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Student Resistance to ChatGPT in Indonesia: Extended IRT with PLS-SEM Analysis

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ABSTRACT

The integration of Artificial Intelligence (AI) in higher education is growing, including the use of ChatGPT as a tool to assist students academically by improving access to information and promoting independent learning. Nonetheless, some students have shown reluctance due to worries about its reliability, academic morals, and changes in conventional learning principles. This research intends to explore how various barriers, such as usage barrier, value barrier, risk barrier, tradition barrier, image barrier, perceived cost barrier, and ethical considerations, contribute to student hesitance regarding ChatGPT. A quantitative method was utilized through Partial Least Squares Structural Equation Modeling (PLS-SEM), gathering data from an online survey of 77 students from Universitas Negeri Makassar. Findings reveal that only the risk barrier ($\beta = 0.417$; $p = 0.006$) and the tradition barrier ($\beta = -0.400$; $p = 0.029$) have a significant impact on resistance, with the risk barrier being the most influential, while the other factors showed no notable effects. These results suggest that psychological and cultural factors are more significant than practical obstacles in influencing resistance to generative AI and broaden the Innovation Resistance Theory (IRT) by factoring in ethical issues. The study advises creating teaching strategies that find a balance between using technology and maintaining academic honesty, while also promoting further research through multigroup and longitudinal methods.

1. INTRODUCTION

Artificial Intelligence (AI) has become a key driver of educational transformation in the era of Industry 5.0, enhancing learning efficiency and access to academic resources [1]. In higher education, ChatGPT provides substantial benefits in personalized learning and academic support, yet it also raises concerns regarding academic integrity, information reliability, and potential misuse for assignments [2]. In Indonesia, the rapid adoption of AI in universities is not fully supported by institutional policy readiness and ethical literacy, creating tension and resistance among students [3].

Innovation Resistance Theory (IRT) explains resistance to new technologies based on six barriers: usage, value, risk, tradition, image, and perceived cost [4]. IRT suggests that resistance occurs when users perceive that an innovation introduces uncertainty or insufficient value in comparison to its expected benefits. In addition to these barriers, resistance in higher education can also arise from ethical considerations such as concerns about academic dishonesty, reduced critical thinking, and dependency on automated tools [5].

Although several studies in Indonesia have explored students' perceptions of ChatGPT and its benefits and challenges, these studies do not specifically address the determinants of student resistance to ChatGPT [6]. Research focusing on resistance in the context of complex academic tasks requiring originality and integrity is still limited. Moreover, the integration of ethical considerations as an extension of IRT remains underexplored, with most ethical discussions dominantly situated in international contexts [5].

This research is necessary to understand how functional, psychological, and ethical barriers interact in shaping student resistance to ChatGPT. Extending IRT by incorporating ethical considerations is expected to provide a more comprehensive theoretical framework and inform responsible AI usage policies in Indonesian universities. And this study aims to analyze the effects of usage, value, risk, tradition, image, perceived cost, and ethical consideration barriers on resistance to ChatGPT and to determine the most dominant influencing factor.

RQ. 1 Do usage, value, risk, tradition, image, perceived cost, and ethical considerations significantly influence resistance toward ChatGPT?

RQ. 2 Which barriers most dominantly affects resistance toward the use of ChatGPT in completing complex academic tasks?

2. METHOD

This study uses a quantitative approach because this method allows researchers to test hypotheses in a structured manner using numerical data [7]. The quantitative approach was chosen to analyze the relationship between variables in the Innovation Resistance Theory (IRT) framework, which has a complex model structure, thus requiring accurate statistical measurements. In addition, this study uses a cross-sectional design, which is the collection of data at a specific time to capture the simultaneous perceptions of respondents [8].This design is relevant because the study aims to analyze student resistance in the context of the rapidly developing use of ChatGPT in an academic environment.

Figure 1 shows seven hypothesized paths (H1–H7) connecting each barrier with the intention to use. This model assumes that students' intention to adopt ChatGPT is influenced by their perceptions of various dimensions of barriers, reflecting the dynamics of innovation resistance in the context of higher education.

Figure 1. Research Construct

The participants in this study were students from the Department of Informatics and Computer Engineering at Makassar State University who met the above inclusion criteria and were willing to complete the research questionnaire. The selection of location and participants was based on the consideration that students from both study programs have adequate technological literacy and considerable experience in using artificial intelligence-based technology. Therefore, they are considered representative for studying the patterns of ChatGPT utilization in an academic environment, even though their level of understanding and views on ChatGPT are still moderate [9], [10].

The target population in this study was all students majoring in Information Technology and Computer Science at Makassar State University. The sampling technique used was purposive sampling with the following criteria: (1) active students from both study programs, (2) have used ChatGPT for academic purposes such as studying and searching for references. This technique was chosen based on the consideration that only students with certain characteristics could provide information relevant to the research objectives [11], [12].

The research instrument was a closed questionnaire divided into two parts. The first part contained demographic data on the respondents, including their names, student ID numbers, class years, and study programs. The second part in Table 1 consists of 40 statements to measure seven independent variables (usage barrier, value barrier, risk barrier, tradition barrier, image barrier, perceived cost barrier, and ethical concern) adapted from research [4], while the 4 items for ethical concern were developed by the researcher with reference to the study by [5] All items were measured using a 5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree) in accordance with the guidelines (Joshi et al., 2015).

Table1 . Research Instrument

Variable	Item	Statement	Source
Usage Barrier	UB 1	I find ChatGPT difficult to use in completing academic tasks	[4]
	UB 2	The process of using ChatGPT takes a long time and is inefficient	

	UB 3	I have difficulty formulating the right prompt to get the desired answer
	UB 4	I find it difficult to use ChatGPT for tasks that require in-depth analysis (such as writing scientific papers)
	UB 5	I need to put in extra effort to ensure ChatGPT's output aligns with the specified academic writing format
Value Barrier	VB 1	In my opinion, the quality of ChatGPT's answers is insufficient to meet academic standards
	VB 2	ChatGPT does not provide significant added value compared to searching for references independently
	VB 3	ChatGPT output is often too general and lacks depth for academic purposes
	VB 4	ChatGPT is less capable of providing original perspectives when analyzing academic issues
	VB 5	ChatGPT does not help me understand the basic concepts of a subject, only providing instant answers
Risk Barrier	RB 1	I am concerned that there may be errors in the information provided by ChatGPT
	RB 2	I am concerned that my personal data and course materials are not secure when using ChatGPT
	RB 3	I fear that dependence on ChatGPT will reduce my analytical and critical thinking skills
	RB 4	I am concerned that using ChatGPT for my final assignment may compromise my originality and academic integrity
	RB 5	I am concerned that educational institutions will impose sanctions if

		they discover that I have used ChatGPT for important assignments
Tradition Barrier	TB 1	I am more comfortable with traditional learning methods (reading books, discussions) than using AI
	TB 2	I believe conventional learning processes are more effective than using ChatGPT
	TB 3	I prefer consulting directly with professors rather than asking ChatGPT
	TB 4	I believe that the process of researching and writing independently without AI assistance is more academically valuable
	TB 5	Learning through ChatGPT feels unnatural to me
Image Barrier	IB 1	I perceive that using ChatGPT for academic tasks is a form of dishonesty
	IB 2	ChatGPT has a negative image among academics as a tool for "cheating"
	IB 3	Students who use ChatGPT are often seen as unable to complete assignments independently
	IB 4	Using ChatGPT can reduce one's academic credibility and reputation in the eyes of professors or peers
	IB 5	I am concerned about being perceived as taking an unethical "shortcut" if I use ChatGPT for academic assignments
Perceived Cost Barrier	PCB 1	The time required to verify the accuracy of ChatGPT's answers is too great
	PCB 2	The effort required to learn how to use ChatGPT effectively is not worth the benefits

	PCB 3	The cost of a ChatGPT Premium subscription is too expensive for students	
	PCB 4	The cost of internet data usage for using ChatGPT is generally considered burdensome	
	PCB 5	The time wasted learning from ChatGPT's output failures is not worth the benefits	
Ethical Consideration	EC 1	Using ChatGPT to complete assignments goes against the principles of academic integrity	[5]
	EC 2	I feel ethically obligated to disclose the use of AI in my academic work	
	EC 3	The use of ChatGPT can undermine the integrity and credibility of the higher education process	
	EC 4	I am concerned that the use of ChatGPT erodes the values of honesty in the academic world	
Intention to Use ChatGPT	IU 1	I plan to use ChatGPT regularly to assist with my academic activities	[4]
	IU 2	I will recommend ChatGPT to my classmates for academic purposes	
	IU 3	I intend to increase the frequency of using ChatGPT for learning activities	
	IU 4	I intend to use ChatGPT to complete my college assignments	
	IU 5	I wish to study ChatGPT's features in greater depth for academic purposes	

In Figure 2, this research procedure was carried out in four main stages. The first stage was the preparation of instruments and content validity testing by lecturers to ensure the suitability of the statement items with the constructs being measured. The second stage was the online distribution of questionnaires using the Google Forms platform, which was carried out over a period of 14 days. The third stage was the screening and verification of respondents to ensure that participants met the inclusion criteria, namely students majoring in Information Technology and Computer Science who had used ChatGPT for academic purposes. The final stage was data collection and cleaning, in which questionnaires that did not meet the inclusion criteria, were incomplete, or showed inconsistent response patterns were disqualified from the data analysis process.

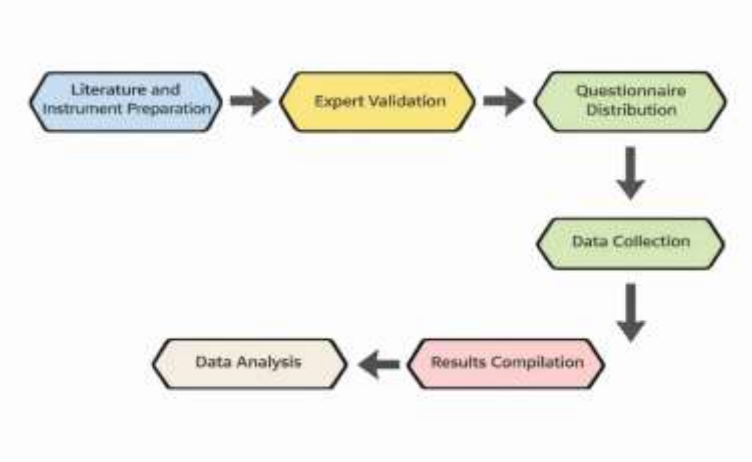

Figure 2. Research Procedure

Data analysis was conducted in two main stages in accordance with the Partial Least Squares Structural Equation Modeling (PLS-SEM) procedure. The first stage is outer model analysis, which tests the reliability and validity of indicators using general constraints such as outer loading ≥ 0.708, Cronbach's alpha ≥ 0.70, Composite Reliability ≥ 0.70, and AVE ≥ 0.50 [13]. Discriminant validity was tested using the Heterotrait-Monotrait Ratio (HTMT) with a conservative limit of 0.85 to ensure that each construct measured empirically different concepts[14].

The second stage was inner model analysis, which assessed the significance of the relationship between variables using bootstrapping with 5,000 resamples [13]. The original sample was used to see the direction and strength of the relationship, while R^2 and f^2 were used to assess the predictive ability of the model and the effect size of each construct.

Descriptive analysis was also conducted to describe the profile of respondents based on their study program and batch. The statistics used included the average, median, mean, standard deviation, and frequency percentage[9]. This demographic analysis was important to understand the variations in students' perceptions of ChatGPT. All analyses were conducted using SmartPLS software as the main data processing tool.

3. RESULT AND DISCUSSION

Descriptive Analysis

Descriptive analysis in this study was used to characterize the profile of respondents from the Informatics and Computer Engineering and Computer Engineering Study Programs. This approach allows mapping the sample composition based on key demographic variables, which are essential for understanding the context and limitations of the generalization of research findings [9].

Table 2. Program Frequency

Study Program	Number	% of total	Cumulative
Computer Science and Information Technology Education	73	94.8	94.8
Computer Engineering	4	5.2	100
Class		1.3%	

2022	1	1.3%	1.3%
2024	57	74	75.3%
2025	19	24.7	100
Indicator			
Program	77	1.05	0.223
Cohort	77	2024.22	0.503

In Table 2, the majority of respondents came from the Informatics and Computer Engineering Study Program, namely 73 people (94.8%), while Computer Engineering only contributed 4 respondents (5.2%). This shows that the composition of participants was dominated by PTIK (Computer Science and Information Technology) students, so that the data characteristics were more representative of that group. The majority of respondents were from the class of 2024, namely 57 people (74%), followed by the class of 2025 with 19 people (24.7%). Meanwhile, the 2022 cohort only had 1 respondent (1.3%). The study program indicator showed a mean value of 1.05 with a standard deviation of 0.223, confirming that the distribution of respondents between study programs was very uneven and tended to be concentrated in one category. Meanwhile, the "Batch" indicator has a mean of 2024.22 and SD 0.503, illustrating that the distribution of respondents is quite concentrated around the year 2024, in line with the highest frequency in that group.

Evaluation of the measurement model

The next stage is to evaluate the reliability and construct validity in the model. This assessment is important to ensure that the measurement instruments used meet methodological standards before being further analyzed in a structural model [14]. Before the evaluation stage was carried out, this study first developed a conceptual model, which is a conceptual model that maps the relationships between variables based on theory [10]. This model then became the basis for the process of evaluating the reliability and construct validity discussed in the next stage.

Table 3. Reliability and Validity

Statement	Cronbach Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)	VIF
UB1	0.899	0.918	0.929	0.766	2.741
UB2					2.307
UB3					2,425
UB4					2,920
VB1	0.879	0.895	0.911	0.673	2.193
VB2					2.211
VB3					2,206
VB4					1,683
VB5					2,189
RB1	0.884	0.937	0.909	0.666	1.845
RB2					2.261
RB3					2,459
RB4					4,691
RB5					3,935
TB1	0.820	0.875	0.879	0.647	2.632
TB2					2.841
TB4					1,494

TB5					1,641
IB1					2.101
IB2					2.813
IB3	0.899	1,202	0.920	0.697	2,694
IB4					3,111
IB5					2,189
PCB1					1.663
PCB2	0.776	0.795	0.852	0.591	1.925
PCB3					1,280
PCB5					1,840
EB2					1.978
EB3	0.803	1,016	0.876	0.704	1.492
EB4					1,988
IU1					2.028
IU2					3.051
IU3	0.903	0.921	0.928	0.721	2,432
IU4					2,375
IU5					2,529

Note: UB = usage barrier; VB = value barrier; RB = risk barrier; TB = traditional barrier; IB = image barrier; PCB = perceived cost barrier; EB = Ethical Barrier; IU = intention to use.

In Table 3, all constructs have Cronbach's Alpha and Composite Reliability values above 0.70, as well as AVE above 0.50, indicating good internal consistency [11], [12]. In addition, all VIF values are below 5, indicating no multicollinearity issues between indicators in the model [13]. Furthermore, this is reinforced by discriminant validity to measure the Heterotrait Monotrait Ratio (HTMT) value, which should not exceed 0.85 [14], [15].

Table 4. Heterotrait Monotrait Ratio

Variable	UB	VB	RB	TB	IB	PCB	EB	IU
UB			0.187	0.146	0.114	0.422	0.110	0.312
VB	0.425		0.585	0.596	0.348	0.610	0.424	0.259
RB					0.495	0.564	0.787	0.319
TB			0.669		0.639	0.762	0.764	0.103
IB							0.848	
PCB					0.632		0.695	0.148
EB								
IU					0.156		0.127	

Note: UB = usage barrier; VB = value barrier; RB = risk barrier; TB = traditional barrier; IB = image barrier; PCB = perceived cost barrier; EB = Ethical Barrier; IU = intention to use.

The HTMT values in Table 4 show that all construct pairs have values below the threshold, thus fulfilling discriminant validity. The fulfillment of discriminant validity reinforces the feasibility of the seven barriers, namely usage barrier, value barrier, risk barrier, tradition barrier, image barrier, perceived cost barrier, and ethical concern, to be further analyzed as distinct independent variables in answering RQ1. This finding also supports the model's ability to identify dominant factors as asked in RQ2, because each barrier contributes uniquely to the variance in ChatGPT usage intention without significant conceptual overlap.

Evaluation of the Structural Model

Figure 1 presents the PLS-SEM structural model produced through the SmartPLS algorithm, illustrating the relationships among the seven resistance barriers and the Intention to Use ChatGPT. The structural model indicates that the predictors collectively explain 26.8% of the variance in intention ($R^2 = 0.268$), which reflects a moderate explanatory power consistent with behavioral technology studies using IRT-based frameworks. This model was then evaluated through the hypothesis-testing stage to determine the significance of each proposed path using the bootstrapping resampling procedure.

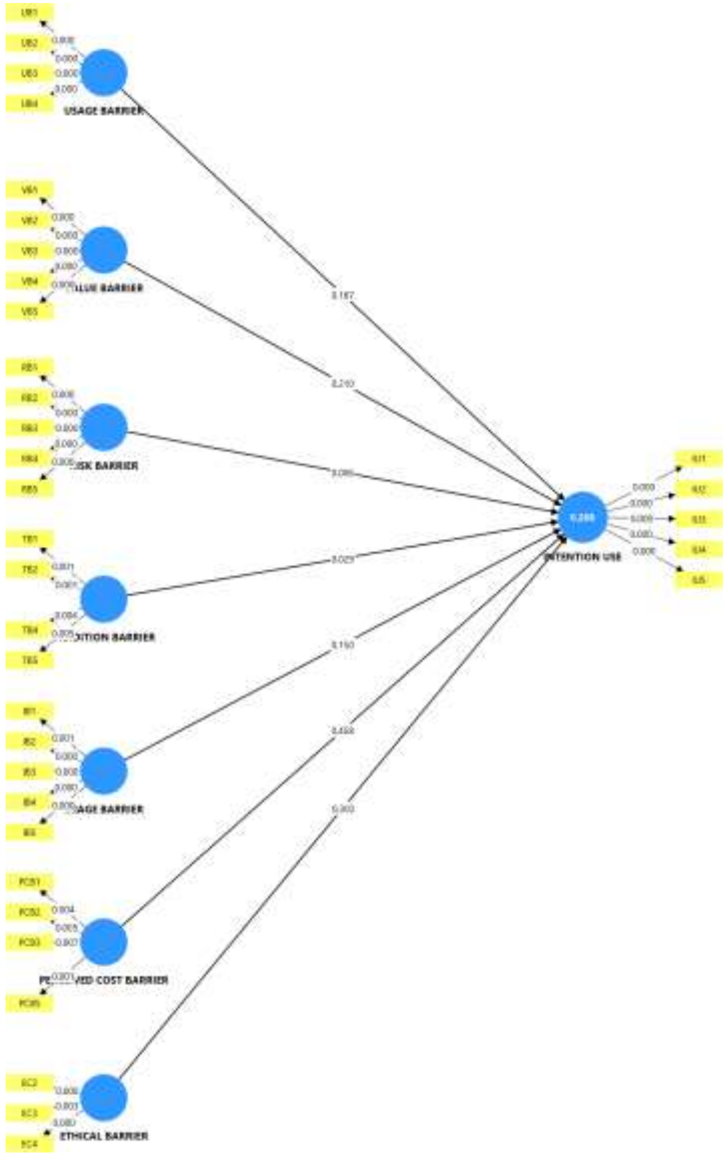

Figure 1. Structural Model Bootstrapping Results

Evaluation of the Hypothesis Testing

Structural model analysis was conducted to test the causal relationships between latent variables in this study. Unlike the outer model, which evaluates the relationship between indicators and their latent variable, the inner model focuses on the relationship between the latent variables themselves [13]. This evaluation used a bootstrapping procedure with 5,000 resamples to test the statistical significance of each hypothesized path [16].

Table 5. Hypothesis Results

Hypothesis	Original sample	Sample mean	Standard deviation	T statistics	P values	Conclusion
H1 UB -> IU	0.146	0.173	0.164	0.890	0.187	Not significant
H2 VB -> IU	0.126	0.111	0.156	0.806	0.210	Not significant
H3 RB -> IU	0.417	0.362	0.166	2.513	0.006	Significant
H4 TB → IU	-0.400	-0.299	0.210	1.903	0.029	Significant
H5 IB → IU	0.247	0.168	0.238	1.038	0.150	Not significant
H6 PCB -> IU	-0.019	0.022	0.183	0.105	0.458	Not significant
H7 EB → IU	-0.118	-0.100	0.228	0.517	0.302	Not significant

Note: UB = usage barrier; VB = value barrier; RB = risk barrier; TB = traditional barrier; IB = image barrier; PCB = perceived cost barrier; EB = Ethical Barrier; IU = intention to use.

Table 5 shows hypothesis testing was conducted using the bootstrapping method with 5,000 resamples. The results show that only Risk Barrier ($\beta = 0.417$, $p = 0.006$) and Tradition Barrier ($\beta = -0.400$, $p = 0.029$) significantly influence student resistance toward ChatGPT, supporting H3 and H4. Meanwhile, Usage Barrier ($p = 0.187$), Value Barrier ($p = 0.210$), Image Barrier ($p = 0.150$), Perceived Cost Barrier ($p = 0.458$), and Ethical Consideration ($p = 0.302$) do not exhibit significant effects, leading to the rejection of H1, H2, H5, H6, and H7. These results indicate that resistance is more strongly shaped by psychological and cultural perceptions than by functional or ethical concerns.

Discussion

This study aimed to examine the extent to which seven resistance barriers influence students' resistance toward ChatGPT and to identify the most dominant factor affecting resistance in the context of complex academic tasks. The results indicate that only the risk barrier and tradition barrier have a significant effect, while usage, value, image, perceived cost, and ethical consideration show no significant influence. Furthermore, the risk barrier emerged as the most dominant factor, suggesting that perceived uncertainty may encourage students to explore rather than avoid the technology.

The findings of this study provide important insights into the dynamics of student resistance toward the use of ChatGPT in academic contexts. The significant positive effect of the risk barrier on intention to use contradicts the conventional assumption of Innovation Resistance Theory (IRT), which generally posits that higher perceived risk reduces the likelihood of adopting new technologies [4].

However, this result aligns with recent research suggesting that uncertainty can stimulate exploratory motivation among digitally literate users, particularly in relation to emerging technological innovations [17]. In the context of Indonesian university students, risks such as misinformation or concerns about technological dependency may encourage critical experimentation with ChatGPT rather than rejection.

Furthermore, the significant negative effect of the tradition barrier reinforces the fundamental premise of IRT, indicating that psychological resistance rooted in established habits and conventional learning values remains a major barrier to innovation acceptance [4]. Students who place strong value on traditional learning approaches such as face-to-face discussions, and independent writing tend to demonstrate reluctance toward generative AI technologies.

This finding is consistent with previous studies that reported students in higher education perceive traditional pedagogical approaches as more authentic and academically credible compared to AI-assisted methods, particularly when evaluating originality and academic integrity [18], [19].

Interestingly, ethical considerations did not significantly influence intention to use ChatGPT, although ethical concerns such as plagiarism and academic dishonesty are widely discussed in existing literature [4], [20]. Students who place strong value on traditional learning approaches such as face-to-face discussions, manual literature review, and independent writing tend to demonstrate reluctance toward generative AI technologies. This finding aligns with prior studies indicating that resistance may arise from strong attachment to established learning norms and habits within higher education environments, which can hinder the acceptance of new technologies [21], [22].

Interestingly, ethical factors did not majorly affect the intention to utilize ChatGPT, even though issues related to plagiarism and academic dishonesty are frequently explored in current literature [5]. This suggests that students may primarily perceive ChatGPT as a supplementary learning tool rather than a replacement for academic effort.

This interpretation is consistent with broader findings regarding student perceptions of AI in educational contexts [23], [24]. Moreover, increased familiarity with AI tools in higher education environments may contribute to reduced sensitivity toward ethical risks as their use becomes normalized.

In contrast, other functional barriers such as usage, perceived value, image, and perceived cost were found to have no significant effect. One possible explanation is that increasing digital literacy and widespread access to technology among students diminish the relevance of technical limitations [25]. Consequently, psychological and cultural dimensions appear to play a more substantial role than functional constraints in shaping student resistance to the adoption of generative AI tools.

Overall, these results broaden the theoretical scope of IRT within the context of generative AI by demonstrating that risk may function as an exploratory driver rather than solely an adoption barrier, and that ethical considerations can represent an important psychological dimension even when not statistically significant. These findings contribute to ongoing discussions regarding the evolving role of AI in higher education and underscore the need for pedagogical strategies that balance technological integration with the preservation of academic integrity.

4. CONCLUSION

This study concludes that among the seven resistance barriers examined within the Innovation Resistance Theory (IRT) framework, only the risk barrier and tradition barrier significantly influence student resistance toward the use of ChatGPT for completing complex academic tasks, with the risk barrier identified as the most dominant factor. These findings demonstrate that perceived risk in the context of generative AI can function as an exploratory driver rather than solely an adoption constraint, thereby offering an important theoretical contribution by expanding IRT through the integration of ethical considerations as an additional psychological dimension. Furthermore, the results indicate that functional barriers such as usage, value, image, and perceived cost are not significant predictors, suggesting that student resistance is shaped more strongly by psychological and cultural factors than by technical or usability limitations. The primary limitations of this study involve the relatively small sample size and single institutional context, which restrict the generalizability of the findings. Future research is recommended to employ multigroup analysis across different academic disciplines or educational levels and to apply longitudinal designs to examine how resistance to AI evolves over time.

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