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Research Article

Ethical Risk and Support for National AI Governance in Bangladesh

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ABSTRACT

Generative artificial intelligence (AI) presents potential privacy, bias, misinformation and safety concerns alongside opportunities for innovation. This study examines how stated concern about these risks coexists with support for a national framework for responsible AI governance in 385 adult, AI-aware survey records from Bangladesh. The mixed sample includes law students, graduates, legal professionals and other respondents; it is not presented as representative of the national population. The analysis separates a direct concern statement from statements about safeguards, risk differentiation, rights protection and the national framework. Individual items are examined using response distributions, joint endorsement, paired comparisons and exploratory rank correlations. Overall, 285 respondents (74.0%) endorsed concern about the specified AI risks and 294 (76.4%) endorsed a clear national framework. A total of 228 (59.2%) endorsed both, 57 endorsed concern without framework support, and 66 endorsed framework support without concern. These categories include different response patterns rather than fixed respondent types. The ordinal correlation between the concern and framework items was small; the analysis cannot identify whether risk causes regulatory support. Among 133 recorded law students, results are presented separately as a descriptive subgroup. The paper argues that perceived risks, support for proportionate safeguards and preference for a national framework should be measured independently before theorising how they relate. It recommends scenario-based studies of specific AI harms and regulatory options, explicit institutional-trust measures, and documented sampling and fieldwork procedures.

Keywords: generative artificial intelligence; ethical risk; national AI governance; regulatory support; responsible AI; Bangladesh

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1. Introduction

Generative artificial intelligence (AI) systems can produce text, images and other content that users encounter in education, professional practice and public services. Their potential benefits coexist with concerns over privacy, discrimination, misinformation, inaccurate outputs and unsafe use. These concerns do not always arise in the same way: a misleading educational answer, an automated administrative decision and disclosure of confidential information involve different contexts, actors and remedies. Governance consequently requires more than an undifferentiated statement that AI is risky.

International AI governance frameworks address these concerns through principles such as safety, accountability, transparency and respect for rights. UNESCO's 2021 recommendation provides a human-rights-oriented framework, while the OECD AI Principles, updated in 2024, encourage trustworthy and innovative AI.[1] Ethical principles, however, do not by themselves establish whether a particular institution has effective safeguards or remedies. Research on AI ethics guidelines stresses that the practical meaning and implementation of broad principles vary across settings.[2]

Bangladesh provides an important setting for examining public-facing governance expectations. The government's AI policy portal presents the National Artificial Intelligence Policy 2026–2030, draft version 2.0, for public review.[3] This document is treated as a draft policy, not as proof of an enacted national AI statute or of the rules applicable when the survey was conducted. The supplied dataset does not establish whether participants read the draft or when they responded.

A clear national AI framework may be supported for many reasons, including a desire for accountability, predictable rules, innovation, public protection or institutional coordination. Concern about AI harms may also lead respondents to support different types of safeguards rather than a single regulatory model. A cross-sectional question about support for a framework cannot determine which reason motivated a respondent or whether their view would change when presented with a specific policy.

A commonly tempting approach combines concern about AI risks with a statement that greater risk increases the need for safeguards. These statements are related, but the second also expresses a normative view about how risk should be managed. Treating their mean as a pure measure of concern makes the proposed risk-to-regulation relationship partly circular. Combining weakly reliable composite variables as predictors would further complicate

[1] UNESCO, Recommendation on the Ethics of Artificial Intelligence (UNESCO 2021) <https://www.unesco.org/ethics-ai/en/recommendation> accessed 27 October 2026; OECD, OECD AI Principles (OECD 2024) <https://oecd.ai/en/ai-principles> accessed 27 October 2026.

[2] Anna Jobin, Marcello Ienca and Effy Vayena, 'The Global Landscape of AI Ethics Guidelines' (2019) 1 Nature Machine Intelligence 389; Brent Mittelstadt, 'Principles Alone Cannot Guarantee Ethical AI' (2019) 1 Nature Machine Intelligence 501.

[3] Information and Communication Technology Division, Government of Bangladesh, National Artificial Intelligence Policy 2026–2030 (Draft v2.0) (2026) <https://aipolicy.gov.bd/docs/national-ai-policy-bangladesh-2026-2030-draft-v2.0.pdf> accessed 27 October 2026.

interpretation. This article instead separates the individual survey items and focuses on the coexistence of direct risk concern and national-framework support.

International research illustrates why risk and trust should be treated as distinct dimensions of AI governance preferences. In a US survey, Bullock and colleagues studied institutional trust, technological trust, risk and support for specific interventions.[4] The outcomes examined there, such as slowing development or banning certain advanced systems, are more specific than the present question about a clear national framework. The US study therefore provides a useful comparison, not a direct validation of findings in Bangladesh.

This article's contribution is an item-level account of the distinction between concern about specific categories of harm, support for proportionate safeguards, support for risk differentiation, a rights-and-innovation balance, and endorsement of a national framework. Unlike studies centred on trust in institutions or responsible-use practices, its main question is whether concern and national-framework support occur together within respondents. The sample is mixed and AI-aware, and it does not support a national prevalence estimate or causal inference.

The study has four objectives: describe the distribution of responses to the five ethical-risk and regulation statements; identify joint patterns of risk concern and framework support; compare selected statements within the same respondents; and explore item-level associations without assuming a validated latent scale. A descriptive law-student subgroup is included to make the composition of the sample visible.

The questions are: How often do respondents endorse the specified risks and a national framework? How frequently do these views coexist? How do the patterns appear in the recorded law-student subgroup? Are ordinal responses to risk concern associated with selected safeguard and governance statements? These questions concern the supplied records rather than a representative public or the effectiveness of any enacted policy.

2. Literature Review and Theoretical Foundation

This section distinguishes ethical-risk concern, policy preferences and trust in institutions. It uses the theoretical literature to interpret the items while avoiding claims that the questionnaire tests a complete causal model.

[4] Justin B Bullock and others, 'Public Opinion and the Rise of Digital Minds: Perceived Risk, Trust, and Regulation Support' (2025) 48 Public Performance & Management Review 1357.

2.1 Ethical risks of generative AI

A generative system can produce plausible material without guaranteeing that the content is accurate or appropriate for a particular purpose. Privacy risks can arise through the use or disclosure of personal information; biased outputs may reflect patterns in data or design choices; misinformation may be generated or disseminated; and unsafe recommendations can arise when outputs are used without adequate checks. These categories are conceptually distinct even when a single respondent agrees that all warrant attention.

The focal concern item groups privacy, bias, misinformation and unsafe use into one sentence. Agreement establishes concern about the combined statement, not the degree of concern about each category separately. The study therefore cannot say that a particular risk is dominant, that a respondent has experienced harm, or that a specific AI system caused it. Those distinctions would require separate questions and, where possible, concrete scenarios or records of actual incidents.

Research on disparate impact demonstrates that data-driven systems may affect groups differently even when protected characteristics are not used explicitly.[5] This illustrates why bias cannot be reduced to an individual user's intention. Fairness also has multiple possible definitions, which may lead to competing assessments of the same system.[6] The present questionnaire does not identify a decision context or measure these competing fairness criteria; the sources provide conceptual context rather than evidence of a specific discriminatory outcome in the sample.

2.2 Risk perception and policy preference

Perceived risk is a judgement about the possibility or seriousness of harm. Policy preference concerns what, if anything, should be done in response. The two can be related without being identical. Someone may recognise risk but prefer professional standards, voluntary technical precautions, existing law, targeted sectoral rules or public education. Another person may support a national framework because it promises coordination or clarity, even when they do not endorse the general concern statement.

The national-framework item states support for a clear framework for responsible AI governance. It does not specify an enforcing institution, sanctions, an implementation budget, a legislative instrument or restrictions on particular AI applications. Agreement should therefore be described as endorsement of that broad proposition, not support for a specific bill, regulator or ban. Similarly, the question does not establish whether a respondent has read Bangladesh's draft policy.

Bullock and colleagues' US research distinguishes trust in actors and technologies from support for specific stronger or softer measures.[7] Their design underlines the value of measuring different policy options separately. The present instrument asks a different, broader question in a different

[5] Solon Barocas and Andrew D Selbst, 'Big Data's Disparate Impact' (2016) 104 California Law Review 671.
[6] Reuben Binns, 'Fairness in Machine Learning: Lessons from Political Philosophy' (2018) 81 Proceedings of Machine Learning Research 149.
[7] Bullock and others (n 4).

sample; the magnitude of any association cannot be directly compared without considering these differences.

2.2.1 The importance of specifying the policy choice

A general framework may include educational guidance, non-binding standards, requirements on developers, obligations on public agencies or enforceable rights for affected individuals. Each instrument distributes responsibilities and costs differently. For example, disclosure about AI use is not equivalent to an opportunity to challenge an adverse decision; risk assessment before deployment is not the same as compensation after harm. Endorsement of a general framework leaves these details unresolved. A useful empirical instrument would present clear alternatives and avoid assuming that agreement with a general statement entails support for every possible obligation.

Policy preferences may also depend on the purpose of an AI system. A respondent might support stronger safeguards for a decision affecting access to employment or essential services while accepting lighter requirements for an assistive educational tool. Risks differ in scale, reversibility and the practical ability of affected people to seek review. It follows that national-framework support is an important starting point, but it is not a complete account of regulatory preferences. A scenario study could ask about a defined benefit, a particular harm, the body responsible for supervision and the avenue of redress, then vary one feature at a time.

2.2.2 From principles to institutional implementation

Instruments for AI governance operate within existing public institutions, professional practices and available resources. A public statement that a system should be fair is not itself a procedure for testing disparate impacts or correcting a harmful decision. Research on AI ethics has shown convergence around general principles but also differences in their interpretation and implementation.[8] This gap between a stated commitment and an implemented safeguard is especially relevant when interpreting a questionnaire that asks what respondents believe should happen.

The distinction does not diminish the value of general principles. Principles provide a shared vocabulary for discussing rights and acceptable uses, and they can guide policy design. Their practical contribution depends on translating them into procedures that can be examined: responsibility for an assessment, the evidence used, the treatment of complaints, and consequences where a rule is not followed. The present survey does not observe these procedures. It can instead inform the questions researchers ask about whether people understand and can access them.

[8] Jobin, Ienca and Vayena (n 2); Mittelstadt (n 2).

2.3 Institutional trust and governance credibility

Institutional trust concerns expectations about an institution's competence, integrity and conduct. It can be distinguished from trust in a technology or agreement that accountability would be valuable. The questionnaire includes statements such as trusting governance more when rules are transparent and believing accountability increases trust. Those are conditional views about trust, not direct measurements of confidence in an identified Bangladeshi regulator.

The OECD's 2026 trust survey examines perceptions of public institutions and public-sector use of AI across participating countries, including concerns over data protection, fairness and transparency.[9] It is useful for identifying dimensions that a future Bangladesh study might measure, but its cross-national findings do not establish the level of institutional trust in this sample. A reliable measure would identify the relevant institution, decision domain and behaviour being evaluated.

Trust should not be assumed to be unconditionally desirable. In work on automation, appropriate reliance depends on the system's actual capabilities and limits.[10] A public authority that communicates clearly but lacks an effective review mechanism may still be unable to remedy harmful decisions. Therefore, the credibility of a governance framework involves both information about its rules and evidence of implementation, oversight and access to remedy.

2.4 Responsible AI and risk-proportionate governance

Responsible-AI frameworks commonly discuss risk assessment, transparency, accountability and human oversight. UNESCO and OECD guidance show that these principles can inform governance across many uses, while acknowledging differences in context and implementation.[11] The questionnaire's ERS2, ERS3 and ERS4 statements concern safeguards, differentiating lower-risk from higher-risk applications, and protecting rights without unnecessarily preventing beneficial innovation. These are distinct preferences, not direct observations of existing safeguards.

Risk differentiation can be operationalised in many ways. It might classify uses by likely severity, probability, affected groups or ability to contest decisions. An abstract endorsement of differentiating high- and low-risk applications does not reveal which uses respondents would classify as high risk, which obligations they would impose, or how they would resolve disagreements. The wording of ERS3 measures support for differentiation in principle, not knowledge of a particular regulatory framework.

The distinction between principles and implementation is central. Mittelstadt argues that ethical AI principles do not

[9] OECD, OECD Survey on Drivers of Trust in Public Institutions 2026 Results: Navigating Rising Expectations and New Horizons (OECD 2026) <https://doi.org/10.1787/9eb63fec-en> accessed 27 October 2026.
[10] John D Lee and Katrina A See, 'Trust in Automation: Designing for Appropriate Reliance' (2004) 46 Human Factors 50.
[11] UNESCO (n 1); OECD, AI Principles (n 1).

automatically translate into reliable professional practice.[12] In a governance setting, implementation can require institutional responsibilities, appropriate resources, monitoring, access to review and clear lines of accountability. This study does not measure whether any such arrangements exist, but the distinction is relevant when interpreting broad support for a framework.

2.5 Theoretical integration and analytical expectations

Institutional trust theory, responsible AI and the theory of planned behaviour provide complementary perspectives. The first draws attention to confidence in institutions; the second specifies governance principles and safeguards; the third distinguishes attitudes, norms, perceived control and behavioural intentions.[13] These perspectives are used to frame questions rather than as a claim that the present items validate all their constructs or mechanisms.

The direct concern item ERS1 is analysed separately from ERS2, which links perceived risk to safeguards. ERS3 concerns risk differentiation, ERS4 the balance between rights and innovation, and ERS5 support for a national framework. These statements do not form a validated scale simply because they appear in the same block. The analysis therefore tests selected item associations as exploratory questions rather than asserting that a mediated or moderated theoretical pathway has been established.

A conceptual pathway from risk to trust to regulation could be informative in later work, but this survey does not establish temporal order or independently measure institutional trust. Treating a conditional trust statement as a mediator would overstate the evidence. Similarly, one broad framework-support item cannot capture variation in attitudes to regulatory powers, costs, enforcement and remedies. Explicitly separating these objects provides a more useful foundation for instrument development.

3. Methodology

This section describes the available records, item wording, analyses and safeguards. It distinguishes the survey's intended research question from the information actually recorded in the workbook.

3.1 Research design and population

The study analyses a cross-sectional questionnaire dataset of 385 records. Each record is coded as consenting, adult eligible and aware of AI. Status categories comprise law students, law graduates, advocates or legal professionals, and other relevant respondents. These categories do not identify a probability sample of Bangladesh's adult population, and they do not establish that every respondent is a student, an AI professional or a user of a particular AI system.

The unit of analysis is an individual recorded response. The design is suited to describing response distributions and exploring associations at a single point in time. It cannot show whether concern preceded regulatory support or whether a particular

[12] Mittelstadt (n 2).

[13] Icek Ajzen, 'The Theory of Planned Behavior' (1991) 50 Organizational Behavior and Human Decision Processes 179.

policy caused a change in either. The findings are not an evaluation of the government's draft policy, whose timing relative to data collection is not documented.

3.2 Sampling, sample size and provenance

The workbook contains 385 unique respondent identifiers. The supplied materials do not establish recruitment dates, sampling frame, invitation and distribution methods, response rate or independent duplicate checks. The number 385 may correspond to a conventional sample-size target under specified assumptions, but the number alone does not establish probability selection or a national margin of error.[14] Unweighted descriptive results are therefore reported for the recorded sample.

The researcher identifies the numerical answers as real survey responses. The Codebook nevertheless describes the respondent sequence and optional contextual comments as synthetic. These labels do not independently prove that numerical responses are synthetic, but the creation of these fields and their relationship to original questionnaires require documentation. The optional contextual-text field was excluded from analysis. Retaining the source records, recruitment details and consent documentation would support independent verification and reproducibility.

3.3 Questionnaire and measurement

The instrument uses five ordered response categories from strongly disagree to strongly agree. The focal items are: ERS1, concern about AI risks involving privacy, bias, misinformation and unsafe use; ERS2, the view that greater perceived risk increases the need for proportionate safeguards; ERS3, support for distinguishing lower- and higher-risk applications; ERS4, support for rules protecting rights without unnecessarily preventing beneficial innovation; and ERS5, support for a clear national framework for responsible AI governance. Their exact wording is reproduced in Appendix A.

ERS1 is the direct risk-concern item and ERS5 is the national-framework item. ERS2 includes a normative conclusion about safeguards and is not used as a second indicator of risk concern. The five items differ in content and direction of inference, so they are not averaged into a validated risk or regulation-support scale. Conditional trust statements and self-reported responsible-use items are likewise not treated as direct measures of institutional trust or verified conduct.

All focal numerical items have valid responses for the 385 records. The supplied documentation does not establish a separate pilot, validated item adaptation, test of comprehension, preregistration or measurement-model validation. Low internal consistency in preliminary scale diagnostics reinforces the need for caution

[14] William G Cochran, Sampling Techniques (3rd edn, John Wiley & Sons 1977).

but does not by itself identify why items differ.[15] No PLS-SEM paths, composite reliability or latent-variable effects are claimed.

3.4 Descriptive and paired analysis

Response distributions are reported using counts for each scale category and endorsement percentages. Endorsement combines agree and strongly agree. Neutral and disagreeing responses are shown separately in the distributions; they are combined only as non-endorsement for joint and paired summaries. A neutral response should not be equated with opposition.

Three exploratory within-person contrasts compare ERS1 with ERS2, ERS3 and ERS5. Exact McNemar tests use discordant pairs and Holm adjustment covers the three p-values. Percentage-point differences have pointwise percentile bootstrap intervals from 10,000 respondent-level resamples.[16] Because the statements ask different questions, a paired difference does not show a causal effect, a ranking of priorities or the effectiveness of a governance measure.

3.5 Exploratory associations and subgroup analysis

Four Spearman correlations compare the five-category ERS1 responses with ERS2, ERS3, ERS4 and ERS5. Holm adjustment covers the four tests; percentile bootstrap intervals based on 2,000 respondent-level resamples are pointwise and not multiplicity-adjusted. These analyses were selected for the current exploratory study and are not presented as preregistered confirmatory tests. A small or statistically non-significant association does not prove that the variables are unrelated.[17]

The 133 records coded as law students are described separately using the same item definitions. This subgroup is not necessarily representative of all law students in Bangladesh. No formal group-difference test or subgroup causal interpretation is claimed. The choice allows readers to distinguish the student portion of the mixed sample from the full dataset without excluding other respondents.

[15] Klaas Sijtsma, ‘On the Use, the Misuse, and the Very Limited Usefulness of Cronbach’s Alpha’ (2009) 74 Psychometrika 107.

[16] Quinn McNemar, ‘Note on the Sampling Error of the Difference between Correlated Proportions or Percentages’ (1947) 12 Psychometrika 153; Sture Holm, ‘A Simple Sequentially Rejective Multiple Test Procedure’ (1979) 6 Scandinavian Journal of Statistics 65; Bradley Efron and Robert J Tibshirani, An Introduction to the Bootstrap (Chapman & Hall 1993).

[17] Douglas G Altman and J Martin Bland, ‘Absence of Evidence Is Not Evidence of Absence’ (1995) 311 BMJ 485; Ronald L Wasserstein and Nicole A Lazar, ‘The ASA Statement on p-Values: Context, Process, and Purpose’ (2016) 70 American Statistician 129.

3.6 Data handling and uncertainty

The analysis uses numerical fields and retains all 385 records for the focal items; no imputation or weighting is applied. The optional comment field is not analysed. Survey responses are presented in aggregate. Wilson intervals provide pointwise uncertainty summaries under conventional assumptions, but undocumented recruitment means that they cannot be interpreted as representative national confidence intervals.

The descriptive and inferential analyses are sensitive to question wording, the common response format and the respondent population. A single response may represent uncertainty, indifference, lack of familiarity or another reason not recorded by the instrument. Grouping neutral responses with non-endorsement for a paired table is an analytical convention, not a claim that those respondents reject regulation. Exact wording and full distributions are included so that readers can assess this choice.

3.7 Ethical considerations

The authors state that formal ethical approval was not obtained because an accessible formal review mechanism for this non-interventional adult questionnaire research was unavailable in their institutional setting. They report informed consent, voluntary participation, an anonymous questionnaire, the opportunity to discontinue and aggregate reporting. Consent and adult eligibility are coded affirmatively for the analysed records; the workbook alone cannot independently verify the consent process or the institutional context. The authors' declarations are reproduced in Section 8.

4. Results

The findings concern stated perceptions and support in the supplied records. They do not establish national public opinion or the effects of a regulatory intervention.

4.1 Respondent profile

Table 1 presents age and status categories as recorded. It establishes the mixed composition of the sample and identifies the law-student subgroup.

Table 1. Recorded age and respondent status

Measure	Category	Count (%)
Age	21-23	158 (41.0%)
	24-26	74 (19.2%)
	18-20	72 (18.7%)
	31+	42 (10.9%)
	27-30	39 (10.1%)
Status	Other relevant respondent	146 (37.9%)
	Law student	133 (34.5%)
	Law graduate	59 (15.3%)
	Advocate or legal professional	47 (12.2%)

N = 385. Recorded status does not establish a representative national sample.

Of 385 records, 146 (37.9%) are other relevant respondents, 133 (34.5%) are law students, 59 (15.3%) are law graduates and 47 (12.2%) are advocates or legal professionals. The largest age category is 21–23, with 158 respondents (41.0%). These categories do not establish representativeness or independent employment histories.

4.2 Ethical-risk and governance statements

Table 2 reports the full distribution of responses to the five ERS items. Their different wording matters for interpreting both the percentages and subsequent comparisons.

Table 2. Ethical risk and AI governance statements

Item	Counts 1 / 2 / 3 / 4 / 5	Endorsed n (%)	95% CI (%)
ERS1	0 / 8 / 92 / 172 / 113	285 (74.0%)	69.4–78.2
ERS2	0 / 5 / 87 / 168 / 125	293 (76.1%)	71.6–80.1
ERS3	2 / 25 / 134 / 162 / 62	224 (58.2%)	53.2–63.0
ERS4	0 / 4 / 78 / 177 / 126	303 (78.7%)	74.3–82.5
ERS5	0 / 7 / 84 / 182 / 112	294 (76.4%)	71.9–80.3

N = 385. Endorsement means agree or strongly agree; neutral answers are not opposition. Wilson intervals are pointwise; exact wording is in Appendix A.

Direct concern about the specified risks was endorsed by 285 respondents (74.0%), while 294 (76.4%) endorsed a clear national framework. The rights-and-innovation statement was endorsed by 303 (78.7%); risk differentiation was endorsed by 224 (58.2%). These results describe agreement with statements, not the preferred details of a national law or demonstrated knowledge of a risk classification system.

4.3 Joint risk concern and framework support

Table 3 shows the joint endorsement of ERS1 and ERS5. A respondent can endorse both because the two items ask about different matters.

Table 3. Joint endorsement of risk concern and national framework

Response configuration	Count (%)
Both endorsed	228 (59.2%)
Concern only	57 (14.8%)
Framework only	66 (17.1%)
Neither endorsed	34 (8.8%)

N = 385. Neither includes neutral answers; categories describe responses, not fixed types of people.

A total of 228 (59.2%) endorsed both the risk-concern and national-framework statements. Fifty-seven endorsed concern without endorsing framework support, while 66 endorsed framework support without endorsing concern. The latter two categories include neutral responses to the non-endorsed item. These patterns do not establish why respondents answered as they did or whether a policy change would alter their views.

4.4 Law-student subgroup

Table 4 presents the same five items for the 133 respondents recorded as law students. This is a descriptive subgroup rather than a representative student survey or an estimate of differences between professions.

Table 4. Endorsement among recorded law students

Item	Endorsed n (%)	95% CI (%)
ERS1	96 (72.2%)	64.0–79.1
ERS2	96 (72.2%)	64.0–79.1
ERS3	71 (53.4%)	44.9–61.6
ERS4	97 (72.9%)	64.8–79.8
ERS5	94 (70.7%)	62.4–77.7

n = 133. Pointwise Wilson intervals do not establish representativeness or compare groups.

The subgroup results indicate the distribution within the recorded student category. They should be read with the smaller denominator and the same limits on undocumented recruitment. No institution-level or educational-exposure comparison can be inferred from these records.

4.5 Paired endorsement comparisons

Table 5 compares endorsement of the direct concern item with three other statements within the same individuals. The confidence intervals are pointwise and the tests are adjusted for the three exploratory comparisons.

Table 5. Paired endorsement comparisons

Contrast	First only / second only	Difference pp	95% CI pp	Holm p
ERS1 – ERS2	59 / 67	-2.1	-7.8 to 3.6	0.942
ERS1 – ERS3	103 / 42	15.8	9.9 to 21.6	<.001
ERS1 – ERS5	57 / 66	-2.3	-8.1 to 3.4	0.942

N = 385; pp = percentage points. Exact McNemar tests, Holm adjusted across three tests. Bootstrap intervals are pointwise. Items have different wording.

The tests describe differences between statements with different objects. They cannot identify whether respondents prefer one policy instrument over another, because the questionnaire did not ask them to choose among alternatives. Nor does a difference in endorsement prove that one governance measure would reduce AI harm.

4.6 Exploratory ordinal associations

Table 6 uses all five response categories to examine associations with direct risk concern. The four p-values are adjusted together; the bootstrap intervals are pointwise.

Table 6. Exploratory associations with risk concern

Items	Spearman ρ	95% CI	p	Holm p
ERS1 / ERS2	0.155	0.058 to 0.258	0.002	0.007
ERS1 / ERS3	0.187	0.087 to 0.282	<.001	<.001
ERS1 / ERS4	0.022	-0.082 to 0.127	0.668	0.668
ERS1 / ERS5	0.098	-0.008 to 0.199	0.056	0.112

N = 385. Holm adjustment covers four tests; 95% percentile bootstrap intervals are pointwise, based on 2,000 resamples.

Risk concern had small positive ordinal associations with the safeguards statement ($\rho = 0.155$; Holm-adjusted $p = 0.007$) and the risk-differentiation statement ($\rho = 0.187$; adjusted $p < 0.001$). The association with national-framework support was $\rho = 0.098$ (adjusted $p = 0.112$). The confidence intervals are pointwise and should be interpreted alongside the adjusted p-values. The results cannot establish causality, and statistical uncertainty does not show that an association is absent. The analysis does not establish that risk is transformed into regulatory support through institutional trust.

5. Discussion

The central result is the coexistence of direct risk concern and endorsement of a national AI-governance framework in many records. The analysis also shows why that coexistence should not be treated as evidence of a causal governance pathway.

5.1 Concern and support are distinct

Both the direct concern item and the national-framework item were endorsed by substantial proportions of the mixed sample. Their joint distribution is more informative than comparing two average scores: 228 respondents endorsed both, but others endorsed only one of the two statements. The categories describe survey answers at one time and do not reveal the reasons for them.

This distinction is consistent with international work that separates risk, trust and different kinds of regulatory preferences.[18] A person may regard privacy or misinformation as serious while favouring a sector-specific response, professional safeguards or education. Another may favour a clear national framework for consistency or coordination. The questionnaire does not ask respondents to choose among these reasons; they are possible interpretations, not findings about the motivations of particular participants.

The national-framework item also does not specify which institution would implement it or how it would be enforced. A favourable response cannot establish support for an AI ban, a particular regulator, penalties or a law. A future questionnaire could present alternative regulatory designs with specified responsibilities and trade-offs, allowing respondents to evaluate concrete options rather than a general label.

5.2 Interpretation of small associations

The ordinal association between ERS1 and ERS5 is small. The appropriate interpretation is that the data provide limited evidence about their relationship in this sample, not that risk is irrelevant to governance preferences. The item combines four kinds of risk and the framework item combines multiple possible policy interpretations. Variation in their meanings may weaken or otherwise affect an observed relationship.

Cross-sectional responses cannot determine whether concern produces support, support affects reported concern, or an unmeasured factor influences both. Shared survey format and unknown selection processes also complicate interpretation.[19] Weakly reliable composites do not justify claiming that AI literacy is a stronger independent predictor. Item-level analysis keeps the inference closer to the recorded questions.

A well-designed follow-up could measure separate harms, risk probability and perceived severity, then present a set of regulatory choices. Longitudinal measurement could establish whether changes in concern precede changes in stated preferences, although confounding would still need attention. Randomised descriptions of specific safeguards could examine how policy features affect preferences under defined assumptions. These are future designs; none was conducted here.

[18] Bullock and others (n 4).
[19] Wasserstein and Lazar (n 17).

5.3 Safeguards, proportionality and innovation

ERS2 connects greater risk with proportionate safeguards; ERS3 asks about distinguishing risk levels; ERS4 asks that rules protect rights without unnecessarily preventing beneficial innovation. Agreement with these statements describes support for broad design principles. It does not identify which risks are high, what safeguards should be required, how costs should be distributed or who should decide.

The observed pattern is compatible with the policy relevance of proportionality, but it does not establish which framework would achieve it. The OECD principles and UNESCO recommendation discuss risk management and rights in broad terms.[20] Implementation requires decisions about assessment, documentation, oversight and remedy. Ethical principles become meaningful in practice when responsibilities and institutional capacity are specified, a concern emphasised by the AI ethics literature.[21]

The rights-and-innovation item itself contains two attractive objectives. Endorsement does not reveal how respondents would choose where the objectives conflict or what level of restriction they consider unnecessary. Future research should present cases with explicit trade-offs and ask respondents to explain or rank the options. That approach could clarify whether broad agreement persists when enforcement costs or limits on particular applications are made concrete.

5.4 Trust and institutional credibility

Trust is a plausible factor in how a person evaluates AI governance, but the present analysis does not measure trust in a named institution. Conditional statements about transparent rules or accountability do not establish whether respondents trust a regulator, government agency or AI company. The OECD trust survey distinguishes perceptions of public institutions and their conduct; the distinction should be retained when designing a Bangladesh study.[22]

The results also do not show that transparency causes trust or that trust mediates the relationship between risk concern and framework support. Even a well-communicated rule may not be credible if complaints are not addressed, decisions cannot be reviewed or harms are not remedied. Conversely, the absence of a high trust score would not identify which institutional feature needs improvement. Measurement should ask about a specified authority, service or incident and distinguish expectations from direct experience.

[20] OECD, AI Principles (n 1); UNESCO (n 1).
[21] Jobin, Ienca and Vayena (n 2); Mittelstadt (n 2).
[22] OECD, Trust Survey (n 9).

5.5 Bangladesh context and limits of policy inference

Bangladesh's AI policy portal presents a draft national policy for 2026–2030.[23] Its draft status and the absence of survey dates make it impossible to determine whether respondents considered that document. The survey did not ask them to approve particular provisions. Results should therefore not be characterised as public support for that draft or as a mandate for any specific regulatory authority.

The mixed sample also limits claims about national opinion. The recorded categories are valuable for showing who is in the workbook, but they are not a sampling frame. Students, graduates, professionals and other respondents may have different experiences of AI, and some populations affected by automated decisions may be underrepresented or absent. Future national research should document recruitment and include people with varying access, language needs and experiences of public services.

A public consultation is most informative when people understand what is being proposed and have a practical opportunity to respond. Access can depend on language, internet connectivity, disability access, available time and familiarity with technical or legal terms. The present workbook does not measure these barriers or participants' engagement with a consultation. It therefore cannot identify which groups are excluded or estimate consultation effects. Nevertheless, a future policy study can ask whether people received accessible information, understood their available choices and could see how their input was considered.

These questions should be analysed separately from whether a participant supports a national framework. A person may favour regulation while being dissatisfied with the consultation process; another may oppose a particular proposal while trusting the process. Observing those combinations requires separate measures and avoids using general support as a proxy for institutional legitimacy. The OECD trust framework likewise distinguishes expectations about openness, fairness and institutional conduct.[24]

5.6 Integrated interpretation

The study supports a careful separation of four empirical questions: whether respondents are concerned about specific harms; whether they favour safeguards; whether they support a clear national framework; and whether they trust an institution to implement it. It measures the first three through individual statements and does not adequately measure the fourth. This separation prevents a broad framework endorsement from being mistaken for proof of a functioning, trusted regulatory system.

Institutional trust, responsible AI and planned-behaviour theory remain useful for framing later research.[25] In the current dataset, however, they do not establish a

[23] Bangladesh Draft AI Policy (n 3).
[24] OECD, Trust Survey (n 9).
[25] Ajzen (n 13); Lee and See (n 10).

mediation mechanism. The practical research contribution is to identify what should be measured more precisely and to show the limits of inferring a causal risk-to-regulation pathway from simultaneous survey responses.

6. Theoretical and Practical Implications

The implications distinguish observed questionnaire patterns from proposed actions. The recommendations require evaluation and should be adapted to the relevant legal and institutional context.

6.1 Theoretical implications

First, direct ethical-risk concern should be measured independently of a statement that risk requires safeguards. Combining the two introduces a policy judgement into a purported risk measure. Similarly, agreement with a national-framework statement should be distinguished from endorsement of specific oversight tools. Validated measures could examine privacy, bias, misinformation and safety separately before evaluating their relationships with policy preferences.[26]

Second, institutional trust requires an identified actor and object of trust. A scale could distinguish confidence in a regulator's competence, belief in its impartiality, the expected accessibility of review and perceptions of actual performance. Such measures would allow a future study to test whether institutional credibility relates to support for a particular rule without assuming that conditional attitudes are direct trust scores.

Third, theoretical integration requires the measurement of each proposed mechanism and an appropriate design. A planned-behaviour analysis would need measures of attitudes, norms, perceived control and an identifiable intention or behaviour.[27] A mediation claim would require additional assumptions and temporal or experimental evidence. The present results provide an exploratory descriptive foundation, not confirmation of that model.

6.2 Practical implications

Universities and professional organisations can explain AI risks through concrete examples involving confidentiality, misinformation and bias, while teaching how to verify outputs and seek human review. The workbook's agreement with broad statements does not establish existing knowledge or training effectiveness; educational programmes should assess comprehension before and after instruction with appropriately designed comparison groups.

Organisations considering AI deployment can document intended use, foreseeable harms, responsible decision-makers and channels for complaints. Procedures for review should be designed for the people affected, not merely stated in a policy document. These measures reflect established responsible-AI principles and implementation concerns; the current survey did not evaluate their performance.[28]

[26] Sijtsma (n 15).
[27] Ajzen (n 13).
[28] OECD, AI Principles (n 1); Mittelstadt (n 2).

6.3 Policy and societal implications

A national dialogue can distinguish a broad desire for governance from preferences over specific obligations. Consultation materials might explain proposed scope, institutional responsibilities, risk assessment, review and costs in accessible language. They should also offer meaningful opportunities for those affected by AI systems to respond. The government's published draft can be considered in that process, while its legal status and any later revisions should be checked at the time of submission.[29]

Policy assessment should not rely on a single overall endorsement percentage. It should test how people respond to specific applications and enforcement arrangements, including the balance between protecting rights and permitting beneficial uses. The mixed survey sample is informative for developing questions but is not a mandate for a national regulatory design.

7. Conclusion, Limitations and Future Research

The analysis examined 385 adult, AI-aware survey records on ethical-risk concern and AI governance. Of these, 74.0% endorsed concern about the listed risks and 76.4% endorsed a clear national framework; 228 respondents endorsed both. These results show coexisting stated views in the recorded sample. They do not show that risk causes framework support, that respondents endorse a specific draft policy, or that a framework would prevent harm.

The study's distinctive contribution is to separate direct concern from statements about safeguards and regulatory design. It avoids interpreting a heterogeneous composite as a validated risk construct and does not infer a causal pathway from cross-sectional responses. This distinction is useful for future theory and policy research even though the questionnaire cannot establish a complete model of institutional trust or regulatory preference.

The limitations include a mixed sample, undocumented recruitment and dates, cross-sectional self-report, a single broad national-framework item, and no direct institutional-trust measure. The researcher identifies the numerical responses as real survey data. The Codebook's synthetic labels for identifiers and optional comments require documentation against source records; the contextual text was not analysed. Neither the full sample nor the law-student subset supports a national population estimate.

Future studies should document recruitment, consent and source-data linkage; measure specific perceived harms separately; and identify institutions and policy options precisely. Scenario-based questions could compare support for risk assessments, human review, transparency and remedies in different AI applications. Longitudinal or experimental studies could evaluate how information or regulatory design affects preferences, while qualitative interviews could clarify respondents' reasoning and institutional expectations.

[29] Bangladesh Draft AI Policy (n 3).

Declarations

Ethical approval and oversight

Formal ethical approval was not obtained because, at the time of the study, the authors' institutional setting did not provide an accessible formal review mechanism applicable to this non-interventional adult questionnaire research. The study nevertheless followed participant-protection safeguards, including informed consent, voluntary participation, the opportunity to discontinue, an anonymous questionnaire and aggregate reporting. The methodological safeguards are detailed in Section 3.7.

Informed consent

Informed consent was obtained from adult participants before questionnaire completion. The questionnaire explained the study purpose, voluntary participation, anonymity and the option to discontinue. All analysed records contain affirmative consent and adult-eligibility responses.

Data availability

The numerical data supporting the reported analyses are held by the research team. Requests for de-identified data and analytical specifications may be directed to the corresponding author. Any sharing is subject to participant confidentiality and applicable institutional requirements. The contextual-text field was excluded from the analysis.

Conflict of interest

The authors declare that they have no conflicts of interest.

Author contributions

Shyma Islam: Lead student researcher; conceptualisation; preparation of study materials; organisation and curation of survey data; manuscript development. The project was conducted under the supervision of Prof. Dr Kazi Abdul Mannan.

Kazi Abdul Mannan: Conceptual and methodological guidance; supervision; interpretation of statistical findings; critical review and editing of the manuscript.

Generative AI disclosure

Generative AI assisted manuscript drafting, language editing, organisation and the development of analytical code. Statistical estimates were computed programmatically from the numerical survey data. Responsibility for the study's analysis, interpretation and reporting rests with the authors.

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Appendix A. Analytical questionnaire items

Table A1 reproduces the survey statements so that each estimate can be interpreted against its exact wording.

Table A1. Exact wording of analytical items

Code	Questionnaire statement
ERS1	I am concerned about AI risks involving privacy, bias, misinformation and unsafe use.
ERS2	Greater perceived AI risk increases the need for proportionate safeguards.
ERS3	AI regulation should distinguish between lower-risk and higher-risk applications.
ERS4	Rules should protect rights without unnecessarily preventing beneficial innovation.
ERS5	I support a clear national framework for responsible AI governance.

Source: Group 17 Codebook. Response options range from strongly disagree to strongly agree.

Items are analysed separately and do not establish a single validated latent construct.