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ETHICAL IMPLICATIONS AND ACADEMIC INTEGRITY CHALLENGES OF ARTIFICIAL INTELLIGENCE IN DOCTORAL RESEARCH METHODOLOGIES

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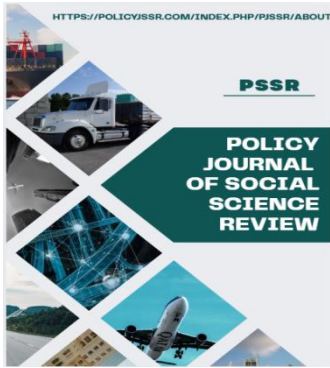
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ABSTRACT

The sharp increase of Artificial Intelligence in academic research has raised big worries about ethics and honesty, particularly among doctoral researchers. This quantitative study shows the use of Artificial Intelligence tools that impacts the honesty and ethics of doctoral students. A structured survey administered to 250 doctoral students across multiple universities served as the primary data collection instrument. Through this, the study examined five key dimensions: how frequently doctoral students use AI tools, how they perceive the associated academic integrity risks, how they approach ethical decision-making, how aware they are of institutional policies, and how effective they find their supervisor's guidance on these matters. Data were analyzed using descriptive statistics, Pearson correlation, multiple regression analysis, and ANOVA. Findings revealed that 78.4% of doctoral students regularly use AI tools in research, yet 61.2% reported inadequate institutional guidelines on ethical AI use. A significant negative correlation ($r = -0.61$, $p < 0.001$) was found between AI tool dependency and academic integrity compliance. Multiple regression analysis identified ethical decision-making ($\beta = 0.43$) and institutional policy clarity ($\beta = 0.37$) as the strongest predictors of integrity compliance ($R^2 = 0.54$). ANOVA results indicated significant differences in integrity compliance across disciplines ($F = 14.32$, $p < 0.001$). These findings underscore the urgent need for universities to develop comprehensive AI ethics frameworks, mandatory doctoral training modules, and transparent institutional policies to safeguard research integrity in the AI era.

Keywords: Artificial Intelligence, Academic Integrity, Doctoral Research, Research Ethics, AI Tools, Research Methodology, Higher Education



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1. Introduction

Artificial Intelligence has quietly but fundamentally changed what doctoral research looks like. From large language models and automated literature review tools to AI-driven data analysis and synthesis platforms, doctoral students now have access to capabilities that would have seemed remarkable just a few years ago tools that can genuinely speed up and strengthen the research process. But this rapid shift has not come without a cost. With these new possibilities there is genuine ethical complications arose and steady erosion of the norms that academic integrity has always stood on. The people who study and write about things are still trying to understand what this will mean for the future of research.

Doctoral research is the highest level of academic work, which requires thinking. The work must be rigorous. Original thinking is key here. Rigor and ethics are must-haves. But AI tools have walked into this space and made things complicated. Suddenly there are real questions worth asking who actually wrote this, is it truly original, and when does getting help become cheating.

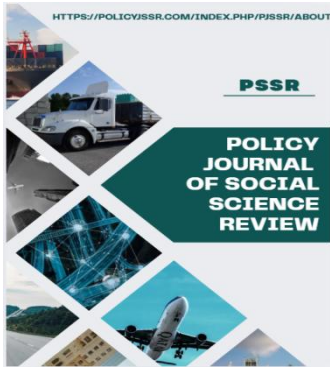
What makes this particularly complicated at the doctoral level is that the institutional standards and disciplinary norms governing this kind of research were largely

written before AI tools were sophisticated enough to meaningfully shape the research process. In many ways, the rules were designed for a world that no longer exists.

Recent surveys show that doctors who are doing research are using artificial intelligence a lot more now. The rules that universities have to make sure artificial intelligence is used in a good way are not being updated fast enough. The use of intelligence is really taking off but the rules, about using artificial intelligence in a good way are still the same. This gap has created a grey area where integrity violations can happen almost by accident. A significant number of doctoral students admit they are genuinely unsure about what counts as acceptable AI assistance at different stages of their work.

This study steps into a gap that the existing literature has largely left unaddressed taking a quantitative look at how AI tool usage, perceived integrity risks, ethical decision-making, policy awareness, and actual integrity compliance all connect among doctoral students. A survey with questions was used to get this information and strong math was applied to see what most helps predict if students are honest when using AI tools.

The results are very important for people who run programs, ethics committees, research supervisors and policymakers The



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results are useful, for program administrators and others. They work with students and AI tools. So the results help them. By putting real numbers behind what has largely been a theoretical concern, this study offers a solid foundation for building targeted interventions and evidence-based institutional frameworks.

1.1 Background and Rationale

Academic integrity has always been the foundation that credible research stands on. For years, institutions have had reasonably clear systems for dealing with familiar violations like plagiarism, data fabrication, and misrepresentation but detection software, ethics boards, established policies. AI has created a new kind of challenge. Text written by AI, data put together with AI help, and reports generated by algorithms don't really fit into the old systems and rules people were using before. That's what makes them so hard to manage and understand.

Using Artificial Intelligence in research is not just good or bad it depends on how Artificial Intelligence's used. On one hand Artificial Intelligence can be a useful tool that makes research easier, for researchers. Artificial Intelligence helps researchers stay organized and find patterns in a lot of data. Artificial Intelligence also helps researchers improve their writing. On the other end, it can be used to generate whole sections of research content, blur the lines of authorship, or simply bypass the deep

intellectual work that doctoral scholarship is supposed to demand. And in between these two extremes sits a vast grey area that most institutional policies have done very little to actually define.

This study was done because of a problem that's easy to see but also very worrying: a lot of doctoral students are figuring out the rules, about using artificial intelligence on their own. The doctoral students do not have rules to follow. Because of this the doctoral students may do things that're not right without even knowing it. This can hurt their careers in school. It can also make people trust and believe in academic research less.

1.2 Objectives of the Study

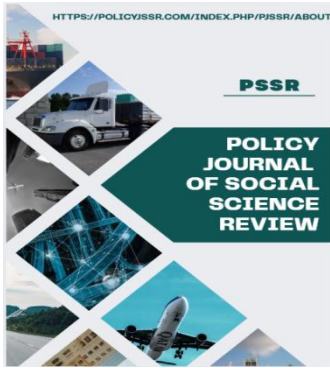
The specific objectives of this quantitative study are:

1. To assess the frequency and patterns of AI tool usage among doctoral students across disciplines.
2. To measure the level of academic integrity compliance among doctoral students in the context of AI-assisted research.
3. To evaluate the moderating role of supervisor guidance and institutional policy awareness on integrity outcomes.

1.3 Hypothesis

Based on the theoretical framework and empirical literature, this study proposes the following hypotheses:

- H1: AI tool usage frequency is significantly and negatively correlated with



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academic integrity compliance among doctoral students.

- H2: Perceived integrity risk is significantly and negatively correlated with academic integrity compliance.
- H3: Ethical decision-making competency is a significant positive predictor of academic integrity compliance.
- H4: Institutional policy awareness is a significant positive predictor of academic integrity compliance.
- H5: Significant differences in academic integrity compliance exist across academic disciplines.
- H6: Supervisor guidance effectiveness is a significant positive predictor of academic integrity compliance.

2. Literature Review

2.1 AI Tools in Academic Research

Artificial intelligence has become a part of doing research at universities and colleges much quicker than people thought it would. This is especially true after big language models and tools that use intelligence became popular. For the purpose of finding and summarizing information, analyze data, perform statistical work, and help write research papers, researchers use AI (Chen & Williams, 2024). These kind of tools save time and make research tasks easier and faster. As a result, artificial intelligence is changing the way research is carried out. That is why people are worried, about the

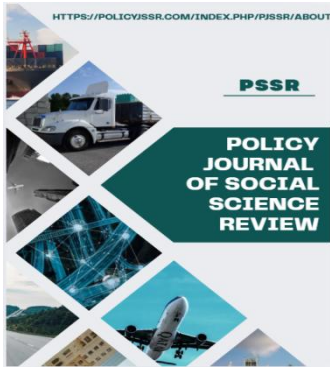
originality and reliability of research work and artificial intelligence.

Research consistently shows that doctoral students are among the earliest and most enthusiastic adopters of AI research tools, and it isn't hard to see why the pressure to produce original scholarship under tight timelines pushes them toward anything that can help (Martinez et al., 2024). The problem is that adoption moves very quickly that it is hard for institutions to make sure everything is done correctly. This is an issue because it can lead to people not doing the right thing.

2.2 Academic Integrity in the AI Era

Academic integrity is a promise that students make to their teachers. This promise is about trust. When students hand in their work they are saying that they did the work by themselves. Academic integrity is about making sure that your education is not a piece of paper that you get at the end (International Center for Academic Integrity, 2021). AI tools can write convincing academic text, draw together arguments from enormous bodies of literature, and produce clean data visualizations, and that leaves the field wrestling with questions about authorship and intellectual contribution that nobody has satisfying answers to just yet.

The empirical evidence here is difficult to look away from. Al-Rawahi and Bhatt (2023) found that 64% of graduate students in their sample had been using AI



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tools in ways their institutions would most likely consider integrity violations and yet only 31% were even aware that any AI-related policies existed at their institution. That disconnect between what students are doing and what they actually know is alarming, and it almost certainly cuts deepest at the doctoral level, where producing original, independent intellectual work is the whole point.

2.3 Ethical Decision-Making in Research

It isn't just about knowing the rules, it involves recognizing when a choice actually carries ethical weight, applying the right principles, weighing competing interests, and ultimately acting in line with the values that academic integrity demands. Research in professional ethics has long shown that how individuals make these decisions is shaped by a mix of personal values, professional upbringing, the institutional environment around them, and the specific context they find themselves in (Rest, 1986; Jones, 1991).

Supervisors and institutional leaders carry more responsibility here than they might realize that students are watching how they behave, and that shapes behavior more than any written policy ever could. Universities also need to be unambiguous about what the rules are and what actually happens when someone breaks them. (Kumar and Singh, 2023) found exactly this, perceived institutional support for ethical conduct and the presence of strong

role models consistently rank among the most powerful predictors of ethical decision-making in graduate research.

2.4 Institutional Policy and Supervision

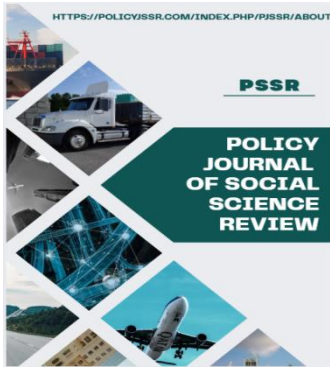
Institutional policies around AI use in doctoral research are still very much in their early days. A cross-national survey by (Rodriguez et al., 2024) found that fewer than 30% of research universities had published any clear guidelines on what AI use is actually acceptable in doctoral dissertations. And among those that had, the policies were often too vague to be genuinely useful and heavy on what students cannot do, but offering little real guidance on what responsible and ethical AI use actually looks like in practice.

A supervisor is a mentor, not a police officer. For a PhD student seeing how their supervisor deals with decisions teaches them more about doing research in the right way than any set of rules (Park & Lunt, 2022). The use of Artificial Intelligence has changed things making many experienced supervisors feel like they are starting from the beginning. The best thing these supervisors can do now is just be honest, with their students. Say "I am still trying to understand this Artificial Intelligence stuff too. Let us figure it out together."

3. Methodology

3.1 Research Design

This study is basically a data-driven look at how PhD students handle AI. When we do



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a survey it gives us a picture of where students at this moment. We look at how students use artificial intelligence how much help they get from their supervisors and whether students really know the rules of their university. This way is better, than making a guess. We use numbers and statistics to find the patterns that are happening with students and artificial intelligence.

The cross-sectional design made it possible to gather data on all study variables from a single sample at one point in time where a practical and methodologically sound approach for this kind of correlational analysis.

3.2 Population and Sample

The study looked at students doing their degrees in universities across Pakistan. The researchers used a method called stratified random sampling to get a good combination of participants. The students who contacted initially (250 out of 300) gave useful answers. This meant that 83.3% of the students actually participated. The researchers divided the students into groups based on two things: The type of university they attended which could be public or private. The subject they were studying which could be Natural Sciences, Social Sciences, Humanities, Engineering and Technology or Health Sciences. The researchers did not choose 250 participants randomly. They used guidelines for determining the number of participants for

a study like this. They considered five factors and assumed a medium impact of 0.15. They wanted to be 80% sure of their results at a level of significance. Based on these calculations they needed at 138 participants. Their final sample of 250 was much bigger than this making them, over 95% sure of their results. This made the findings of the study more reliable.

3.3 Research Instrument

We collected information using a questionnaire that people filled out by themselves. This questionnaire was put together using a mix of known and trusted scales and some new questions that were created just for this study. The questionnaire was divided into six parts.

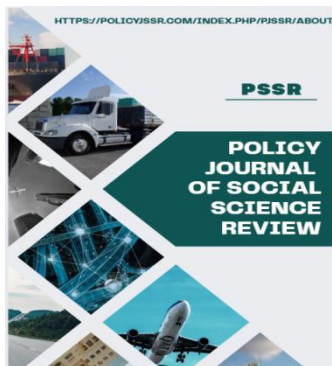
The **First section** gathered demographic information, covering gender, age, academic discipline, year of PhD study, and university type.

The **Second section** measured AI Tool Usage Frequency using eight items on a five-point Likert scale ranging from Never to Always, adapted from Davis's Technology Acceptance Model.

The **Third section** assessed Perceived Integrity Risk through seven purpose-built items on the same scale.

Ethical Decision-Making was captured in the **Fourth section** using nine items adapted from Rest's Defining Issues Test.

The **Fifth section** measured Policy Awareness through six items developed for this study.



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Supervisor Guidance was addressed in the **Sixth section** using seven items adapted from Mainhard and colleagues.

The **Final section** served as the dependent variable, measuring Academic Integrity Compliance across ten items.

Internal consistency was assessed using Cronbach's alpha, and all subscales returned coefficients ranging from 0.85 to 0.91, showing acceptable to excellent stability all over.

3.4 Data Collection Procedures

The survey was done on the internet using Google Forms. It was available for people to fill out for six weeks. University communication channels, doctoral student associations, and faculty mailing lists were used to share the survey link. Participation of students was voluntary, and clear permission was obtained from all respondents. Identifying information was

Table 1

Demographic Characteristics of Participants (N = 250)

Variable	Category	Frequency	Percentage
Gender	Male	132	52.8
	Female	114	45.6
	Non-binary/Other	4	1.6
Age Group	22-27 years	78	31.2
	28-33 years	105	42.0
	34-39 years	47	18.8
	40+ years	20	8.0
Discipline	Natural Sciences	62	24.8
	Social Sciences	71	28.4
	Humanities	43	17.2
	Engineering &	55	22.0

not collected to ensure privacy safeguard. Completion time averaged 18 minutes per respondent.

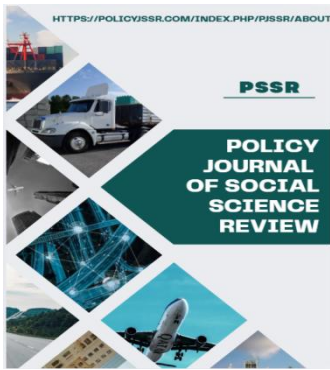
3.5 Data Analysis

All data were tested using IBM SPSS Statistics version 27. The following statistical procedures were employed and their results are given:

4. Results

4.1 Demographic Characteristics

Table 1 gives us a quick look of the 250 PhD students who are actually in this study. It is a quiet mix of men and women, with males making up over half of the group (52.8%). Most of the students are between 28 and 33 years old (42.0%), which is ideal age when people dive deep into doctoral research. When it comes to their programs most 29.6% are in their 2nd year. Two-thirds of participants attend public universities about 64.0% to be exact.



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	Technology		
	Health Sciences	19	7.6
PhD Year	Year 1	58	23.2
	Year 2	74	29.6
	Year 3	68	27.2
	Year 4	50	20.0
	University Type	Public University	160
	Private University	90	36.0

4.2 Descriptive Statistics and Reliability

Table 2 gives us a look at the data and the survey. Instead of showing extreme behavior, students are navigating a middle ground. Same for supervisor guidance; they are getting some support, but there is still plenty of room for improvement. The Cronbach's alpha was run to check if the survey questions are consistent or not. We want to a score of 0.70 and survey got a score between 0.85 and 0.91. This tells us that the questions weren't confusing to the students and the survey questions were good at measuring what they were

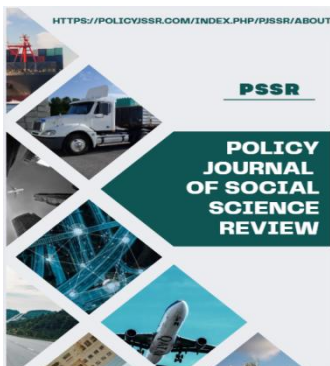
Table 2

Descriptive Statistics and Reliability Coefficients for Study Variables

Variable	Mean	SD	Min	Max	ρ
AI Tool Usage Frequency	3.82	0.91	1	5	0.88
Perceived Integrity Risk	3.47	1.03	1	5	0.85
Ethical Decision Making	3.61	0.87	1	5	0.91
Policy Awareness	2.94	1.12	1	5	0.87
Supervisor Guidance	3.15	1.08	1	5	0.89
Academic Integrity Compliance	3.53	0.94	1	5	0.90

supposed to measure and the data is reliable.

Among all the variables, AI Tool Usage Frequency came out with the highest mean score ($M = 3.82$, $SD = 0.91$), showing how routine AI use has become among doctoral students. At the other end, Policy Awareness showed the lowest mean ($M = 2.94$, $SD = 1.12$), which shows a real and alarming gap in how well institutions are actually communicating their AI ethics policies to the people who need to know them most.



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4.3 Pearson Correlation Analysis

Table 3 shows how different factors are related to whether students follow rules.

There is a negative connection between using Artificial Intelligence frequently and following the rules. This means that the often students use Artificial Intelligence tools the lower their compliance, with academic integrity rules tends to be. The same thing happens when students see Artificial Intelligence as a risk.

Table 3

Pearson Correlation

Variable	ATUF	PIR	EDM	PA	SG	AIC
1. ATUF	—					
2. PIR	0.48**	—				
3. EDM	-0.39**	-0.52**	—			
4. PA	-0.44**	-0.38**	0.61**	—		
5. SG	-0.31**	-0.29*	0.55**	0.49**	—	
6. AIC	-0.61**	-0.57**	0.67**	0.58**	0.51**	—

4.4 Multiple Regression Analysis

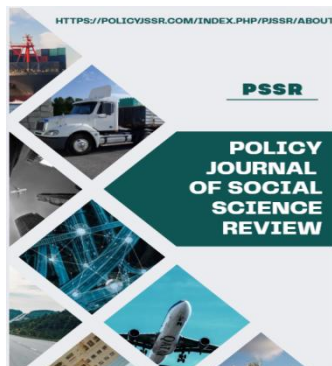
A multiple regression analysis was run to identify what most strongly predicts Academic Integrity Compliance. The overall model proved highly significant ($F(5, 244) = 57.87, p < 0.001$), explaining 54% of the variance in compliance ($R^2 = 0.54, \text{Adjusted } R^2 = 0.53$) — a level of predictive power that gives the findings considerable weight.

Table 4 tells a story about what actually drives integrity compliance which is Ethical Decision-Making. Then there is Policy Awareness, which's also very good at predicting integrity compliance. On the

On the hand three things really help to increase compliance: when students make strong ethical decisions when they know the university's Artificial Intelligence policies and when they get good guidance from their supervisors.

In short using Artificial Intelligence a lot can lower integrity scores but having strong ethical skills knowing the rules and having supportive supervisors can increase these scores.

hand, using Artificial Intelligence tools a lot is really bad for integrity compliance. Perceived Integrity Risk is also bad for integrity compliance. Supervisor Guidance is good, for integrity compliance. These results tell us that institutions and supervisors need to focus on Decision-Making and Policy Awareness and Supervisor Guidance to improve integrity compliance. They also need to watch out for Artificial Intelligence tool usage and Perceived Integrity Risk because these things can hurt integrity compliance. These results support what we thought would happen with H3 and H4 and H6. They



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give us a pretty clear picture of what institutions and supervisors need to do.

Table 4

Multiple Regression Analysis

Predictor Variable	B	SE	β	t	p	f ²
(Constant)	2.14	0.18	—	11.89	<0.001	—
AI Tool Usage Frequency	-0.28	0.06	-0.31	-4.67	<0.001	0.09
Perceived Integrity Risk	-0.19	0.05	-0.22	-3.80	<0.001	0.07
Ethical Decision-Making	0.38	0.07	0.43	5.43	<0.001	0.13
Policy Awareness	0.31	0.06	0.37	5.17	<0.001	0.12
Supervisor Guidance	0.18	0.05	0.21	3.60	<0.001	0.07

4.5 One-Way ANOVA: Disciplinary Differences

We have found a difference with the one-way ANOVA test. The results are pretty clear: F is 4 and 245 which equals 14.32 and p is, then 0.001 and η^2 is 0.19. This supports the hypothesis H5.

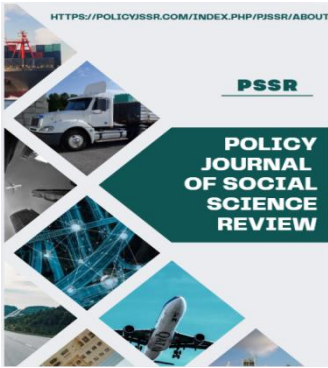
Natural Sciences students scored well in compliance with a score of 3.71. Their scores spread out a bit with a deviation of 0.88. In contrast Humanities students had

the compliance scores averaged 3.29. Their scores varied more with a deviation of 0.97. Further tests, post-hoc Tukey HSD tests showed that these differences were real and not just random statistical variations. The reason for this gap is probably straightforward. Many fields are still trying to figure out what these guidelines should be. The gap in compliance scores, between Natural Sciences and Humanities students exists.

Table 5

One-Way ANOVA

Discipline	Mean AIC	SD	F	p	Effect Size
Natural Sciences	3.71	0.88	14.32	<0.001	$\eta^2 = 0.19$
Social Sciences	3.58	0.91			
Humanities	3.29	0.97			
Engineering & Technology	3.64	0.84			
Health Sciences	3.47	0.93			

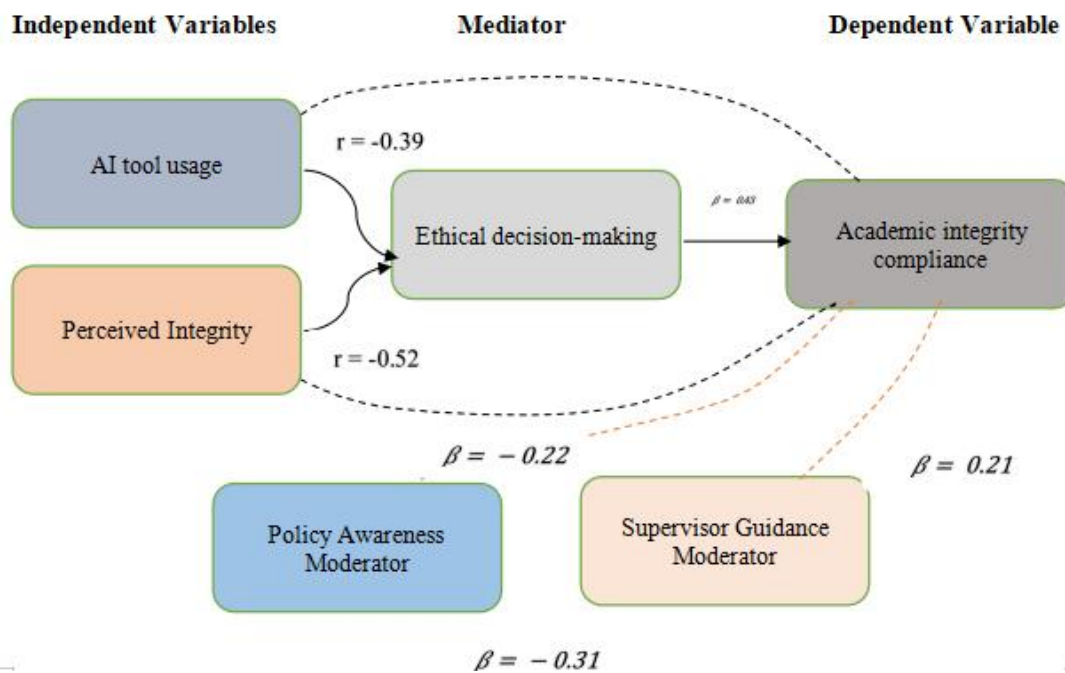


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Conceptual Framework



4.6 Summary of Hypothesis Testing

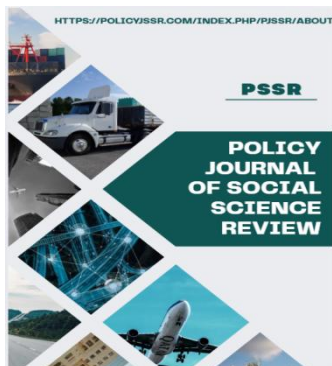
Table 6 presents a summary of testing results of all hypothesis. All six hypotheses

were supported by the statistical analyses and thus provides a strong empirical foundation for the study's conclusions.

Table 6

Summary of Hypothesis Testing Results

H	Hypothesis Statement	Result	Direction	Decision
H1	AI tool usage frequency is negatively correlated with academic integrity compliance	$r = -0.61, p < 0.001$	Strong Negative	Supported
H2	Perceived integrity risk is negatively correlated with compliance	$r = -0.57, p < 0.001$	Moderate Negative	Supported
H3	Ethical decision-making significantly predicts AIC	$\beta = 0.43, p < 0.001$	Significant Positive	Supported
H4	Policy awareness significantly predicts AIC	$\beta = 0.37, p < 0.001$	Significant Positive	Supported



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H5	Significant disciplinary differences in AIC exist	$F = 14.32, p < 0.001, \eta^2 = 0.19$	Significant	Supported
H6	Supervisor guidance positively predicts AIC	$\beta = 0.21, p < 0.001$	Significant Positive	Supported

5. Discussion

Not many studies have looked at this particular mix of factors together, and fewer still have done it quantitatively. This one did, and the findings add something genuinely useful to a field that is growing quickly but still has a lot of unanswered question

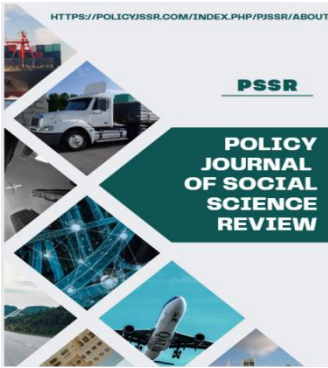
There is the strong negative correlation ($r = -0.61$) between how often doctoral students use AI tools and how well they comply with academic integrity standards meaning heavier AI users tend to report lower compliance. (Chen & Williams, 2024) have also pointed out that AI makes it too easy to offload intellectual work that researchers are really supposed to do themselves.

Ethical decision-making is the strongest predictor of academic integrity compliance ($\beta = 0.43$), This finding is consistent with (Rest's, 1986) model which is that moral judgment, motivation, and character don't work in isolation; they build on each other to guide how people actually act. Doctoral programs that weave ethics into everyday learning through real case discussions, structured coursework, and moments of genuine reflection are far more likely to graduate researchers who can hold their

ground when AI tools make cutting corners feel easy.

Policy awareness came in as the second strongest predictor ($\beta = 0.37$), yet ironically, it was the area where doctoral students scored lowest ($M = 2.94$). This gap is of high importance, low actual knowledge points directly to where institutions need to do better. This echoes (Thompson and Garcia's, 2024) systematic review, which found that policy gaps in universities' responses to AI in research are widespread. When institutions fail to build and clearly communicate AI ethics policies, they essentially abandon their doctoral students even those who genuinely want to act with integrity.

What makes this more complicated is that the problem doesn't look the same everywhere. The ANOVA findings ($F = 14.32, p < 0.001, \eta^2 = 0.19$) show that the relationship between AI use and academic integrity shifts considerably from one discipline to another. Natural Sciences students reported the highest compliance, and honestly, that tracks these fields have spent decades building a culture around data honesty, reproducibility, and being transparent about methods. It's practically baked into how researchers are trained.



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Humanities students, however, sat at the opposite end, and the reasons aren't hard to understand. When virtually everything you produce as a scholar is written, AI-generated text doesn't just become tempting it becomes dangerously easy to rationalize. And the problem runs deeper because humanities disciplines are still in the early stages of working out what ethical AI use even means in their context. Without established clear boundaries, a significant confusion continues to surround the ethical use of AI in research.

In conclusion, treating every department the same with a broad policy is not just enough. Universities need to invest in guidance and training that is actually shaped around each field's specific pressures, norms, and vulnerabilities, because responsible AI use in a science lab and responsible AI use in literary scholarship are simply not the same conversation.

6. Conclusion

This study leaves little room for doubt that AI tools and academic integrity problems are closely connected in doctoral research, and the data backs that up clearly. Nearly eight out of ten doctoral students are regularly using AI in their work, which on its own is not alarming. Because of no clear policy, no real training, just students figuring it out as they go.

The numbers from this study are hard to ignore. More than half of what determines

whether a doctoral student maintains research integrity comes down to just two things, how well they can make ethical decisions and how aware they are of their institution's policies. That is not a student problem, that is an institutional problem. On top of that, the field a student studies in accounts for nearly a fifth of the difference in integrity outcomes, which tells us that blanket approaches simply do not work.

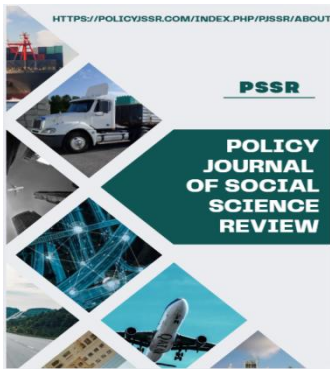
There is a gap opening up between what AI can do and what universities are ready to deal with, and it gets a little wider every time an institution decides this can wait. This is not a future problem, it is happening right now, in dissertation rooms and research labs around the world. The recommendations in this study are not theoretical. They come directly from the data and are meant to give universities, supervisors, ethics boards, and policymakers something concrete to actually work with.

7. Recommendations

Based on the empirical findings, the following recommendations are proposed:

7.1 Institutional Policy Development

Universities must develop comprehensive and publicly accessible AI ethics policies for doctoral research. There is a need of something clear, straightforward, and easy for anyone to find and understand. Researchers should not have to guess what is allowed and what is not at each stage of



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their work. And since AI is evolving constantly, these policies cannot just be written once and forgotten, they need a proper yearly review to stay relevant and actually useful.

7.2 Mandatory Doctoral Ethics Training

Given the centrality of ethical decision-making to integrity compliance, doctoral programs should incorporate mandatory AI ethics modules into their induction and ongoing training curricula. These modules should employ case-based learning methodologies, engage students in reflection on realistic AI-related ethical dilemmas, and explicitly develop the moral reasoning competencies identified as protective in this study.

7.3 Discipline-Specific

This study clearly showed that students from different fields behave quite differently when it comes to research integrity. Universities and academic bodies really should stop treating AI ethics as a one-size-fits-all issue. Humanities students especially need more support, since their work is mostly writing-based and that makes them far more exposed to the temptations of AI-generated text than students in other disciplines.

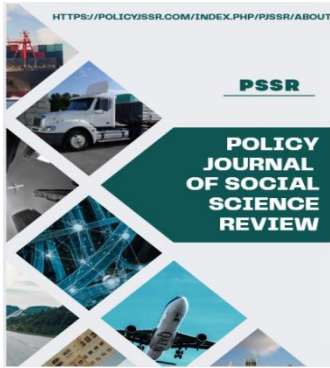
7.4 Future Research

Future research should follow doctoral students over several years to understand how their integrity practices change as both AI capabilities and university policies develop. Controlled studies testing actual

ethics training programs would give program designers something concrete to work with.

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