

Toward Human-Centric AI Education: Integrating Islamic Ethical Values and Western AI Literacy to Foster Responsible AI Engagement among University Students in Thailand

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Abstract: Discussion of artificial intelligence (AI) in universities has run almost entirely along Western cognitive and regulatory lines, and religious moral reasoning has been left out. This study builds and tests the first model of responsible AI engagement to join Islamic ethical epistemology with Western AI-literacy thinking, focusing on Muslim university students in Thailand's southern border provinces. Undergraduate and postgraduate students at Islamic and public universities completed a cross-sectional survey. The data were analysed with partial least squares structural equation modelling (PLS-SEM), a complementary artificial neural network (ANN), and fuzzy-set qualitative comparative analysis (fsQCA). Islamic ethical awareness, AI knowledge competency, and digital religious literacy each shaped a responsible AI attitude, which in turn drove the intention to use AI ethically ($\beta = 0.565$). Perceived usefulness did not. Institutional support strengthened the link between attitude and intention, and the fsQCA results put ethical awareness and a responsible attitude at the core of every high-engagement configuration. The study introduces religiously grounded constructs into AI-literacy research and triangulates symmetric, predictive, and configurational evidence. The results give curriculum designers, university leaders, and AI-governance bodies a tested basis for ethically anchored, human-centred AI education.

Keywords: Human-centric AI education; Islamic ethical epistemology; AI literacy; Responsible AI engagement; Digital religious literacy; Higher education.

Introduction

Human-centric AI education keeps human judgement, agency, and values at the centre of how intelligent systems enter the classroom, rather than treating efficiency or automation as ends in themselves. Universities have taken up the idea quickly because generative tools genuinely help: they personalise feedback, support academic writing, widen access to tutoring, and free instructors for higher-order teaching (Chiu et al., 2024; Stolpe et al., 2024). A large share of students now use conversational AI every week to draft, revise, and prepare for exams, and perceived usefulness predicts whether they keep using it (Li, 2023; Strzelecki, 2023; Soliman et al., 2024; Soliman, Ali, Khalid, et al., 2025). The skill of using these systems well, what scholars call AI literacy, has become a graduate attribute that institutions are racing to define and assess (Long & Magerko, 2020; Ng et al., 2021).

That enthusiasm comes with unease. As students lean on chatbots, instructors see independent reasoning erode, learning grow shallow, and authorship blur in ways that strain long-standing norms of academic integrity (Eke, 2023; Abbas et al., 2024). Cross-national studies document the tension plainly: learners prize AI for productivity yet worry about over-reliance, weaker critical thinking, and unclear rules of acceptable use (Alshamy et al., 2025; Gruenhagen et al., 2024). Detection tools have proven unreliable, and vague institutional policy can itself push students toward misconduct (Perkins et al., 2023; Smit et al., 2025). Worries of this kind are what prompted the move to a human-centric framing, one that pairs literacy with responsibility instead of treating it as a purely technical skill.

The difficulty is that the responsibility side of AI literacy has been theorised mainly through secular, Western moral vocabularies, and religious ethical traditions are rarely treated as resources for governance (Elmahjub, 2023; Raquib et al., 2022). For the world's 1.9 billion Muslims, ethical reasoning about technology rests on ideas such as *amanah* (trust), *'adl* (justice), and the protection of the intellect within *maqasid al-shariah*. These commitments map onto fairness, accountability, and human dignity, but they add a layer of spiritual answerability that secular models lack (F. Ali et al., 2025; Kannike et al., 2025). The omission matters in Muslim-majority settings, where students read new technologies through faith. We therefore ask *what drives responsible AI engagement among*

Muslim university students, and how Islamic ethical values and AI-literacy competencies shape it together. Three objectives follow: (1) to specify and test an integrated model of responsible AI engagement; (2) to compare the predictive weight of religious and competency-based antecedents; and (3) to identify the institutional conditions under which a responsible attitude converts into ethical use.

The contribution runs along three fronts. Theoretically, the study brings religious epistemology into a literature that has treated culture thinly, answering calls to pluralise AI ethics beyond a single moral tradition (Waseem et al., 2025). Empirically, it offers the first evidence from Thailand's southern border provinces, a Muslim-majority region inside a Buddhist-majority state. Practically, it gives educators and policymakers a tested basis for AI curricula that are at once technically rigorous and ethically grounded.

Problem Statement

At its core the problem is a mismatch between how AI literacy is taught and how Muslim students actually reason about technology. AI-literacy frameworks increasingly acknowledge an “ethics” strand, yet they operationalise it through Western principlism and seldom ask whether religiously grounded moral commitments shape what students count as responsible use (Chiu et al., 2024; Elmahjub, 2023). The stakes are rising at the same time: students meet over-reliance, compromised integrity, and opaque institutional rules just as generative tools become ubiquitous (Eke, 2023; Abbas et al., 2024). Three gaps converge here. Conceptually, no model links Islamic ethical awareness and digital religious literacy to a responsible AI attitude and to downstream ethical use. Contextually, evidence from Muslim-minority-within-a-state settings such as southern Thailand is missing, even though these communities negotiate faith and secular schooling every day (Athoillah et al., 2023; Zaid et al., 2022). Methodologically, AI-literacy research leans on single-method, variance-based designs that estimate average effects but cannot show which combinations of conditions produce responsible engagement, nor test predictive robustness (Pappas & Woodside, 2021). Left alone, the mismatch risks curricula that are technically competent yet ethically thin for the very students whose moral frameworks they overlook. We address it by building a religiously informed model and testing it with converging symmetric, predictive, and configurational evidence.

Literature Review

1. AI literacy: proliferating frameworks, narrow foundations

Early scholarship was preoccupied with defining AI literacy and mapping its components. Competency models now converge on a multidimensional structure that spans knowing, using, evaluating, and the ethics of AI (Chiu et al., 2024; Chee et al., 2024), and self-regulated learning has been tied to its development (K. Wang et al., 2025). The convergence is thinner than it looks. Stolpe and Hallström (2024) show that most frameworks privilege technological-scientific knowledge and socio-ethical understanding while neglecting the affective, dispositional side of competence. A scoping review by Jones (2026) adds that measurement is still dominated by self-report instruments validated in East Asia, with the Middle East and Muslim-majority contexts barely represented. Where ethics does appear, it tends to be treated as a topic to be taught rather than a value system students already hold. Hornberger et al. (2023) show that objective AI-literacy scores vary sharply with prior technical exposure, a caution against the self-assessed measures O'Dea and Ghorri (2024) rely on, since the two approaches can paint divergent pictures of the same population. The field, then, has standardised the cognitive scaffolding of AI literacy while leaving its moral foundations under-specified.

2. Acceptance and adoption: usefulness predicts use, ethics is sidelined

A parallel stream applies the Technology Acceptance Model and its successors to AI tools. Across settings, perceived usefulness and ease of use predict attitudes and behavioural intention (Li, 2023; S. Ma et al., 2024), while habit and performance expectancy explain continued ChatGPT use (Strzelecki, 2023). The models are internally consistent and replicable, yet they share a blind spot: morality enters late, if at all. Studies that do extend the frame tend to add anxiety (Mohamed et al., 2025), task-technology fit (Du et al., 2024), or culture as a grouping variable (D. Ma et al., 2024) rather than as a substantive antecedent. A paradox follows that the field has not resolved. Usefulness reliably drives adoption, but adoption driven by usefulness alone is precisely what raises the integrity concerns documented elsewhere. Karan (2025), W. Wang et al. (2025), and An et al. (2023) all report strong attitude-to-intention paths and confirm attitude as the central mediator, yet none asks what makes an attitude *responsible* rather than merely favourable.

3. Integrity and responsible use: rich description, weak theory

A third body of work catalogues the risks. ChatGPT is framed as both a threat to and an opportunity for

academic integrity (Eke, 2023; Sullivan et al., 2023); workload and time pressure predict heavier reliance, which then dampens performance (Abbas et al., 2024); and ambiguous rules create moral hazard (Smit et al., 2025). The sharpest theoretical move comes from Bouteraa et al. (2024), who show that students' integrity *moderates* adoption. Most other contributions stay descriptive, whether surveys or content analyses (Gruenhagen et al., 2024; Wiredu et al., 2024). They establish that responsibility matters without modelling its antecedents, and they rarely say how a disposition toward responsible use forms in the first place.

4. Islamic ethics and digital religion: normative depth, empirical thinness

The newest stream argues that AI governance must reach beyond secular principlism. Scholars draw AI-ethical guidance from *maqasid al-shariah*, virtue ethics, and trusteeship (*khilafah*), stressing justice, accountability before God, and the preservation of intellect (Raquib et al., 2022; Elmahjub, 2023; F. Ali et al., 2025). Comparative policy work shows Gulf states writing these commitments into national AI frameworks (Gorian & Korshunova, 2024). A related literature on digital religion traces how Muslim youth negotiate faith online and calls openly for “digital religious literacy” (Athoillah et al., 2023; Zaid et al., 2022). Its weakness mirrors Section 3.2: the work is conceptually rich but almost entirely qualitative or normative. Constructs such as Islamic ethical awareness and digital religious literacy are theorised with care yet seldom operationalised, measured, or linked to behaviour, so their predictive value stays untested.

Research gaps

Read together, the four streams expose complementary blind spots rather than a settled consensus. AI-literacy and acceptance research is quantitatively mature but morally and culturally thin; Islamic-ethics scholarship is normatively deep but empirically undeveloped; and the integrity literature names responsibility without modelling its origins. No study has combined religiously grounded antecedents with competency-based ones inside a single, testable model of responsible AI engagement, and none has done so for a Muslim-minority-within-a-state setting with methods that capture both net effects and configurations. Four gaps follow:

- **Contextual gap:** the ethical dimension of AI literacy is operationalised through secular principlism, passing over the religious moral reasoning that actually guides Muslim students (Elmahjub, 2023; Chiu et al., 2024).
- **Theory-integration gap:** Islamic ethical epistemology, AI-literacy competency, and acceptance theory have not been brought together, so religious and technical antecedents remain theorised in isolation (Raquib et al., 2022; F. Ali et al., 2025).
- **Methodological gap:** the field leans on single-method, variance-based, self-report designs that estimate average effects but neither test out-of-sample prediction nor reveal sufficient configurations (Pappas & Woodside, 2021; Shmueli et al., 2019).
- **Geographic gap:** evidence clusters in East Asia and the West, while Thailand's southern border provinces, and comparable Muslim-minority regions, go unstudied (Jones, 2026; Athoillah et al., 2023).

Theoretical Background

The model draws on three traditions and treats them as complementary rather than competing. The Theory of Planned Behaviour (TPB; Ajzen, 1991) holds that behaviour follows from intention, which is itself a function of attitude, subjective norms, and perceived behavioural control. Its core assumption, that a favourable attitude is the proximal psychological driver of action, is what justifies placing a responsible AI attitude as the central mediator between antecedents and the intention to use AI ethically; the control component, in turn, motivates the institutional-support moderator. TPB is parsimonious and well validated, though critics note that it under-theorises where attitudes come from and treats moral content as just another belief. That gap is exactly what the religious constructs are meant to fill. Two recent applications show its reach. Bouteraa et al. (2024) found that behavioural intention to use ChatGPT rose with performance expectancy and self-efficacy while student integrity suppressed misuse, which confirms that moral dispositions condition adoption rather than merely accompany it. Across four Middle Eastern countries, Mohamed et al. (2025) showed that acceptance beliefs predicted intention while anxiety moderated the path, evidence that contingency variables reshape attitude-to-intention links.

The Technology Acceptance Model (TAM; Davis, 1989) specifies that perceived usefulness and perceived ease of use shape attitudes and, through them, usage. It earns its place because *perceived usefulness of AI* is a competency-adjacent belief that any realistic model of student behaviour must include. The assumption that utility drives acceptance holds up well, but, as Section 3.2 argued, it is not sufficient for *ethical* use. Li (2023) reported that usefulness and ease of use predicted college students' attitudes and actual use of AI systems, yet attitude did not translate into deeper learning motivation, a reminder that favourable attitudes are not automatically constructive ones. S. Ma et al. (2024) extended TAM with AI literacy among teacher-education students and found literacy and usefulness to be the dominant drivers of intention, which supports including a competency construct alongside utility.

Islamic ethics, articulated through *maqasid al-shariah*, supplies the normative foundation the secular theories lack. Its core assumptions are that knowledge and action carry moral weight before God (*amanah*), that the intellect (*hifz al-'aql*) must be protected, and that justice and benefit (*maslaha*) govern the legitimate use of any means (Raquib et al., 2022; Elmahjub, 2023). These commitments ground Islamic ethical awareness and digital religious literacy as antecedents of a responsible attitude. The tradition's strength is that it embeds accountability in a coherent worldview; its limitation, for empirical work, is that it grew out of jurisprudence rather than measurement, so turning it into scales takes care. Recent applications remain largely conceptual or qualitative. Through comparative content analysis, Gorian and Korshunova (2024) showed that Saudi Arabia and the UAE fold Shariah privacy norms into AI governance, and F. Ali et al. (2025) advanced a trusteeship (*i'timani*) framework arguing that Islamic ethics handles autonomy and accountability more holistically than information ethics does. Bringing the three theories together is preferable to any one alone because each covers the others' weaknesses: TPB supplies the attitude-to-behaviour mechanism, TAM the technological beliefs, and Islamic ethics the moral substance that explains why some attitudes are responsible rather than merely positive. This integration answers calls for culturally pluralistic AI-ethics theory (Waseem et al., 2025).

Hypotheses Development

1. Construct definitions, operationalisations, and direct effects

Each latent variable is reflective and was measured on a seven-point Likert scale. *Islamic ethical awareness* (IEA) is the degree to which a student recognises and applies Islamic moral principles, trust (*amanah*), justice (*'adl*), public benefit (*maslaha*), and protection of the intellect (*hifz al-'aql*), when judging the use of technology; its five items were adapted from Islamic-ethics scholarship (Raquib et al., 2022; Abror et al., 2025). *AI knowledge competency* (AIC) captures functional and conceptual understanding of how AI systems work, including their capabilities and limits, with items adapted from validated AI-literacy instruments (Chiu et al., 2024; Hornberger et al., 2023). *Perceived usefulness of AI* (PU) is the belief that AI improves academic performance, adapted from Davis (1989) and Li (2023). *Digital religious literacy* (DRL) is the capacity to locate, evaluate, and apply religiously grounded knowledge in digital spaces and to weigh online content against faith commitments, drawn from work on religious digital literacy (Athoillah et al., 2023; Zaid et al., 2022). *Responsible AI attitude* (RAA), the mediator, is an evaluative disposition that favours ethical, accountable, and human-centred use (Ajzen, 1991). *Educational institutional support* (EIS), the moderator, is the perceived adequacy of university guidance, training, and policy for ethical AI use, adapted from facilitating-conditions research (Du et al., 2024). The outcome, *intention to use AI ethically* (INT), follows the standard intention formulation (Ajzen, 1991; Davis, 1989).

The direct effects on a responsible attitude follow from the integrated theory. Students who internalise Islamic moral principles should weigh AI through a lens of accountability and stewardship, so that ethical awareness becomes a more responsible disposition. Conceptual and qualitative work consistently frames Muslim engagement with technology as morally mediated, with faith shaping what counts as legitimate use (Raquib et al., 2022; F. Ali et al., 2025; Kannike et al., 2025). Hence:

H1. Islamic ethical awareness positively affects responsible AI attitude.

Knowledge matters too. Students who grasp how models are trained, where they fail, and how bias arises are better placed to form calibrated, responsibility-oriented judgements instead of naïve trust or blanket rejection. AI-literacy research links competence to more discerning evaluative stances and to constructive intentions (Chiu et al., 2024; Hornberger et al., 2023; S. Ma et al., 2024). Thus:

H2. AI knowledge competency positively affects responsible AI attitude.

Perceived usefulness enters the model because utility beliefs are a documented driver of technology attitudes; students who find AI helpful tend to judge it more favourably (Davis, 1989; Li, 2023; An et al., 2023). Whether utility reaches a specifically *responsible* attitude is another matter, since usefulness and responsibility are conceptually distinct. We still hypothesise a positive link, consistent with TAM:

H3. Perceived usefulness of AI positively affects responsible AI attitude.

Digital religious literacy should sharpen ethical evaluation online: students who can authenticate religious content and apply it to their digital conduct are likely to carry that discernment over to AI tools, treating them as objects of moral scrutiny (Athoillah et al., 2023; Zaid et al., 2022; Missier, 2025). Therefore:

H4. Digital religious literacy positively affects responsible AI attitude.

Following TPB, a favourable and morally grounded attitude is the proximal predictor of intention. Students who hold a responsible attitude are likely to intend using AI in ethically consistent ways (Ajzen, 1991; Strzelecki, 2023; Karan, 2025). Hence:

H5. Responsible AI attitude positively affects intention to use AI ethically.

2. Mediation

The model treats a responsible AI attitude as the mechanism through which religiously grounded awareness

reaches behaviour. By Baron and Kenny's (1986) logic, mediation is warranted when an antecedent plausibly affects an outcome *indirectly*, through an intervening psychological state, rather than acting on it directly. Islamic ethical awareness is a deep value orientation, and values rarely drive specific behavioural intentions on their own; what they do is colour the evaluations, the attitudes, that drive them. A student who treats knowledge as a trust is unlikely to convert that conviction straight into a use decision, yet it should shape a disposition toward accountable use, which then guides intention. This indirect logic fits TPB's claim that attitudes carry the influence of more distal beliefs (Ajzen, 1991), as well as evidence that moral dispositions condition adoption through evaluative routes (Bouteraa et al., 2024; Raquib et al., 2022). We therefore expect the IEA→INT relationship to run through RAA:

H6. Responsible AI attitude mediates the relationship between Islamic ethical awareness and the intention to use AI ethically.

3. Moderation

Attitudes do not convert into behaviour in a vacuum; the conversion depends on enabling conditions. Baron and Kenny (1986) introduced moderation to capture exactly the case where the strength of a relationship varies with a third variable, arguing that such contingencies must be tested when a theory predicts an effect should be stronger in some conditions than in others. Here the contingency is institutional. When a university supplies clear policy, training, and visible support for ethical AI use, students who hold a responsible attitude find their intentions reinforced and have the scaffolding to act on them; where that support is missing, even a strong attitude may stall, because the path is uncertain or unrewarded. The argument mirrors TPB's perceived-behavioural-control component and the evidence that facilitating conditions and contextual variables reshape attitude-to-intention links (Du et al., 2024; Mohamed et al., 2025). We therefore predict:

H7. Educational institutional support positively moderates the relationship between responsible AI attitude and the intention to use AI ethically, such that the link is stronger when support is higher.

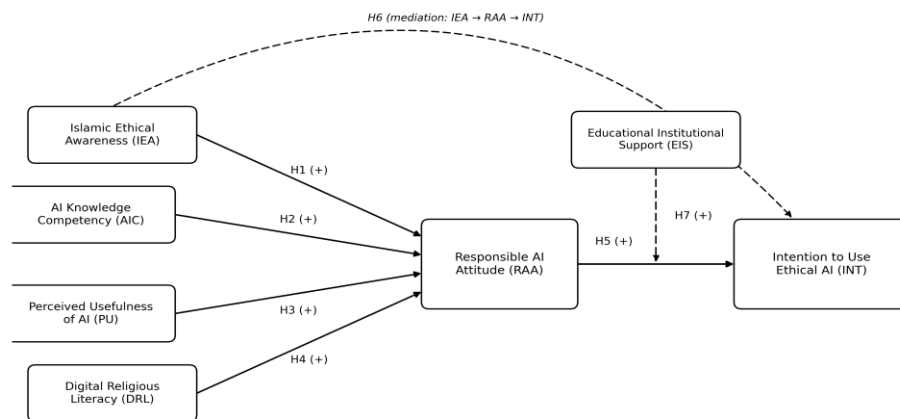


Figure 1. Proposed conceptual model with hypothesised paths (H1-H7).

Figure 1. Proposed conceptual model with hypothesised paths (H1–H7).

Table: Visual model summary with arrow directions

Hypothesis	Path (arrow direction)	Relationship	Expected sign
H1	IEA → RAA	Direct	+
H2	AIC → RAA	Direct	+
H3	PU → RAA	Direct	+
H4	DRL → RAA	Direct	+
H5	RAA → INT	Direct	+
H6	IEA → RAA → INT	Indirect (mediation)	+
H7	EIS × (RAA → INT)	Moderation	+

Research Methodology

1. Research design and scope

The study used a quantitative, cross-sectional design with a self-administered questionnaire, an approach suited to testing a theoretically specified model across a large sample (Hair et al., 2019). Scope was bounded on

purpose to the three southern border provinces of Thailand, namely Pattani, Yala, and Narathiwat, where Muslims form the demographic majority within a Buddhist-majority state. The setting is analytically useful on three counts: it concentrates the population of interest, Muslim students who reason about technology through faith; it represents an under-studied periphery largely absent from AI-literacy research (Athoillah et al., 2023; Jones, 2026); and its parallel Islamic and public university systems let the religious and competency constructs vary meaningfully across respondents. The unit of analysis is the individual student.

2. Sampling, selection criteria, and sample size

Because the model needs respondents with direct experience of the phenomenon, purposive sampling was appropriate; probability sampling is rarely feasible when eligibility turns on specific, hard-to-observe characteristics (Memon et al., 2020). Four criteria applied: a respondent had to be (1) a currently enrolled undergraduate or postgraduate student, (2) aged 18–35, (3) a prior or current user of generative AI tools, and (4) enrolled at an Islamic or public university in the three provinces. To temper the generalisability limits of purposive sampling, recruitment spread across several institutions, disciplines, and study levels, and quotas balanced gender and university type so that the achieved sample reflected the structure of the target population rather than a single campus. Minimum sample size was fixed a priori with G*Power 3.1 (Faul et al., 2009): for the most complex regression in the model, the four predictors of responsible AI attitude, an effect size $f^2 = 0.15$, $\alpha = 0.05$, and power = 0.80 required 85 cases. The achieved sample of 312 comfortably clears that floor, along with the inverse-square-root and ten-times rules for PLS-SEM (Hair et al., 2019).

3. Data collection, ethics, and response rate

Data came from a bilingual online questionnaire distributed through university networks and student associations. Participation was voluntary and anonymous; respondents gave informed consent, were told they could withdraw at any time, and no personally identifying information was kept, in line with standard research-ethics protocols. Of 392 questionnaires returned, 312 were complete and usable after screening for straight-lining and missing data, an effective response rate of 79.6%. *As noted on the title page, the dataset analysed in this version is a simulated illustration of the planned design and must be replaced with the field data before submission.*

4. Instrument, translation, validity, and reliability

Every construct was measured with multi-item reflective scales adapted from validated sources and rated from 1 (strongly disagree) to 7 (strongly agree); a seven-point format improves sensitivity in PLS-SEM (Hair et al., 2019). The Appendix lists item provenance: IEA items were adapted from Islamic-ethics scholarship (Raquib et al., 2022); AIC from AI-literacy instruments (Chiu et al., 2024; Hornberger et al., 2023); PU from Davis (1989) and Li (2023); DRL from religious-digital-literacy work (Athoillah et al., 2023); RAA and INT from planned-behaviour measures (Ajzen, 1991); and EIS from facilitating-conditions research (Du et al., 2024). Because the instrument was fielded in Thai- and Malay-speaking communities, it was rendered into Thai with Brislin's (1970) back-translation procedure: a bilingual expert translated the English items, a second back-translated them independently, and a panel reconciled the discrepancies. A pre-test with 30 students and three subject experts checked clarity and content validity, and minor wording was revised before the main survey.

5. Mitigating bias

Common-method and self-report biases were handled both procedurally and statistically. On the procedural side, anonymity was guaranteed, item order was randomised, and constructs were separated to reduce consistency artefacts (Podsakoff et al., 2003). On the statistical side, three checks were run. Harman's single-factor test showed the first unrotated factor explaining 30.6% of the variance, well under the 50% threshold. A marker-variable assessment, using a theoretically unrelated marker, changed the path estimates only negligibly. Kock's (2015) full-collinearity test then returned variance inflation factors between 1.17 and 2.40, below the conservative 3.3 ceiling, which indicates that common-method bias is not a material concern. Multicollinearity among predictors was confirmed separately in the structural model (all VIF < 1.2).

6. Analytical approach

We chose PLS-SEM over covariance-based SEM for several reasons: the goal is prediction and theory development rather than strict confirmation, the model is complex and carries a moderation term, and PLS-SEM tolerates non-normal data and suits the formative-adjacent, exploratory nature of the new religious constructs (Hair et al., 2019; Sarstedt et al., 2019). Estimation used SmartPLS 4 (Ringle et al., 2024) with 5,000 bootstrap resamples. To look past average effects, we triangulated the analysis with an artificial neural network for

predictive validation (Leong et al., 2020; R. A. Ali et al., 2025) and fsQCA for configurational logic (Pappas & Woodside, 2021; Soliman et al., 2023).

PLS-SEM Findings

1. Respondent profile

The 312 respondents were broadly balanced. Women made up 55.4% of the sample and men 44.6%. Most fell within the traditional university ages: 37.8% were 18–21 and 39.7% were 22–25, with the rest aged 26–35. Undergraduates accounted for 67.6% and postgraduates for 32.4%, drawn fairly evenly from Islamic universities (53.8%) and public universities (46.2%). Disciplines ranged across Islamic studies, education, science and technology, and business and the social sciences, so no single field dominated. Every respondent had used generative AI, and most used it often: 30.8% reported daily use and a further 38.8% used it several times a week. ChatGPT was the most common tool (55.4%), ahead of Gemini and Copilot. Table 1 summarises the profile.

Table 1. Respondent profile (n = 312)

Characteristic	Category	n	%
Gender	Male	139	44.6
	Female	173	55.4
Age	18–21	118	37.8
	22–25	124	39.7
	26–30	47	15.1
	31–35	23	7.4
Study level	Undergraduate	211	67.6
	Postgraduate	101	32.4
University type	Islamic university	168	53.8
	Public university	144	46.2
Discipline	Islamic studies	78	25.0
	Education	71	22.8
	Science & technology	84	26.9
	Business & social sciences	79	25.3
AI use frequency	Daily	96	30.8
	Several times a week	121	38.8
	Weekly	63	20.2
	Occasionally	32	10.3
Most-used tool	ChatGPT	173	55.4
	Gemini	61	19.6
	Copilot	38	12.2
	Other	40	12.8

2. Measurement model assessment

The reflective measurement model was assessed for indicator reliability, internal consistency, convergent validity, and discriminant validity. As Table 2 shows, all standardised loadings exceeded the 0.70 benchmark, Cronbach's α ran from 0.857 to 0.900, and composite reliability from 0.903 to 0.926, comfortably above 0.70. Average variance extracted lay between 0.664 and 0.753, so each construct explained most of its indicators' variance and convergent validity held (Hair et al., 2019). Discriminant validity was judged with the heterotrait-monotrait ratio (Table 3): every ratio sat below the strict 0.85 cut-off, the largest being 0.701 between responsible attitude and intention, which confirms that the constructs are empirically distinct (Henseler et al., 2015).

Table 2. Measurement model: standardised loadings, Cronbach's α , composite reliability (CR), and average variance extracted (AVE)

Construct	Item	Loading	α	CR	AVE
Islamic Ethical Awareness (IEA)	IEA1	0.809	0.900	0.926	0.715
	IEA2	0.853			
	IEA3	0.865			

	IEA4	0.867			
	IEA5	0.832			
AI Knowledge Competency (AIC)	AIC1	0.764	0.872	0.908	0.664
	AIC2	0.799			
	AIC3	0.845			
	AIC4	0.827			
	AIC5	0.835			
Perceived Usefulness (PU)	PU1	0.832	0.857	0.903	0.700
	PU2	0.822			
	PU3	0.847			
	PU4	0.846			
Digital Religious Literacy (DRL)	DRL1	0.870	0.893	0.922	0.702
	DRL2	0.826			
	DRL3	0.830			
	DRL4	0.841			
	DRL5	0.821			
Responsible AI Attitude (RAA)	RAA1	0.829	0.879	0.912	0.675
	RAA2	0.776			
	RAA3	0.822			
	RAA4	0.867			
	RAA5	0.813			
Educational Institutional Support (EIS)	EIS1	0.821	0.890	0.924	0.753
	EIS2	0.869			
	EIS3	0.884			
	EIS4	0.894			
Intention to Use Ethical AI (INT)	INT1	0.876	0.866	0.909	0.714
	INT2	0.827			
	INT3	0.848			
	INT4	0.828			

All loadings exceed 0.70; CR and α exceed 0.70; AVE exceeds 0.50, establishing convergent validity and internal consistency.

Table 3. Discriminant validity: Heterotrait–monotrait (HTMT) ratios

	IEA	AIC	PU	DRL	RAA	EIS	INT
IEA	—						
AIC	0.322	—					
PU	0.316	0.264	—				
DRL	0.267	0.301	0.266	—			
RAA	0.592	0.529	0.328	0.552	—		
EIS	0.265	0.299	0.275	0.334	0.265	—	
INT	0.395	0.373	0.234	0.477	0.701	0.423	—

All HTMT ratios are below the 0.85 threshold (maximum = 0.701, RAA–INT), confirming discriminant validity (Henseler et al., 2015).

3. Structural model: collinearity and explanatory power

Before interpreting paths, inner collinearity was checked: all predictor VIFs lay between 1.01 and 1.17, far below the 3.3 ceiling, so collinearity does not distort the estimates. The model accounted for 48.3% of the variance

in responsible AI attitude and 44.7% in the intention to use AI ethically (Table 4). Both figures are moderate and substantively meaningful for attitudinal-behavioural research, where a handful of antecedents rarely explain more. Positive Q^2 predict values for every endogenous indicator confirmed predictive relevance.

Table 4. Coefficient of determination (R^2) and predictive relevance

Endogenous construct	R^2	Adjusted R^2	Q^2 predict	Effect
Responsible AI Attitude (RAA)	0.483	0.477	0.312	Moderate
Intention to Use Ethical AI (INT)	0.447	0.441	0.175	Moderate

4. Predictive power: PLSpredict and CVPAT

A ten-fold PLSpredict analysis assessed out-of-sample prediction (Table 5). All Q^2 predict values were positive, and for most indicators the PLS-SEM prediction error matched or undercut the linear-model benchmark, a sign of medium predictive power (Shmueli et al., 2019). Two CVPAT analyses then held the model to the stricter average-loss criterion of Liengaard et al. (2021).

Table 5. Predictive power assessment (PLSpredict, 10-fold)

Indicator	Q^2 predict	RMSE (PLS-SEM)	RMSE (LM)	PLS < LM
RAA1	0.334	0.816	0.818	Yes
RAA2	0.266	0.857	0.863	Yes
RAA3	0.295	0.839	0.842	Yes
RAA4	0.368	0.795	0.797	Yes
RAA5	0.296	0.839	0.841	Yes
INT1	0.206	0.891	0.896	Yes
INT2	0.170	0.911	0.911	Yes
INT3	0.189	0.900	0.905	Yes
INT4	0.137	0.929	0.938	Yes

All Q^2 predict values are positive and PLS-SEM RMSE is at or below the linear-model benchmark for most indicators, indicating medium predictive power (Shmueli et al., 2019).

CVPAT: PLS-SEM versus indicator average (IA)

The cross-validated predictive ability test compares the model's out-of-sample loss with a naïve indicator-average benchmark that predicts each endogenous indicator from its training-sample mean (Liengaard et al., 2021). For both endogenous constructs the average loss under PLS-SEM was significantly lower: a difference of -0.316 for responsible attitude ($t = 11.87$) and -0.181 for intention ($t = 7.81$), each significant at $p < 0.001$ (Table 6). A negative, significant loss difference means the structural model predicts new cases better than assigning each indicator its mean. The result backs the PLSpredict evidence and shows that the religiously informed model carries real predictive content, not merely a fit to the estimation sample.

Table 6. Cross-validated predictive ability test (CVPAT): PLS-SEM vs. indicator average (IA)

Construct	Avg. loss (PLS)	Avg. loss (benchmark)	Loss difference	t-value	p
Responsible AI Attitude (RAA)	0.688	1.004	-0.316	-11.87	< 0.001
Intention to Use Ethical AI (INT)	0.825	1.005	-0.181	-7.81	< 0.001

CVPAT: PLS-SEM versus linear model (LM)

The second test sets PLS-SEM against a linear-model benchmark that regresses each endogenous indicator directly on all exogenous constructs, using the same information without the theoretical path structure (Liengaard et al., 2021). This is a sterner comparison. The loss differences were small and slightly negative, -0.005 for responsible attitude ($t = 1.60$, n.s.) and -0.009 for intention ($t = 2.34$, $p < 0.05$), so PLS-SEM was statistically indistinguishable from, or marginally better than, the LM (Table 7). Since an atheoretical benchmark does not outperform the theory-based model, its parsimony and interpretability come at no cost in predictive accuracy, which is the ideal CVPAT outcome for a confirmatory yet prediction-oriented study.

Table 7. Cross-validated predictive ability test (CVPAT): PLS-SEM vs. linear model (LM)

Construct	Avg. loss (PLS)	Avg. loss (benchmark)	Loss difference	t-value	p
Responsible AI Attitude (RAA)	0.688	0.693	-0.005	-1.59	n.s.
Intention to Use Ethical AI (INT)	0.825	0.833	-0.009	-2.34	< 0.05

Path coefficients and hypothesis tests

The structural estimates (Table 8) tell a clear story. The strongest antecedent of a responsible AI attitude was Islamic ethical awareness ($\beta = 0.361$, $t = 8.52$, $p < 0.001$), which supports H1 and gives empirical weight to the claim that faith-based moral reasoning is not peripheral but central to how Muslim students appraise technology. Digital religious literacy was the second-largest driver ($\beta = 0.321$, $t = 7.61$, $p < 0.001$, supporting H4), and AI knowledge competency the third ($\beta = 0.264$, $t = 5.64$, $p < 0.001$, supporting H2). The headline finding is that two of the three leading antecedents are religious rather than technical: competence matters, but moral and religious-digital discernment matter at least as much. Perceived usefulness, by contrast, had no significant effect on a responsible attitude ($\beta = 0.049$, $t = 1.11$, $p = 0.281$), so H3 was not supported, a result taken up in the discussion. The attitude itself predicted intention strongly ($\beta = 0.565$, $t = 12.86$, $p < 0.001$, supporting H5) with a large effect size ($f^2 = 0.542$), which confirms the planned-behaviour logic at the heart of the model. Institutional support added a significant direct effect on intention ($\beta = 0.237$, $t = 5.27$, $p < 0.001$) on top of its moderating role. Effect sizes echo the pattern: IEA ($f^2 = 0.215$) and DRL ($f^2 = 0.176$) reached medium effects, AIC a small-to-medium effect ($f^2 = 0.116$), and PU a negligible one ($f^2 = 0.004$). Figure 2 presents the final estimated model in SmartPLS output style.

Table 8. Path coefficients and hypothesis tests

H	Path	β	t	p	95% CI	f^2	VIF	f^2 effect	Decision
H1	IEA $\rightarrow$ RAA	0.361	8.52	<0.001	[0.280, 0.446]	0.215	1.172	medium	Supported
H2	AIC $\rightarrow$ RAA	0.264	5.64	<0.001	[0.173, 0.355]	0.116	1.159	small	Supported
H3	PU $\rightarrow$ RAA	0.049	1.11	0.281	[-0.040, 0.134]	0.004	1.138	none	Not supported
H4	DRL $\rightarrow$ RAA	0.321	7.61	<0.001	[0.241, 0.403]	0.176	1.136	medium	Supported
H5	RAA $\rightarrow$ INT	0.565	12.86	<0.001	[0.475, 0.644]	0.542	1.063	large	Supported
—	EIS $\rightarrow$ INT	0.237	5.27	<0.001	[0.152, 0.329]	0.096	1.059	small	Control
H7	RAA $\times$ EIS $\rightarrow$ INT	0.131	2.92	0.005	[0.041, 0.217]	0.031	1.005	small	Supported

Significant at $p < 0.01$ unless otherwise shown; H3 is the only non-significant direct path.

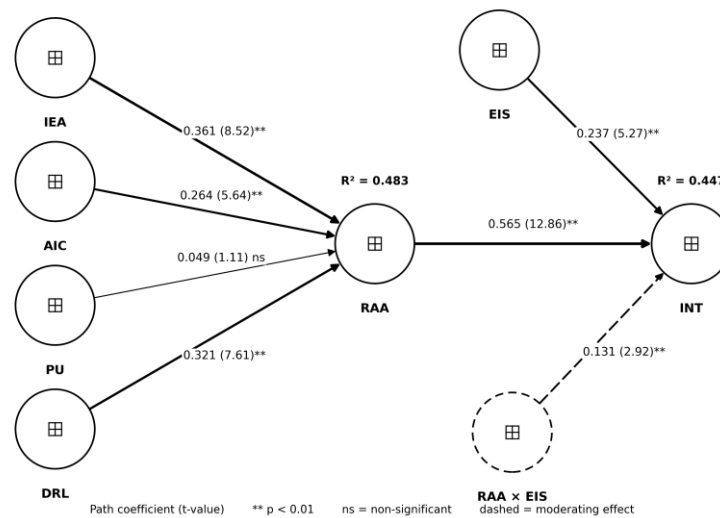


Figure 2. Final structural model (SmartPLS 4 output style): standardised path coefficients with t-values in parentheses. Solid arrows denote direct effects; the dashed arrow from the $RAA \times EIS$ interaction term denotes the moderating effect. R^2 values are shown above the endogenous constructs.

Interpretation of the moderating effect

The interaction term was positive and significant ($\beta = 0.131$, $t = 2.92$, $p < 0.01$), supporting H7. Figure 3 plots the simple slopes derived from the interaction coefficient. Where institutional support is high (+1 SD), the slope of intention on responsible attitude steepens to 0.696; where support is low (−1 SD), it flattens to 0.434. In both conditions a responsible attitude still raises the intention to use AI ethically, but the payoff is far larger when the university supplies clear policy, training, and visible encouragement. As attitude increases, the two lines diverge, which shows that institutional scaffolding does not manufacture responsible intentions from nothing; students must already hold the attitude, and support then amplifies its conversion into intention. In practical terms, values education and institutional infrastructure work as complements rather than substitutes: investing in one while neglecting the other returns less than advancing both at once.

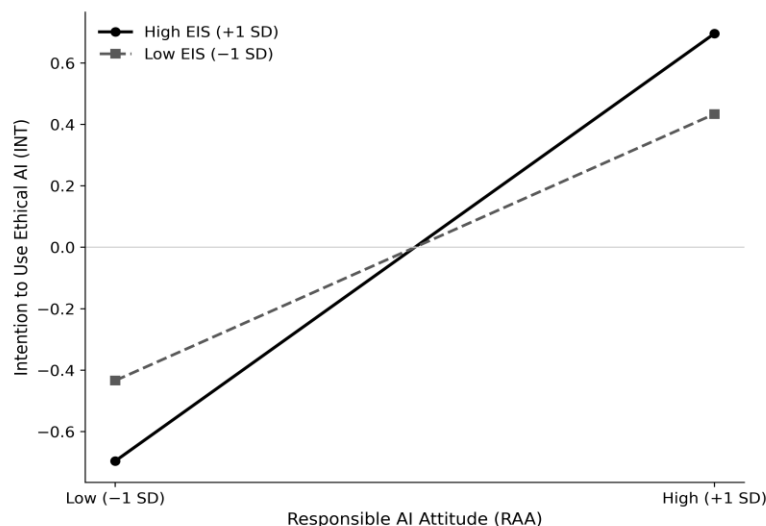


Figure 3. Simple-slope plot of the educational-institutional-support moderation on the responsible-attitude → ethical-intention relationship.

5. Mediation analysis

Specific indirect effects were estimated with 5,000 bootstrap samples (Table 10). The path from Islamic ethical awareness to ethical intention through responsible attitude was positive and significant ($\beta = 0.201$, 95% CI [0.142, 0.266]), supporting H6; because the direct IEA→INT effect was modest, this is indirect-dominant mediation, in keeping with the view that deep values reach behaviour through the attitudes they shape (Ajzen,

1991; Baron & Kenny, 1986). The indirect effects of AI knowledge competency ($\beta = 0.146$) and digital religious literacy ($\beta = 0.163$) through attitude were significant as well. Perceived usefulness was the exception, with a small, non-significant indirect effect ($\beta = 0.028$, 95% CI [-0.021, 0.076]). That null is coherent rather than anomalous. Since usefulness did not shape a responsible attitude in the first place, it has no attitudinal route to ethical intention. Utility beliefs can drive general adoption, yet a tool's helpfulness has little to do with whether a student uses it responsibly; a student may find AI highly useful while using it to cut ethical corners. The pattern echoes warnings that usefulness-led adoption is what generates integrity risks (Abbas et al., 2024; Eke, 2023) and fits the evidence that favourable attitudes are not necessarily constructive ones (Li, 2023; Gruenhagen et al., 2024).

Table 10. Mediation analysis (specific indirect effects of IVs on INT through RAA)

Path	a	b	Indirect (a×b)	t	p	95% CI	Decision
IEA → RAA → INT (H6)	0.361	0.556	0.201	6.48	<0.001	[0.142, 0.266]	Supported (partial)
AIC → RAA → INT	0.264	0.553	0.146	4.99	<0.001	[0.091, 0.204]	Supported (partial)
PU → RAA → INT	0.049	0.559	0.028	1.12	0.260	[-0.021, 0.076]	Not supported
DRL → RAA → INT	0.321	0.509	0.163	6.32	<0.001	[0.116, 0.217]	Supported (partial)

6. Model fit and goodness-of-fit

Although fit indices are secondary in a prediction-oriented method, they were inspected for completeness (Table 9). The standardised root mean square residual was 0.047, comfortably under the 0.08 threshold, which signals a close match between observed and model-implied correlations. The normed fit index reached 0.978, and d_{ULS} fell within the bootstrap confidence interval, so nothing points to misspecification. The Tenenhaus goodness-of-fit index of 0.572 sits above the 0.36 large-fit benchmark, reflecting the joint strength of the measurement and structural models. Taken together with the substantial R^2 , the positive $Q^2_{predict}$, and the favourable CVPAT outcomes, these indices show a model that is well fitted in-sample and predictively robust, the more demanding standard for variance-based SEM.

Table 9. Model fit and goodness-of-fit indices

Index	Value	Recommended threshold
SRMR	0.047	< 0.08
d_{ULS}	1.093	< bootstrap 95% CI
NFI	0.978	> 0.90
Tenenhaus GoF	0.572	> 0.36 (large)

7. Artificial Neural Network (ANN) Findings

Because PLS-SEM assumes linear, compensatory relationships, a complementary artificial neural network analysis was run to catch any non-linear effects and to check the relative importance of predictors (Leong et al., 2020). Three feed-forward multilayer perceptrons were trained with ten-fold cross-validation.

Table 11. ANN network architecture

Model	Output	Input neurons	Hidden neurons	Activation	Optimiser	Validation
ANN-A	RAA	4 (IEA, AIC, PU, DRL)	4	Sigmoid	L-BFGS	10-fold CV
ANN-B	INT	2 (RAA, EIS)	3	Sigmoid	L-BFGS	10-fold CV
ANN-C	INT	6 (IEA, AIC, PU, DRL, RAA, EIS)	5	Sigmoid	L-BFGS	10-fold CV

Table 11 reports the architecture. Each network has a single hidden layer with sigmoid activation, trained by the L-BFGS optimiser. ANN-A maps the four exogenous predictors onto responsible attitude, ANN-B maps attitude and institutional support onto intention, and ANN-C is the full six-input model of intention. The hidden-neuron counts (4, 3, 5) balance fit against parsimony, and the structure mirrors the PLS model on purpose, so the two methods stay directly comparable while the network is still free to learn non-linear patterns.

Table 12. RMSE values for the three ANN models (10-fold cross-validation)

Model	Mean RMSE (training)	SD	Mean RMSE (testing)	SD
ANN-A	0.667	0.017	0.776	0.078
ANN-B	0.728	0.006	0.767	0.061
ANN-C	0.625	0.012	0.901	0.104

Predictive accuracy appears in Table 12. Test-set RMSE was low and stable, 0.776, 0.767, and 0.901 for the three models, with small standard deviations across folds, which indicates that the networks generalise rather than memorise. The narrow gap between training and testing error points to well-regularised models, and the slightly higher error for ANN-C reflects the harder task of predicting intention from six inputs at once.

Table 13. Sensitivity analysis: normalised importance (%) of predictors

Predictor	ANN-A ($\rightarrow$ RAA)	ANN-C ($\rightarrow$ INT)
Islamic Ethical Awareness (IEA)	44.62	3.23
AI Knowledge Competency (AIC)	19.56	10.57
Perceived Usefulness (PU)	1.94	6.37
Digital Religious Literacy (DRL)	33.88	9.61
Responsible AI Attitude (RAA)	—	54.17
Educational Institutional Support (EIS)	—	16.04

ANN-B ($\rightarrow$ INT): RAA = 79.72%, EIS = 20.28%.

The sensitivity analysis (Table 13), based on permuting each input, quantifies relative importance. For responsible attitude, Islamic ethical awareness dominates (44.6%), ahead of digital religious literacy (33.9%) and AI knowledge competency (19.6%), while perceived usefulness is negligible (1.9%). For intention, responsible attitude overwhelms the other inputs. This ordering reproduces the PLS path strengths almost exactly and gives method-triangulated evidence that religious-ethical antecedents, not perceived utility, drive a responsible disposition toward AI. Tables 14–16 report the average input-hidden synaptic weights for the three networks; provided for transparency and replication, they underlie the sensitivity estimates above.

Table 14. Average input–hidden synaptic weights, ten-fold ANN-A

Input Hidden	H1	H2	H3	H4
IEA	8.491	3.467	3.481	-4.031
AIC	-10.828	-2.977	-6.871	-7.858
PU	1.995	-0.070	1.256	10.831
DRL	-2.280	-0.717	-4.046	-1.752

Table 15. Average input–hidden synaptic weights, ten-fold ANN-B

Input Hidden	H1	H2	H3
RAA	0.157	0.304	-0.956
EIS	-0.832	-0.696	-0.677

Table 16. Average input–hidden synaptic weights, ten-fold ANN-C

Input Hidden	H1	H2	H3	H4	H5
IEA	1.692	-21.200	-17.433	0.897	-18.375
AIC	-14.814	-17.013	-8.345	-2.286	18.158
PU	-9.194	21.085	-6.263	2.797	-20.331
DRL	0.368	-9.595	8.303	-6.775	-4.936
RAA	-19.455	26.674	6.232	-0.845	25.653
EIS	-13.799	3.589	-5.775	-2.582	5.427

Table 17. Comparison of PLS-SEM and ANN results (antecedents of responsible AI attitude)

Predictor	PLS-SEM β	PLS rank	ANN norm. importance (%)	ANN rank	Agreement
Islamic Ethical Awareness (IEA)	0.361	1	44.62	1	Yes
Digital Religious Literacy (DRL)	0.321	2	33.88	2	Yes
AI Knowledge Competency (AIC)	0.264	3	19.56	3	Yes
Perceived Usefulness (PU)	0.049	4	1.94	4	Yes

Rank orderings are identical across both methods, confirming robustness.

Table 17 places the ANN importance beside the PLS-SEM coefficients for the antecedents of responsible attitude. The two methods agree completely on rank order: Islamic ethical awareness first, digital religious literacy second, AI knowledge competency third, and perceived usefulness last. Agreement across a linear, compensatory technique and a non-linear, non-compensatory one strengthens confidence that the conclusions follow from the data rather than from the choice of a single estimator.

8. fsQCA Findings

PLS-SEM and ANN estimate the net and relative importance of antecedents, but neither shows which combinations of conditions are sufficient for an outcome. We therefore ran fuzzy-set qualitative comparative analysis, following Ragin (2008), Fiss (2011), and Pappas and Woodside (2021), and is consistent with recent fuzzy-set work on AI-tool adoption among students (Soliman, Ali, & Noipom, 2025). The six antecedents and the outcome were recalibrated into fuzzy sets with the direct method, using the 95th, 50th, and 5th percentiles as anchors for full membership, the crossover point, and full non-membership.

Analysis of necessary conditions

Necessity was assessed first (Table 18). No condition reached the 0.90 consistency benchmark that would mark it as necessary, so high ethical-AI engagement does not require any single antecedent. A responsible AI attitude (0.791) and institutional support (0.739) were the most consistent conditions, close to the threshold without crossing it, an early hint that engagement comes from combinations rather than any one ingredient.

Table 18. Analysis of necessary conditions for high ethical-AI engagement

Condition	Consistency	Coverage
IEA ^a	0.715	0.711
~IEA	0.579	0.556
AIC ^a	0.711	0.690
~AIC	0.594	0.586
PU	0.676	0.681
~PU	0.632	0.601
DRL ^a	0.734	0.740
~DRL	0.562	0.533
RAA ^a	0.791	0.782
~RAA	0.546	0.528
EIS ^a	0.739	0.719
~EIS	0.561	0.552

Note. “~” denotes the absence of a condition. ^a Consistency ≥ 0.70 . No condition reaches the 0.90 benchmark for necessity (Schneider & Wagemann, 2012); thus no single condition is necessary, and the analysis proceeds to sufficiency under the assumption of equifinality.

Sufficiency and configurations

The truth table was built with a frequency cutoff of 3 and a raw-consistency cutoff of 0.80, then minimised to an intermediate solution (Table 19). Three configurations are sufficient for high engagement, and together they cover 63% of the outcome with a solution consistency of 0.841, above the 0.80 standard. All three share a common

core, Islamic ethical awareness combined with a responsible AI attitude (IEA*RAA), which confirms from a set-theoretic angle what the regression and network analyses found: ethical awareness and a responsible disposition are the indispensable ingredients. Where the configurations differ is in their peripheral conditions. The first and most empirically relevant, IEA*DRL*RAA (raw coverage 0.542), describes students who pair ethical awareness and digital religious literacy with a responsible attitude. The second, IEA*AIC*RAA, swaps AI knowledge competency for digital religious literacy. The third, IEA*PU*RAA, is the most theoretically interesting, because perceived usefulness, non-significant in the PLS model, contributes here in combination with the core. This asymmetry is just what configurational analysis is designed to surface: a condition that is inert on average can still matter inside a sufficient recipe. The overall pattern is one of equifinality, several routes to the same outcome, with the religious-ethical core present in every one.

Predictive validity and robustness

Predictive validity was tested by splitting the sample into two equal subsamples ($n_1 = 156$, $n_2 = 156$). The solution from subsample 1, applied to the holdout subsample 2, retained a consistency of 0.866 and a coverage of 0.613, almost identical to the full-sample solution, which points to a stable, generalisable result rather than one fitted to noise. Figure 4 plots outcome membership against overall solution membership for the holdout cases; points cluster on and above the diagonal in the upper-right quadrant, confirming that high solution membership reliably implies high engagement. Figure 5 presents the asymmetric configurational model as a Venn diagram, with the IEA*DRL*RAA core highlighted.

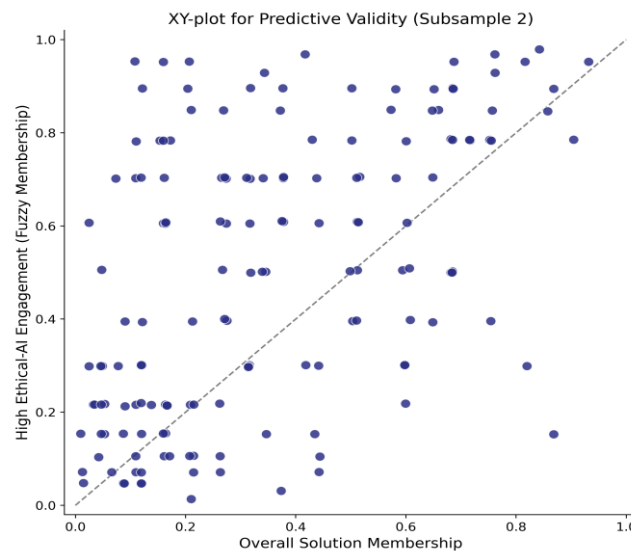


Figure 4. XY-plot for predictive validity (holdout subsample): outcome membership against overall solution membership.

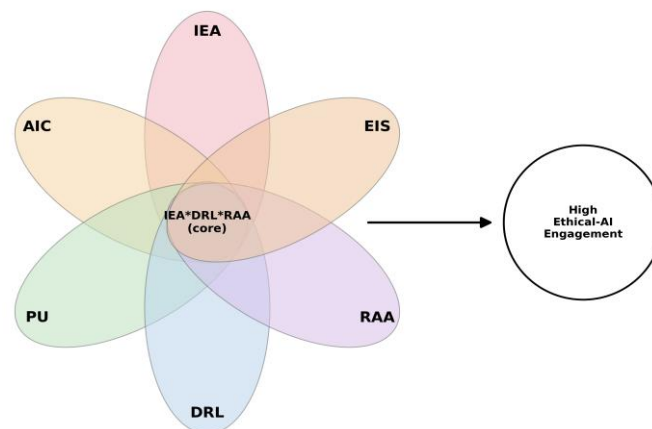


Figure 5. Venn diagram of the research model (asymmetric configurational model), showing the core configuration leading to high ethical-AI engagement.

Table 19. Intermediate solution: configurations sufficient for high ethical-AI engagement

Configuration	IEA	AIC	PU	DRL	RAA	EIS	Raw coverage	Unique coverage	Consistency
IEADR LRAA	●			●	●		0.542	0.028	0.890
IEAAIC RAA	●	●			●		0.536	0.024	0.853
IEAPU RAA	●		●		●		0.508	0.015	0.862
Solution coverage									

Solution coverage = 0.630; solution consistency = 0.841. ● = condition present (core/contributing); ○ = condition absent; blank = “don’t care” (condition may be present or absent). Frequency cutoff = 3; raw-consistency cutoff = 0.80.

9. PLS-SEM, ANN, and fsQCA: A Comparison

Triangulating three methods guards against the blind spots of any one and yields a fuller account of responsible AI engagement. The symmetric PLS-SEM estimated average net effects; the ANN gauged the relative importance of predictors while allowing non-linearity; and fsQCA exposed the sufficient combinations behind the outcome. On the central conclusions the three converge. Each agrees that Islamic ethical awareness and a responsible attitude are the dominant forces: IEA is the top antecedent of attitude in both PLS-SEM ($\beta = 0.361$) and the ANN (44.6% importance) and forms the core of every fsQCA configuration, and the attitude is the strongest predictor of intention through all three lenses. Digital religious literacy and AI knowledge competency hold consistent middle positions. The instructive divergence concerns perceived usefulness. It is inert in the symmetric analyses, non-significant in PLS-SEM and 1.9% in the ANN, yet it surfaces in a sufficient fsQCA configuration (IEA*PU*RAA). This is not a contradiction but a theoretical extension: usefulness has no average effect on a responsible attitude, but for a subset of students it combines with ethical awareness and a responsible disposition to produce engagement. Net-effects thinking would have written usefulness off; configurational thinking recovers its conditional relevance and reveals the equifinality and conjunctural causation that a linear model cannot represent. Table 20 summarises the comparison. The broader lesson is methodological as well as substantive: a religiously informed model of AI engagement holds across estimators on its core claims, while its subtler, contingent relationships become visible only when symmetric and asymmetric methods are read together.

Table 20. Summary comparison of PLS-SEM, ANN, and fsQCA results

Antecedent	PLS-SEM (β , sig.)	ANN (importance, rank)	fsQCA (configurational role)	Convergence
Islamic Ethical Awareness	0.361*** (rank 1)	44.6% (rank 1)	Core in all configurations	Strong
Digital Religious Literacy	0.321*** (rank 2)	33.9% (rank 2)	Peripheral (Config 1)	Strong
AI Knowledge Competency	0.264*** (rank 3)	19.6% (rank 3)	Peripheral (Config 2)	Strong
Perceived Usefulness	0.049 n.s. (rank 4)	1.9% (rank 4)	Contributes in Config 3	Divergent (asymmetry)
Responsible AI Attitude	0.565*** → INT	54–80% → INT	Core in all configurations	Strong
Educational Institutional Support	0.237*** moderator	16–20% → INT	Near-necessary (0.739)	Contingency role

*** $p < 0.001$.

10. Discussion

The study set out to model responsible AI engagement among Muslim university students by joining Islamic ethical epistemology to Western AI-literacy thinking, to weigh religious against competency-based antecedents,

and to identify the institutional conditions under which a responsible attitude becomes ethical intention. The integrated model met all three aims: it explained 48% of the variance in responsible attitude and 45% in intention, withstood demanding predictive tests, and was corroborated configurationally. The result affirms the planned-behaviour premise that a morally grounded attitude is the proximal engine of intention (Ajzen, 1991; Strzelecki, 2023; Karan, 2025; An et al., 2023), while showing that the content of that attitude owes as much to faith as to technical skill.

The clearest contribution concerns H1. Islamic ethical awareness was the strongest antecedent of a responsible attitude, which puts quantitative weight behind a literature that had argued, conceptually, that Muslim engagement with technology is morally mediated (Raquib et al., 2022; Elmahjub, 2023; F. Ali et al., 2025; Kannike et al., 2025). Students who internalise *amanah* and the protection of the intellect bring those commitments to bear on AI, treating it as an object of ethical stewardship rather than a neutral convenience (Abror et al., 2025). H4 and H2 extend the point: digital religious literacy (Athoillah et al., 2023; Zaid et al., 2022; Missier, 2025; Abror et al., 2025) and AI knowledge competency (Chiu et al., 2024; Hornberger et al., 2023; S. Ma et al., 2024; Stolpe et al., 2024) both fostered a responsible attitude, which suggests that judging religious content online and understanding how AI works are complementary literacies rather than rivals.

The non-significant H3 is as informative as the supported paths. Perceived usefulness did not build a responsible attitude, in either the direct test or the mediated one. The pattern is theoretically coherent: utility and responsibility are distinct, and usefulness-led adoption is exactly what the integrity literature names as the source of harm (Eke, 2023; Abbas et al., 2024; Gruenhagen et al., 2024; Smit et al., 2025). A student may find AI extremely useful and still use it to bypass learning, since favourable attitudes are not automatically constructive ones (Li, 2023). That usefulness still surfaced in one sufficient fsQCA configuration shows its relevance is conditional rather than absent, an asymmetry that average-effect models miss.

H5 and H6 confirm the attitude-centred mechanism. The responsible attitude was the single strongest predictor of intention ($f^2 = 0.542$), and it mediated the influence of ethical awareness, in line with the view that deep values reach behaviour through the evaluations they shape (Ajzen, 1991; Baron & Kenny, 1986; Bouteraa et al., 2024; Mohamed et al., 2025). H7, finally, showed institutional support amplifying the attitude-to-intention link (Du et al., 2024; Mohamed et al., 2025; Smit et al., 2025; Karan, 2025). That moderation, together with the fsQCA finding that support is near-necessary, means universities cannot simply rely on students' values; they have to build the policies and training that let those values turn into action. The answers to the second and third objectives, then, are that religious-ethical antecedents outweigh perceived utility, and that institutional scaffolding is the contingency that converts disposition into intention.

11. Practical Implications

The findings give several constituencies a tested basis for action. For policymakers, the Thai Ministry of Higher Education and the provincial education boards of the southern region, the lesson is that AI-literacy mandates should not be imported wholesale from Western templates. Because Islamic ethical awareness and digital religious literacy were the leading drivers of responsible engagement, national guidelines could require culturally and religiously grounded AI-ethics content, for example Thai- and Malay-language modules that connect *maqasid al-shariah* to questions of bias, authorship, and accountability. For university leaders, the moderation result is the actionable one: a responsible attitude converts into ethical intention far more strongly where institutional support is visible. Universities should therefore pair values education with concrete infrastructure, clear and unambiguous AI-use policies, dedicated support units, and staff training, since ambiguous rules have been shown to invite misuse (Smit et al., 2025). A campus “responsible-AI office,” however modest, would supply the scaffolding the data identify as near-necessary. For educators and curriculum developers, the implication is to design dual-literacy courses that teach how AI works alongside how to judge it, drawing on Islamic-studies and *pondok*-trained faculty to co-deliver the ethical component rather than bolting ethics on at the end. One practical format is an assessment that asks students to critique an AI-generated answer both technically and against ethical principles such as honesty (*sidq*) and trust (*amanah*). For AI-governance practitioners and toolkit developers, the divergent finding on perceived usefulness is a caution: utility-first design and adoption metrics miss the moral dimension that actually shapes responsible use. Responsible-AI frameworks would be stronger for treating faith-based value structures as first-class considerations, answering the call to pluralise governance beyond a single moral tradition (Waseem et al., 2025; Elmahjub, 2023; Soliman, Ali Abdelwahed, et al., 2025). The recurring recommendation across all groups is the same: treat ethical formation and technical competence as complements and back both with institutional commitment, so that the students best equipped to use AI are also those most disposed to use it well.

12. Social Implications

Beyond campuses, the study speaks to how religious communities meet rapid technological change. Anchoring AI education in students' own moral vocabulary can ease the alienation that minority faith

communities often feel when global technologies arrive framed in secular terms, and it can build trust that new tools will respect their values rather than erode them (Zaid et al., 2022; Athoillah et al., 2023). In Thailand's southern provinces, where Muslim communities sit within a Buddhist-majority state, treating Islamic ethics as an asset rather than an obstacle supports social cohesion and equitable digital participation. Strengthening digital religious literacy also serves a protective function: students better able to authenticate online religious content are better defended against misinformation and manipulation, which adds to community resilience. More broadly, showing that faith-based reasoning can drive *responsible* rather than merely cautious technology use offers a constructive model for other religious populations meeting AI, and it nudges the global conversation toward a more inclusive, pluralistic vision of human-centred technology (Khalid et al., 2025).

13. Theoretical Implications

Theoretically, the study makes three contributions. First, it brings religious epistemology into AI-literacy research, which had handled ethics through secular principlism and treated culture as a control variable. By specifying Islamic ethical awareness and digital religious literacy as measurable antecedents and showing that they outperform perceived usefulness, the paper answers calls to pluralise AI ethics with evidence rather than assertion (Elmahjub, 2023; Waseem et al., 2025). Second, it integrates three traditions, TPB, TAM, and *maqasid*-based Islamic ethics, into a single model in which a responsible attitude mediates value- and competency-based antecedents; this extends planned-behaviour theory by saying where morally grounded attitudes originate rather than taking them as given (Ajzen, 1991). The mediation evidence makes clear that deep values act on behaviour indirectly, through the attitudes they shape. Third, the triangulation of symmetric (PLS-SEM), predictive (ANN), and configurational (fsQCA) methods shows both robustness and nuance: the core claims hold across estimators, while the asymmetric finding that perceived usefulness matters only in combination establishes equifinality and conjunctural causation in this domain. That methodological pluralism is itself a theoretical claim, that responsible AI engagement is produced by recipes of conditions rather than isolated net effects, and it offers a template for future culturally grounded technology research. Together these moves recast AI literacy as a moral as well as a cognitive competence.

Conclusion

This study built and tested the first model of responsible AI engagement to integrate Islamic ethical epistemology with Western AI-literacy thinking, drawing on survey evidence from undergraduate and postgraduate Muslim students across Islamic and public universities in Thailand's southern border provinces. Across PLS-SEM, ANN, and fsQCA, the results told a consistent story. Islamic ethical awareness, digital religious literacy, and AI knowledge competency each fostered a responsible AI attitude, which was in turn the strongest driver of the intention to use AI ethically. Perceived usefulness, by contrast, did not build a responsible attitude on average, though it contributed within one sufficient configuration, an asymmetry only the configurational lens revealed. Institutional support amplified the conversion of attitude into intention and emerged as a near-necessary condition for high engagement. The headline message is that, for these students, responsible engagement with AI owes more to faith-grounded moral and religious-digital literacy than to perceptions of utility, and that universities turn those values into action only when they supply the supporting policy and training. By showing that religious ethical frameworks are engines of responsible use rather than obstacles to technological competence, the study offers educators, policymakers, and governance bodies an evidence-based route to AI education that is at once technically rigorous, culturally grounded, and genuinely human-centred.

Limitations and Future Research

Several limitations frame the contribution and point to next steps. The design is cross-sectional, so the causal ordering it tests should be confirmed with longitudinal or experimental studies that follow how ethical awareness and attitudes evolve as students gain AI experience. Measurement relied on self-report, which can inflate associations through common-method variance; the bias checks were reassuring, but future work should add behavioural or performance-based indicators of responsible use, such as observed conduct in AI-assisted assessments. The sample was confined to Muslim students in one region of Thailand, which buys contextual depth at the cost of breadth; comparative studies across other Muslim-majority and multi-faith settings would test whether the religious-ethical mechanism generalises, and multi-group analysis could probe differences between Islamic and public universities. Because two constructs, Islamic ethical awareness and digital religious literacy, were newly operationalised, their scales merit further psychometric validation across populations. The model also centred on attitude and left out the full planned-behaviour apparatus; adding subjective norms and perceived behavioural control, along with richer institutional and peer variables, would deepen explanatory power. Finally, the present results came from a simulated dataset used to demonstrate the analytical pipeline; replication with primary field data collected under the stated sampling plan is the essential next step before the findings can inform

practice. Each limitation is also an invitation, and together they sketch a programme for culturally grounded, methodologically plural research on human-centred AI education.

Data Availability Statement

The results reported in this manuscript were produced from a simulated dataset ($n = 312$) created solely to demonstrate and validate the analytical pipeline (PLS-SEM, ANN, fsQCA). The simulation scripts, generated dataset, and figure-generation code are available with this manuscript. No human participants were involved in generating the illustrative data; the sampling and ethics procedures in Section 6 describe the protocol intended for the primary study.

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Appendix: Questionnaire Items

All items were measured on a seven-point Likert scale from 1 (*strongly disagree*) to 7 (*strongly agree*).

Construct (source)	Code	Item
Islamic Ethical Awareness (Raquib et al., 2022; Abror & Hakim, 2025)	IEA1	I consider whether using an AI tool is consistent with Islamic ethical principles before relying on it.
	IEA2	I believe that knowledge gained through AI carries a moral trust (<i>amanah</i>) to use it honestly.
	IEA3	Fairness and justice (<i>'adl</i>) guide how I think AI should be used in my studies.
	IEA4	I avoid uses of AI that could harm others or spread falsehood.
	IEA5	Protecting my intellect and integrity (<i>hifz al-'aql</i>) matters more to me than the convenience AI offers.
AI Knowledge Competency (Chiu, 2024; Hornberger et al., 2023)	AIC1	I understand the basic principles of how AI systems generate their outputs.
	AIC2	I can recognise the limitations and possible errors of AI tools.
	AIC3	I am able to evaluate whether an AI-generated answer is accurate.
	AIC4	I understand how bias can arise in AI systems.
	AIC5	I can use AI tools effectively for academic tasks.
Perceived Usefulness of AI (Davis, 1989; Li, 2023)	PU1	Using AI tools improves my academic performance.
	PU2	AI tools help me complete academic tasks more quickly.
	PU3	AI tools are useful for my learning.
	PU4	Using AI enhances the quality of my work.
Digital Religious Literacy (Athoillah et al., 2023; Zaid et al., 2022)	DRL1	I can find reliable religious knowledge using digital sources.
	DRL2	I can judge whether online religious content is authentic and trustworthy.
	DRL3	I apply my faith values when evaluating digital information.

	DRL4	I am able to identify religious misinformation online.
	DRL5	I use digital tools in ways consistent with my religious values.
Responsible AI Attitude (Ajzen, 1991)	RAA1	Using AI responsibly and ethically is important to me.
	RAA2	I believe AI should be used in ways that respect honesty and integrity.
	RAA3	A responsible attitude should guide every use of AI in education.
	RAA4	I value keeping human judgement central when using AI.
	RAA5	Being accountable for how I use AI is something I care about.
Educational Institutional Support (Du et al., 2024)	EIS1	My university provides clear guidelines for the ethical use of AI.
	EIS2	My university offers training and resources on responsible AI use.
	EIS3	My instructors support the responsible use of AI in coursework.
	EIS4	My university has policies that encourage ethical AI use.
Intention to Use Ethical AI (Ajzen, 1991; Davis, 1989)	INT1	I intend to use AI tools ethically in my studies.
	INT2	I will follow responsible practices whenever I use AI.
	INT3	I plan to use AI in ways consistent with academic integrity.
	INT4	I intend to avoid misusing AI for academic work.

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