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Research Article

Algorithmic Bias Concerns and Acceptance of AI Supported Legal Decision Making in Bangladesh

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ABSTRACT

Artificial intelligence can assist legal work while creating risks of discrimination, opaque reasoning and diminished accountability. This study examines whether concern about biased training data coexists with perceived usefulness and support for safeguards among respondents to a Bangladesh legal-AI survey. The analysis uses 385 adult, AI-aware survey records supplied by the research team. Because the questionnaire combines risk perceptions, utility and governance preferences, the analysis retains individual items rather than presenting the blocks as validated scales. Descriptive distributions, paired endorsement comparisons and exploratory Spearman correlations assess distinct aspects of the research question. Concern about biased training data was endorsed by 334 respondents (86.8%), regular audits by 317 (82.3%) and a right to review or appeal by 328 (85.2%). AI assistance with organising information was endorsed by 247 (64.2%); 219 (56.9%) endorsed both this usefulness item and bias concern. The rank correlation between bias concern and perceived usefulness was small ($\rho = .075$), with no clear evidence of association after adjustment for multiple comparisons. These self-reported attitudes cannot establish the fairness of a system, causal effects or the actual conditions under which a respondent would rely on an AI recommendation. The results point to the importance of measuring perceived benefits, risk and procedural protections separately. The article integrates technology acceptance and procedural justice as a framework for future scenario-based studies and proposes proportionate auditing, meaningful human review and accessible contestation for legal decision support.

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1. Introduction

AI-enabled systems are increasingly capable of classification, prediction, summarisation, document retrieval, and pattern detection. In legal settings, such functions can assist with sorting case files, identifying potentially relevant authorities, managing workloads, and supporting preliminary analysis. Yet legal decisions are not ordinary consumer choices. They can affect liberty, livelihood, family relations, access to public benefits, reputation, and the practical ability to vindicate rights. The legitimacy of a legal decision depends not only on speed or predictive performance, but also on lawful authority, reason-giving, consistency, impartiality, opportunities to be heard, and the availability of review.

This creates a tension for AI adoption. A system may be useful and easy to operate while being difficult to audit, trained on historically skewed data, or insensitive to local legal and social context. A decision-support tool may also influence a human decision-maker through automation bias: a recommendation can receive undue weight because it appears computationally precise or institutionally endorsed.[1] Conversely, a blanket rejection of AI may forgo practical benefits such as document triage and improved access to information. The central question is therefore not whether AI should be accepted in the abstract, but under what conditions its use can be considered legitimate, contestable, and compatible with human legal judgment.

Bangladesh provides an important context in which to examine these questions. The current survey includes law students, graduates, practitioners and other respondents. Their stated views can inform questions for legal-AI governance, while the records do not establish that any particular judicial AI system is in use or meets legal standards.

The problem addressed here is the possible mismatch between functional acceptance and procedural legitimacy. Conventional technology-adoption models explain uptake through beliefs such as usefulness and ease of use,[2] but those beliefs alone do not capture whether a legal AI system treats affected people fairly or permits effective challenge. In legal contexts, a person may consider AI efficient while remaining concerned that biased data or opaque processes could produce discriminatory outcomes. Alternatively, a strong concern about bias may not necessarily produce total rejection if the system is independently audited, explainable, appealable, and confined to an assistive role.

This article examines perceived algorithmic-bias concerns and the acceptance of AI-supported legal decision-making in Bangladesh, with particular attention to perceived risk, usefulness and procedural safeguards.

Three gaps motivate the proposed model. First, a construct-level gap exists between general technology acceptance and fairness-sensitive acceptance in high-stakes

[1] Linda J Skitka, Kathleen L Mosier and Mark Burdick, 'Does Automation Bias Decision-Making?' (1999) 51 International Journal of Human-Computer Studies 991; Ifeoma Ajunwa, 'The Paradox of Automation as Anti-Bias Intervention' (2020) 41 Cardozo Law Review 1671.
[2] Fred D Davis, 'Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology' (1989) 13 MIS Quarterly 319.

legal settings. Second, a mechanism gap concerns how perceived bias, explainability, and procedural safeguards may jointly relate to willingness to use AI as an aid while retaining human authority. Third, a contextual gap concerns how these relationships should be studied in Bangladesh, where legal institutions, digital capacity, and AI governance are evolving. The available project materials do not establish that these gaps are absent from all prior scholarship; rather, they identify a focused, locally testable combination of constructs requiring careful empirical examination.

The objective is to examine reported bias concerns, perceived usefulness and support for procedural safeguards in the surveyed Bangladesh sample.

RQ1: How are perceived algorithmic bias and acceptance of AI-supported legal decision-making related?

RQ2: How often do respondents endorse individual statements about usefulness, human authority and clear rules?

RQ3: Which governance safeguards—human review, independent validation, audit for discriminatory outcomes, clear rules, and opportunities to challenge recommendations—should be distinguished in measurement and policy?

RQ4: What measurement limitations must be considered when interpreting these responses?

This article frames acceptance as conditional rather than as unqualified enthusiasm. Legal AI should be evaluated by both its practical usefulness and the fairness of the process in which it is used. The analytical framework combines the Technology Acceptance Model (TAM), research on explainable AI and trust, and Procedural Justice Theory. It also identifies a measurement issue in the supplied questionnaire: the acceptance items combine perceived usefulness, preferences for human control, support for clear rules, and opposition to autonomous adjudication. The bias/fairness items similarly combine risk concerns, audit preferences, appeal rights, and beliefs about how fairness affects acceptance. These concepts are related, but they are not interchangeable.

Section 2 develops the theoretical foundation. Section 3 describes the survey and analysis. Section 4 reports the results; Sections 5 and 6 discuss interpretation and implications. Section 7 sets out conclusions and limitations, followed by the authors' declarations.

2. Literature Review and Theoretical Foundation

The literature connects instrumental technology acceptance with concerns about accountability, bias and procedural justice. This section develops those connections while distinguishing beliefs about a system from direct evidence of its performance.

2.1 Conceptual background

AI-supported legal decision-making refers here to systems that generate classifications, predictions, summaries, rankings, or recommendations intended to inform a legal professional or institution. The term does not assume that AI itself has legal authority to decide a case. The study should explicitly distinguish low-stakes administrative support, professional research assistance, and systems that materially influence decisions about rights or legal outcomes. Their risk profiles and acceptable governance arrangements are not equivalent.

Algorithmic bias is used as a broad term for systematic unfairness in outputs or effects, which may arise from unrepresentative training data, historical discrimination, proxy variables, label choices, deployment conditions, or feedback loops.[3] Studies of algorithm-in-the-loop risk assessment also show why fairness must be considered in the interaction between a model and the people using it.[4] Perceived algorithmic bias is a respondent's belief or concern about such risks. It is not the same as a technical audit finding that a particular system is discriminatory. A survey can measure stakeholder perceptions and acceptance conditions; it cannot, by itself, establish whether an algorithm is objectively biased.

Explainability concerns whether users and affected people can understand relevant aspects of a system's output, its main contributing factors, limitations, and grounds for contestation. Technical opacity can make such scrutiny difficult,[5] and explanations are not automatically faithful, complete, or useful; an apparently clear explanation can create unwarranted confidence.[6] The ethics of algorithms also involves questions of responsibility, values, and the social context in which systems are deployed.[7] Trust should therefore be treated as calibrated reliance rather than a blanket belief that an AI system is dependable. Procedural safeguards include independent validation, regular bias audits, transparent rules, human review, the ability to challenge outputs, and meaningful appeal.

[3] Ninareh Mehrabi and others, 'A Survey on Bias and Fairness in Machine Learning' (2021) 54 ACM Computing Surveys, article 115; Solon Barocas, Moritz Hardt and Arvind Narayanan, Fairness and Machine Learning: Limitations and Opportunities (MIT Press 2023); Moritz Hardt, Eric Price and Nathan Srebro, 'Equality of Opportunity in Supervised Learning' (2016) 29 Advances in Neural Information Processing Systems.

[4] Ben Green and Yiling Chen, 'Disparate Interactions: An Algorithm-in-the-Loop Analysis of Fairness in Risk Assessments' in Proceedings of the Conference on Fairness, Accountability, and Transparency (ACM 2019) 90.

[5] Jenna Burrell, 'How the Machine Thinks: Understanding Opacity in Machine Learning Algorithms' (2016) 3(1) Big Data & Society.

[6] Alon Jacovi and Yoav Goldberg, 'Towards Faithfully Interpretable NLP Systems: How Should We Define and Evaluate Faithfulness?' in Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics (2020) 4198.

[7] Brent D Mittelstadt and others, 'The Ethics of Algorithms: Mapping the Debate' (2016) 3(2) Big Data & Society.

2.2 Theoretical foundation

TAM proposes that beliefs about a technology's perceived usefulness and ease of use help explain acceptance and use.[8] Its strength is parsimony and its focus on the user's evaluation of a system's instrumental value. In a legal context, usefulness may include efficient organisation of material, pattern detection, and support for professional work. However, a conventional TAM account can understate institutional legitimacy, rights impacts, and the distribution of risk. This article retains TAM as the instrumental layer but does not assume that usefulness is sufficient for legitimate acceptance.

Research on interpretability emphasises that explanations require rigorous definition and evaluation, and that interpretability is not a single universal property.[9] In legal decision support, explanations are relevant not only to user confidence but also to error detection, accountability, and contestability. The proposed model treats explainability and independent validation as potential conditions for calibrated reliance. A transparent interface is not a substitute for evidence of performance, nor does it resolve distributive unfairness by itself.

Procedural justice scholarship examines how people evaluate the fairness of decision processes, including opportunities for voice, neutrality, respectful treatment, and trustworthy motives.[10] These dimensions are particularly salient when decisions are consequential and decision-makers exercise authority. An AI recommendation may be viewed as procedurally deficient if its reasoning cannot be questioned or if affected people have no effective avenue for review. Conversely, human review, reason-giving, and appeal mechanisms may support legitimacy even when an AI tool is used. The theoretical implication is that acceptance in legal settings should be understood as governance-conditioned.

The integrated account distinguishes three layers: instrumental evaluation, represented by perceived usefulness; epistemic confidence, represented by explainability and validation; and procedural legitimacy, represented by fairness, contestability, and human oversight. AI literacy may help users recognise both potential benefits and limitations. The model predicts associations rather than causation because the survey is cross-sectional. It also recognises that perceptions of bias may correlate positively with support for safeguards without necessarily correlating negatively with all forms of AI assistance.

[8] Davis (n 2).

[9] Finale Doshi-Velez and Been Kim, 'Towards a Rigorous Science of Interpretable Machine Learning' (2017) arXiv:1702.08608.

[10] Tom R Tyler, Why People Obey the Law (Yale University Press 1990); E Allan Lind and Tom R Tyler, The Social Psychology of Procedural Justice (Plenum Press 1988).

2.3 Construct-specific literature and conceptual distinctions

Perceived algorithmic bias concerns whether respondents believe that AI recommendations may reflect biased data or unfair treatment. Such concerns may lower acceptance if respondents regard the risk as unmanaged. But concern can also signal risk awareness and motivate conditional acceptance when robust governance exists. This ambiguity makes a simple one-direction hypothesis insufficient unless the dependent variable is clearly defined.

Acceptance must be measured as a coherent outcome. The current AADS block contains items about organising information, finding patterns, human final authority, the value of clear rules, and rejection of autonomous judicial outcomes. Those items span perceived usefulness, conditional acceptance, policy preferences, and opposition to automation. A revised instrument should measure intention to use AI assistance separately from support for autonomous decision-making and support for safeguards.

Explainability/trust items similarly combine trust when reasons are understandable, disclosure of important factors, ability to challenge recommendations, independent validation, and caution toward unexplained outputs. These are theoretically connected but may represent at least two dimensions: explanation quality and contestability/validation. AI literacy items combine awareness of inaccuracy, verification behaviour, bias awareness, confidentiality, and human oversight. These may be responsible-use competencies rather than a single reflective trait. Measurement should be driven by theory and validated data rather than by the convenience of averaging five items.

2.4 Analytical expectations

The study examines the direction and magnitude of associations between the training-data bias concern item (ABPF1) and five items on legal AI assistance and governance (AADS1–AADS5). Higher concern could coincide with recognition of bounded usefulness, or with caution about AI decision support; neither direction is presumed to demonstrate causality. This analysis is exploratory because the supplied records do not document a preregistered hypothesis family.

2.5 Conceptual framework

Technology acceptance informs the usefulness dimension, while procedural justice directs attention to audit, challenge and human authority. The present survey measures these dimensions as separate responses. It does not measure an interaction between experimentally manipulated safeguards and acceptance, so conditional acceptance is a conceptual interpretation and not a tested moderation effect.[11]

[11] Davis (n 2); Tyler (n 10).

3. Methodology

This section explains the available records, the survey items, safeguards and statistical procedures. The analysis is designed to avoid conflating perceptions of bias with support for particular safeguards or with acceptance of autonomous decision-making.

3.1 Research design and population

The research uses a quantitative cross-sectional questionnaire. The unit of analysis is the respondent, not a court, a legal case or an AI system. The recorded categories include law students, graduates, advocates or legal professionals and other relevant respondents. Findings therefore describe this mixed sample rather than all legal practitioners in Bangladesh. Cross-sectional associations cannot determine whether one attitude preceded or caused another.[12]

3.2 Sample and records

The workbook contains 385 records with affirmative consent, adult eligibility and AI awareness coded for every respondent. The supplied file does not document the sampling frame, recruitment method, fieldwork dates, invitations or response rate. The 385 target is consistent with a common large-population sample-size calculation under specified assumptions, but the number alone does not establish random selection, population representativeness or statistical power for every analysis.[13] Respondent IDs are unique. Frequencies are reported as percentages of 385 unless otherwise stated.

The Codebook describes the identifier sequence and optional comment field as synthetic. The research team confirmed that the numerical questionnaire responses were collected from actual participants. The source and preparation of the identifier and optional text should be documented separately; optional comments were excluded. This distinction is material to reproducibility and should be clarified in the data documentation.

[12] Erik von Elm and others, 'The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Statement: Guidelines for Reporting Observational Studies' (2007) 4 PLOS Medicine e296.
[13] William G Cochran, Sampling Techniques (3rd edn, John Wiley & Sons 1977).

3.3 Questionnaire and measures

The group questionnaire uses five-point response categories from strongly disagree to strongly agree. ABPF1 asks about concern that biased training data can produce unfair recommendations; ABPF2–4 address auditing, appeal and equal-treatment testing. ABPF5 addresses the perceived role of fairness in acceptance. AADS1 and AADS2 concern usefulness for organising material and identifying patterns; AADS3 refers to human final authority; AADS4 concerns clear rules; and AADS5 favours support rather than autonomous judicial outcomes. These different statements cannot be treated as interchangeable indicators of a single acceptance outcome.

3.4 Instrument development and pilot

The available records do not identify the provenance of individual items, a documented pilot or subsequent revisions. No pilot, validation or adaptation procedure is assumed. The original questionnaire and Codebook provide the item wording. The measurement block combines distinct concepts; a high or low reliability coefficient alone cannot establish or disprove construct validity.[14] Future research should investigate item interpretation, dimensionality and measurement invariance before estimating latent paths.

3.5 Data collection and screening

The records encode consent, adult eligibility, AI awareness, demographics and closed-ended answers. The dates, recruitment venues, distribution method, nonresponse and independent duplicate-screening procedures are not documented in the supplied workbook. Numeric items analysed in this study are complete; optional text and fields unrelated to the focal analysis do not determine the denominator. We do not infer a response rate or the extent of any prior data cleaning from the final file.

3.6 Analytical strategy

For each focal item, the response distribution and endorsement count are presented. Endorsement means a response of 4 or 5; non-endorsement also includes neutral responses, so it is not synonymous with opposition. Pointwise 95% Wilson intervals describe sampling uncertainty under conventional assumptions; their interpretation as population intervals depends on a sampling design that is not documented.[15]

A paired comparison describes endorsement of ABPF1 and AADS1 among the same respondents; the two statements differ in wording and are not alternatives in a forced choice. Exact McNemar testing examines discordant paired responses. Five Spearman rank correlations compare ABPF1 with each AADS item; Holm adjustment controls the family-wise error rate across these five

[14] Klaas Sijtsma, ‘On the Use, the Misuse, and the Very Limited Usefulness of Cronbach’s Alpha’ (2009) 74 Psychometrika 107.
[15] Cochran (n 13).

exploratory tests. The adjusted p-values should not be used as proof that associations are absent. Results are descriptive and exploratory, with no claims of causation, interaction, scale validity or actual system bias.[16]

3.7 Ethical considerations

The authors report that formal approval was not obtained because no accessible formal review mechanism applied in their institutional setting at the time of this non-interventional adult questionnaire study. The authors state that participants received information about the purpose, voluntary participation, anonymity and discontinuation, and provided consent before completing the questionnaire. Analysis uses aggregate numerical records; the optional contextual text was excluded. The absence of formal review does not remove the authors' responsibility for participant protection and accurate disclosure. The authors' complete statements appear in Section 8.

4. Results

The following findings describe the 385 coded respondents and their self-reported views. The analysis separates perceived bias, support for procedures and perceived usefulness, rather than treating their coexistence as evidence of causal acceptance.

4.1 Sample profile

Table 1 displays recorded current status. Students comprise most records; the professional category is substantially smaller, limiting comparisons between groups and generalisation to practising lawyers.

Table 1. Respondents by recorded current status

Current status	Count (%)
Law student	250 (64.9%)
Law graduate	73 (19.0%)
Advocate or legal professional	36 (9.4%)
Other relevant respondent	26 (6.8%)

N = 385. Percentages may not sum to 100 because of rounding.

The composition supports careful description of the total sample but not a claim that the percentages represent the national legal profession. Education level and current status are separate fields and should not be equated.

4.2 Bias concern and safeguards

Table 2 presents the distributions of five fairness items. They measure related but distinct concerns and preferences, and are therefore not averaged into a single construct.

Table 2. Bias concern and governance preferences

Item	Response counts 1 / 2 / 3 / 4 / 5	Agree n (%)	95% CI (%)
ABPF1	0 / 2 / 49 / 182 / 152	334 (86.8%)	83.0–89.8
ABPF2	0 / 5 / 63 / 177 / 140	317 (82.3%)	78.2–85.8
ABPF3	0 / 6 / 51 / 186 / 142	328 (85.2%)	81.3–88.4
ABPF4	1 / 15 / 119 / 189 / 61	250 (64.9%)	60.0–69.5
ABPF5	0 / 14 / 123 / 175 / 73	248 (64.4%)	59.5–69.0

N = 385. Endorsement combines agree and strongly agree; neutral responses are not opposition. Wilson intervals are pointwise.

[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; Ronald L Wasserstein and Nicole A Lazar, 'The ASA Statement on p-Values: Context, Process, and Purpose' (2016) 70 American Statistician 129.

Exact item wording appears in Table 6.

Concern about biased training data was endorsed by 334 respondents (86.8%). Regular audits were endorsed by 317 (82.3%), and review or appeal by 328 (85.2%). Endorsement of equal-treatment testing and of fairness affecting acceptance was lower, at 250 (64.9%) and 248 (64.4%), respectively. Different wording and response distributions preclude interpreting these differences as evidence that respondents rank safeguard importance.

4.3 Usefulness, human authority and rules

Table 3 reports the five decision-support items separately. Support for a clear-rules statement is not itself a measurement of actual use, and the human-authority items should not be equated with an experimentally measured preference for autonomous adjudication.

Table 3. Decision-support and governance responses

Item	Response counts 1 / 2 / 3 / 4 / 5	Agree n (%)	95% CI (%)
AADS1	0 / 17 / 121 / 179 / 68	247 (64.2%)	59.2–68.8
AADS2	0 / 18 / 112 / 171 / 84	255 (66.2%)	61.4–70.8
AADS3	1 / 24 / 117 / 173 / 70	243 (63.1%)	58.2–67.8
AADS4	0 / 7 / 57 / 168 / 153	321 (83.4%)	79.3–86.8
AADS5	0 / 17 / 122 / 186 / 60	246 (63.9%)	59.0–68.5

N = 385. Endorsement combines agree and strongly agree; neutral responses are not opposition. Wilson intervals are pointwise. Exact item wording appears in Table 6.

The item on assistance in organising information was endorsed by 247 respondents (64.2%). Clear rules increasing acceptance was endorsed by 321 (83.4%). Human final authority and support rather than autonomous determination were endorsed by 243 (63.1%) and 246 (63.9%), respectively. Each item has a substantial neutral category, so the remainder cannot be classified as opposing oversight.

4.4 Coexistence of concern and perceived usefulness

Table 4 cross-tabulates endorsements of bias concern and usefulness for organising legal material. This is a descriptive joint distribution, not a test of how one item causes the other.

Table 4. Joint endorsement of bias concern and usefulness

Response configuration	Count (%)
Both items endorsed	219 (56.9%)
Bias concern only	115 (29.9%)
Usefulness only	28 (7.3%)
Neither endorsed	23 (6.0%)

N = 385. Neither includes neutral as well as disagreement. These are not fixed participant types.

A total of 219 respondents (56.9%) endorsed both items. Bias concern alone was endorsed by 115 (29.9%), and usefulness alone by 28 (7.3%); 23 (6.0%) endorsed neither. The paired endorsement difference was 22.6 percentage points in favour of concern; the exact McNemar p-value was less than .001. This contrast reflects different questions and response tendencies rather than a measured difference in importance.

4.5 Exploratory associations

Table 5 reports the five rank correlations between bias concern and the individual AADS responses, with Holm-adjusted p-values. These ordinal associations do not establish validated latent relationships or indicate how attitudes would change under a real deployment.

Table 5. Exploratory correlations with bias concern

Item	Spearman ρ	95% CI	p	Holm p
AADS1	0.075	-0.031–0.176	0.143	0.286
AADS2	0.095	-0.003–0.193	0.062	0.247
AADS3	0.086	-0.013–0.184	0.093	0.278
AADS4	0.106	0.003–0.208	0.037	0.185
AADS5	0.054	-0.049–0.157	0.292	0.292

N = 385. Pointwise percentile intervals from 2,000 respondent-level bootstrap resamples; five p-values adjusted using Holm's method. Intervals are not multiplicity adjusted.

The relationship between bias concern and perceived usefulness for organising material was small (ρ = .075). None of the five correlations remains distinguishable from zero after Holm adjustment. Confidence intervals and the limitations of self-report mean the analysis should not be interpreted as proving that bias concerns and acceptance are unrelated. The clear-rules item has an unadjusted association, but the multiplicity-adjusted result does not support singling it out as a confirmed finding.[17]

5. Discussion

The results suggest that concern about bias and recognition of a specific practical use can coexist in the same sample. They do not establish that safeguards increase acceptance or that biased recommendations occur in a particular Bangladeshi institution. This section considers the descriptive patterns alongside technology acceptance, procedural justice and algorithmic accountability research.

5.1 Bias concern and bounded usefulness

Most respondents endorsed concern about biased training data, while a majority also endorsed the potential usefulness of organising legal information. More than half endorsed both. This joint pattern is compatible with the view that perceived utility and risk are distinguishable, but the questionnaire did not ask respondents to choose a trade-off, evaluate a named tool, or disclose how they would use one. Agreement with one statement cannot be treated as an answer to the other. TAM helps explain why instrumental usefulness matters, while work on algorithmic fairness identifies different sources of discriminatory outcomes. Neither theory implies that perceived usefulness overrides concerns about equal treatment.[18]

[17] Douglas G Altman and J Martin Bland, 'Absence of Evidence Is Not Evidence of Absence' (1995) 311 BMJ 485; Wasserstein and Lazar (n 16).
[18] Davis (n 2); Mehrabi and others (n 3); Barocas, Hardt and Narayanan (n 3).

The small correlation between the two focal items limits support for a simple claim that bias concern is tightly associated with rejection of useful assistance. The uncertainty around an association is not evidence of a zero effect. The distinction matters because the source instrument measures usefulness for organisation, not a general willingness to rely on high-stakes recommendations. A different legal task or a specific unfair outcome could generate a different relationship.[19]

5.2 Audits, appeal and procedural justice

High endorsement of auditing and review rights gives a descriptive basis for discussing safeguards. Procedural justice theory draws attention to voice, neutrality and the opportunity to question decisions; these features differ from a user's evaluation of speed or efficiency.[20] However, the survey does not show that respondents would accept an otherwise unacceptable tool if particular protections were provided. The questionnaire also cannot show whether an appeal procedure is accessible or effective in practice.

Auditing is not a single technical action. It may involve testing errors and disparate impacts, examining data provenance, documenting intended use and monitoring post-deployment effects. Meaningful review requires an accountable decision-maker with authority, information and time to reconsider a recommendation. Auditing and review are complementary and should not be substituted for one another.[21]

A Norwegian vignette experiment found differences in perceived fairness when human involvement and explainability varied; its sentencing setting and experimental design differ from this Bangladesh questionnaire, so the results are not directly comparable.[22]

5.3 Explainability and trust

Understanding why a recommendation was produced may help a professional identify missing information and challenge an output. Yet explanations differ in accuracy, audience and purpose, and an intelligible presentation need not prove that a system is fair or reliable.[23] The present items measure agreement with statements about trust and disclosure rather than independently verified explainability. Future research should distinguish what the system explains, whether the explanation faithfully reflects its operation and whether users can act on it.

Automation bias further complicates human oversight. If a reviewer automatically defers to a recommendation, the formal presence of a human may not prevent an error. Training, independent checks and institutional authority to disagree are relevant to meaningful supervision, but their

[19] Altman and Bland (n 17); Green and Chen (n 4).

[20] Tyler (n 10); Lind and Tyler (n 10).

[21] Joshua A Kroll and others, 'Accountable Algorithms' (2017) 165 University of Pennsylvania Law Review 633; Inioluwa Deborah Raji and others, 'Closing the AI Accountability Gap: Defining an End-to-End Framework for Internal Algorithmic Auditing' in Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency (ACM 2020) 33; Andrew D Selbst and others, 'Fairness and Abstraction in Sociotechnical Systems' in Proceedings of the Conference on Fairness, Accountability, and Transparency (ACM 2019) 59.

[22] Henrik Litleré Bentsen and Mikael Poul Johannesson, 'Algorithmic Sentencing and Fairness Perceptions' (2026) DOI: 10.1177/2755323X261486564.

[23] Burrell (n 5); Doshi-Velez and Kim (n 9); Jacovi and Goldberg (n 6).

effectiveness requires direct evaluation.[24]

5.4 Implications of the measured associations

After correction for five exploratory comparisons, no bias-concern/AADS association provided clear evidence against a null association. The results should neither be presented as confirmation of a negative relationship nor as proof that bias perceptions play no role. The associations are between single items with substantial ties, recorded simultaneously; unmeasured prior exposure, legal experience and interpretations of AI may affect responses. A study based on explicitly defined scenarios and separate measures of risk, willingness, trust and safeguards would permit a more informative test.

The questionnaire combines several attitudes in each named block. Composite regression could conceal whether an apparent relationship reflects support for audits, concern about discrimination or a preference for human authority. The item-level approach gives up a single summary measure but makes the basis of each conclusion visible. A subsequent study can develop and validate separate constructs if its data and design support them.[25]

5.5 Bangladesh context and interpretation

The sample is dominated by students, with a smaller number of practising professionals. It offers insight into the respondents recorded in the workbook, not a representative account of judges, advocates or the public. In addition, attitudes to hypothetical legal uses cannot identify a real system's accuracy or compliance. Local evaluation would need task-specific information, consultation with affected communities and documentation of actual deployment conditions. Sociotechnical research shows why fairness must be examined within the institution and workflow where a system is used.[26]

6. Theoretical and Practical Implications

The study contributes a distinction between perceived risk, perceived task-specific benefit and governance preferences. The implications are grounded in reported responses and the literature; they are proposals for assessment, not evidence that any intervention is effective.

[24] Skitka, Mosier and Burdick (n 1); Green and Chen (n 4).
[25] Sijtsma (n 14).
[26] Selbst and others (n 21); Mittelstadt and others (n 7).

6.1 Theoretical implications

Technology acceptance and procedural justice are complementary: one concerns instrumental evaluations, while the other foregrounds the legitimacy of processes and treatment. The joint endorsement of concern and usefulness supports keeping the concepts separate in future models. It does not validate the integrated framework or show that procedural justice moderates acceptance.[27]

The instrument also points to a measurement problem: acceptance of assistance for organisation is distinct from willingness to let AI decide an outcome. Future research should specify which task, user and decision are being evaluated, and distinguish support for safeguards from the risk that makes safeguards desirable. Qualitative interviews and scenario experiments can test whether the same wording has comparable meaning across students, legal professionals and affected persons.

6.2 Practical and policy implications

Institutions considering a tool should define its use, identify relevant legal and procedural duties, and assess error, security and potential unequal impacts before deployment. A documented validation plan should identify limitations, use cases, oversight responsibilities and monitoring arrangements. Risk-management guidance can inform this process, but general frameworks do not replace applicable local law or evidence about a particular tool.[28]

Human oversight should include access to the underlying materials and authority to reject a recommendation. Affected persons should receive meaningful information and an available route to challenge a decision where applicable. Institutions should train users to check sources and avoid placing confidential material in unsuitable systems. These recommendations are prospective and require evaluation of feasibility and effectiveness.

7. Conclusion, Limitations and Future Research

Among 385 recorded respondents, 86.8% endorsed concern about biased training data and 64.2% endorsed potential assistance with organising legal information. A majority endorsed both. Audit and appeal items also attracted high endorsement. Exploratory correlations did not establish clear relationships between the bias-concern item and the five decision-support statements after multiplicity adjustment.

The findings distinguish beliefs about risk, usefulness and governance. They do not demonstrate that a system is fair or unfair, that safeguards cause acceptance, or that an AI tool has been deployed in a particular court. The data are cross-sectional and self-reported; sampling and fieldwork details are unavailable, and the instrument does not establish validated latent scales. The Codebook's synthetic identifier and text labels, alongside the authors' confirmation of real numerical responses, should be reconciled in a data-provenance record.

[27] Davis (n 2); Tyler (n 10).

[28] National Institute of Standards and Technology, Artificial Intelligence Risk Management Framework (AI RMF 1.0) (US Department of Commerce 2023) <https://doi.org/10.6028/NIST.AI.100-1>; Raji and others (n 21).

Future studies should document recruitment and dates, validate distinct measures and use scenarios that vary the task, degree of human control, audit information and review rights. Follow-up interviews can clarify how respondents understand fairness and oversight. Technical audits and observed decisions, where lawful and feasible, would complement perceptions and help assess real-world performance.

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. The absence of an accessible review mechanism describes the institutional context; responsibility for ethical conduct remained with the researchers.

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.

Author contributions

Israt Jahan Maisha: 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. Focal questionnaire items

Table 6 reproduces the statements analysed in this article so that the scope of each result can be assessed against its exact wording.

Table 6. Exact wording of focal survey items

Code	Statement
ABPF1	I am concerned that biased training data can produce unfair AI recommendations.
ABPF2	AI systems used in legal settings should be regularly audited for discriminatory outcomes.
ABPF3	People affected by AI-supported decisions should have access to review or appeal.
ABPF4	Equal treatment should be tested before AI is deployed in legal decision making.
ABPF5	Perceived fairness strongly affects my acceptance of AI-supported legal decisions.
AADS1	AI decision-support tools could assist legal professionals in organizing relevant information.
AADS2	AI tools could be useful for identifying patterns in large volumes of legal material.
AADS3	I would use AI decision support only when a human decision-maker retains final authority.
AADS4	Clear rules for AI use would increase my acceptance of AI decision-support systems.
AADS5	I believe AI should support rather than autonomously determine judicial outcomes.

Source: Group 3 Codebook. Five response categories range from strongly disagree to strongly agree.

These items are not treated as interchangeable indicators of a single latent construct.