

ORCID of JARH: <https://orcid.org/0009-0000-0723-9485>

DOI Number of the Paper: <https://zenodo.org/records/17264827>

Link of the Paper: <https://jar.bwo-researches.com/index.php/jarh/article/view/580>

Edition Link: [Journal of Academic Research for Humanities JARH, 5\(4\) Oct-Dec 2025](#)

HJRS Link: [Journal of Academic Research for Humanities JARH \(HEC-Recognised for 2024-2025\)](#)

ACADEMIC SELF-EFFICACY, ACADEMIC STRESS, AND AI DEPENDENCY: A PREDICTIVE MODEL FOR UNDERGRADUATE THESIS STUDENTS

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Paper Information

Citation of the paper:

(JARH) Habib. U., Hassan Z., Sahar F., (2025). Academic Self-Efficacy, Academic Stress, and AI Dependency: A Predictive Model for Undergraduate Thesis Students. In *Journal of Academic Research for Humanities*, 5(4), 89-99.

QR Code for the Paper:



Abstract

The increasing use of artificial intelligence (AI) tools in higher education has raised concerns about students' growing dependency on AI, particularly during academically demanding tasks such as undergraduate thesis writing. Excessive reliance on AI may undermine independent thinking and critical reasoning, making it essential to understand the psychological factors that contribute to AI dependency. Academic self-efficacy and academic stress play a central role in shaping how students engage with AI tools. Purposive convenience sampling was used to select 120 individuals, ages 21-24 (22.08 (.98)). The correlational design was used in the study. The General Academic Self-Efficacy Scale (GASE-5) by [Perception of Academic Stress Scale \(PAS-18\)](#) by [Dalia Bedewy & Gabriel \(2015\)](#), and a modified version of the Technology Acceptance Model TAM Questionnaire (AITU-5) by [Oluwanife-Falebita \(2024\)](#) were used. The primary research variables met normality assumptions. Correlational results revealed that academic self-efficacy and AI use were significantly positively related, while academic stress and AI use were significantly negatively correlated. Multiple Hierarchical regression analysis revealed 10% variance in AI dependency founding academic self-efficacy as a significant positive predictor ($B = .32, p < .001$). All the dimensions of academic stress remained non-significant predictors of AI dependency in model 2, while increasing the explained variance to 14%. Practically, the study underscores the need for students to develop balanced AI use habits, for educators to integrate AI literacy while promoting independent academic skills, and for universities to design learning environments that encourage ethical and responsible use of AI without compromising academic integrity and originality.

Keywords: Academic self-efficacy; Academic stress; Use of Artificial Intelligence (AI); Undergraduate; Theses Students

Subject Areas for JARH:

- 1 Social Sciences
- 2 Education

Timeline of the Paper at JARH:

- Received on: 21-10-2025.
- Reviews Completed on: 16-12-2025.
- Accepted on: 25-12-2025.
- Online on: 31-12-2025.

License:



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Recognised for BWO-R:



Published by BWO Research INTL:



DOI Image of the paper:

DOI [10.5281/zenodo.15649213](https://doi.org/10.5281/zenodo.15649213)

Introduction

A wide range of integrative and cross-disciplinary studies has emerged as a result of Artificial Intelligence's (AI) increasing impact on modern civilisation. AI has completely changed how we engage with the outside world (Gruetzmacher & Whittlestone, 2022). AI in education refers to the application of technology, such as the processing of natural languages and machine learning, to enhance the educational process (Alneyadi et al., 2023; Miao & Holmes, 2021). The digitalisation of educational materials and individualised learning experiences are examples of how AI applications in the education sector can significantly benefit both students and teachers (Zhai et al., 2021). AI offers automated support, enables virtual contact, and can create a more flexible curriculum that can meet the demands of the twenty-first century at all educational levels (Lu, 2019).

Students may become less motivated and lose their cognitive abilities if they rely too much on AI (Ahmad et al., 2023). However, a number of factors, including academic stress, academic self-efficacy, and performance expectations, cause over-reliance on AI (Zhang et al., 2024). When it comes to university students and AI, most people are hopeful about its potential benefits, which include increased productivity, effectiveness and individualised learning. However, this could be related to AI dependency, which is characterised by both a substantial psychological dependence and an overuse of AI-assisted equipment (Lund & Wang, 2023).

Academic self-efficacy (ASE) is a social-cognitive process that focuses on building confidence in one's capacity to acquire and maximise the intellectual, psychological, behavioural, and social resources needed to perform more effectively at academic-related activities (Nielson et al., 2018; Khan, 2013; Li et al., 2020; Parmaksız, 2022). Self-efficacy theory (Jackson et al., 2019) states that students who lack academic confidence are more likely to become frustrated and may find it difficult to finish education-related tasks. In these

situations, they might look for additional support, like AI tools, to make up for their shortcomings. By only asking questions, it enables students to get prompt and straightforward responses, which may improve their academic performance in a short while (Alshater, 2022; Rahman & Watanobe, 2023). As a result, rather than working through challenges themselves, learners would depend more on AI for quick fixes.

Academic stress is another related term that should be investigated in educational settings. It is a psychological strain brought on by constant pressure to achieve academic goals (Bedewy & Gabriel, 2015; Struthers et al., 2000) and has the potential to cause behavioural and psychological problems in students (Reddy et al., 2018). According to a further investigation on the stress-coping theory by Folkman (2013), people in demanding circumstances are driven to create strategies to deal with stress and the difficulties they face. AI technology gives students an easy and rapid method to acquire academic information and solutions, satisfying their short-term academic needs and lessening academic stress (Rani et al., 2023; Zhu et al., 2023).

Literature Review

Recent scholars increasingly emphasise that students' reliance on artificial intelligence (AI) in higher education is shaped not only by technological accessibility but also by underlying psychological factors. Rather than treating AI dependency as a purely technological phenomenon, contemporary research highlights academic self-efficacy and academic stress as central determinants of how students adopt and rely on AI tools in academic contexts.

A growing body of literature links academic self-efficacy to students' engagement with AI technologies, though findings remain inconsistent. Several studies report that higher academic self-efficacy is associated with more confident and purposeful use of AI tools, suggesting that self-efficacious students perceive AI as a supportive resource that enhances efficiency and learning outcomes (Jia & Tu, 2024; Tanveer et al., 2024). Similarly, Bouzar

[et al. \(2024\)](#) found that students with stronger writing self-efficacy were more inclined to integrate ChatGPT into academic tasks, viewing it as a complementary aid rather than a substitute for effort. In contrast, [Estrada-Araoz et al. \(2025\)](#) reported a negative association between academic self-efficacy and AI dependence, indicating that students with lower confidence may rely excessively on AI as a compensatory mechanism. Collectively, these findings suggest that academic self-efficacy plays a critical role in AI engagement; however, the direction and nature of this relationship appear to vary across academic levels, cultural contexts, and task demands.

Academic stress has also emerged as an important, though inconsistently supported, factor in AI dependency. [Zhang et al. \(2024\)](#) found that academic stress mediated the relationship between self-efficacy and problematic AI use, implying that stressed students may turn to AI as a coping strategy under performance pressure. Similarly, [Abbas et al. \(2024\)](#) reported that time constraints and heavy workloads increased students' use of generative AI tools, supporting the notion that stress-related academic demands can encourage reliance on AI. Conversely, [Folkman \(2013\)](#) and [Zhu et al. \(2023\)](#) suggest that high levels of academic stress may reduce engagement with AI due to cognitive overload, reduced exploratory behaviour, or avoidance-oriented coping strategies. This divergence indicates that academic stress may function both as a driver and an inhibitor of AI use depending on students' coping styles and perceived technological competence ([Rani et al., 2023](#)).

Across the literature, scholars increasingly agree that AI dependency becomes problematic when AI replaces independent cognitive effort rather than supporting learning ([Ahmad et al., 2023; Lund & Wang, 2023](#)). However, much of the existing research focuses on general university populations, postgraduate students, or broad academic tasks, with limited attention given to undergraduate thesis students. Furthermore, empirical studies examining AI

dependency within non-Western contexts—especially in Pakistani higher education—remain scarce, despite cultural differences in academic pressure, learning environments, and technology adoption.

Overall, the literature converges on the understanding that AI dependency is not inherently problematic but becomes concerning when AI replaces independent cognitive effort rather than supporting it. The mixed findings regarding academic self-efficacy and stress underscore the need for context-specific research, particularly among undergraduate thesis students who face heightened demands for originality, sustained effort, and academic integrity.

Theoretical Framework

The I-PACE model ([Brand et al., 2016](#)) provides a conceptual framework for comprehending the processes underlying the development and maintenance of addictive behaviours associated with certain websites or Internet applications. Academic stress is a significant social cognitive element that fosters problematic technology use within the scope of the I-PACE model ([Vantieghem & Van Houtte, 2015](#)). The four components of this model are human, affective, cognitive, and executive. Within the I-PACE model ([Brand et al., 2016](#)), academic self-efficacy and academic stress function as key person-related and affective-cognitive components that shape the development of AI dependency. Academic self-efficacy operates primarily at the person and cognitive levels by influencing students' beliefs about their competence, control, and expected outcomes when engaging with AI tools; students with higher self-efficacy are more likely to intentionally adopt AI as a performance-enhancing strategy, which can gradually reinforce habitual use and potential dependency ([Li et al., 2020; Tanveer et al., 2024](#)). Academic stress, on the other hand, functions within the affective component of the model by generating negative emotional states such as pressure, anxiety, and cognitive overload, which activate coping responses; depending on coping

orientation, students may either avoid AI due to reduced cognitive flexibility or use it excessively as a short-term relief mechanism (Folkman, 2013; Zhang et al., 2024). Over time, repeated reliance on AI as a coping or performance tool may shift into the execution stage of the I-PACE model, where learned behaviour patterns and reinforcement processes contribute to sustained AI dependency. (Li et al., 2020; Mun, 2023; Parmaksız, 2022).

Goals

1. To examine relationships among academic self-efficacy, academic stress, and AI dependency.
2. To identify key predictors of AI dependency among undergraduate thesis students.
3. To analyse demographic differences influencing AI dependency.

Objectives

1. To study the association between academic self-efficacy, academic stress, and AI dependency among these students of BS programs.
2. To identify predictors of AI dependency in these students.
3. To identify the demographic differences influencing AI dependency among undergraduate thesis students.

Research Questions

1. What is the relationship between academic self-efficacy and AI dependency?
2. How does academic stress (and its sub-dimensions) relate to AI dependency?
3. Which predictor contributes more strongly to AI dependency?
4. Do demographic variables significantly influence AI dependency levels?

Innovation

1. The study uses a rare combination of ASE, academic stress, and AI dependency variables in the context of Pakistani higher education.
2. Incorporates validated international scales and the I-PACE model, giving theoretical depth.

3. Provides empirical evidence on the psychological factors behind AI dependency, which is still a developing research area.

Hypotheses

1. Academic self-efficacy and academic stress will have a relationship with AI dependency among undergraduate thesis students.
2. Academic self-efficacy and academic stress will predict AI dependency among undergraduate thesis students.
3. There is likely to be a demographic difference in terms of academic self-efficacy, academic stress and AI dependency among undergraduate thesis students.

Method

Research Design

The quantitative investigation used a cross-sectional correlational research method, which is suitable for investigating correlations between academic stress, academic self-efficacy, and AI dependency without concluding causal linkages.

Sample and Sampling Strategy

The research acquired a sample of 120 undergraduate theses students, including boys ($n = 49$) and girls ($n = 71$) with mean age ($M = 22.08$, $SD = .98$) studying in private or government institutions (Government Graduate College Women Gujranwala, Government Graduate College Boys Gujranwala; Punjab University Gujranwala Campus and Gift University Gujranwala) in Gujranwala, Pakistan. G-power analysis was used to estimate the sample size in order to guarantee adequate statistical power for identifying significant correlations between the variables. The current study was conducted using a purposive sampling strategy to select the participants.

Inclusion/Exclusion Criteria

The selection criteria of the study included undergraduate theses students who are enrolled in the BS degree program studying in government or private institutions in Gujranwala. Both participants included girls and boys who were living with their parents. Exclusion criteria of the study included: Undergraduate thesis students who are enrolled in an online degree program or doing some part-

time work. Married students were excluded from the study.

Table 1

Demographic Characteristics of the Study's Sample (N = 120)

Characteristics	f	%	M	SD
Age			22.08	.98
Gender				
Boys	49	40.8		
Girls	71	59.2		
Family System				
Joint	52	43.3		
Nuclear	68	56.7		
Study Institute				
Government	78	65.0		
Private	42	35.0		
Residential Area				
Rural	37	30.8		
Urban	83	69.2		
Birth Order				
First Born	43	35.8		
Middle Born	49	40.8		
Last Born	28	23.3		

Instruments

General Academic Self-Efficacy Scale

The General Academic Self-Efficacy scale ([GASE: Nielsen et al., 2018](#)) measures the level of confidence in the ability to plan, organise, and carry out academic tasks effectively. This five-item self-report scale uses a five-point Likert scale, with 1 denoting "strongly disagree" and 5 denoting "strongly agree," to gauge academic self-efficacy. With a Cronbach's alpha of 0.81, [Akanni and Oduaran \(2019\)](#) reported satisfactory indices of internal consistency.

Perception of Academic Stress Scale

[BeDewy and Gabriel \(2015\)](#) used an 18-item scale with a global internal consistency reliability of 0.70 to measure students' perceptions of stressors. Students were asked to place their opinions and knowledge of sources of academic stress on a 5-point Likert-type scale, with 1 denoting strongly disagree and 5 denoting strongly agree.

The scale has three subscales. The academic expectations subscale gauges excessive stress brought on by parents' expectations, teachers' critical remarks about student performance, and competing peer pressure. It consists of 4 items

and has an internal consistency of 0.60 ([Bedewy & Gabriel, 2015](#)). Perceptions of workload and examination subscale consisted of 8 items measures stresses related to extensive tasks, an enormous workload, and anxiety about failing exams and had an internal consistency of 0.60 ([Bedewy & Gabriel, 2015](#)). The academic self-perceptions subscale gauges students' confidence in their ability to succeed academically and in their potential professional lives. The internal consistency of the six items was 0.60 ([Bedewy & Gabriel, 2015](#)).

Dependence on AI

The dependence on AI (DAI) by [Morales-Garcia et al. \(2024\)](#) is used to guarantee an evaluation that takes into account the variety of personal experiences related to AI dependency. A five-point Likert scale is used to present the five DAI items. Five response alternatives are available in this format, which vary from "Completely false for me" to "Describe me perfectly." Individual peculiarities of reliance on AI can be precisely and thoroughly reflected in this structure. Both the alpha (α) and omega (ω) coefficients, which are reliability indications, demonstrated strong internal consistency (α and $\omega = .87$).

Procedure

The topic for the research study was selected, and related scales were properly searched. Data were collected from undergraduate thesis students enrolled in the BS degree program. After obtaining necessary ethical approvals from relevant authorities and institutions, recruitment of participants was commenced. Informed consent was taken from the participants. Before collecting the data, participants were given a brief introduction to the research as well as the purpose of the research. The participants were informed that their information would remain confidential. The time to complete questionnaires was 10-15 minutes approximately.

Ethical Considerations

Ethical factors were taken into consideration when conducting the research. Respondents' confidentiality was guaranteed. Through

informed consent, every individual was made mindful of the importance of the study. They had the choice to discontinue participating in the study at any time. Approval was obtained from the relevant authorities to gather the data and from the authors to use the scales.

Results

The hypotheses were tested using SPSS-26. Demographics were subjected to descriptive analysis, and psychometric properties of the scales were measured. Pearson Product-Moment Correlation was used to find out the relationship between academic self-efficacy, academic stress and AI use. Predictions of independent variables on the use of AI were checked by Multiple Hierarchical Linear Regression. Demographic differences on main study variables were checked through an independent test.

Table 2

Psychometric Properties of Study Variables in the Sample (N = 120)

Variables	<i>k</i>	<i>M</i>	<i>SD</i>	Rang e	α	Sk w	Ku r
Academic Self-efficacy	5 4	18.2 8	3.7	7-25 0	.7 .0	- .49	.0 9
Academic Stress	1 8	50.9 1	8.7 2	18- 90	.7 1	- .30	- .3
Academic Expectations	4 5	10.9 8	3.1	4-20 9	.6 .24	- .3	2 8
Workload and Examination	8 2	22.1 7	4.4	8-40 8	.6 .15	.15 .7	- 2
Academic Self-Perception	6 4	17.8 2	4.2	6-30 9	.6 .19	- .5	- 7
AI Dependency	5 4	17.7 5	3.0	11- 25	.6 .10	- .6	- 5

The psychometric characteristics of the scales utilised in the current research are displayed in Table 2. Academic self-efficacy and academic stress had Cronbach's alphas of .70 and .71, respectively (>.70), indicating acceptable reliability. The internal consistency values for the three subscales of Academic Stress (Academic

Expectations, Workload and Examinations and Academic Self-Perception) is approximate to .70, which also indicates fair reliability. The Cronbach's alpha for AI Dependency is .68, which is very close to the satisfactory reliability range of .70. The sample is normally distributed; the values of skewness and kurtosis fall within the acceptable range of ± 1.96 .

Table 3

Intercorrelations for Study Variables (N = 120)

Variables	1	2	3	4	5	5	7
Age	-						
Academic self-efficacy	.13	-					
Academic stress	.17	.12					
Academic expectations	.12	.07	.3**	-			
Workload and examination	.14	.15	.5**	.6**	-		
Academic self-perception	.18	.02	.6**	.06	.0**	-	
AI Dependency	.05	.2**	.23*	.14	.18	.18	-

* $p < .05$, ** $p < .01$

Table 3 shows the association of academic self-efficacy and academic stress with AI use among undergraduate thesis students. The correlation between AI use and age is not statistically significant. Academic self-efficacy and AI use are significantly positively correlated. AI dependency increases with an increase in academic self-efficacy and vice versa. There is also a significant negative association between academic stress and the use of AI. As academic stress increases, the use of AI decreases. There is a non-significant association of academic expectations, workload and examination and academic self-perception with AI dependency.

Table 4

Multiple Hierarchical Regression Results for the Predictors of AI dependency

Variables	<i>B</i>	<i>SE</i>	β	<i>P</i>	<i>95%</i> CI LL UL	<i>R</i> ²	ΔR ²
Step 1						.10*	.1
Constant	13.1 0	1.3 1				10.5 0, 15.7 0	*
Academic	.25	.07	.3	.00	.12		

Impact of Social Networking Usage on Sleep Quality						
self-efficacy		1	0	.39		
Step 2					.14	.04
Constant	16.7	2.1		12.4		
	4	5		8,		
				21.0		
				0		
Academic self-efficacy	.24	.07	.30	.00	.10,	
Academic expectation	-.10	.08	-1.1	.24	-.27,	
on Workload and Examination	-.02	.07	-0.5	.79	-.16,	
Academic self-perception	-.11	.07	-0.4	.14	-.25,	
n				5	.04	

The Durbin-Watson value fell between 1 and 3; the assumption of independent errors was satisfied. Tolerance values were used to test the hypothesis of no multicollinearity, and each value was higher than 0.2.

In the first step, the regression model was found significant when academic self-efficacy was incorporated as an independent variable, $F(1, 118) = 13.04, p < .001$. It accounted for 10% variance in the outcome. In the second model, three domains of academic stress were entered along with the academic self-efficacy, and it remained significant, $F(4, 115) = 4.70, p < .01$. It explained an additional 4% variance in the AI use. Among the predictors, academic self-efficacy emerged as a significant positive predictor, while academic expectation, workload and examination and academic self-perception emerged as non-significant predictors of use of AI among undergraduate thesis students.

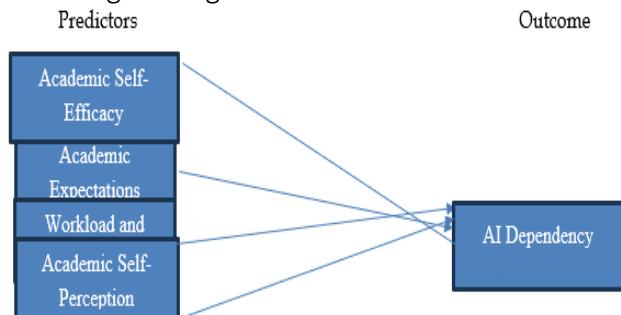


Figure 1:

An emerging model of the predictors of AI dependency among undergraduate thesis students.

Table 5

Means, SDs, and T-values of Demographics Variables on Artificial Intelligence (AI) Dependency (N = 120)

	n	M	SD	t(118)	95 % CI	
					Cohe n's d	LL UL
AI Dependency						
Gender						
Boys	4	17.	3.0			
	9	86	3			
Girls	7	17.	3.0	.34	-	-
	1	66	8			.93 2
Study Institu						
n						
Governm	7	17.	3.1	-.30	-	-
ent	8	68	1			1.3
Institute						4
Private	4	17.	2.9			
Institute	2	86	6			
Family System						
Joint	5	17.	3.8	.63	-	-
Family	2	92	0			.76 7
Nuclear	6	17.	4.5			
Family	8	78	4			

Table 5

Revealed non-significant mean differences across gender ($t(118) = .34, p > .05$), study institution ($t(118) = -.30, p > .05$), and family system ($t(118) = .63, p > .05$) on AI dependence.

Discussion

The present study investigated the relationship between academic self-efficacy, academic stress, and AI dependency among undergraduate thesis students in Pakistan, offering valuable insights into the psychological mechanisms underlying AI reliance in higher education. The findings indicate that academic self-efficacy is positively associated with AI dependency, whereas academic stress is negatively related to AI dependency. Moreover, academic self-efficacy emerged as a significant positive predictor of AI dependency, while academic stress and its sub-dimensions did not significantly predict AI dependency when

examined collectively.

The positive relationship between academic self-efficacy and AI dependency aligns with international research indicating that self-efficacious students tend to adopt AI tools strategically to enhance productivity, efficiency, and performance (Li et al., 2020; Tanveer et al., 2024; Jia & Tu, 2024). Rather than reflecting helplessness or avoidance, AI use among confident students may represent an intentional effort to optimise academic outcomes. Within the I-PACE framework (Brand et al., 2016), academic self-efficacy functions as a stable person-related cognitive factor that reinforces repeated engagement with AI, potentially increasing the likelihood of habitual use and dependency over time. This finding contrasts with studies showing that lower academic self-efficacy is associated with greater AI dependency (Estrada-Araoz et al., 2025). Such differences may stem from variations in cultural context, academic level, and task demands. Unlike prior research focused on general coursework or postgraduate students, this study examines undergraduate thesis students, for whom thesis work represents a high-stakes academic requirement in Pakistan. As a result, students with higher self-efficacy may use AI proactively to enhance performance rather than as a stress-driven coping tool.

The negative association between academic stress and AI dependency further distinguishes the present findings from some international studies suggesting that stress increases reliance on AI as a coping mechanism (Zhang et al., 2024; Abbas et al., 2024). While stress-coping theories propose that individuals seek external aids during periods of academic pressure (Folkman, 2013), the current results indicate that higher stress levels may actually reduce AI engagement among Pakistani undergraduate students. One plausible explanation is that persistent academic stress, which is often normalised in Pakistani educational culture, may lead to cognitive overload, reduced motivation, and avoidance-oriented coping rather than exploratory or adaptive technology use. Under such conditions,

AI tools may be perceived as an additional cognitive burden requiring effort, learning, and decision-making, rather than as a convenient solution (Zhu et al., 2023; Rani et al., 2023). Cultural factors in Pakistani higher education, such as strong parental expectations, academic competition, and limited resources, may intensify and normalise academic stress. This chronic stress can reduce students' capacity to adaptively engage with new technologies, consistent with Folkman's (2013) stress-coping perspective.

The regression results further reinforce the centrality of academic self-efficacy, as it remained a significant predictor of AI dependency even after controlling for academic stress dimensions. This finding supports international research emphasising that cognitive beliefs about competence exert a stronger and more consistent influence on technology-related behaviours than situational stressors alone (Brand et al., 2016; Parmaksız, 2022). The non-significant predictive role of academic stress sub-dimensions suggests that stress may influence AI dependency through mediating or moderating pathways rather than as a direct predictor, consistent with findings reported by Zhang et al. (2024).

Finally, the absence of significant demographic differences across gender, institution type, and family system aligns with emerging international literature suggesting that AI dependency is increasingly shaped by psychological and cognitive variables rather than socio-demographic factors (Majeed et al., 2024). This pattern reflects the growing accessibility and normalisation of AI tools across diverse student groups, reinforcing the idea that internal psychological processes, rather than background characteristics, are more influential in determining AI reliance.

Overall, the findings emphasise the importance of interpreting AI dependency through culturally grounded and context-specific perspectives. In the Pakistani undergraduate thesis context, confidence-driven engagement with AI appears to be more influential than

stress-induced coping, highlighting academic self-efficacy as a key psychological factor shaping students' interaction with emerging educational technologies.

Conclusion

This study contributes to the understanding of AI dependency in higher education by demonstrating that academic self-efficacy is a key psychological factor influencing undergraduate thesis students' reliance on AI, while academic stress does not directly predict dependency. By focusing on the Pakistani context, the findings extend international research and highlight the role of culturally shaped academic expectations in AI engagement. The study offers practical value for educators by emphasising the need to strengthen students' self-efficacy while promoting ethical and balanced AI use. For students, the results underscore the importance of self-regulated learning and responsible AI practices. At the institutional level, universities can manage AI dependency by integrating AI literacy, establishing clear usage guidelines, and designing assessments that encourage originality. Overall, the findings provide actionable insights for educators, students, and policymakers to ensure that AI supports learning without undermining academic integrity.

Limitations

The participants used in the study consisted of undergraduate thesis students with no other postgraduate MPhil or PhD scholars, which might hinder the findings' generalisation to larger populations. Furthermore, the measurements used might not accurately represent the multifaceted aspect of AI use, indicating the necessity for additional qualitative or mixed-methods research to complement the quantitative data.

Future Recommendations

Future research should focus on studying the sample to include a broader range of students, such as postgraduate MPhil and PhD scholars, to enhance generalizability. Employing qualitative or mixed-methods approaches to better capture the multidimensional nature of AI use among

students. Future researchers can focus on exploring the psychological and behavioural effects of AI dependency to provide deeper insights beyond quantitative correlations.

Implications

Understanding the dynamics of AI use in academic settings informs policymakers and developers to design AI tools that support learning without encouraging dependency. Insights into how academic self-efficacy influences AI dependency can guide educators to reduce overreliance on AI tools while managing academic stress. AI tools to be leveraged as stress-relief resources; however, the psychological impacts of dependency necessitate careful attention.

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