Ethical Awareness of ICT Students and Their Support for Responsible AI Use: Evidence from Rangsit University

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Abstract

Artificial Intelligence (AI) increasingly shapes everyday communication, decision-making, and digital services, raising ethical concerns about bias, transparency, accountability, and trust. This study examines undergraduate ICT students' awareness of these ethical issues and its relationship with their support for responsible and socially beneficial AI use. A quantitative cross-sectional survey was conducted with 417 ICT students at Rangsit University (International College), measuring ethical awareness across four dimensions (bias, transparency, accountability, and trust) alongside support for responsible and ethical AI use. Descriptive results indicate moderate levels across domains, suggesting that students recognize key AI ethics concerns but do not strongly endorse them. Correlational and regression analyses indicate that ethical awareness is positively associated with support for responsible AI, with accountability and transparency showing the strongest unique effects. Nevertheless, internal consistency reliability was suboptimal for multiple scales (Cronbach's α values below widely accepted thresholds), necessitating cautious interpretation of the findings as exploratory. The findings highlight the importance of strengthening AI ethics education, particularly governance-oriented competencies such as responsibility assignment, oversight, and explainability to prepare future ICT professionals better to develop and use AI in ways that prioritize fairness, transparency, accountability, and human well-being.

Keywords: *artificial intelligence ethic, ethical awareness, responsible AI, ICT students, Thailand, AI governance, algorithmic accountability*

1. Introduction

AI is part of daily life, sometimes working in the background without customers realizing how it works or makes decisions. For facial recognition, social media and streaming platform recommendation systems, predictive text, and automated customer service, AI processes data and provides outputs at scale. Healthcare, education, transportation, and finance use AI for complex analysis, prediction, and decision-making. AI's capability and scope present ethical questions about design and use. AI ethics concern bias, transparency, responsibility, and trust (Doshi-Velez & Kim, 2017; Verma & Rubin, 2018). AI trained on biased or incomplete datasets or with imprecise decision-making algorithms may have these issues. Limited openness may raise responsibility questions and weaken public trust when AI produces harmful or unfair results (Buolamwini & Gebru, 2018; Longoni et al., 2019). IEEE, European Commission, and UNESCO have proposed ethical frameworks for responsible AI development, but implementation is difficult (Hagendorff, 2020). These issues concern ASEAN more. In July 2022, saw the Cabinet approve the Thailand 4.0 agenda and the Thailand National AI Strategy and Action Plan (2022–2027), which prioritizes AI and sets strategic goals for an AI ecosystem, encompassing social, ethical, legal, and regulatory readiness. National readiness evaluations emphasize AI governance, institutional competence, and ethics-related implementation. In this context, ICT students matter. As programmers, designers, and data analysts, ICT students can shape AI system development, implementation, and governance. Early ethical education creates human-centered and responsible AI systems, but insufficient ethical awareness may lead to bias or ambiguous accountability (Floridi & Cowls, 2019). Though crucial, Thai students' ethical understanding and support for appropriate AI use are poorly studied (Holstein & Aleven, 2020). The study examines how ICT students' ethical awareness affects their AI ethics. The findings should inform AI ethics education and support Thailand's digital development by training future ICT professionals in ethics and technology.

2. Related Work / Literature Review

AI ethics are becoming more important as AI systems influence education, business, and public service decisions. Bias/fairness, transparency/explainability, accountability, and trust are key components of responsible AI across ethical frameworks and empirical research. ICT students are future developers and system designers who will shape AI deployment, evaluation, and governance (Bostrom & Yudkowsky, 2014; Cath, 2018).

2.1 Bias/Fairness Awareness

Bias (fairness) awareness means students understand that biased data, unrepresentative training samples, and socio-technical design choices that disadvantage certain groups can make AI outputs unfair. Research shows that fairness is multi-dimensional and can be operationalized in different ways, making bias awareness essential when designing or evaluating AI systems (Barocas et al., 2023; Verma & Rubin, 2018). Algorithmic performance can vary across demographic groups, highlighting real-world harms and the need for systematic assessment and mitigation (Buolamwini & Gebru, 2018). Related studies demonstrate how algorithmic bias can impact high-stakes fields like policing and hiring, raising concerns about discrimination and inequality (Lum & Isaac, 2016; Raghavan et al., 2020).

2.2 Transparency/Explainability Awareness

Students' transparency (explainability) awareness reveals that AI systems should be intelligible and provide relevant output explanations. Explainability reduces “black-box” decision-making and informs users and stakeholders (Doshi-Velez & Kim, 2017; Adadi & Berrada, 2018). Research on “invisible algorithms” implies that non-algorithmists may make false assumptions or fail to analyze constraints, which weakens responsible usage and monitoring (Eslami et al., 2015). Transparency concerns impact students' perception and use of AI-enabled technologies, affecting confidence and AI support (Holstein & Aleven, 2020).

2.3 Accountability Awareness

Accountability awareness involves students' belief that humans and institutions must establish oversight mechanisms, documentation, auditing, and processes for contesting or correcting harmful AI outcomes. Governance-oriented literature emphasizes that responsible AI requires clearly defined responsibility and institutional procedures, not just technical performance (Bryson & Winfield, 2017; Cath, 2018). Major ethical frameworks emphasize accountability, governance, oversight, and implementation (European Commission, 2019; IEEE, 2019; UNESCO, 2021). Reviews of AI ethics guidelines show strong convergence around accountability, but many guidelines remain high-level and difficult to operationalize, emphasizing the importance of accountability awareness among future practitioners.

2.4 Trust in AI

Trust means believing AI systems are trustworthy, safe, and ethical. Research shows that trust affects algorithmic system acceptance and use, especially in high-risk contexts where AI makes important decisions (Longoni et al., 2019). Ethics and governance directly affect stakeholders' trust in AI (European Commission, 2019; Jobin et al., 2019). Trust is shaped by perceived fairness, transparency, and accountability. How AI decisions are presented and whether limitations are visible can also affect learner trust in education, highlighting the importance of transparency in building trust (Holstein & Aleven, 2020).

2.5 Synthesis for Developing the Conceptual Model

Research shows that ethical knowledge of bias/fairness, transparency/explainability, accountability, and trust can influence support for responsible and socially beneficial AI use. Technology designed and governed by ICT students may mimic or reduce ethical issues (Cath, 2018; IEEE, 2019). Policy-level ethics frameworks and education implementation differ in ASEAN/Thailand, suggesting students' ethical awareness and support for responsible AI use should be examined. These four ideas should be synthesized and used to operationalize ethical awareness and assess students' support for ethical AI use. Data and socio-technical algorithmic bias might promote inequity in high-stakes situations (Barocas et al., 2023; Buolamwini & Gebru, 2018; Raghavan, 2020). Governance and ethical frameworks emphasize accountability, monitoring, and unambiguous responsibility, but execution is difficult (Cath, 2018; Jobin et al., 2019; IEEE, 2019; UNESCO, 2021). Transparency helps people assess constraints and direct monitoring, whereas algorithmic invisibility might confuse and over rely. Trust affects justice and governance, especially in high-risk situations (Longoni et al., 2019; European Commission, 2019). These results link AI responsibility to the four ethical awareness elements.

3. Objectives

The overaching objective of this research is to examine how ICT students understand and perceive the moral and ethical challenges of AI, and how their awareness of these challenges affects their support for responsible AI use in society. Simply put, this research aims to achieve the following specific objectives:

1) To analyze ICT students' level of awareness regarding ethical issues in AI;
2) To examine ICT students' attitudes toward the responsible use of AI technologies;
3) To explore how ICT students see their role in promoting ethical and responsible AI development; and
4) To identify how their awareness influences their support for responsible AI adoption.

3.1 Research Questions

This research addresses the following research questions:

RQ1: What are ICT students' overall levels of ethical awareness regarding AI in four dimensions (i.e., bias, transparency, accountability, and trust)?

RQ2: To what extent do bias, transparency, accountability, and trust relate to ICT students' support for responsible and ethical AI use?

RQ3: Which ethical awareness dimensions significantly predict support for responsible and ethical AI use?

3.2 Hypotheses

Based on the conceptual framework, the study proposes the following hypotheses:

H1: Bias awareness positively predicts support for responsible and ethical AI use.

H2: Transparency awareness positively predicts support for responsible and ethical AI use.

H3: Accountability awareness positively predicts support for responsible and ethical AI use.

H4: Trust in AI positively predicts support for responsible and ethical AI use.

4. Research Methodology

This study employed a quantitative research design to examine ICT students' ethical awareness regarding Artificial Intelligence (AI) and its influence on their support for responsible AI use. A questionnaire-based survey was used as the primary data collection instrument, as it allows for systematic measurement of perceptions across a large group of respondents.

4.1 Population and Sample

The population of this study consisted of undergraduate students in the Information and Communication Technology (ICT) program at Rangsit University, Thailand. Purposive sampling was used to ensure that participants had an ICT background and basic exposure to AI-related concepts. The online questionnaire was distributed through university communication channels, and participation was voluntary. After data screening, 417 valid responses were retained for analysis.

4.2 Research Instrument

The research instrument was a structured questionnaire adapted from prior studies and major AI ethics frameworks. The questionnaire consisted of six sections: (A) demographic information, (B) bias awareness (6 items), (C) transparency/explainability awareness (8 items), (D) accountability awareness (7 items), (E) trust in AI (6 items), and (F) support for responsible and ethical AI use (7 items). Items in Sections B–F were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). To enhance transparency and replicability, Table 1 summarizes the constructs, number of items, and item sources. The full list of questionnaire items is provided in Appendix A. No reverse-coded items were used; all items were coded so that higher scores consistently indicated higher levels of the intended construct (i.e., greater ethical awareness, trust, and support for responsible AI use). To establish content validity, the initial item pool was reviewed by experts in ICT/AI and research methods to evaluate clarity, relevance, and alignment with each construct definition. Based on feedback, minor wording revisions were made before data collection.

Table 1 Construct, number of items, and sources

Construct	No. of items	Common measurement approach	Source(s)	Reverse-coded items
Bias awareness	6	Likert-scale items on perceived unfairness, discrimination risk, and impacts of biased data/models	Verma & Rubin (2018); Buolamwini & Gebru (2018); Barocas et al. (2023)	None
Transparency/Explainability awareness	8	Likert-scale items on explainability, black-box concerns, evidence/source provision, and disclosure of limitations	Doshi-Velez & Kim (2017); Adadi & Berrada (2018); Eslami et al. (2015)	None
Accountability awareness	7	Likert-scale items on responsibility, liability/oversight, reporting/challenging outputs, monitoring and governance	IEEE (2019); European Commission (2019); Cath (2018); Bryson & Winfield (2017)	None
Trust in AI	6	Likert-scale items on confidence, reliability, safety, and intention to continue/recommend use with responsible conditions	Longoni et al. (2019); Holstein & Aleven (2020)	None
Support for Responsible AI use (DV)	7	Likert-scale items on supporting ethical guidelines/policies, risk assessment, ethics education, and ethical intention in future career	Floridi & Cowls (2019); UNESCO (2021); European Commission (2019); IEEE (2019)	None

Section B: Bias Awareness (6 items)

B1. I believe AI systems may produce biased outcomes toward certain groups of people.
B2. I am concerned that AI may treat different users unfairly.
B3. I think biased training data can lead to biased AI results.
B4. I believe AI may provide different qualities of outputs depending on the user's background or language.
B5. I believe AI systems may reinforce stereotypes in their responses.
B6. I worry that AI may disadvantage minority groups in real-world applications.

Section C: Transparency/Explainability Awareness (8 items)

C1. I prefer AI systems that can explain why they provide a particular output.
C2. Transparency in AI increases my confidence in using AI systems.
C3. I want AI systems to provide sources or evidence to support their outputs.
C4. I think users should be informed about the limitations of AI systems.
C5. AI systems that are explainable help me make better decisions.

C6. I think AI should disclose when it cannot access up-to-date or verified information.
C7. Clear explanations of AI outputs make AI systems feel more trustworthy.
C8. I prefer AI systems that clearly distinguish facts from opinions or generated content.

Section D: Accountability Awareness (7 items)

D1. There should be a responsible person or organization if AI causes harm or negative impacts.
D2. Developers or organizations should be accountable for the outcomes produced by their AI systems.
D3. Users should be able to report issues and challenge incorrect AI outputs.
D4. Clear rules or policies should exist to guide the appropriate use of AI.
D5. Strong accountability mechanisms make AI systems more trustworthy.
D6. Organizations using AI should monitor AI performance and risks over time.
D7. Accountability for AI should be shared among developers, organizations, and users when appropriate.

Section E: Trust in AI (6 items)

E1. Overall, I trust AI systems to support my study or work tasks.
E2. I believe AI systems provide reliable information in many situations.
E3. I feel comfortable using AI because it is generally safe when used appropriately.
E4. I intend to continue using AI systems in the future.
E5. I would recommend using AI to others, provided it is used responsibly.
E6. I trust AI systems more when they provide clear reasoning or evidence.

Section F: Support for Responsible and Ethical AI Use (DV) (7 items)

S1. I support the development and use of AI that prioritizes fairness, transparency, and accountability.
S2. I believe AI should be designed and used in ways that protect human rights and public safety.
S3. I support the idea that organizations should follow ethical guidelines when deploying AI systems.
S4. I support requiring ethical review or risk assessment for high-impact AI applications.
S5. I support integrating AI ethics education into ICT curricula at universities.
S6. In my future career, I intend to follow ethical principles when developing or using AI technologies.
S7. I am willing to encourage others (friends/peers) to use AI responsibly.

4.3 Conceptual Framework / Research Model

This study proposes a research model in which ICT students' ethical awareness is represented by four dimensions:bias awareness**,** transparency/explainability awareness**,** accountability awareness, and trust in AI,and these dimensions are expected to influence students' support for responsible and ethical AI use**.** The model assumes that students who recognize ethical risks (e.g., unfair outcomes), value explainability, emphasize human responsibility, and develop ethically grounded trust in AI are more likely to endorse responsible AI practices, guidelines, and socially beneficial adoption. Figure 1 presents the research model, where bias awareness, transparency awareness, accountability awareness, and trust in AI are specified as independent variables predicting support for responsible and ethical AI use (dependent variable).

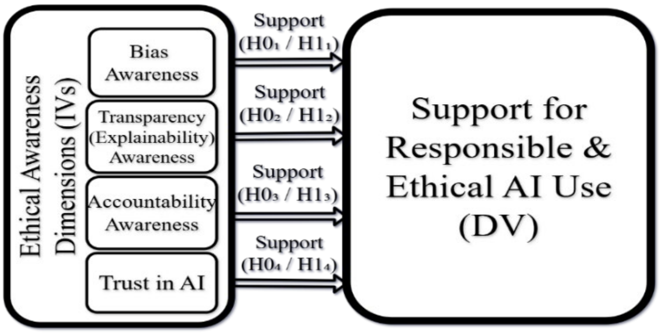

Figure 1 Conceptual framework linking ethical awareness dimensions (IVs) to support responsible and ethical AI use (DV)

Bias awareness → Support. Students who are aware that AI can produce biased or unfair outcomes are more likely to support responsible AI practices because they recognize potential harms to individuals and groups. Greater bias awareness can motivate stronger endorsement of safeguards such as fairness checks, bias mitigation, and ethical guidelines.
Transparency awareness → Support. When students value transparency and explainability, they are more likely to support responsible AI use because explainable systems allow users and stakeholders to understand limitations and evaluate decisions more appropriately. Transparency also supports informed oversight and reduces blind reliance on AI outputs.
Accountability awareness → Support. Students who emphasize accountability tend to support responsible AI because they believe that humans and institutions should remain responsible for AI outcomes. Accountability awareness reinforces support for governance mechanisms such as oversight, auditing, clear responsibility, and processes to challenge or correct harmful outputs.
Trust in AI → Support. Trust in AI can increase support for adoption when it is grounded in perceptions that AI is reliable and ethically governed. Students who trust AI under responsible conditions are more likely to endorse its use, while low trust may reduce willingness to support adoption due to concerns about risk and misuse.

4.4 Data Collection

Data were collected through an online questionnaire, which was distributed to ICT students via university communication channels. Participation was voluntary, and respondents were informed that their responses would remain anonymous and be used solely for academic research purposes.

4.5 Data Analysis

Python (pandas, numpy, scipy, statsmodels) was used to analyze the data. Demographic characteristics and construct levels (bias awareness, transparency/explainability awareness, accountability awareness, trust in AI, and support for responsible and ethical AI use) were summarized using descriptive statistics (frequency, percentage, mean, and standard deviation). Pearson's correlation was used to examine variable relationships. Multiple linear regression (OLS) was used to test the proposed model with Support for Responsible & Ethical AI Use (DV) as the dependent variable and Bias, Transparency, Accountability, and Trust as predictors. Statistical significance was determined at $p < 0.05$. Before interpreting regression results, assumptions were checked. Multicollinearity was assessed using VIF and tolerance. All VIF values were low (VIF = 1.04–1.06; tolerance ≈ 0.94–0.96), indicating no multicollinearity issues. The Shapiro–Wilk test (W = 0.994, $p = 0.121$) and residual diagnostics indicated approximate residual normality. No heteroscedasticity was found in the Breusch–Pagan test ($p = 0.192$). Standardized residuals and Cook's distance were used to identify outliers and influential cases. The maximum Cook's distance was 0.078, well below 1.0, indicating no highly influential observations. The regression results are presented using unstandardized coefficients (b), standard errors (SE), standardized coefficients (β), 95% confidence intervals (CI), and p-values to indicate effect magnitude and statistical significance.

4.6 Ethical Considerations

Participants were informed of the study's purpose and that participation was voluntary. No personally identifiable information was collected. Responses were treated confidentially and used solely for academic purposes. Participants could discontinue at any time without penalty.

4.7 Reliability of Measures

Internal consistency reliability was assessed using Cronbach's alpha (α) for each construct. The results are reported in Table 2. Overall, alpha coefficients were low across constructs, indicating limited internal consistency in the current measurement set. Therefore, findings should be interpreted with caution. Future studies should refine the items and revalidate the scales using expert review, pilot testing, item analysis (item–total correlations; alpha if item deleted), and factor validation (EFA/CFA).

Table 2 Cronbach's alpha reliability by construct

Construct	No. of items (k)	N	Cronbach's α
Bias	6	416	0.058
Transparency	8	417	0.221
Accountability	7	417	0.344
Trust	6	417	0.222
Support (DV)	7	417	0.229

5. Results

A total of 417 responses were included in the analysis. Respondent demographics were summarized in Table 3. The sample consisted of ICT students from different age groups, genders, and years of study. In addition, respondents reported varying levels of AI usage experience, which provided sufficient variation for subsequent statistical analyses.

Table 3 Respondent Profile

Variable	Category	n (%)
Gender	Female	186 (44.6%)
	Male	135 (32.4%)
	Other / Prefer not to say	96 (23.0%)
Age group	20–21	139 (33.3%)
	22–23	138 (33.1%)
	Under 20	72 (17.3%)
	Above 23	68 (16.3%)
Year of study	Year 3	110 (26.4%)
	Year 2	106 (25.4%)
	Year 4	103 (24.7%)
	Year 1	54 (12.9%)
	Above Year 4	44 (10.6%)
Used AI/GenAI tools	Yes	216 (51.8%)
	No	200 (48.0%)
	Missing	1 (0.2%)
Frequency of AI use	Several times per week	114 (27.3%)
	1–2 times per week	104 (24.9%)
	Rarely	103 (24.7%)
	Every day	53 (12.7%)
	Never	43 (10.3%)

5.1 Descriptive Statistics

Descriptive statistics indicated moderate mean levels across all constructs on a five-point Likert scale. Following are the mean and SD values for each construct: Bias (M = 3.040, SD = 0.558), Transparency (M = 3.029, SD = 0.491), Accountability (M = 3.042, SD = 0.550), Trust (M = 3.058, SD = 0.550), and

Support for Responsible and Ethical AI Use (M = 3.054, SD = 0.525). These findings suggest neither strong endorsement nor rejection of the measured ethical awareness dimensions and responsible AI support.

Table 4 Descriptive Statistics of Study Constructs

Construct	Mean (M)	SD	Min	Max
Bias	3.040	0.558	1.200	5.000
Transparency	3.029	0.491	1.875	5.000
Accountability	3.042	0.550	1.429	5.000
Trust	3.058	0.550	1.333	5.000
Support (DV)	3.054	0.525	1.714	5.000

5.2 Correlation Analysis

Bias, Transparency, Accountability, Trust, and Support for Responsible and Ethical AI Use were examined using Pearson correlation analysis. Support was positively correlated with all ethical awareness dimensions. Accountability showed the strongest correlation with Support ($r = 0.285$, $p < .001$), followed by Transparency ($r = 0.191$, $p < .001$), Bias ($r = 0.164$, $p < .001$), and Trust ($r = 0.136$, $p < .01$). These correlations indicate associations but do not account for overlap among predictors. Therefore, multiple regression analysis was conducted to identify which dimensions uniquely predict Support when all factors are considered.

Table 5 Pearson Correlations Among Study Variables (N = 417)

Variable	1	2	3	4	5
1. Bias	—				
2. Transparency	0.172***	—			
3. Accountability	0.188***	0.144**	—		
4. Trust	0.062	0.153**	0.133**	—	
5. Support (DV)	0.164***	0.191***	0.285***	0.136**	—

Note. Values are **Pearson's r**. ** $p < .01$. *** $p < .001$.

5.3 Multiple Regression Analysis

Multiple linear regression was used to determine if bias, transparency, accountability, and trust predicted Support for Responsible and Ethical AI Use. The statistically significant model ($F(4, 412) = 13.78$, $p <.001$) explained 11.8% of support variation ($R^2 =.118$; adjusted $R^2 =.109$), indicating modest explanatory power. Ethical understanding may considerably affect students' support, but other variables may be more relevant. Diagnostics showed no major assumptions to violate. There was no evidence of multicollinearity (VIF = 1.04–1.06; tolerance ≈ 0.94–0.96), normal residuals (Shapiro–Wilk $p = 0.121$), no violation of homoscedasticity (Breusch–Pagan $p = 0.192$), and no extremely influential cases (maximum Cook's distance = 0.078). In Table 6, accountability and transparency predicted support, while bias and trust were minor ($p =.055$) and insignificant ($p =.093$).

Table 6 Multiple Regression Predicting Support for Responsible and Ethical AI Use

Predictor	b	SE	95% CI for b	t	p
Intercept	1.451	0.233	[0.994, 1.908]	6.231	< .001
Bias	0.086	0.045	[-0.002, 0.174]	1.926	0.055
Transparency	0.138	0.051	[0.038, 0.238]	2.697	0.007
Accountability	0.228	0.046	[0.138, 0.318]	5.000	< .001
Trust	0.076	0.045	[-0.012, 0.164]	1.683	0.093

Note. Dependent variable = Support for Responsible and Ethical AI Use.

6. Discussion and Implications

This study assessed ICT students' ethical knowledge of AI (bias, transparency, accountability, and trust) and support for responsible AI usage. Students were moderately knowledgeable and supported, with accountability being the main element. Accountability and transparency predicted support better than bias and trust in the regression model. When predictors were examined simultaneously, accountability and transparency were found to be more associated with responsible AI support than bias awareness or general trust. A small proportion of variance was explained ($R^2 = 0.118$), suggesting that additional factors including ethics education, policy literacy, AI experience, perceived benefit, and institutional norms may also impact student support. Because this study was cross-sectional, data show associations, not causation. Due to low reliability across constructs and limited internal consistency, data should be taken cautiously, and the instrument should be modified by expert review, pilot testing, item analysis, and factor validation. Finally, purposeful sample from one university restricts generalizability; thus, future study should include numerous institutions and subgroup variations (e.g., year of study and AI usage experience).

6.1 Educational Implications

ICT curricula may benefit from explicit learning activities on AI governance and accountability mechanisms (e.g., role responsibility, auditing, monitoring, and reporting/appeal processes) and explainability practices (e.g., communicating limitations, uncertainty, and appropriate use), as accountability and transparency showed the strongest associations with support. Including these topics in learning modules, labs, or case-based assignments may encourage students to apply ethics in their studies and future work.

6.2 Practical Implications

Institutions using AI tools can boost support for responsible AI by showing users accountability and transparency. Clear guidance on AI decision-making, system limitations, monitoring processes, and channels for reporting or correcting harmful outputs are practical steps. Improving students' AI literacy in evaluating AI outputs, understanding when to use them, and governance safeguards may encourage responsible adoption.

7. Conclusion

This study assessed ICT students' AI ethics awareness in four dimensions of bias, transparency, accountability, and trust and their support for ethical AI use. In all categories, 417 Rangsit University ICT students exhibited moderate levels, indicating they recognize AI ethical problems and advocate responsible AI use. Multiple regression study showed that accountability and transparency predicted ethical AI adoption, while bias and trust did not. Governance- and implementation-focused ethical traits like clear accountability and explainability are more strongly linked to student support for responsible AI than trust or prejudice. The findings imply that educational and institutional practices should emphasize accountability and transparency to promote ethical AI attitudes among future ICT professionals.

8. Suggestions / Recommendations

Limitations: This cross-sectional investigation found correlations, not causality. Purposeful sample from one university ICT program reduces generalizability. Response biases may affect self-report data. Low reliability across constructs suggests insufficient scale refinement; therefore, results should be regarded cautiously. The model explains modest variance in support for ethical AI usage ($R^2 = 0.118$), suggesting additional factors may be significant.

Future Research: Future research should employ multi-university, multi-program samples for representativeness. Educational impacts can be assessed using longitudinal or ethics-training intervention approaches. Pilot testing, item analysis, factor validation, and expert review can be employed to improve measurement quality; SEM reduces measurement error and tests latent correlations. Qualitative approaches (interviews/focus groups) can explain why some aspects have smaller impacts, whereas AI literacy, perceived risk/utility, and ethical training may increase explanatory power.

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