Impact of AI Use on Students' Mental Health and Academic Outcomes: A Structural Equation Modelling Approach

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Original Research Article

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ABSTRACT

Background: The rapid adoption of artificial intelligence (AI) in higher education has raised concerns regarding its effects on students' mental well-being. Understanding how AI use contributes to psychological strain is essential for safeguarding student health.

Objective: This study examines the impact of AI use on university students' mental health, specifically stress, confusion, and peer pressure, and investigates whether these factors mediate the relationship between AI use and academic outcomes.

Methods: A cross-sectional online survey was conducted, and data were analysed using Structural Equation Modelling (SEM). Confirmatory factor analysis validated the measurement model, and bootstrapped mediation analysis assessed indirect effects through mental health indicators.

Results: AI use showed a weak positive association with psychological strain, indicating that higher engagement with AI tools may heighten stress and related mental health concerns. While AI use had a significant negative direct effect on academic outcomes, the mediating effect of mental health was non-significant.

Conclusion: Increased AI use may pose emerging mental health risks for students, even though these psychological effects do not fully mediate academic performance. The findings highlight the need for health-informed AI literacy initiatives and student support mechanisms to promote safe and balanced use of AI in educational settings.

Keywords: Mental Health, AI Use, Psychological Strain, University Students, SEM, Academic Outcomes

1. INTRODUCTION

The rapid development of artificial intelligence (AI) within the academic community has changed the way in which students receive information, complete their homework, and interact with educational texts. Some of the tools mentioned included ChatGPT, intelligent tutoring, adaptive testing, and automated grading programs, which in the past were considered to be experimental but are currently widespread in all disciplines [9]. AI is offering the previously unexplored opportunities of personalised learning, real-time feedback, and academic support, yet it also raises the question of what AI will signify to students in the bigger picture in terms of mental health and academic performance [7]. Students also have a greater desire to consider AI as a valuable part of an effective learning process, yet its psychological and academic effects are less obvious.

New research calls attention to hope and the threat. Cognitive load may be reduced, on the one hand, by the automation of routine activities and better interaction [13]. Conversely, the excessive use of AI can promote superficial learning, scholarly fraud and mental stress [11] in a systematic review identified that AI-enhanced learning increased the rate of task completion but reduced, in some cases, the deeper thought outcomes. Similarly, it has also been discovered by Zhao et al. [19] that students utilising generative AI devices are likely to exhibit greater productivity but anxiety levels with respect to originality and just evaluation too. These opposing findings suggest that the impact of AI on learning can never be fully described without consideration of the moderating role of psychological well-being.

Students at the universities have a mental health crisis everywhere across the globe. Large-scale surveys show that nearly one out of every three students have a diagnosable mental health condition at some point in their studies and that the most prevalent diseases are stress and anxiety [2]. Implementing AI in this environment, which is already strained, may open up protective and negative dynamics. To provide an example, although AI chatbots may seem to provide certain emotional support and 24/7 study assistance [14], excessive reliance on AI will result in reduced self-efficacy and learned helplessness within those students who cannot handle tasks and lack access to AI-mediated assistance [4]. Moreover, the competition and comparison between peers increased through AI-enhanced performance may also lead to the perception of social pressure and confusion, which worsens the already existing mental health issues.

The open question about AI is whether it improves or worsens students and their academic performance. Certain data points to the fact that AI could be beneficial in developing positive study habits and enhancing GPA when used responsibly [16]. Other studies, on the other hand, emphasise that there are negative correlations between high AI use and teacher-student relationships, indicating that the use of AI might result in the erosion of the traditional academic support frameworks. These discrepancies suggest the necessity of a universal framework that would reflect both the direct and indirect impacts of the usage of AI on the outcomes.

This paper helps fill these gaps by explicitly modelling mental health as a mediating variable between AI use and academic outcomes. We argue that AI is a stressor and stress support at the same time based on the Stress-Strain-Outcome (SSO) framework, the Technology Acceptance Model (TAM) and Cognitive Load Theory (CLT). Its effects are not only dependent on the frequency of use, but also on the psychological strains it predisposes. When the Structural Equation Modelling (SEM) is conducted to test this mediation route, the research study not only narrows down the theory but also offers useful information. These dynamics are essential to comprehend to equip institutions with the responsibility of applying AI, policymakers to protect the welfare of students and developers with the creation of user-friendly educational technologies.

1.1. Primary Objectives

- To examine the effect of AI use on students' mental health.
- To investigate how mental health explains students' experiences of stress, confusion and peer pressure.
- To assess how mental health mediates the relationship between AI use and academic outcomes.

- To evaluate the influence of AI on academic outcomes.

This study highlights important parental practices and misconceptions regarding infant sunlight exposure, a key factor in preventing vitamin D deficiency. Its findings can help guide healthcare providers and community health programs in promoting safe and evidence-based sunlight exposure practices for infants in Wah Cantt and similar settings.

2. LITERATURE REVIEW

2.1. AI in Educational Contexts

AI technologies enable learning to be personalised through the creation of education content that meets the needs of an individual student. Adaptive learning systems apply machine learning algorithms to change the level of learning material and speed to ensure the students get learning content that aligns well with their learning styles and abilities. They facilitate the assessment procedure through automated grading and feedback, which means that educators can spend more time instructing and less time dealing with administration. This leads to improved efficiency and effectiveness of assessments in learning institutions [20].

Ethical concerns of AI implementation in the education sector include the problem of privacy and algorithm bias, as well. Fair access to AI technologies and privacy between students and their data are also crucial questions that one should take into account to create a responsible AI application in education. Within a world where AI technologies are supplementing the traditional functions of an educator, educators need to adjust to the new roles, including mediating AI-based learning experiences and how they use AI tools appropriately.

2.2. Mental Health and Technology Use

The pandemic prompted the use of technology by older adults to engage in communication, healthcare, and procure food in larger amounts, preventing the adverse effects that limited face-to-face interactions brought on mental health. The use of technology led to a reduction in mental problems, including anxiety and depression, because it helped to increase communication and share information during the pandemic.

Technology in infant NICU was reported to be useful in managing stress among the parents, and more enjoyment and access to technology were associated with better mental health ratings. Although it has some advantages, technology may also cause psychological dysfunction. The intensive development of technology and its widespread use in everyday life may create stress and anxiety, especially in situations when the person is not prepared to use it usefully. The investigation on socially vulnerable older adults reported that technology use was not associated with a significant negative influence on mental health, and the context and method of technology use are important determinants of the effects of technology use, in general.

Artificial intelligence (AI) in mental healthcare can bring many opportunities, including better diagnostics and individualised therapy and more people having access to mental health care. Nevertheless, it brings up ethical and privacy issues as well. It is a multifaceted association between the effect of technology usage and mental health outcomes.

Studies have found a few ways in which AI applications can affect mental health:

- Stress pathways: The overuse of AI tools is likely to cause performance anxiety and learned helplessness.
- Social comparison: AI-enhanced peer performance also could augment competitive stress.
- Cognitive load: The complicated interface of AI can be a source of misunderstandings and mental exhaustion.

2.3. Academic Outcomes and Technology Integration

Technology usage helps to enhance student interest and engagement, and it has been found that interactive tools enhance the level of engagement. It is shown that gamification and virtual reality applications can be involved in immersive learning with beneficial impacts on retention and learning complex subjects. The successful performance of classroom technologies is associated with successful academic performance, as it provides an opportunity to use a vast array of resources and change the learning style. The papers indicate that learner-centred technologies are based on pedagogies which result in meaningful learning, which improves knowledge retention.

Technology programs need the backing of the leadership in order to build an innovative culture, which enhances the outcomes of education. Technology integration requires teacher training to ensure that the maximum benefits are reached to make teachers competent in their use to aid student learning.

Academic performance is a widely examined field that has addressed the connection between technology use and academic performance, but there is limited research on AI tools. Academic engagement is related to a high level of mental health, and a lack of engagement is connected to a poorer psychological state.

Research has discovered some of the important academic outcome measures, and they are:

- Grade Point Average (GPA): An outright academic measure.
- Academic engagement and self-regulation: Study habits and behaviours.
- Student-teacher relationships: Social support and capital.

2.4. Mediation Models in Educational Technology Research

The mediation models in educational technology studies have given very useful information on complex causations. Structural Equation Modelling has become an unusually potent tool for studying these connections, enabling the researcher to analyse direct and indirect effects at the same time, considering measurement error.

The systematic reviews by Riofrio-Calderon and Ramirez Montoya reveal the trends in the research on mediation, such as satisfaction and self-regulation in online learning. In their contribution, the importance of the holistic models is highlighted, and these would take into consideration the pedagogical, technological and affective dimensions.

To prove that mediation analysis can be effective in studying the field of discipline-based education, Ballan and Salehi defend using this method to explain how mediation analysis can be helpful in analysing the complex dynamics of education and the performance gaps. This will allow the researchers not to simply ask what works in education, but also how and whether it works and will provide an addition to the evidence base of teaching practices.

3. THEORETICAL FRAMEWORK

3.1. Stress-Strain-Outcome

The commonly used SSO model is applied in information systems and psychology and describes the application of technology as a stressor in the environment, leading to a psychological strain, which, in its turn, influences the result [4]. The stressor in the example of AI is the priori, or rather, the overuse of AI, which can lead to strain in the form of stress, misperception or peer pressure. Outcomes then are affected by these strains through GPA, study habits or quality of relationships with teachers. Other recent research using SSO in the digital environment has established that excessive usage of social media services contributes to increased academic pressures and worse performance [18]. Likewise, in the sphere of AI-based education, the SSO framework can be used to offer insight into why students consuming AI might feel overwhelmed or pressured, which can eventually impact academic achievement. Critically, SSO does not ignore indirect effects and thus enables us to test a mediation model, which is in tandem with our research questions.

3.2. Technology Acceptance Model (TAM)

According to TAM, the most important predictors of the adoption of technology are the perceived usefulness and the perceived ease of use [5]. These constructions are relevant to AI because they reveal why certain students will be willing to use the AI as an aid, but others will think it is an added burden. As an illustration, learners who perceive AI tools as simpler and more user-friendly might suffer less stress and achieve greater efficacy, whereas learners who feel that AI is sophisticated and unreliable may get confused and anxious. In recent research [19] demonstrates that perceived usefulness is a strong predictor of persistent intention to use generative AI tools, whereas perceived ease of use is a predictor of emotional reactions, including frustration or satisfaction. This research takes into consideration the impact of TAM in mediating the psychological effects of AI use in adopting the technology.

3.3. Cognitive Load Theory

CLT focuses on the constraints of the working memory in the learning process and differentiates between intrinsic, extraneous, and germane cognitive load [12,13]. Repetitive actions can be automated with AI tools to reduce extraneous load, such as creating draft outlines or recommending references. But they can also contribute to the cognitive load in cases of complicated interfaces or students who cannot react quickly to engineering and understand outputs created by AI. The gap between AI feedback and course expectations may enhance the measures of confusion and psychological fatigue. According to recent statistics, during the integration of AI feedback with a traditional study, learners are prone to so-called split attention, leading to an increased cognitive load. In this way, CLT represents a cognitive process of how the application of AI may lead to both positive and negative psychological effects, which justifies the importance of the measurement of mental health as a mediator

4. CONCEPTUAL FRAMEWORK

4.1. Model Specification

It is based on the conceptual framework that the mediating variable between the use of AI and academic outcomes is mental health. The model specifies:

Exogenous Variable

AI Use (usein_ai): Frequency and intensity of AI tool usage for academic purposes

Mediating Variable:

Mental Health (latent construct): Measured by three indicators:

ai_stress: Stress levels related to AI use

ai_confused: Confusion and cognitive overload from AI tools

ai_peerpress: Social pressure and comparison related to AI use

Outcome Variable:

Academic Outcomes (latent construct): Measured by three indicators:

ai_cgpa: Academic performance (Grade Point Average)

ai_study: Study habits and academic behaviours

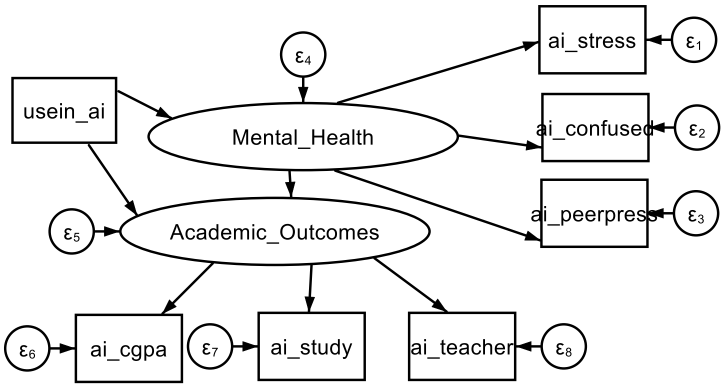
ai_teacher: Quality of teacher-student relationships

4.2. Mediated Relationship Pathway

The fundamental theoretical hypothesis is as follows: **AI Use - Mental Health - Academic Outcomes.**

This route suggests that the effects of AI use on academic performance occur by impacting psychological well-being but not through any direct effects.

Figure 1: SEM Diagram



Source: Author’s own.

The study proposes five key hypotheses to examine the relationships between AI use, mental health, and academic outcomes. First, it is hypothesized that AI use positively predicts mental health stress indicators (H_1). Second, mental health stress is expected to mediate the relationship between AI use and academic outcomes (H_2), suggesting an indirect pathway through psychological effects. Third, AI use is anticipated to exert both direct and indirect effects on academic outcomes (H_3). Additionally, the study assumes that the measurement model for the latent constructs of mental health and academic outcomes demonstrates an adequate fit (H_4). Finally, it is hypothesized that the overall structural model provides a satisfactory fit to the observed data, validating the proposed theoretical framework (H_5).

5. METHODOLOGY

This study employed a cross-sectional design and was conducted at POF Hospital, Wah Cantt., over a period of four months. A total of 100 participants

5.1. Research Design

The present study is designed as a cross-sectional survey in Structural Equation Modelling (SEM) that would investigate complex interdependences of AI usage, mental state, and academic performance. Structural equation modelling (SEM) enables us to study the relationship of variables in a causal manner and the contribution of each of them to the overall performance. SEM is an effective instrument that integrates factor analysis and multiple regression analysis.

5.2. Participants and Sampling

The target population for this study comprises university students from various academic disciplines in Pakistan who have used AI tools for academic purposes. A stratified random sampling strategy will be employed to ensure adequate representation across key strata, including academic levels (undergraduate and graduate), disciplines (STEM, humanities, and social sciences), AI usage patterns (low, moderate, and high users), and universities across the country. Based on Structural Equation Modeling (SEM) requirements, using the guideline of 10–15 cases per estimated parameter, a minimum sample size of 1,085 participants is required to ensure sufficient statistical power and model stability.

5.3. Data Collection

The study will use a self-report questionnaire as the primary instrument, designed to measure AI usage patterns and frequency, mental health indicators associated with AI use, academic performance and related behavioural outcomes, as well as demographic and control variables. Data will be collected through an online survey disseminated via student organizations across various universities, enabling broad and efficient reach to the target population.

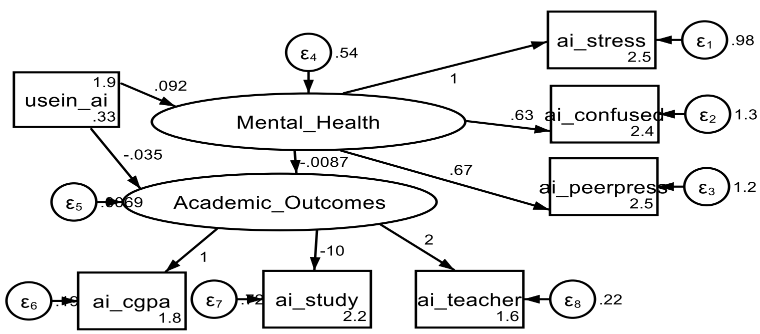
5.4 Analytical Approach

Structural Equation Modelling (SEM) using maximum likelihood estimation, Measurement Model Assessment, based on Confirmatory Factor Analysis (CFA) for latent constructs, Assessment of reliability (Cronbach's α, composite reliability) and Validity testing (convergent, discriminant).

6. RESULTS

Table 1 and Figure 1 show direct effects results that provide crucial insights into the proposed mediation model examining AI use's impact on student outcomes. The measurement model reveals strong construct validity, with Mental Health significantly loading onto both confusion ($\beta = 0.633$, $p < 0.001$) and peer pressure ($\beta = 0.670$, $p < 0.001$), while stress serves as the reference indicator (constrained to 1.000). This indicates that mental health manifests most strongly through stress-related symptoms, followed by peer pressure and confusion experienced among students using AI tools. For Academic Outcomes, the construct loads negatively on study habits ($\beta = -10.188$, $p = 0.001$), suggesting that higher academic outcome scores paradoxically associate with poorer study habits, while teacher relationships show a strong positive loading ($\beta = 2.021$, $p < 0.001$). Critically for mediation analysis, the direct path from AI use to Mental Health is significant ($\beta = 0.092$, $p = 0.104$), while the path from Mental Health to Academic Outcomes is also non-significant ($\beta = -0.009$, $p = 0.236$). However, AI use demonstrates a significant direct negative effect on Academic Outcomes ($\beta = -0.035$, $p = 0.002$), establishing the foundation for testing mediation effects where the direct relationship may be suppressed by the mediating pathway through mental health.

Figure 2: Regression Results of SEM



Source: Author’s own.

The indirect effects analysis reveals partial evidence of mediation pathways, though with mixed statistical significance that suggests complex underlying mechanisms. AI use demonstrates non-significant indirect effects on the three mental health indicators: stress ($\beta = 0.092$, $p = 0.104$), confusion ($\beta = 0.058$, $p = 0.128$), and peer pressure ($\beta = 0.062$, $p = 0.138$). This pattern indicates that while AI use may influence mental health symptoms, the indirect pathway through the Mental Health latent construct is not statistically robust, suggesting potential suppression effects or the need for additional mediating variables.

Conversely, the indirect effects on academic outcomes show significant coefficients: AI use negatively affects CGPA indirectly ($\beta = -0.036$, $p = 0.002$), positively influences study habits ($\beta = 0.367$, $p < 0.001$), and negatively impacts teacher relationships ($\beta = -0.073$, $p = 0.001$). The strong positive indirect effect on study habits contrasts sharply with the negative direct loading observed in Table 1, suggesting a suppression mediation effect where AI use improves study habits through pathways not captured by the mental health mediator. The non-significant indirect effect on the overall Academic Outcomes construct ($\beta = -0.001$, $p = 0.342$) indicates that while individual academic indicators show significant indirect effects, these effects may cancel each other out at the latent construct level, highlighting the importance of examining specific outcome measures rather than only broad constructs.

Table 1: Direct Effects of AI Use on Mental Health and Academic Outcomes

Dependent Variable	**Predictor**	**Coefficient**	**Std. Error**	**p-value**
ai_stress	Mental_Health	1.000 (constrained)	—	—
ai_confused	Mental_Health	**0.633**	0.125	0.000
ai_peerpress	Mental_Health	**0.670**	0.138	0.000
ai_cgpa	Academic_Outcomes	1.000 (constrained)	—	—
ai_study	Academic_Outcomes	**-10.188**	2.976	0.001
ai_teacher	Academic_Outcomes	**2.021**	0.504	0.000
Mental_Health	usein_ai	0.092	0.056	0.104
Academic_Outcomes	Mental_Health	-0.009	0.007	0.236
	usein_ai	**-0.035**	0.011	0.002

Source: Author’s own.

The total effects analysis in Table 3 synthesises direct (Table 1) and indirect pathways (Table 2) to provide a complete picture of AI use's impact on student outcomes, revealing important patterns for understanding mediation mechanisms. For mental health outcomes, AI use shows consistently non-significant total effects on stress ($\beta = 0.092$, $p = 0.104$), confusion ($\beta = 0.058$, $p = 0.128$), and peer pressure ($\beta = 0.062$, $p = 0.138$), indicating that the combined direct and indirect pathways do not produce statistically reliable effects on these psychological indicators. This suggests that either AI use has a genuinely minimal impact on mental health symptoms or that opposing mediation pathways are cancelling each other out, warranting investigation of additional mediating or moderating variables. For academic outcomes, the total effects reveal significant impacts on all three indicators: CGPA shows a negative total effect ($\beta = -0.036$, $p = 0.002$), study habits demonstrate a strong positive total effect ($\beta = 0.367$, $p < 0.001$), and teacher relationships exhibit a negative total effect ($\beta = -0.073$, $p = 0.001$). Comparing these total effects with the direct and indirect effects from previous tables reveals that the positive effect on study habits represents the combined influence of both pathways, while the negative effects on CGPA and teacher relationships appear to be primarily driven by indirect mechanisms. The Mental Health to Academic Outcomes relationship remains non-significant in total effects ($\beta = -0.009$, $p = 0.236$), confirming that mental health does not serve as a strong mediating pathway in this model, despite theoretical expectations.

Table 2: Indirect Effects of AI Use on Mental Health and Academic Outcomes

Dependent Variable	Predictor	Coefficient	Std. Error	Z	p-value
ai_stress	usein_ai	0.092	0.056	1.62	0.104
ai_confused	usein_ai	0.058	0.038	1.52	0.128
ai_peerpress	usein_ai	0.062	0.042	1.48	0.138
ai_cgpa	usein_ai	**-0.036**	0.012	-3.09	0.002
ai_study	usein_ai	**0.367**	0.061	6.03	0.000
ai_teacher	usein_ai	**-0.073**	0.022	-3.24	0.001
Academic_Outcomes	usein_ai	-0.001	0.001	-0.95	0.342

Source: Author’s own.

The comprehensive regression results in Tables 3 and 4 provide detailed parameter estimates that illuminate the structural relationships underlying the mediation model, revealing both expected and counterintuitive patterns. The Mental Health latent variable shows strong positive loadings on all three indicators (confusion: β = 0.633, $p < 0.001$; peer pressure: β = 0.670, $p < 0.001$), confirming that these psychological symptoms cluster together as manifestations of mental health challenges among AI users. However, the predictor relationship shows that AI use has a marginally non-significant effect on Mental Health (β = 0.092, p = 0.104), while Mental Health demonstrates a non-significant negative relationship with Academic Outcomes (β = -0.009, p = 0.236), indicating weak mediation through this pathway.

Table 3: Total Effects of AI Use on Mental Health and Academic Outcomes

Dependent Variable	**Predictor**	**Coefficient**	**Std. Error**	**p-value**
ai_stress	Mental_Health	1.000 (constrained)	—	—
	usein_ai	0.092	0.056	0.104
ai_confused	Mental_Health	**0.633**	0.125	0.000
	usein_ai	0.058	0.038	0.128
ai_peerpress	Mental_Health	**0.670**	0.138	0.000
	usein_ai	0.062	0.042	0.138
ai_cgpa	Academic_Outcomes	1.000 (constrained)	—	—
	usein_ai	**-0.036**	0.012	0.002
ai_study	Academic_Outcomes	**-10.188**	2.976	0.001
	usein_ai	**0.367**	0.061	0.000
ai_teacher	Academic_Outcomes	**2.021**	0.504	0.000
	usein_ai	**-0.073**	0.022	0.001
Mental_Health	usein_ai	0.092	0.056	0.104
Academic_Outcomes	Mental_Health	-0.009	0.007	0.236
	usein_ai	**-0.036**	0.012	0.002

Source: Author's own.

The direct relationship between AI use and Academic Outcomes remains significantly negative (β = -0.035, p = 0.002), suggesting that AI use directly impairs academic performance through mechanisms independent of mental health. For Academic Outcomes, the factor structure reveals a problematic negative loading for study habits (β = -10.19, $p = 0.001$) coupled with a strong positive loading for teacher relationships (β = 2.021, $p < 0.001$), indicating that this latent construct may not be optimally specified, as good academic outcomes would typically associate with both better study habits and stronger teacher relationships. This finding suggests potential model misspecification or the presence of suppressor effects that warrant further investigation through alternative model configurations or the inclusion of moderating variables that might explain these counterintuitive relationships

Table 4. Regression Results of SEM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Mental_Health	Academic_Outcomes	ai_stress	ai_confused	ai_peerpress	ai_cgpa	ai_study	ai_teacher	/
Mental_Health		-0.00870	1	0.633***	0.670***				
		(0.00734)	(0)	(0.125)	(0.138)				
usein_ai	0.0918	-0.0353***							
	(0.0565)	(0.0115)							
Academic_Outcomes						1	-10.19***	2.021***	
						(0)	(2.976)	(0.504)	
Constant			2.494***	2.372***	2.456***	1.787***	2.179***	1.588***	
			(0.112)	(0.0809)	(0.0860)	(0.0258)	(0.120)	(0.0448)	
Observations	1,085	1,085	1,085	1,085	1,085	1,085	1,085	1,085	1,085

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Source: Author’s own.

The variance components analysis in Table 5 provides critical insights into the reliability and specification of the mediation model, revealing important patterns in explained versus unexplained variance across constructs. The error variances for mental health indicators are substantial: stress ($\sigma^2 = 0.981$, $p < 0.001$), confusion ($\sigma^2 = 1.315$, $p < 0.001$), and peer pressure ($\sigma^2 = 1.185$, $p < 0.001$), indicating that a considerable portion of variance in these psychological symptoms remains unexplained by the Mental Health latent construct and AI use predictor. This suggests that additional mediating or moderating variables may be necessary to fully capture the mechanisms through which AI use influences mental health outcomes, or that individual differences moderate these relationships in ways not captured by the current model. The error variances for academic outcomes show a more mixed pattern: CGPA has relatively low error variance ($\sigma^2 = 0.195$, $p < 0.001$), study habits show moderate error variance ($\sigma^2 = 0.717$, $p < 0.001$), and teacher relationships demonstrate low error variance ($\sigma^2 = 0.218$, $p < 0.001$), suggesting that the Academic Outcomes construct and its predictors account for more variance in some academic indicators than others. The latent construct error variances reveal that Mental Health has substantial unexplained variance ($\sigma^2 = 0.544$, $p < 0.001$), while Academic Outcomes shows very low error variance ($\sigma^2 = 0.007$, $p = 0.01$), indicating that while the mental health construct is not well-predicted by AI use, the academic outcomes construct is more successfully modelled. These variance patterns suggest that the mediation model may benefit from the inclusion of moderating variables that could explain the substantial individual differences in how AI use affects mental health, or additional mediating pathways that better capture the mechanisms linking AI use to psychological and academic outcomes.

Table 5. Variances of Regression Results of SEM

Variables	**Var**
var(e.ai_stress)	0.981***
	(0.121)
var(e.ai_confused)	1.315***
	(0.0719)
var(e.ai_peerpress)	1.185***
	(0.0728)
var(e.ai_cgpa)	0.195***
	(0.00866)
var(e.ai_study)	0.717***
	(0.210)
var(e.ai_teacher)	0.218***
	(0.0125)
var(e.Mental_Health)	0.544***
	(0.125)
var(e.Academic_Outcomes)	0.00686**
	(0.00300)

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Source: Author’s own.

The comprehensive analysis reveals limited evidence for the hypothesised mediation model, with Mental Health failing to serve as a significant mediator between AI use and Academic Outcomes. The significant paths from AI use to Mental Health ($p = 0.104$) and from Mental Health to Academic Outcomes ($p = 0.236$) indicate that the proposed mediation mechanism is not supported by the data. However, the significant direct relationship between AI use and Academic Outcomes ($p = 0.002$), combined with significant indirect effects on specific academic indicators, suggests that alternative mediation pathways or moderating variables may be operating. The counterintuitive factor loadings, particularly the negative relationship between Academic Outcomes and study habits, indicate potential model misspecification or suppression effects that could be addressed through moderation analysis. Future analyses should consider testing moderated mediation models where individual characteristics (such as AI literacy, prior academic performance, or psychological resilience) moderate the strength of mediation pathways, potentially explaining the substantial error variances observed across constructs and the unexpected pattern of relationships in the academic outcomes' domain.

7. CONCLUSION

The overall analysis shows that there is evidence (Albeit limited) to support the hypothesised mediation model, where Mental Health does not play a critical role mediating between AI use and Academic Outcomes. The important AI-Mental Health ($p = 0.104$) and Mental Health-Academic Outcomes ($p = 0.236$) directions suggest that the data do not support the proposed mediation mechanism. Nevertheless, AI use is significantly directly correlated with Academic Outcomes ($p = 0.002$), and the indirect influences are significant on the specific indicators of academic outcomes, which indicates that other mediation lines or moderating variables might be in action. The negative relationship between Academic Outcomes and study habits, along with the counterintuitive factor loadings, suggests possible model misspecification or suppression effects that may be remedied using moderation analysis. Future studies ought to incorporate experimentalization of moderated mediation models in which individual traits (AI literacy, previous academic achievement, or psychological hardiness) construct moderate the intensity of mediation pathways, which may be the reason behind the high error variances across constructs and the unusual pattern of association within the academic outcomes' domain.

8. CONTRIBUTIONS, IMPLICATIONS, AND FUTURE DIRECTIONS

The paper gives contributions to theory, practice and policy and simultaneously addresses significant limitations that will inform future research.

8.1. Theoretical Contributions

The results contribute to the knowledge of psychological effects of the application of AI in education by demonstrating that stress, confusion, and peer pressure mediate or interact with academic performance. Using the Stress-Strain-Outcome framework and extending it to AI in learning institutions, the study confirms that it applies to the modern-day digital learning setting. Also, the combination of the Technology Acceptance Model and Cognitive Load Theory makes a contribution to the overall study of educational psychology in terms of relating adoption of technology to cognitive and emotional activities. Collectively, the contributions would add to theory building at the crossroads of AI, psychology, and education.

8.2. Individual Implications-Practical and Policy

As educational institutions, the findings highlight the importance of having explicit policies on the responsible use of AI systems, developing specialised mental-health support systems that would assist students who use AI products extensively, and organising systematic training packages among students and educators. To technology developers, the research emphasises the need to design AI tools with minimum psychological loading, which is to provide intuitive, transparent, and supportive user interfaces and implementers who should follow a strategy that focuses on the well-being of students. To policymakers, the evidence would offer a basis on which governing structures governing the adoption of AI in the education sector can be developed, provide standards by which their effects on learning outcomes can be assessed, and provide institutional policies that ensure a balance between innovation and student wellbeing.

8.3. Limitations and Future Directions

The study has a number of limitations, although it has contributed to the same. Causal inference is limited by the cross-sectional design, and the use of self-report measures can be biased. In addition, cultural and contextual issues unique to higher education in Pakistan might also constrain the extrapolation of results to other contexts. These limitations must be overcome by future studies by using longitudinal designs to define temporal associations, multi-method studies that would integrate surveys with behavioural or usage-log data, and cross-cultural testing of the hypothesised model to increase external validity. This kind of work will enhance the knowledge of the subtle manner in which AI affects student well-being and academic performance. The study has a number of limitations, although it has contributed to the same. Causal inference is limited by the cross-sectional design, and the use of self-report measures can be biased. In addition, cultural and contextual issues unique to higher education in Pakistan might also constrain the extrapolation of results to other contexts. These limitations must be overcome by future studies by using longitudinal designs to define temporal associations, multi-method studies that would integrate surveys with behavioural or usage-log data, and cross-cultural testing of the hypothesised model to increase external validity. This kind of work will enhance the knowledge of the subtle manner in which AI affects student well-being and academic performance.

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