The Dual Impact of Artificial Intelligence: Stressor or Support?

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Abstract

Universities and higher education departments are rapidly integrating Artificial Intelligence tools into their curricula; without really understanding how different student populations can experience varying levels of intellectual insecurity based on their usage patterns, stress levels, and developmental stages. In recent years, the use of Artificial Intelligence has increased rapidly in higher education, at a scale that was not previously observed. We have used the ordered logit probit model, and the sample size for this study is 1085 respondents. The ordered logistic regression results show that peer pressure ($\beta = 0.219$, $p < 0.01$) and AI-related stress–use interaction ($\beta = 0.252$, $p < 0.01$) are the strongest predictors of AI-induced intellectual insecurity. also, The age–use interaction variable demonstrates generational differences. We suggest that younger students experience increased insecurity with AI due to identity formation vulnerability, while older students may establish credentials to adopt AI confidently.

Keywords*:* Artificial intelligence in education, AI insecurity, psychological adaptation to AI, technology acceptance, AI anxiety among university students, and mental health in AI-assisted learning.

Introduction

The rapid integration of Artificial Intelligence (AI) into university education systems has transformed learning methods, yet it has also raised concerns about students' psychological adaptation to Artificial Intelligence (AI). The AI insecurity refers to the apprehension, discomfort, or uncertainty individuals experience when interacting with AI systems. These issues are grounded in the Technology Acceptance Model (TAM), Cognitive Dissonance Theory, and the Stress-Appraisal-Coping Framework. These theories explain the different challenges associated with AI insecurity, which captures the cognitive, mental, and emotional challenges faced by learners adjusting to technological innovation. AI insecurity is strongly linked with confusion, stress, peer pressure, mental health, and demographic factors such as age or family background. Hardly any study has looked into these factors, particularly for the case of Pakistani universities' students. This study thus focusses focusing solely on AI anxiety; this paper integrates social and emotional dimensions to construct a holistic understanding of AI insecurity among students.

The research carried out so far converges on several evidence-based recommendations for maximizing the benefits of AI, while also limiting potential harms in educational background settings. However, the issue is deep, with the use of AI, it has also been seen that the critical abilities of students have suffered. Resultantly,

recruiters are silently blacklisting graduates of universities who are only good on paper. This is thus blacking out the careers of students. These AI and human interactions emphasize (a) human oversight and capacity building, (b) fairness and privacy protection, and (c) balanced system design. At the universities, both public and private, teacher support and scaffolding have emerged as critical factors for successful AI integration. Hao et al. found that instructors' endorsement and their support have strongly increased the students' engagement with AI, as well as the benefits of AI use and reduced associated anxiety according to one study. However, this finding of researchers suggests that AI should be introduced with explicit pedagogical guidance rather than simply made available to students without instructional framing, as is being adopted widely. This is important. The next major question then arises is what should be the right kind of pedagogical guidance that should be given to students for using AI, and how much we can really control the students' use of AI in classrooms and beyond [1].

There appears to be no doubt that accepting the fact that AI literacy and self-efficacy training represent essential components of effective implementation at university levels. Multiple studies have also suggested that teaching students with AI skills, prompt engineering, and critical appraisal may assist students in developing the appropriate AI self-efficacy and avoiding any dependence [2][3]. Building meta-cognitive awareness about AI's strengths and limitations is very important, too.

However, the literature has shown very interesting results, and we see that Emotion-Aware and those models that are hybrid models may combine AI capabilities with human empathy and human emotions, and this shows very promising results for mental health applications. For example, the two recent studies by Ahmad et al. [4] and Nurtanto et al. [5] have also shown that systems that may integrate AI-based emotion detection while taking care of human counseling and mental and emotional health support may yield better AI scalability and empathy. Thus, we can conclude that the hybrid approach, which may address AI's limitations while providing genuine empathy and ethical judgments, can be the new frontier for research, growth, and higher productivity in the future.

Furthermore, another study has also seen that privacy-preserving design is very important when dealing with AI systems, particularly when dealing with university students. The important thing is the privacy-preserving design for AI systems that need to process students' data very carefully while giving them the flavor of AI. This is very important. A study by Ebrahimi et al. [6] also recommended that adopting federated learning and other privacy-conscious architectures of AI can help with the mental health and behavior analytics of students. These new approaches, which allow AI systems to learn from distributed data without centralizing sensitive information, raise legitimate privacy concerns about educational surveillance and the future of education.

Moreover, fairness and continuous monitoring must be embedded in AI system-

based learning and education development, and also in its deployment. A study by Liu et al. [7] called for implementing bias detection and fairness checks while using AI for students, particularly university students.

Finally, the literature shows that researchers have done a huge amount of research. However, the topic is new, and they have looked into the importance of balance and rigorous evaluations. For example, Nurtanto et al. [5], Lee [8] and Hao et al. have also recommended that encouraging balanced AI can supplement traditional learning among university students. Similarly, integrating AI may also bring integrated effects on mental health, and this needs to be included in the curriculum. Providing counseling access and conducting code evaluations, such as randomized control trials or quasi-experiments, can further help to measure objective learning and the well-being outcomes of students [1]. All of these approaches show the importance of guiding AI adoption decisions for university students.

Data were collected from 1,085 students across multiple universities in this study, analyzing their perceptions of AI through an ordered logistic regression model. The objectives of this research are to: (1) the cognitive and psychological determinants of AI insecurity, (2) Examine the moderating roles of age and stress in shaping AI use-related insecurity, and (3) Provide evidence-based policy recommendations to foster healthier AI adaptation. The paper is structured as follows: Section 2 reviews the literature, Section 3 outlines the theoretical and conceptual framework, Section 4 details the methodology, Section 5 presents empirical results, and Section 6 concludes with implications.

Literature Review

Research on AI insecurity is relatively promising but builds upon established constructs such as technology anxiety and perceived risk. Studies show that AI-related confusion arises from limited understanding and overexposure to complex systems [3]. Peer pressure has been identified as a significant determinant of digital behavior, often amplifying stress and performance anxiety [9]. Furthermore, mental health issues related to digital overload have been linked to reduced confidence in managing AI tools [10]. Empirical evidence also suggests that younger users (such as those in our sample in this study), while more tech-savvy, may experience higher insecurity due to competitive academic environments [11]. Interaction effects between AI use, stress, and age have rarely been examined in a unified framework, representing a novel contribution of this study.

The Technology Acceptance Model (TAM) is important for understanding students' perceptions of AI, particularly in terms of perceived usefulness and ease of use. When these perceptions conflict with students' academic self-concept; Cognitive Dissonance Theory may explain the resulting psychological discomfort, which often manifests as AI-related intellectual insecurity.

Academic Performance and Learning Outcomes

Basically, the use of AI and AI-related tools in educational settings or educational needs of the students has generated a measurable amount of shifts in how university students particularly receive and also experience their learning processes, and also how they are now competing in academia. So basically, results so far have provided evidence which points out improvements in the subjective measures such as study efficiency, the engagement levels of students in the class and in different activities, and the creative outputs, and through this, the picture has become not easy but rather more complex, which requires examining the objective-based academic metrics for student learning. So, students interact with generative AI technologies, and these AI technologies are not always the kind of technologies that are suggested by the teacher. So, not all AI tools are for the students; however, there is strict monitoring and a strict need to help the students find the best AI-based learning opportunities. So, basically, the use of generative AI technology results in increased learning efficiency; however, it may also lead to less cognitive thinking and fewer critical abilities.

So, the studies so far have shown increased creativity and stronger independent thinking capabilities of AI, but on the other hand, students who are not able to compete and are not able to learn AI as fast as their companions face issues of mental worries, mental stress, mental anxiety, or compromised mental health, in very simple terms. However, the studies report that improvement does not always correspond with significant changes in the students' actual grade performance. So, if a student is performing really well in the classes based on AI, it is not always reflected in their grades, and again, there comes a divorce between what the student thinks he is doing and what he actually gets in the grade of a class.

So, controlled learning with AI is the new option, but how to control and what kind of right policies and what kind of right curriculum we need to design with the changing AI facilities available is the need of the hour and a challenge faced by the admissions and university management. For example, a study by Ibrahimi et al. [12] has already revealed a potential disconnect between the perceived and the measured academic outcomes of the students, and this observation is very important because it raises important questions, such as how we evaluate the true impact of AI on students' learning. One particularly promising finding of a study shows the impact of AI on test anxiety. In a semester-long experimental study, undergraduate students who used ChatGPT, an AI-enabled tool, showed a meaningful reduction in test-related anxiety; however, it also led to negative academic emotions, while simultaneously they experienced an increase in their positive emotions and various indicators of educational attainment. This study was done by Raghavendra et al. [2].

So, this study suggests that AI tools may support academic success and actually help students with less mental anxiety and less stress than students used to face before AI. Again, there is mixed literature, mixed policies, and mixed suggestions found in

the literature. One strand of the literature says that AI has enabled students with higher cognitive ability, higher thinking abilities, and less stress. On the other hand, the studies are saying that AI is not helping students as it was predicted to help, and rather than helping, AI is leading students towards less critical thinking, less thinking abilities, less cognitive abilities, as well as more mental stress or more anxiety.

Moreover, the potential for emotion-aware AI systems represents another challenge. Particularly, it shows an important challenge for the development of the human mind or the development of the student's mind. Research so far has documented moderate positive correlations between emotion-aware AI usage and the students' mental health. However, this is only true for the case of university outcomes, and the results may vary if the experiment is repeated in colleges and schools. However, the study by Hao et al. also pointed toward the indirect pathways through which AI can benefit academic performance, and such systems could offer more responsive as well as more personalized kinds of learning environments for students [1].

AI-powered interventions have also demonstrated value in identifying students who are struggling. Before, students had to struggle more, for example, to find a question they might need to go to approx. 9 to 10 books, physically get these books, read them, and then answer the question. But now, answering complex questions is just a matter of seconds by using tools such as ChatGPT, Claude, or Bard. There are hundreds of other tools students can use to get answers in seconds. So, explainable student performance prediction models and AI tutoring systems can flag at-risk learners, and this also raises concerns over providing customized feedback, which enables timely support before academic difficulties even become entrenched. This has been done in studies by Hamad et al. [13] and Lee [8]. So, the productive approach that contrasts favorably with the traditional reactive models of academic support is here.

Psychological Effects and Mental Health

In this section, we look at the psychological effects and mental health effects of AI use in students. The relationship between AI usage and university students' mental health proves to be not a simple answer. It is very complex, multi-faceted, and documents benefits and risks equally, particularly focusing on how AI tools are implemented in the educational context, how teachers are facilitating students to use AI tools, and also the availability of appropriate support structures for the usage of AI. Empirical investigations have further revealed that AI actually helps in anxiety reduction because when AI use is properly guided, the literature seems to support that the potential harms of AI are controlled and minimized. So basically, the need of the hour is not to stop students from using AI but to actually provide a system that is properly guided and that warns students of the potential harms that may emerge from over-reliance on AI tools.

These potential harms in psychological terms can be multiple. For example,

dependency formation, social isolation, and exposure to biased feedback systems. Students get quick answers from AI and over-rely on the answers provided by AI. However, practice also shows that AI makes up the answers in a very good way, and usually, the data or the results reported by AI are not correct and made up. So, considering that, over-reliance on AI is also a major factor of misinformation and unnecessary kinds of research, bringing false results for students and young researchers.

Among vocational education students, AI usage has become more associated with reduced academic anxiety, and it shows very interesting mediation pathways. Specifically, the mediation goes into class engagement, which appears to mediate the relationship between AI and lower anxiety levels. Moreover, teacher support further amplifies the positive effect of these engagements, as shown by the study of [4].This finding underscores that AI can benefit, and AI benefits emerge not only in isolation but through the changes in classroom dynamics, teacher methodologies, and instructor involvement with the students.

Importantly, the point here to make is that students are quicker to learn AI as compared to the teachers themselves. And why is it so? Because university students are now one or more generations ahead of the teachers. So, they find it easier to learn technological advancements as compared to a professor who has spent their life in the books. This poses another challenge of how far the teacher is and how good the teacher is in guiding students with the right use of AI.

Direct experimental evidence also supports that anxiety reduction is one of the major benefits of AI. When undergraduate students were exposed to ChatGPT in controlled conditions by teachers or instructors, researchers observed decreased test anxiety and fewer negative academic outcomes, as shown by the study of Raghavendra et al. [2]. The experimental design of this work provides much stronger causal evidence than the correlational studies that have been done before.

Moreover, emotion-aware AI systems and intelligent approaches to mental health support show promise for promoting student well-being in universities using AI. These systems work together by detecting indicators of stress and emotional strain, and then they deliver appropriate pathways in response to the findings to help students achieve better learning opportunities, as suggested by the studies of Hao et al. [1]and Nootanto et al [14]. Such technologies or such AI embedded technologies offer the potential for scalable mental health support that can complement traditional counseling services.

However, again, the picture is not as simple as its form, and the debate is not as simple as it seems. At this time, AI is also becoming stronger, and it is improving with each day, every second. Similarly, students are also learning the use of AI, and teachers are also learning the use of AI. So, all sides the receptive side, the controlling side, as well as the technology itself are in an evolving phase, and the challenges of the future of AI are still undefined.

Systematic reviews or literature have identified several risk factors that can increase as well as decrease anxiety and depression when AI implementation lacks proper controls in the classrooms and beyond, to achieve the course learning objectives, student learning objectives, or program learning objectives.

This pattern suggests that AI serves as a complement to rather than a substitute for professional mental health care, which may ease concerns about AI replacing human support systems. The reseachers' has so far identified significant gaps in the current evidence base. Multiple authors have called for privacy-preserving methodologies and higher-quality randomized controlled trials to properly validate claimed clinical benefits and minimize potential harms [7][5]. Without rigorous research designs, the field risks making recommendations based on incomplete evidence.

Behavioral Changes and Mechanisms of Effect

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These potential harms in psychological terms can be multiple. For example, dependency formation, social isolation, and exposure to biased feedback systems. Students get quick answers from AI and over-rely on the answers provided by AI. However, practice also shows that AI makes up the answers in a very good way, and usually, the data or the results reported by AI are not correct and made up. So, considering that, over-reliance on AI is also a major factor of misinformation and unnecessary kinds of research, bringing false results for students and young researchers.

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In a somewhat counterintuitive finding, AI-induced anxiety itself may sometimes function as a motivator. Under certain conditions, particularly when students hold higher AI self-efficacy, anxiety about AI can paradoxically increase motivated learning behaviors [3]. This suggests that moderate levels of concern about AI, when paired with confidence, may drive productive engagement of university students.

The negative behavioral consequences of AI merit equal attention in both literature and practical world. When AI replaces rather than supplements active learning, several studies by researchers have documented concerning patterns, including overreliance on AI tools, generative (Gen) AI, which reduced peer-to-peer interaction, diminished learning autonomy, and potential loss of critical and creative thinking skills [4] Yola et al. [15]. These risks materialize the most clearly when AI

serves as a substitute for rather than a support to traditional learning activities.

Research Gap

This section is another important section that looks at the interventions and recommendations for the use of AI. Based on the literature review carried out so far, the important information we deduced from the above sections is that AI can have potential risks on mental health. One strand of literature suggests that AI has reduced mental stress and anxiety, whereas on the other hand, another strand of literature supports the idea that AI is non-beneficial for the human mind and, particularly, it is a core cause of mental stress among university students. Considering that, this section looks at the interventions and recommendations from the literature review carried out so far.

It is important to note that very few studies so far have done their research on AI because AI is a growing and evolving technological phenomenon, and hence, the studies are fewer. However, this study comprehensively deals with the issues that are emerging related to AI, particularly the mental and psychological issues that students are incorporating into their lives because of AI. The accumulating research evidence points toward several practical interventions that can be used to benefit educational AI while also limiting the potential harms that AI may cause to students.

The recommendations include an emphasis on the importance of human oversight and the need for proper capacity building among students as well as educators to bring fairness and equity, protect the privacy of students, and also protect the privacy of institutions and teachers through thoughtful system design that will maintain appropriate balances. Moreover, teacher preparation and teacher involvement emerge as critical factors for the successful application of AI integration in academia.

Educational institutions should also invest in comprehensive teacher training and ensure that instructors are supporting students' use of AI in the most appropriate way and are well-equipped with the necessary knowledge. Similarly, a study by Ahmad et al. [4], has reported that without adequate faculty development programs, AI implementation is very unlikely to achieve its potential benefits. Building AI literacy among both students and teachers represents another essential intervention. Educational programs should explicitly teach AI skills, including prompt engineering, the use of generative AI, and critical evaluation of AI outputs, both at the academic and teacher levels.

Enabling students to develop robust AI self-efficacy while also avoiding uncritical dependence on these tools is important, as suggested by Zhou [3]and Yola et al. [15]. Competence building is a very essential part for students, particularly those who are becoming passive consumers of AI-generated content. It is important to note that the design of AI systems should be based upon trust, effectiveness, and student feedback.

The study considering all these elements has taken the perceptions of students towards AI and how AI is affecting their mental health and educational outcomes. Educational institutions, such as universities in our case, should implement explainable predictive models and personalized attention systems that can identify the struggles students are facing in achieving their academic goals and deliver more supportive intervention-type systems, as suggested by Hamad [13].

Moreover, privacy protection requires technical safeguards as well. Developers should adopt federated learning architecture and other privacy-preserving approaches when implementing mental health and related behavioral analytical systems that process sensitive student data, as suggested by Liu et al. [7]. Equity considerations must remain central to AI implementation, and institutions such as universities need to build bias detection capabilities. They need to conduct regular fairness audits of recommendations and move toward the personalization of algorithms.

Moreover, continuous monitoring of different impacts of AI across student groups is essential. Algorithmic systems can inadvertently perpetuate or amplify existing educational inequalities without active monitoring and correction. Finally, institutions such as universities should pursue balanced implementation strategies that include multiple safeguards.

However, for all that, it is important that student perceptions are considered and that it is done at the grassroots level. Surveys should be conducted at the grassroots level to evaluate the basic impacts of AI on students' mental health and stress levels. In this regard, the current study conducts an important survey among university students. The sample size is more than 1,000, and it is taken from Pakistani universities to know exactly how students from Pakistan i.e., from developing countries are facing challenges in adopting AI and how these challenges are affecting their mental health and academic outcomes.

Theoretical & Conceptual Framework

The theoretical grounding of this model draws from multiple frameworks. There are strong relationships between AI anxiety, different age groups, and various AI-related theories. I developed a quadrant model with four distinct frameworks that help explain how AI adoption patterns intersect with the academic pressures that university students face, ultimately leading to intellectual insecurity.

In the top-left quadrant, we have the "Anxious Traditionalists," primarily older students who experience paradoxical insecurity due to fears of obsolescence. These older students often struggle with high academic stress, rigorous coursework, and a competitive environment, making it difficult for them to keep up with AI advancements. This can lead to mental insecurity, stemming from factors like unfamiliarity with AI tools, ethical concerns, and skepticism about AI reliability. As a result, these students may feel technologically inadequate, fearing that their peers who

adopt AI are gaining an unfair advantage. This can lead to impostor syndrome and a sense of being outdated or less capable, ultimately undermining their intellectual confidence.

On the other hand, the top-right quadrant represents the "Over-Reliant Achievers." These are younger students who, despite being highly familiar with AI, still experience significant stress. They become cognitively dependent on AI, which raises doubts about their own intellectual contributions and creativity. This can lead to identity erosion, fears of skill atrophy, and competitive anxiety, as they struggle to distinguish themselves in an AI-pervasive environment. This cycle of stress and dependency can lead to mental health challenges, even as they adapt to technological changes.

In the bottom-left quadrant, we have the "Comfortable Traditionalists." This group typically consists of older students who are in less competitive programs or who maintain confidence in traditional methods. They generally have stable profiles, low stress levels, and are not overly concerned about missing out on AI advancements. Consequently, these students experience minimal anxiety regarding AI adoption.

Several factors contribute to this comfort. First, they have strong methodological confidence, relying on proven study techniques and research methods. Second, they experience reduced peer pressure, as they are less exposed to AI-dominated academic cultures. Third, their motivation is intrinsic, driven by genuine interest rather than competitive anxiety. Finally, they adopt AI selectively, using it minimally for specific tasks without feeling overly dependent on it.

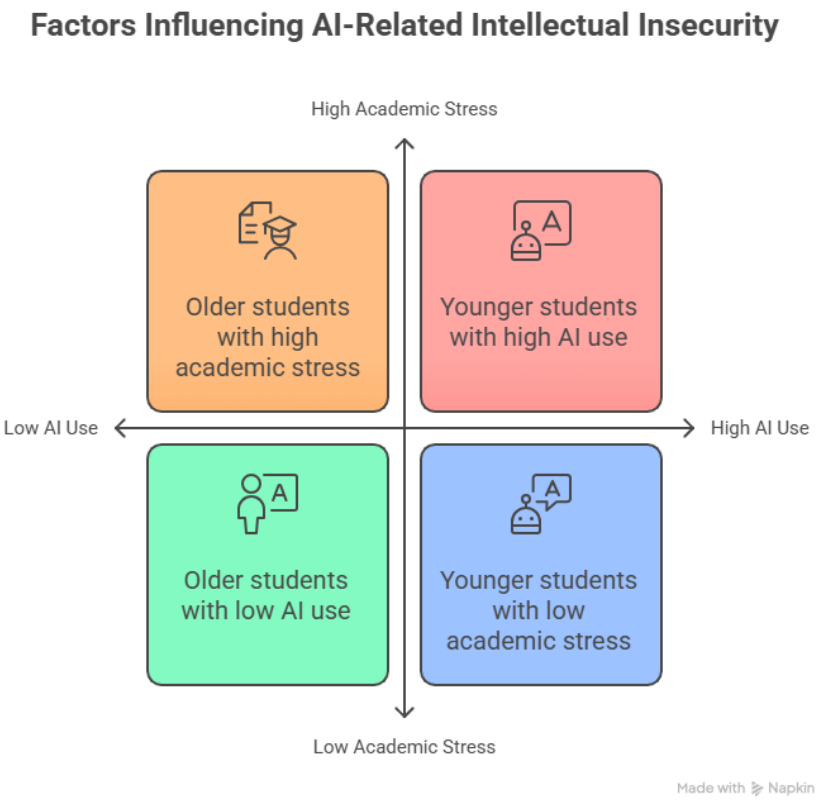
However, this stability can be fragile. If environmental conditions shift such as increased program competitiveness or mandatory AI integration these students might quickly feel pressured and potentially shift into one of the more anxious quadrants.

In the bottom-right quadrant, we have the "Adaptive Integrators." This quadrant represents the ideal relationship with AI technology, where students benefit from AI without experiencing mental stress. These younger students thrive in a low-stress environment and demonstrate technological fluency while maintaining their intellectual agency.

Several factors contribute to their success. First, they view AI as an enhancement tool rather than a replacement for human thinking. Second, they possess meta-cognitive awareness, meaning they know when and how to effectively use AI, while also recognizing its limitations and ethical concerns. Third, they maintain a balanced skill set, leveraging AI to improve efficiency while still honing core competencies. Finally, they enjoy psychological security, confident that AI proficiency complements rather than substitutes their intellectual value.

This group thrives in educational environments that promote responsible AI integration, fostering both ethical use and intellectual independence.

Figure 1: *The four Quadrants on AI induced Stress with age group*



From a theoretical perspective, the foundational Technology Acceptance Model (TAM) provides key insights. In the AI academic context, TAM's concepts of perceived usefulness and ease of use become more complex. Students may recognize AI's practical utility while also questioning whether it aligns with their learning goals. Additionally, perceived usefulness can conflict with perceived legitimacy, and the usefulness of AI can vary depending on the task. For example, AI might be highly useful for literature reviews but less so for original analysis. Similarly, if AI tools are too easy to use, they might increase insecurity by making students feel their contributions are minimal. On the other hand, complex AI tools may require significant learning and increase stress, reducing adoption.

Moderating variables, such as AI confusion and academic stress, play a crucial role. AI confusion, for instance, creates uncertainty about when AI-generated outputs can be trusted, which can reduce effective adoption even when AI is perceived as

useful. Meanwhile, academic stress acts as a double-edged sword: moderate stress can motivate strategic AI adoption, while high stress may lead to either over-reliance or avoidance due to cognitive overload.

Another important theory is the Social Influence Theory, which highlights how peer dynamics and normative pressures affect AI adoption. Descriptive norms, for example, mean that if everyone is using AI tools, there's pressure to conform. Injunctive norms involve peer judgments about what constitutes smart academic behavior, and competitive comparisons can turn AI use into an academic arms race. These social dynamics can either normalize AI-related concerns, reducing individual anxiety, or amplify them through social validation. Cognitive Dissonance Theory also plays a role, explaining the internal conflicts students face. For instance, students who value authentic learning but rely heavily on AI may experience psychological discomfort. Resolving this dissonance might involve redefining what authentic learning means. The conceptual model posits that AI insecurity is a function of AI use, confusion, stress, peer pressure, and mental health, moderated by age and AI-stress interactions.

Methodology and Econometric Model

This study employs an ordered logistic regression (ologit) model given the ordinal nature of the dependent variable, AI insecurity. The dependent variable (ai_insec) measures levels of insecurity ranging from low to high, while independent variables include AI use, confusion, stress, peer pressure, mental health, and age. Interaction terms capture moderation effects between AI use, age, and stress.

The regression results paint a rather complex picture of how students are experiencing intellectual insecurity in relation to AI usage, and the findings strongly support the theoretical frameworks we have been discussing throughout this analysis. Looking at the descriptive statistics first, we can see that the mean AI insecurity score is 2.697 with a standard deviation of 1.212, which tells us that students are generally experiencing moderate levels of insecurity but with considerable variation across the population. This heterogeneity itself validates our quadrant model because it suggests different student profiles are coexisting within the same academic environment, each experiencing AI-related anxieties through different pathways and mechanisms.

Table 1: *Description of Variables*

Variable	Survey Question	Measurement / Scale
ai_insec	"Does your frequent use of AI create feelings of intellectual insecurity within you?"	Ordinal scale (1–5 Likert): 1 = Strongly disagree → 5 = Strongly agree

usein_ai	"How often do you use AI?"	Ordinal categorical scale: 1 = Never, 2 = 30–120 minutes, 3 = 120 minutes and above
ai_confused	"Has AI feedback ever made you feel confused?"	Likert scale (1–5): 1 = Strongly disagree → 5 = Strongly agree
ai_stress	"Has the common use of AI tools increased your academic stress?"	Likert scale (1–5): 1 = Strongly disagree → 5 = Strongly agree
ai_peerpress	"Do you feel pressured to use AI tools to match peers' performance?"	Likert scale (1–5): 1 = Strongly disagree → 5 = Strongly agree
ai_mental	"Do you find yourself using AI for mental health support?"	Likert scale (1–5): 1 = Strongly disagree → 5 = Strongly agree
Agegrp	"Age group"	Categorical (dummy-coded): 1 = Below 20, 2 = 21–30, 3 = 31–40, 4 = Above 40
inter_use_age	*Interaction term* between AI use and age group	Computed variable: usein_ai × agegrp
inter_use_stress	*Interaction term* between AI use and academic stress	Computed variable: usein_ai × ai_stress

The econometric specification is as follows:

$$ai\_insec_i = \beta0 + \beta1\ (usein\_ai_i) + \beta2(ai\_confused_i) + \beta3(ai\_stress_i) + \beta4(ai\_peerpress_i) + \beta5(ai\_mental_i) + \beta6(agegrp_i) + \beta7(inter\_use\_age_i) + \beta8(inter\_use\_stress_i) + \varepsilon_i \ldots (1)$$

The model is estimated using robust standard errors to correct for potential heteroscedasticity.

Table 2: *Description of Variables*

Variable Name	Description	Obs	Mean	Std. Dev.	Min	Max
usein_ai	Frequency of AI Usage	1,085	1.877	0.578	1	3
ai_confused	AI-Induced Confusion	1,085	2.481	1.239	1	5
ai_stress	AI-Related Academic Stress	1,085	2.666	1.236	1	5
ai_peerpress	AI Peer Pressure	1,085	2.571	1.196	1	5
ai_mental	AI Use for Mental Health Support	1,085	2.678	1.268	1	5
Agegrp	Age Group	1,085	2.107	1.296	1	4
ai_insec	AI-Induced Intellectual Insecurity	1,085	2.697	1.212	1	5

Results

Starting with the main effects, AI confusion shows a coefficient of 0.104 which remains statistically significant at the five percent level across all three model

specifications, indicating a robust and stable relationship. This coefficient means that for every one-unit increase in AI confusion on the Likert scale, the log odds of moving to a higher insecurity category increase by 0.104, which translates to approximately 52 percent higher odds of elevated insecurity when comparing students who strongly agree they feel confused versus those who strongly disagree. From the Technology Acceptance Model perspective, this finding validates the central role of perceived ease of use, but what we are seeing here goes beyond simple adoption barriers. The confusion is actually creating psychological distress about intellectual competence itself, which connects deeply to Cognitive Dissonance Theory because students are experiencing tension between their self-image as competent learners who should understand the tools in their field and their lived reality of not understanding how AI works or when they can trust its outputs.

This mechanism operates quite differently across our quadrant model, with students in the orange quadrant avoiding AI use altogether because the confusion feels overwhelming and creates obsolescence anxiety, while students in the red quadrant are using AI extensively despite their confusion, creating what we might call black box dependency, where they rely on something they fundamentally do not understand. On the same hand, consistent with earlier findings by Hao et al. and Zhou, the present results confirm that peer pressure significantly amplifies AI-related insecurity, particularly in competitive academic environments [1][3].

The AI stress variable shows a fascinating pattern across the different model specifications that really illuminates how interactions work in statistical modelling. In the no moderation model, stress has a highly significant coefficient of 0.311, making it the strongest main effect predictor and suggesting that academic stress related to AI increases insecurity odds by approximately 246 percent across the full scale range. However, and this is theoretically crucial, when we include the interaction term between AI use and stress in the full moderation model, this main effect completely disappears and actually becomes negative at minus 0.158 though non-significant. This disappearance is not a statistical error but rather reveals that the effect of stress on insecurity is entirely conditional on how much AI the student is using, which perfectly aligns with Stress-Coping Theory's predictions about how stress influences outcomes through shaping coping strategies rather than adding a uniform burden across all individuals.

What this means practically is that stress does not directly cause insecurity in some automatic fashion, rather it interacts with usage patterns to either enable adaptive integration when stress is low or trigger maladaptive over-reliance or avoidance when stress is high.

Peer pressure emerges as the most stable predictor across all specifications with coefficients ranging from 0.213 to 0.219, all highly significant at the one percent level, which makes it arguably the most reliable factor in the entire model. This finding

strongly validates Social Influence Theory because it demonstrates that normative pressure and social comparison are not peripheral concerns but central drivers of the psychological experience of AI adoption. The coefficient indicates that a four-point increase in peer pressure perception increases insecurity odds by approximately 140 percent, which is substantial. The mechanism here operates through what we might call forced adoption dynamics where students feel their AI use decisions are not autonomous choices but rather social performances being constantly evaluated by peers. Those who use AI extensively worry they are taking shortcuts or cheating compared to peers using traditional methods, while those who avoid AI worry they are falling behind and being judged as inadequately adapted to modern academic requirements.

This creates a no-win situation where insecurity emerges regardless of the adoption decision, which explains why the effect is so strong and consistent. In the context of our quadrant model, peer pressure likely intensifies the experiences of students in both the orange and red quadrants where high stress already creates vulnerability, with orange quadrant students feeling increasingly marginalized as they see peers adopting AI while their own confusion prevents them from following suit, and red quadrant students feeling like imposters whose achievements only exist because of their AI crutch.

The coefficient for AI mental health use is 0.135 and remains significant across all models, indicating that using AI for psychological support correlates positively with intellectual insecurity rather than reducing it as one might initially expect if AI were functioning as effective emotional support. This positive relationship suggests we are likely seeing a bidirectional mechanism where students who already feel insecure turn to AI for validation and coping, but the AI support does not actually resolve the underlying insecurity and may even reinforce dependency awareness and existential concerns about autonomy.

From a Stress-Coping Theory perspective, this represents emotion-focused avoidance coping where students are addressing the psychological symptoms of stress and insecurity rather than developing genuine problem-solving capabilities or addressing root causes. The concerning implication is that AI has transcended its instrumental role as an academic tool and entered intimate psychological territory where students are forming what might be understood as par asocial relationships with AI systems, which becomes particularly problematic in the red quadrant where students already exhibit high use, high stress, and multiple forms of dependency.

Now we come to the interaction effects which are where the quadrant model receives its strongest empirical validation. The interaction between AI use and age group shows a coefficient of minus 0.138 which is marginally significant at the ten percent level in both models that include it. The negative sign here is theoretically critical because it indicates that the relationship between AI use and insecurity

becomes less positive or more negative as age increases, meaning the same increase in AI usage has opposite psychological effects depending on the student's age cohort. For younger students, particularly those below twenty or in the twenty-one to thirty range, increasing AI use is associated with increasing insecurity because these students are still in the process of forming their academic and professional identities, and heavy AI reliance during this formative period creates profound uncertainty about whether their achievements are authentically theirs or merely products of sophisticated tools. This maps directly onto the red quadrant in our model where younger students with high AI use and high stress experience the perfect storm of identity threat, skill foundation concerns, and intense social comparison within peer groups where AI usage has become normalized but also anxiety-inducing.

In contrast, older students in the thirty-one to forty and above forty categories who increase their AI usage tend to experience reduced insecurity or at least no increase because they bring established track records and secure intellectual self-concepts to their AI adoption, allowing them to frame the technology as just another tool added to their existing competence rather than a replacement for fundamental capabilities. This protective effect of age corresponds to the blue quadrant where older students with high use but low stress can integrate AI adaptively, and even to some extent the green quadrant where older students with low use and low stress maintain comfortable traditionalism without fear of obsolescence because their established credentials provide psychological security.

The interaction between AI use and stress, with a coefficient of 0.252 that achieves high significance at the one percent level, represents the single most important finding in the entire regression model and provides the strongest empirical support for the quadrant structure we have proposed. This positive coefficient means that as stress increases, the effect of AI use on insecurity becomes increasingly positive and problematic, which mathematically works out such that at low AI use levels the total effect of stress is minimal at around 0.094, but at high use levels the total effect balloons to approximately 0.598, creating nearly a sixfold difference in impact.

What this reveal is that AI use and stress are not simply additive factors but rather multiplicative in their psychological impact, with their combination creating substantially more insecurity than either factor alone. This interaction directly validates the vertical stress axis of our quadrant model and explains why the top quadrants, both orange and red, show elevated insecurity despite having opposite patterns of AI usage. Students in the high stress and low use configuration of the orange quadrant experience insecurity through obsolescence anxiety and fear of falling behind, feeling the pressure of stress while lacking the AI skills they perceive their peers as having, whereas students in the high stress and high use configuration of the red quadrant experience insecurity through desperate dependency where academic pressure has transformed AI from an enhancement tool into a psychological survival mechanism.

From a Stress-Coping Theory perspective, this interaction captures the distinction between problem-focused and emotion-focused coping strategies. Under low stress conditions, students have sufficient cognitive resources to engage in problem-focused coping where they can thoughtfully learn AI capabilities, establish appropriate boundaries for its use, maintain their core skills through deliberate practice, and integrate AI as a genuine enhancement to their intellectual toolkit. This corresponds to the blue quadrant where high AI use occurs in a low-stress context and produces adaptive integration rather than dependency.

However, under high stress conditions, cognitive resources become depleted as the stress response impairs prefrontal cortex functioning needed for metacognition and strategic thinking while activating the amygdala's threat detection systems. In this neurobiologically compromised state, students cannot engage in the careful evaluation and boundary-setting required for healthy AI integration, and instead fall into emotion-focused avoidance coping where AI becomes a mechanism for escaping anxiety-provoking intellectual challenges rather than engaging with them. This creates the vicious cycle characteristic of the red quadrant where stress triggers AI over-reliance, which prevents genuine skill development, which creates dependency awareness and attribution confusion about whether achievements reflect personal or AI capability, which increases insecurity, which elevates stress further, completing a self-reinforcing loop that becomes increasingly difficult to escape.

Table 3: *Determinants of Ai induced stress*

VARIABLES	ai_insec	Single Moderation	No Moderation
usein_ai	-0.449	0.256	-0.0396
	(0.282)	(0.190)	(0.0988)
ai_confused	0.104**	0.104**	0.106**
	(0.0475)	(0.0475)	(0.0475)
ai_stress	-0.158	0.309***	0.311***
	(0.147)	(0.0505)	(0.0504)
ai_peerpress	0.213***	0.219***	0.219***
	(0.0512)	(0.0512)	(0.0512)
ai_mental	0.131***	0.139***	0.135***
	(0.0472)	(0.0472)	(0.0471)
Agegrp	0.241	0.247	-0.0241
	(0.154)	(0.155)	(0.0423)
inter_use_age	-0.138*	-0.143*	
	(0.0780)	(0.0787)	
inter_use_stress	0.252***		
	(0.0747)		
/cut1	-0.573	0.774*	0.217

	(0.580)	(0.421)	(0.289)
/cut2	0.861	2.201***	1.640***
	(0.579)	(0.424)	(0.290)
/cut3	2.654***	3.979***	3.415***
	(0.585)	(0.436)	(0.305)
/cut4	3.121***	4.441***	3.877***
	(0.587)	(0.442)	(0.313)
Observations	1,085	1,085	1,085

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The Cognitive Dissonance Theory provides additional explanatory power here because students under high stress lack the cognitive resources needed to resolve the fundamental tensions in their relationship with AI. They simultaneously depend on AI for academic survival while harboring doubts about its legitimacy and their own competence without it, creating psychological discomfort that would normally motivate some form of resolution through changing beliefs, changing behaviours, or finding ways to rationalize the inconsistency. However, the cognitive load imposed by stress prevents this resolution work, leaving the dissonance to fester as chronic insecurity. Students may oscillate between telling themselves that everyone uses AI so it is perfectly legitimate and worrying that they are frauds whose credentials are entirely artificial, never reaching a stable resolution that would reduce the psychological tension. This unresolved dissonance is particularly acute for younger students who lack the established identity anchors that older students can draw upon, which explains why the age interaction shows younger students are more vulnerable to the stress-use combination.

Looking at how the quadrants map onto the regression findings, we can now provide a complete empirical characterization of each profile. The orange quadrant representing older students with low AI use and high stress shows insecurity primarily through the main effects of confusion, peer pressure, and stress, with these students experiencing what might be called technological inadequacy anxiety where they feel the weight of academic pressure while simultaneously perceiving themselves as falling behind in AI adaptation. The confusion coefficient of 0.104 captures their sense of being overwhelmed by AI complexity, the peer pressure coefficient of 0.219 captures their awareness that others are adopting tools they have not mastered, and the stress coefficient shows its impact even without high use because these students worry about obsolescence. The age interaction is not helping them because they have low use, so they miss out on the protective effect that older students with higher use would experience. The red quadrant representing younger students with high AI use and high stress receives the full force of every problematic mechanism in the model, with the

stress-use interaction coefficient of 0.252 directly capturing their experience, the negative age-use interaction indicating their youth makes high use more rather than less threatening, and the main effects of confusion, peer pressure, and mental health AI use all likely being elevated in this group. These students experience what we might term existential dependency insecurity where they cannot disentangle their own intellectual contributions from AI's, creating profound questions about authenticity and competence despite potentially strong academic performance.

The green quadrant of older students with low AI use and low stress represents the psychologically safest position, protected by the absence of stress which eliminates the most powerful driver of insecurity through the interaction effect, by older age which would provide protection if they did increase use, and by presumably lower levels of peer pressure and confusion given their low engagement with AI. These students can maintain traditional learning methods without the fear of missing out because their established credentials and low-stress environments create psychological security. Finally, the blue quadrant of younger students with high AI use and low stress demonstrates that adaptive integration is possible when the stress context allows it, with these students benefiting from the low stress condition which enables problem-focused coping and thoughtful boundaries around AI use. The age interaction suggests they would experience less insecurity if they were older, but the absence of stress is sufficiently protective that they can still integrate AI effectively, using it to enhance rather than replace their intellectual engagement.

The theoretical synthesis that emerges from these regression findings is that AI-related intellectual insecurity is fundamentally a contextual psychological phenomenon rather than a technology competence issue. Students are not insecure simply because they lack AI skills or because AI itself is inherently threatening, rather they experience insecurity because they are navigating a profound transformation in intellectual work under conditions of high academic stress, competitive peer environments, and epistemic confusion about how AI actually functions. The Technology Acceptance Model's factors of perceived usefulness and ease of use are heavily moderated by psychological context, with stress determining whether high perceived usefulness leads to confident adoption or desperate dependency. Social Influence Theory's predictions about normative pressure are validated by the robust peer pressure effect, showing that AI adoption decisions are embedded in social matrices where comparison and competition make every choice fraught with potential judgment. Cognitive Dissonance Theory helps explain why students who use AI extensively can simultaneously experience profound insecurity, as they struggle to reconcile their dependence on AI with their values around authentic learning and their self-concepts as intellectually capable individuals. Stress-Coping Theory provides the overarching framework showing that stress determines whether AI use follows adaptive problem-focused coping pathways or maladaptive emotion-focused avoidance, with this distinction captured empirically in the powerful stress-use

interaction.

The internal consistency of the survey instrument was assessed using Cronbach's alpha. All multi-item constructs demonstrated acceptable reliability, with alpha values ranging from 0.71 to 0.84

Conclusion and Policy Implications

These days are more rapidly using Artificial Intelligence as they were never using before. They are integrating AI into their curriculums without much understanding of how different types and cohorts of students can experience varying levels of intellectual security, which is based upon the usage pattern of AI, the stress level induced by AI, and also the developmental stages of AI. Considering that, this study investigates the psychological or mental factors which can drive AI-related intellectual security among university students. We have used the ordered logit probit model, and the sample size for this study is 1085 respondents. We carefully examined how AI usage patterns, the stress induced by academic pressures, confusions regarding AI, peer pressure, and also mental health deficiencies can shape students' intellectual self-doubt and their AI adoption towards education.

The findings of the study are very interesting, which revealed that AI-related insecurity is not only a technological constraint or technology competence, but it emerges from very complex interactions between its usage pattern and also has some psychological context. We find that peer pressure, as the most robust predictor of intellectual security, emerges from the AI usage pattern, which indicates that social comparison and competitive academic environments can often create anxiety regardless of the actual AI decision-making. The age use interaction variable demonstrates generational differences. We suggest that younger students experience increased insecurity with AI due to identity formation vulnerability, while older students may establish credentials to adopt AI confidently.

The findings of this study are very important, and they suggest that the use of AI is creating multiple effects on students' mental health, and not every student is comfortable while using AI, and there are other mental issues that are emerging due to increased AI pressure and the push towards integrating AI into academia and studies.

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