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Awareness of Generative AI Limitations and Students' Intention to Use ChatGPT: A Moderated Mediation Analysis

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Abstract

This research examined the importance of understanding generative artificial intelligence (GenAI) limitations in predicting college students' likelihood of using ChatGPT, based on a modified Technology Acceptance Model. It treated awareness, perceived usefulness, and perceived anxiety about skills deterioration related to GenAI as independent variables, with intention to use ChatGPT as the dependent variable. The first-stage moderated mediation model was applied to analyze participants' responses, with cooperation from 931 college students from different fields of study at a private higher education institution in the Philippines. The findings revealed that the awareness of GenAI limitations exerted a positive impact on the intention of college students to use ChatGPT, in particular, both its direct positive effect ($c' = 0.169$, $p < .001$) and an indirect effect through the mediation of perceived usefulness. Conditional process analysis confirmed that skill-erosion concern moderated the relationship between awareness and perceived usefulness (moderated mediation index = -0.075, 95% CI [-0.107, -0.046]). Although perceived usefulness remained a significant mediator of the relationship between awareness and intention, the indirect effect diminished as skill-erosion concern increased, dropping from 0.233 for students with low-little concern to 0.105 for students with great concern. The collinearity analysis confirmed that the predictors were empirically distinguishable. The findings show that beliefs about risks regulate the technology acceptance process, and that AI-literacy training can be pursued alongside measured caution about dependency rather than treating these goals as alternatives.

Keywords: generative artificial intelligence, ChatGPT, Technology Acceptance Model, behavioral intention, moderated mediation, higher education

1. Introduction

The release of ChatGPT at the end of 2022 sparked one of the biggest technological shifts in higher education. Generative artificial intelligence (GenAI) technologies have reached a point where students actively use them to draft, brainstorm, revise, or study. This has prompted multiple studies to understand how students perceive and assess GenAI technologies (Chan & Hu, 2023; Ravšelj et al., 2025; Strzelecki, 2024). The findings show that students have a mixed attitude towards GenAI; on the one hand,

students highlight the ability of this technology to save time, receive personalized feedback, and simplify complex tasks, while, on the other hand, they worry that regular use of GenAI may affect the development of critical thinking, collaboration, and problem-solving skills in students (Golding et al., 2025; Khlaif et al., 2025; Nadim & Di Fuccio, 2025; Zhai et al., 2024). However, research has not sufficiently examined the psychological mechanisms that shape users' intentions to use this technology based on their awareness of its drawbacks.

The Technology Acceptance Model (TAM) explains this conversion process simply: usefulness is perceived, and this perception shapes behavioral intention (Davis, 1989). Applying TAM to generative AI in the educational realm nowadays has shown that usefulness is still one of the key indicators of how inclined people are to use it (Almogren et al., 2024; Damiano et al., 2024; Jia & Tu, 2024; Yu et al., 2024), which has not turned out to be impeded by the fact that GenAI has one difference from transactional technologies for which TAM was created, which is the risk concerning the user's intellectual capacities. Namely, students not only evaluate the convenience of the tool but also consider possible losses in terms of skills, too much dependence, and fewer opportunities for an independent learning process (Khlaif et al., 2025; Walter, 2024). Thus, the risk associated with GenAI shows that the process described in TAM cannot be fully relevant for each student, since the level of concern students have with regard to the losses in skills might influence it, which is in line with the research on the impact of perceived risk on the process of accepting technology developed in different realms (Wijaya et al., 2024).

This research addresses this gap by evaluating a moderated mediation framework in which perceived usefulness mediates the relationship between college students' knowledge of generative AI limitations and their behavioral intention to use ChatGPT, while students' apprehension about skill loss and dependence moderates this initial connection. The research fits within a trend in educational technology that emphasizes empirical studies exploring the link between technology and actual educational practices.

The aims of this study can be summarized in three key points: (a) to identify the link between a college student's knowledge about generative AI limitations and how willing they are to use ChatGPT; (b) to find out whether a student's understanding of the usefulness of generative AI will be a mediating factor in this case; and (c) to check if the strength of the awareness/usefulness link changes for students depending on their anxiety that the use of generative AI can hurt their development of skills. By achieving these objectives, this study used quantitative research to provide a well-substantiated answer to the question of the role of beliefs about the risks in the technology acceptance process.

2. Review of Related Literature

2.1 Generative AI Adoption in Higher Education

Surveys conducted since the launch of GenAI have produced a consistent finding: students have both positive and negative impressions of generative AI. In a survey of 399 university students in Hong Kong, Chan and Hu (2023) concluded that students viewed GenAI positively for facilitating the learning process but were wary of its accuracy, ethics, and potential negative consequences for learning. Ngo (2023) found that Vietnamese students liked GenAI for saving time and clarifying difficult information but also noted that its main drawback was its inability to verify data reliability. Ravšelj et al. (2025) surveyed more than 23,000 students from 109 countries and found that students used ChatGPT primarily for brainstorming ideas and summarizing texts but were not satisfied with its usefulness for developing critical thinking and rated it lower than in the classroom. Petricini et al. (2023) and Golding et al. (2025) emphasized that most students think using GenAI to prepare assignments constitutes academic dishonesty, yet they still do it, reinforcing the gap between perceived usefulness and perceived risk. Baek et al. (2023) and Dai et al. (2023) noted that students are willing to adopt the technology reluctantly, while Yang (2024) emphasizes that students want more institutional guidelines rather than a ban on the tool. Similar findings appear in research conducted outside Asia. Romero-Rodríguez et al. (2023) studied 400 Spanish university students and found that perceived usefulness of ChatGPT for complex cognitive tasks strongly correlates with acceptance. Strzelecki (2024) studied 534 Polish students and found that habit and performance expectancy predict both intentions to use the tool and its effective use. Bouteraa et al. (2024) mentioned that students' beliefs about academic integrity influence the spread of ChatGPT in higher education, highlighting the

connection between evaluative and ethical judgments and their use of the technology for academic purposes. Hon (2026) studied the impact on learning outcomes in Microsoft Teams and concluded that outcomes depend on use, not merely on exposure to the tool.

2.2 The Technology Acceptance Model and Perceived Usefulness

The Technology Acceptance Model (TAM) remains the most important theory explaining why users accept or reject technology (Davis, 1989). Perceived usefulness of the technology, defined as the extent of belief that the technology would help one perform better at tasks, has always proved to be more significant than perceived ease of use in predicting the use of technology in different types of applications, from e-government to finance and banking (Wijaya et al., 2024). Damiano et al. (2024) applied TAM and Diffusion of Innovation theory to analyze GenAI use in education settings and concluded that users' perceptions of ChatGPT's accuracy and usefulness influence their decision-making. Nevertheless, they highlighted that users cannot distinguish accurate from inaccurate information and therefore have no real ability to judge information quality. Jia and Tu (2024) studied 637 college students and argued that AI abilities do not directly influence learning outcomes; instead, learning outcomes depend on students' motivation and efficacy beliefs. More recent investigations confirm the central role of usefulness while also complicating it. Almogren et al. (2024) determined perceived usefulness and ease of use to be important predictors of attitudes towards ChatGPT for 458 subjects, while Yu et al. (2024) used the method of structural equation modeling with 328 college students and found that efficiency influenced perceived usefulness and, through this, intention to continue using it. Foroughi et al. (2024) made an important modification by showing that information accuracy negatively moderated the relationships between ChatGPT usage and its determinants, suggesting that judgments about output quality drive acceptance.

2.3 Awareness of AI Limitations and Critical AI Literacy

A related area of research has proposed that understanding the limits, biases, and failings of technology is not simply an attitude toward using technology but a whole new concept. Walter (2024) claimed that AI literacy—defined as well-informed awareness of both the capabilities and limitations of AI systems—is a necessary condition for the productive use of these systems and for keeping critical thinking alive in AI-supported education. Hwang et al. (2023) examined a digital literacy scale for college students and found that the ability to critically assess outputs produced by AI is one of the best predictors of students' perceptions of the technology's usability and ease of use, which shows that it is possible for critical awareness to support the evaluation of usefulness. Consequently, the literature suggests that knowledge of generative AI's limitations should be treated as an important belief within an acceptance model, rather than as an idea that contradicts or completely denies the technology's usefulness. This interpretation is supported by Heard et al. (2024), who found that AI literacy predicted students' willingness to use ChatGPT indirectly through perceptions of its usefulness, supporting the view that awareness knowledge is one of the beliefs that promote technology use.

2.4 Over-Reliance, Skill Erosion, and Risk as a Moderating Concern

Numerous advertising studies note a particular story about generative AI: excessive exposure could harm users' skills and abilities. Khlaif et al. (2025) conducted interviews and held focus groups with 46 teachers and concluded that having constant access to AI leads to skill atrophy, procrastination, and social fragmentation. Nadim and Di Fuccio (2025), through a systematic analysis of existing studies, reached the same conclusion, arguing that although generative AI offers many benefits, it also raises key issues across numerous spheres. Perceived risk has been studied in technology acceptance research. According to Wijaya et al. (2024), the impact of perceived risk on acceptance depends on the action taken. The authors' findings guided us to consider anxiety about skill erosion as a moderator rather than a competing precursor of behavioral intention. Data collected provide positive evidence. Zhai et al. (2024) reviewed the literature on AI dialogue systems and concluded that excessive dependency leads to deficiencies in problem-solving, analysis, and critical thinking skills. Moore and Gerlich (2025) performed a mixed-methods study with the aim of exploring the relations between the extent of AI use and critical thinking level in participants.

2.5 Mediation and Moderation in Technology-Acceptance Research

Conditional process analysis is the standard method for investigating how psychological processes operate (Hayes & Rockwood, 2017). In the first stage of the moderated mediation model, the focus is not limited to determining whether an indirect impact exists. The goal shifts to determining whether another variable affects this indirect impact. Researchers use the moderated mediation approach in various areas to examine how factors affect phenomena such as the adoption of fintech solutions and e-wallets (Wijaya et al., 2024). This method can also be applied to studying generative AI adoption. Nevertheless, researchers rarely use the moderated mediation model when investigating the relationship between technology use and students' knowledge and skills. This study aims to bridge this gap. This study uses the regression-based estimation framework provided by Hayes and Rockwood (2017). As Foroughi et al. (2024) note, moderators of adoption pathways can provide better analytical insight than assuming each belief is an additional direct predictor.

3. Theoretical Framework

This research uses the principles of TAM, developed by Davis (1989), which holds that external beliefs about a system affect perceived usefulness and perceived ease of use, which in turn shape a person's behavioral intention to use the system. TAM includes several highly influential components, and perceived usefulness remains the primary predictor of behavioral intention in the technology sphere (Wijaya et al., 2024). In this investigation, the authors elaborate on TAM in several ways, which aligns with recent studies in the sphere of generative AI. First, as stated in Hwang et al. (2023) and Walter (2024), generative AI awareness limitation as a risk-aversion belief is considered an external belief that contributes to the successful realization of the system's usefulness. Second, the research model views perceived risk, seen as skill-erosion and over-reliance concerns, as a moderator of the belief-formation phase in TAM, building on evidence showing that perceived risk affects the technology adoption process rather than acting as an independent predictor (Wijaya et al., 2024). In Hayes & Rockwood's (2017) conditional process model, this yields a first-stage moderated mediation model in which the extent to which awareness of AI limitations affects behavioral intention through perceived usefulness depends on students' perceived degree of skill-erosion concern.

4. Conceptual Framework

Figure 1 illustrates the conceptual framework utilized in this study. It is suggested that the awareness of the limitations of Generative AI (X) plays a role in predicting the intention to use ChatGPT (Y), both in a direct manner (c') and in an indirect manner via the perceived usefulness of such technology (M). Furthermore, it is proposed that the first-stage relationship between the awareness of the limitations of Generative AI and the perception of its usefulness (a) is moderated by the perceived fear of skill erosion (W). Consequently, the strength of this relationship will decrease as fear increases. In keeping with this specification, all three belief sets mentioned — awareness of restrictions, perceived usefulness, and concern over skill erosion — refer to generative AI as a concept, while the outcome variable refers specifically to the intention to use ChatGPT — the most common tool among the respondents. This distinction will be preserved in the entire manuscript.

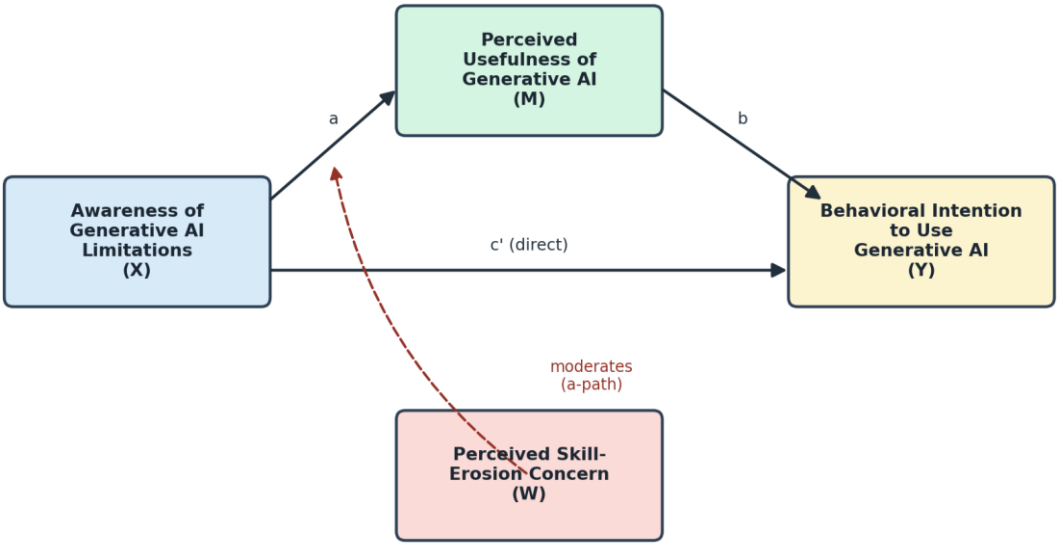


Figure 1. Conceptual framework depicting the first-stage moderated mediation model

5. Statement of the Problem

This study generally aimed to examine the mediating role of perceived usefulness and the moderating role of skill-erosion concern in the relationship between college students' awareness of generative AI limitations and their behavioral intention to use ChatGPT. Specifically, it sought to answer the following questions:

1) What are the respondents' demographics in terms of gender, year of study, and field of study?
2) What are the levels of awareness regarding (a) limitations of generative AI, (b) usefulness of generative AI among college students, (c) their intention to use ChatGPT, and (d) their concern regarding the decline in their skills?
3) Is there a significant direct link between the awareness of limitations of generative AI and the intention to use ChatGPT?
4) Is perceived usefulness of generative AI a significant mediating factor between awareness of limitations of generative AI and intention to use ChatGPT?
5) Is perceived concern of decline in skills a significant moderating factor between awareness of limitations of generative AI and perceived usefulness of generative AI?
6) Does the indirect effect of awareness of generative AI limitations on intention to use ChatGPT through perceived usefulness depend on the level of perceived skill erosion concern?

6. Hypotheses

Correspondingly, the following hypotheses, stated in null form, were tested at the .05 level of significance:

1) H_0: The understanding of limitations associated with generative artificial intelligence has no major influence on the intention to use ChatGPT.
2) H_0: The perceived usefulness does not act as a significant mediator between the awareness of generative limitations and intention to use ChatGPT.
3) H_0: The concern regarding loss of ability does not act as a significant moderator between awareness of generative AI limitations and perceived usefulness.
4) H_0: The indirect effect of awareness of generative AI limitations on intention to use ChatGPT through perceived usefulness will remain almost unaffected by the level of concern about loss of ability.

7. Methodology

7.1 Research Design

This research used a quantitative, non-experimental design, including descriptive-correlational methods and regression-based conditional process analysis. More specifically,

the study used a moderated mediation model, considering both the theoretical and statistical aspects described by Hayes and Rockwood (2017). The moderated mediation approach was chosen because the research assignments required not only examining whether the variables are correlated but also investigating the process underlying that correlation.

7.2 Respondents and Sampling Procedure

Participants in this study included 931 college students with varying degree programs, education levels, and genders from Northeastern College, a private institution not affiliated with any religious organization, located in Santiago City, Isabela, in the Cagayan Valley area of the Philippines. The students were enrolled in various disciplines including education, criminology, information technology, hospitality management, engineering, business, and liberal arts. To recruit respondents, the researchers distributed a survey to intact classes across degree programs such as Criminology, Information Technology, Hospitality Management, Elementary and Secondary Education, Geodetic Engineering, Political Science, Business Administration, and other related courses. This study used convenience sampling. Participation was voluntary and open to all enrolled students with experience using generative AI technologies, including ChatGPT. Table 1 shows the demographic profile of the respondents.

7.3 Research Instrument

The research involved administering structured questionnaires that had two sections. The first section covered demographic factors, while the remaining four sections consisted of Likert items assessing four respondent attributes. The first attribute assessed was that of awareness of the limitations of generative AI. This subscale included seven items assessing respondents' awareness of inaccuracy, contextual relevance, computational bias, statistical over-reliance, and limited emotional intelligence in generative AI. The second attribute was the perceived usefulness of generative AI, and this subscale consisted of six items measuring respondents' beliefs about improving their digital skills, generative AI's time-saving capabilities, the provision of meaningful insights, the provision of customized feedback, and its role as a support tool.

A subscale called Behavioral Intention to Use ChatGPT examined participants' readiness to use ChatGPT in their educational endeavors, including their motivation to learn how to use it. Perceived Skill-Erosion concern was another subscale comprising four questions that evaluated agreement with notions such as the idea that using generative AI lowers the importance of education, prevents social participation, limits the number of transferable skills acquired, and creates dependency among learners. The survey also included some open-ended questions to provide qualitative descriptions, but as a quantitative study, it focused primarily on closed-ended questions. To estimate scale reliability, calculations were conducted based on respondents' answers (see Table 2).

7.4 Data Gathering Procedure

The survey was conducted online with college students currently enrolled in the participating programs, through class representatives and instructors. Before completing the survey, respondents received an informed consent statement explaining the study's purpose, the voluntary nature of participation, and the plan to maintain confidentiality. Only completed responses with valid Likert-scale entries were included in the analysis, resulting in an analytical sample of 931 respondents.

7.5 Ethical Considerations

The research followed standard research ethics for studies involving human participants. Participants were free to participate and were informed of their right to withdraw at any time at no cost. The data were anonymized, and the analysis used only the program classification and demographic variables. The study complies with Republic Act No. 10173 of the Philippines, popularly referred to as the Data Privacy Act of 2012.

7.6 Statistical Treatment

Descriptive statistics (mean and standard deviation) provided information on the levels of each construct, while Cronbach's alpha tested internal consistency. Scale scores were obtained by averaging scores derived from their constituent items. The Pearson correlation test identified relationships between item pairs. For the actual analysis, the researcher followed Hayes's (2021) conditional process analysis to estimate the first stage of the moderated mediation process model. Specifically, (a) the first-stage regression predicted perceived

usefulness as a dependent variable on generative AI limitation awareness, worries about decline of skills, and their interaction term while controlling for the frequency of generative AI usage, sex, and year level; (b) the second-stage regression examined how to predict behavioral intention as the dependent variable from perceived usefulness and awareness of limitations in generative AI while controlling for the same covariates; and (c) the total effect analysis examined behavioral intention based on awareness of limitations and covariates.

The researcher calculated conditional indirect effects at three levels of skill erosion: low (-1 standard deviation), average (mean), and high (+1 standard deviation). To calculate the index of moderated mediation, the researcher multiplied the interaction coefficient by the Stage 2 path coefficient. Because the distribution of both indirect and conditional effects is generally not normal, the researcher used nonparametric percentile bootstrap confidence intervals with 5000 bootstrap samples; a significant effect is defined as one whose 95% bootstrap confidence interval does not include zero. The assumptions behind ordinary least squares estimation were investigated before hypothesis testing began. The researchers checked homoscedasticity and linearity using graphs of standardized predicted values against standardized residuals; evaluated residual normality with normal probability plots, along with skewness and kurtosis; checked residual independence with Durbin-Watson; and assessed multicollinearity using tolerance and VIF values. Because all variables were measured with a single self-report tool, used VIF < 3.3, the most conservative criterion for full collinearity; VIF checks redundancies among predictors and also indicates possible common method variance (Kock, 2015). Inference on indirect and moderating effects was based on percentile bootstrapping rather than assuming normality of the coefficient distribution, to ensure robustness to slight deviations from the assumption (Hayes & Rockwood, 2017).

8. Results

Table 1. Demographic Profile of Respondents

Demographic Variable	Category	f	%
Sex	Male	473	50.8
	Female	458	49.2
Year Level	First Year	267	28.7
	Second Year	272	29.2
	Third Year	282	30.3
	Fourth Year	110	11.8
Academic Program	BS Criminology	279	30.0
	BS Information Technology	162	17.4
	BS Hospitality Management	141	15.1
	Bachelor of Elementary Education	72	7.7
	BSEd English	66	7.1
	BSEd Filipino	63	6.8
	BS Geodetic Engineering	51	5.5
	BSEd Mathematics	33	3.5
	BSEd Science	30	3.2
	AB Political Science	15	1.6
	Other programs (< 1% each)	18	1.9
Total		**931**	**100.0**

Note. Programs with fewer than 1% of respondents each (BS Business Administration, BS Management Accounting, AB Mass Communication, Midwifery-related programs, and single-case program-title variants) were collapsed into "Other programs."

Table 2. Descriptive Statistics and Internal Consistency Reliability of Study Constructs

Construct	Items	M	SD	Cronbach's α	Descriptive Level
Awareness of Generative AI Limitations (X)	7	3.31	0.94	.934	Moderate
Perceived Usefulness of Generative AI (M)	6	3.17	0.89	.930	Moderate
Behavioral Intention to Use ChatGPT (Y)	2	3.09	0.94	.799	Moderate
Perceived Skill-Erosion Concern (W)	4	3.04	0.86	.854	Moderate
Generative AI Usage Frequency (covariate)	1	3.08	1.09	—	Moderate

Note. Scale range = 1.00-5.00; descriptive levels: 1.00-2.33 = Low, 2.34-3.67 = Moderate, 3.68-5.00 = High. All alpha coefficients exceeded the .70 acceptability threshold, with the two-item Behavioral Intention scale in the acceptable range and the remaining scales in the excellent range.

Table 3. Pearson Correlations Among Study Variables

Variable	1	2	3	4	5
1. Usage Frequency	—				
2. Awareness of Limitations (X)	.462**	—			
3. Perceived Usefulness (M)	.553**	.649**	—		
4. Behavioral Intention (Y)	.502**	.625**	.804**	—	
5. Skill-Erosion Concern (W)	.442**	.654**	.675**	.583**	—

***p < .001 (two-tailed), N = 931.*

According to the data provided in Table 2, the participants demonstrated moderate awareness about the limitations of generative AI (M = 3.31, SD = 0.94), its usefulness (M = 3.17, SD = 0.89), the intention to implement generative AI (M = 3.09, SD = 0.94), and the skill erosion worry (M = 3.04, SD = 0.86). These moderate positions indicate that, across all aspects mentioned, students held neutral but slightly positive views. Further, Table 3 shows correlations among the constructs ($p < .001$). These findings show that perceived usefulness and behavioral intention are closely related, consistent with TAM predictions. These correlations support the model but should not be taken as proof of its validity, since bivariate correlations cannot confirm a model's theory. Moreover, the research also revealed that concern about skills erosion is positively correlated with limitation awareness (r = .654) and perceived usefulness (r = .675). Thus, students are concerned about the negative effects of GenAI, but they also recognize its advantages.

Given the notable bivariate relationships in Table 3, the uniqueness of the variables and the possibility of multicollinearity were investigated before interpreting the regression models. The collinearity measures for the Stage 1 independent variables were acceptable: limitations awareness (tolerance = .535, VIF = 1.87), concern about skill erosion (tolerance = .547, VIF = 1.83), and frequency of generative AI usage (tolerance = .752, VIF = 1.33). All measures were below the conservative multicollinearity threshold of 3.3, as suggested by Kock and Ned (1AD), and below the usual threshold of 10, indicating that neither predictor redundancy nor excessive common method bias could explain the findings.

The largest link in the matrix is between perceived usefulness and behavioral intention (r = .804), meaning about 65% of the variance is shared, leaving roughly 1/3 of the variance in intention unexplained by usefulness. These two concepts are also theoretically distinct in the TAM framework, where usefulness refers to an evaluative belief about the outcome of an action, and intention is viewed as motivational readiness to act (Davis, 1989; Strzelecki, 2024). Nevertheless, this correlation raises the question of whether the two scales are fully independent, a limitation of the current measurement model. The residual diagnostics for both stage models were also checked: the plots of standardized residuals against the standardized predicted values showed no systematic funneling or

curvature, and normal probability plots of the residuals followed the diagonal.

Table 4. Stage 1 Regression: Perceived Usefulness Regressed on Awareness of Limitations, Skill-Erosion Concern, and Their Interaction (Moderated a-Path)

Predictor	b	SE	t	p	95% CI [LL, UL]
Constant	3.305	0.028	115.99	< .001	—
Awareness of Limitations (X)	0.241	0.028	8.68	< .001	[0.166, 0.319]
Skill-Erosion Concern (W)	0.396	0.029	13.50	< .001	—
X × W (interaction)	-0.106	0.018	-5.78	< .001	[-0.148, -0.067]
Usage Frequency (covariate)	0.195	0.020	9.81	< .001	—
Sex (Female = 1) (covariate)	-0.168	0.038	-4.46	< .001	—
Year Level (covariate)	0.023	0.019	1.21	.225	—

Note. Outcome variable: Perceived Usefulness of Generative AI. $R^2 = .601$, $F(6, 924) = 231.80$, $p < .001$. Predictors and interaction term were mean-centered. 95% CI computed from 5,000 bootstrap resamples; CI reported for focal terms.

Table 4 displays the results of Stage 1 of the moderated a-path regression analysis. The model was significant, $R^2 = .601$, $F (6, 924) = 231.80$, $p < .001$, meaning that the limitations of generative AI concerns about skill erosion, as well as their combination and control variables, accounted for nearly 60.1% of the variance in its utility perception. According to the results, the limitations of generative AI were a significant predictor of its utility perception (b = 0.241, p < .001, 95% CI [0.166, 0.319]), which confirms the proposition stating that better understanding of the limitations of what generative AI can and cannot do goes hand in hand with better understanding of its utility. Importantly, the interaction between awareness of limitations and skill-erosion concern was significant and negative (b = -0.106, p < .001, 95% CI [-0.148, -0.067]), suggesting that concern about potential skill erosion moderated the relationship.

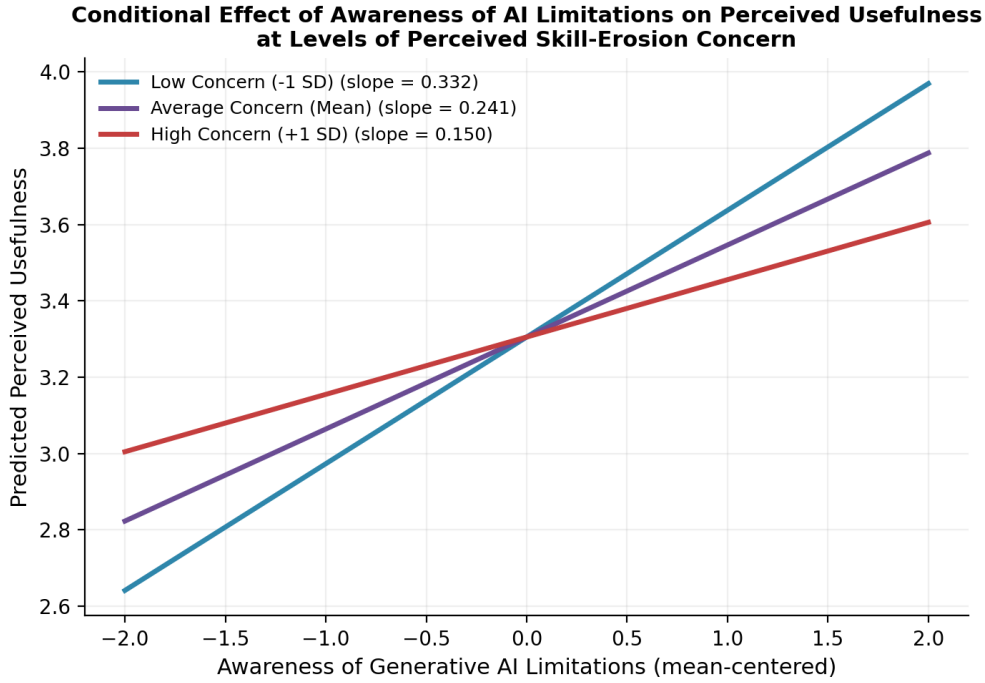


Figure 2. Conditional effect of awareness of generative AI limitations on perceived usefulness at low, average, and high levels of perceived skill-erosion concern

Figure 2 shows that the positive relationship between awareness of limitations and perceived usefulness had the highest 'simple slope' for low skill-erosion concern students (simple slope = 0.332), and the lowest for great concern students (simple slope = 0.150), with average concern students positioned in the middle (simple slope = 0.241). The observations show that awareness of the limitations posed by generative AI continues to drive perceived usefulness across student groups, but with much greater weight among students with low concern about skill erosion from technology use.

Table 5. Stage 2 (b and c′ Paths) and Total Effect (c Path) Regression Results

Predictor	b	SE	t	p	95% CI [LL, UL]
Stage 2 Model: DV = Behavioral Intention (Y)					
Constant	3.090	0.025	122.15	< .001	—
Perceived Usefulness (M) → Y (b path)	0.701	0.029	24.49	< .001	[0.620, 0.778]
Awareness of Limitations (X) → Y (c′ direct path)	0.169	0.026	6.63	< .001	[0.098, 0.241]
Usage Frequency (covariate)	0.050	0.020	2.48	.013	—
Sex (covariate)	0.005	0.036	0.13	.898	—
Year Level (covariate)	-0.016	0.018	-0.87	.383	—
Total Effect Model: DV = Behavioral Intention (Y)					
Constant	3.144	0.032	97.25	< .001	—
Awareness of Limitations (X) → Y (total effect c)	0.506	0.028	18.33	< .001	[0.452, 0.560]
Usage Frequency (covariate)	0.237	0.024	9.96	< .001	—
Sex (covariate)	-0.106	0.046	-2.29	.022	—
Year Level (covariate)	-0.011	0.023	-0.46	.645	—

Note. Stage 2 model R2 = .667, F(5, 925) = 370.94, p < .001. Total effect model R2 = .452, F(4, 926) = 190.59, p < .001. 95% CI computed from 5,000 bootstrap resamples for focal paths.

Based on the data in Table 5, the results support the mediation hypothesis. The model on total effect indicated the existence of a very important and statistically significant effect of variable awareness on behavioral intention (c = 0.506, p < .001, 95% CI [0.452, 0.560]), thus leading to rejection of the null hypothesis (H01) and approval of a meaningful association of variables under investigation. In the Stage 2 Model, which included usefulness alongside awareness, usefulness proved to be a strong predictor of behavioral intention (b = 0.701, p < .001, 95% CI [0.620, 0.778]). Based on the obtained results, it can be observed that a significant direct effect of awareness on behavioral intention was noted, but it was considerably diminished (c′ = 0.169, p < .001, 95% CI [0.098, 0.241]). This pattern is typical of partial mediation, where the direct path is reduced but does not disappear completely with the mediator.

Table 6. Conditional Indirect Effects of Awareness of Limitations on Behavioral Intention Through Perceived Usefulness, at Levels of Skill-Erosion Concern

Level of Skill-Erosion Concern (W)	Conditional a-path	Conditional Indirect Effect (a×b)	95% Bootstrap CI [LL, UL]
Low Concern (-1 SD)	0.332	0.233	[0.172, 0.298]
Average Concern (Mean)	0.241	0.169	[0.114, 0.230]

High Concern (+1 SD)	0.150	0.105	[0.043, 0.173]
Index of Moderated Mediation	—	**-0.075**	**[-0.107, -0.046]**

Note. Indirect effects and the index of moderated mediation were estimated using 5,000 percentile bootstrap resamples. An effect is considered statistically significant at α = .05 when the 95% confidence interval does not include 0. Conditional a-paths were determined at the mean of concern about skill erosion and at ±1 SD (SD = 0.86) from Stage 1 coefficients provided in Table 4 using a = 0.241 + (-0.106 x W). Each conditional indirect effect constitutes the multiplication of the respective conditional a-path and b-path from Stage 2 (b = 0.701). The moderated mediation index is calculated by multiplying the interaction coefficient by the b-path coefficient. All numbers were computed from unrounded coefficients; thus, they may differ slightly from products calculated using rounded figures. We report only percentile bootstrapped confidence intervals; bootstrapped standard errors were not reported.

Table 6 presents findings related to the study's main hypotheses regarding mediation and moderated mediation. The indirect impact of knowledge of generative AI limitations on behavioral intention through perceived usefulness was significantly positive across skill-erosion worry levels, as none of the bootstrap confidence ranges contained zero. In addition, the findings allow us to reject H02 and state that perceived usefulness significantly mediates the relationship between awareness of limitations and behavioral intention, accounting for approximately one-third of the total effect (indirect effect at the mean = 0.169 relative to a total effect of 0.506, or 33.4%). The more crucial factor here is the variance of the existing indirect effect. For example, it was more than double for students with low skill-erosion worries (0.233) compared with those with high skill-erosion worries (0.105). The index of moderated mediation, which reveals whether the conditional pattern is statistically trustworthy, is significant and negative (index = -0.075, 95% CI [-0.107, -0.046]). Therefore, zero is not in this range, and H04 cannot be accepted.

9. Discussion

This research examined whether perceived usefulness mediates the link between college students' knowledge of the limitations of generative AI and their intention to use ChatGPT, and whether concern about skill spoilage moderates this path. Three research findings require attention.

First, the knowledge of the limitations of generative AI was positively correlated, not negatively, with perceived usefulness and behavioral intention. This result runs contrary to the intuitive expectation that awareness of technology's disadvantages would reduce willingness to use it. Instead, the findings align with the body of knowledge on AI literacy, which states that critical awareness of technology's strengths and shortcomings involves acquiring the competency to use it intelligently (Heard et al., 2024; Hwang et al., 2023; Walter, 2024). Students who are aware that generative AI can produce incorrect, biased, and irrelevant outcomes seem to draw better conclusions about technology's usefulness than those who are unaware.

Secondly, perceived usefulness had a very large and significant mediating effect on the connection between limitation awareness and behavioral intention, confirming the idea put forward by the Technology Acceptance Model that beliefs regarding usefulness are the main channel through which external beliefs impact the intention to adopt (Damiano et al., 2024; Davis, 1989). The existence of a significant but smaller direct effect suggests that limitation awareness affects behavioral intention through a number of other ways, such as normative beliefs about professional preparedness or peer expectations, and the idea is supported by the statement that "students need to learn to use generative AI well for their future careers" present in the intention statement.

Third, the most innovative angle of this study is the significant moderation of the awareness-to-usefulness impact by students' skill erosion fears. With students demonstrating low levels of these concerns, awareness translated into perceived usefulness to a very strong degree (simple slope = 0.332). In contrast, for students with great concerns, the translation into usefulness was much smaller (simple slope = 0.150), although it never ceased to exist. This finding is a refinement of the previous discoveries about the co-existence of the fears of over-dependence and skills decay, alongside an ongoing use of GenAI (Khlaif et al., 2025; Moore & Gerlich, 2025; Ravšelj et al., 2025;

Zhai et al., 2024) and implies that the student's feelings of skill erosion do not act as a simple switch, but rather as a dial that interacts with the efficiency of the awareness translation into the perception of usefulness.

This shows that the findings agree with studies on the role of perceived risk in technology acceptance literature (Wijaya et al., 2024). The implication for teachers and universities is that the promotion of AI literacy and the creation of non-paralyzing concern about excessive reliance are not opposing tasks; the evidence suggests that it is possible and even beneficial to make students believe that GenAI is useful while being sufficiently concerned about its disadvantages to avoid excessive reliance, which can be noticed in the lower indirect influence of high-risk students.

10. Conclusion

This study investigated the influence of awareness of generative AI limitations on behavioral intention to use ChatGPT among college students and whether this process works through perceived utility and is moderated by students' concern about diminishing skills. The analysis of the data, collected from 931 students and using a moderated mediation design, showed that awareness positively influenced both perceived utility and intention to use the tool, perceived utility mediated approximately one-third of the relationship between awareness and intention to use the tool, and the correlation was significantly weaker for students who were more concerned about their skills. Thus, the research disconfirmed all four hypotheses. The results expand the Technology Acceptance Model by showing that beliefs about risks associated with technology use do not simply influence the adoption process through positive and negative effects; benefits were achieved through awareness of utility-channel creation.

11. Recommendations

Based on the results, the following recommendations are provided.

1) Higher education institutions should develop and include focused AI-literacy courses in their curricula. Study results show that understanding the limitations of generative AI supports positive attitudes toward technology and its use.
2) Awareness of the costs of generative AI should be cultivated further by instructors and instructional designers. Although awareness does not prevent people from thinking positively about using generative AI, it tempers their views on its effectiveness.
3) Course design should include independent thinking tasks alongside generative AI. For example, tasks that involve finding unreliable information generated by AI, evaluating AI outputs, or using AI output as a foundation for independent work.
4) Authorities planning generative AI policies must keep in mind students' conflicting attitudes toward this technology; while some students may use generative AI tools without understanding their limitations, others may understand these tools well and be concerned about their risks.
5) Future researchers can apply the moderated mediation model analyzed in this research in different institutional contexts and consider moderators such as instructors' guidance or institutional AI policy clarity, or they may design longitudinal studies to evaluate how generative AI functionality and institutional policies evolve over time.

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