of research motivation showed significant intercorrelations, with coefficients ranging from .320 to .606. The analysis revealed significant positive correlations between ChatGPT usage dimensions and research motivation dimensions, with the strongest relationship observed between Academic Task Support and Extrinsic Reward ($r = .50, p < .01$). Self-efficacy demonstrated significant positive correlations with all dimensions of ChatGPT usage and research motivation, except for a weaker correlation with Failure Avoidance ($r = .148, p < .01$).

Table 3.

Correlation Matrix Among Dimensions of Study Variables.

Variable	1	2	3	4	5	6	7	8	9
1. Academic Writing Aid	1								
2. Academic Task Support	0.88**	1							
3. Reliance and Trust	0.84**	0.85**	1						
4. Total ChatGPT Usage	0.97**	0.95**	0.93**	1					
5. Intrinsic Reward	0.48**	0.48**	0.46**	0.49**	1				
6. Failure Avoidance	0.33**	0.35**	0.32**	0.35**	0.32**	1			
7. Extrinsic Reward	0.47**	0.49**	0.45**	0.50**	0.61**	0.38**	1		
8. Total Research Motivation	0.54**	0.55**	0.52**	0.56**	0.88**	0.67**	0.81**	1	
9 Total. Self-Efficacy	0.56**	0.54**	0.53**	0.57**	0.59**	0.15**	0.50**	0.55**	1

Note: ** $p < .01$

To test the hypothesized mediation model, Hayes' PROCESS macro (Model 4) was employed. As shown in Table 4 and Figure 1, ChatGPT usage significantly positively predicted self-efficacy ($\beta = .574, p < .001$) and research motivation ($\beta = .372, p < .001$). Additionally, self-efficacy significantly positively predicted research motivation ($\beta = .336, p < .001$). The total effect of ChatGPT usage on research motivation was significant ($\beta = .564, p < .001$).

Bootstrap analysis with 5,000 samples confirmed a significant indirect effect of ChatGPT usage on research motivation through self-efficacy (standardized indirect effect = .193, SE = .052, 95% CI [.092, .296]). The direct effect remained significant after accounting for the mediator (standardized direct effect = .372, SE = .065, 95% CI [.329, .586]), indicating partial mediation. The mediating effect of self-efficacy accounted for 34.13% of the total effect, while the direct effect accounted for 65.86%.

Table 4.

Mediation Analysis Results for the Effect of ChatGPT Usage on Research Motivation Through Self-Efficacy.

Pathway	B	SE	t	p	β	95% CI
Direct Effects						
XC → MS	0.33	0.05	12.58	<.001	0.57	[0.277, 0.380]
MS → YM	0.72	0.11	6.32	<.001	0.34	[0.497, 0.945]
XC → YM	0.46	0.07	7.00	<.001	0.37	[0.329, 0.586]
Total Effect						
XC → YM	0.69	0.06	12.26	<.001	0.56	[0.583, 0.806]
Indirect Effect						
XC → MS → YM	0.237	0.06	-	-	0.193	[0.113, 0.362]

Note: Unstandardized coefficient = B; Standardized coefficient = β ; Bootstrap sample size = 5,000.

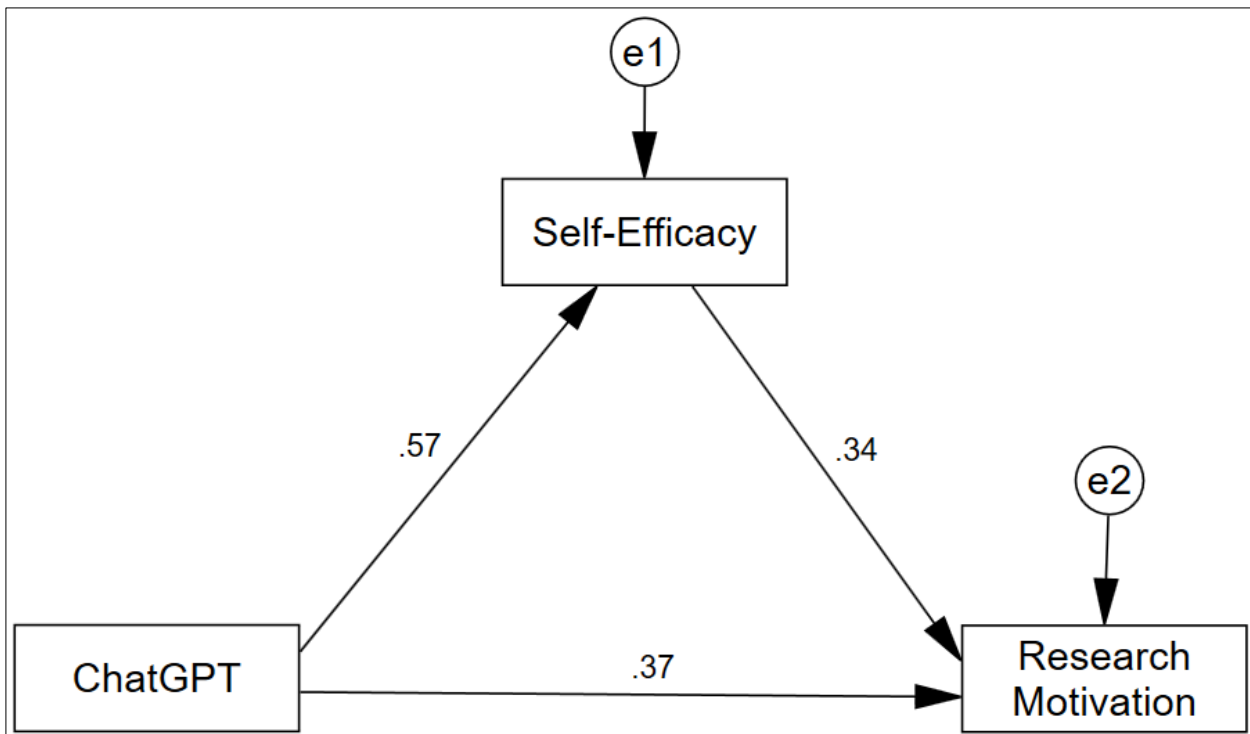


Figure 2.
Standardized coefficients for the mediation model of ChatGPT usage, self-efficacy, and research motivation.

The mediation analysis (Figure 2) illustrates that while ChatGPT usage has a substantial direct effect on research motivation ($\beta = .372$), a significant portion of its influence operates through self-efficacy. The total model explained 39.37% of the variance in research motivation ($R^2 = .3937$, $F(2, 321) = 104.24$, $p < .001$), indicating a robust explanatory power. The path from ChatGPT usage to self-efficacy was strong ($\beta = .574$), as was the path from self-efficacy to research motivation ($\beta = .336$), supporting the theoretical framework that posits self-efficacy as an important psychological mechanism linking technological tool usage with academic motivation.

Further decomposition of effects revealed that the indirect effect through self-efficacy constituted 34.13% of the total effect, while the direct effect accounted for 65.86%. This distribution suggests that, while a considerable portion of ChatGPT's influence on motivation operates through enhancing students' self-efficacy beliefs, most of its impact occurs directly.

5. Discussion

This study investigated the mediating role of self-efficacy in the relationship between ChatGPT usage and research motivation among postgraduate students. The findings revealed a significant partial mediation model where self-efficacy accounted for 34.13% of the total effect, while ChatGPT usage maintained a substantial direct effect (65.86%) on research motivation. Through the analysis of these results, valuable insights are revealed about the process of using AI tools in academic research and the psychological consequences for postgraduate students.

The significant impact of ChatGPT on improving research motivation ($\beta = .372$, $p < .001$) reveals its intrinsic power to stimulate postgraduates to lack research motivation. These results were consistent with previous findings that demonstrated that technology use has the capacity to directly enhance students' motivation by making tasks more confident, lessening their mental strain, and increasing output [13, 14]. The wide scope of the magnitude of this effect clearly indicates that ChatGPT is not merely an operational tool but rather a transformative intellectual asset, altering postgraduates' approach to research as well as the methods they use to conduct research.

More specifically, ChatGPT appears to address some motivational challenges identified in previous research, including maintaining engagement [1], protecting autonomy [10] and overcoming typical research obstacles [12]. The positive correlation of a major value between Academic Task Support and Extrinsic Reward ($r = .495$, $p < .01$) proves that students think that ChatGPT helps to improve their research yields, hence generating a possible increase of being recognized by outside sources. This result is grounded in previous studies by Aldulaijan and Almalky [15], which show that some AI tools enhance academic productivity.

The significant indirect effect of self-efficacy ($\beta = .193$, $SE = .052$, 95% CI [.092, .296]) reveals an important psychological mechanism underlying the relationship between ChatGPT usage and research motivation. ChatGPT usage reinforces students' self-confidence regarding success in research tasks and enables them to work on more complex academic tasks with greater confidence. The study supports Bandura [56] self-efficacy theory, which asserts that individuals' beliefs about their abilities influence their motivation, persistence, and achievement.

The study reveals that ChatGPT usage ($\beta = .574$, $p < .001$) significantly enhances students' self-efficacy in their research abilities. This is due to the immediate feedback and suggestions provided by the AI tool, which creates successful mastery experiences—the most powerful source of self-efficacy according to Bandura [56]. Moreover, ChatGPT may reduce anxiety

associated with challenging research tasks, as suggested by Zhou [39]. Additionally, the personalized support offered by ChatGPT may act as verbal persuasion, another key source of self-efficacy beliefs. This study contributes to the theoretical understanding of technology adoption in educational contexts, extending the Technology Acceptance Model (TAM) by highlighting the psychological mechanisms that mediate the relationship between technology usage and user outcomes.

Moreover, the findings bridge two previously separate research streams: studies on AI integration in education [34, 35] and research on academic self-efficacy [17, 18]. This study provides a comprehensive understanding of the psychological effects of AI tools on postgraduate students' research experiences, highlighting that self-efficacy is a key mechanism, but other factors like task value, interest development, and improved learning strategies may also contribute to the relationship between ChatGPT usage and research motivation. Additionally, this research explores how technological tools like ChatGPT can serve as sources of self-efficacy beliefs in academic contexts, enhancing traditional self-efficacy theory by providing immediate feedback, scaffolding complex tasks, and offering consistent support, thus creating a technological environment that fosters confidence and capability beliefs, thereby contributing to academic self-efficacy.

The results demonstrate the importance of integrating AI beneficial practices into postgraduate research and supervision education without interruptions. It suggests that institutions should focus on leveraging the motivational benefits of AI tools while establishing appropriate boundaries for their use. The mediating role of self-efficacy emphasizes the need for a balance between technical skill development and the psychological aspects of technology integration. It is important for research supervisors to recognize how AI tools can enhance students' confidence regarding their research abilities, especially when students experience self-doubt or research anxiety. The study indicates that AI tool usage can offer motivational benefits such as Academic Writing Aid for language barriers and Academic Task Support for research methodology or data analysis challenges. However, it raises concerns about overreliance on AI tools, which could impede students' development of critical research skills. Therefore, educational institutions should develop frameworks that balance AI assistance with opportunities for independent skill development and critical thinking.

The study findings on AI adoption and self-efficacy development in Egyptian universities are influenced by demographic characteristics. The predominantly female sample (83.3%) raises questions about potential gender differences in technology adoption and its psychological impacts. Previous research has shown gender variations in technology acceptance patterns and self-efficacy development. The distribution across academic levels, with most participants enrolled in Graduate Diploma programs (74.4%), may influence the generalizability of findings to doctoral or research-intensive master's students. The distribution across theoretical (61.4%) and applied disciplines suggests potential field-specific variations that warrant further investigation.

The cross-sectional design of the study limits definitive causal inferences about the relationships between variables. The theoretical model positions ChatGPT usage as an antecedent to self-efficacy and research motivation, but alternative temporal sequences cannot be ruled out. Longitudinal research tracking changes in these variables over time would provide stronger evidence for causal relationships. The self-report nature of all measures introduces potential common method bias, which could be addressed in future research. The study's focus on Egyptian universities limits generalizability to other cultural and institutional contexts where attitudes toward AI and research practices might differ substantially.

The study suggests that future research could explore the relationship between ChatGPT usage, self-efficacy, and research motivation over time, as students progress through different stages of their projects. Experimental studies could provide stronger evidence for causal relationships and identify optimal approaches for enhancing self-efficacy and motivation. Qualitative research could provide deeper insights into the mechanisms through which AI tools influence self-efficacy beliefs and motivation. Future studies could examine potential moderators, such as prior technology experience, academic discipline, or supervision style, to identify conditions that benefit most from ChatGPT usage for research motivation. A comprehensive understanding of both benefits and risks is crucial for developing balanced approaches to AI integration in postgraduate education.

6. Conclusion

This study makes a significant contribution to understanding the complex relationship between ChatGPT usage and research motivation among postgraduate students, highlighting self-efficacy as a crucial mediating mechanism. The evidence reveals that ChatGPT does not just ease the research process for students but also inspires students to feel more confident in their abilities to undertake research and to participate more in research activities. Such findings have profound implications for postgraduate education, suggesting that purposeful use of AI tools may enhance students' research exercises and achievements.

However, evidence shows that a balanced stance is critical; here, AI can increase motivation without compromising crucial opportunities for students to develop their independent research competencies. As AI technologies continue to evolve and transform educational landscapes, understanding their psychological impacts becomes increasingly important. With this foundation, the study provides rich theoretical visions as well as practical recommendations to influence educators' ability to improve AI integration in postgraduate research environments.

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