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Research Article

Views on AI Decision Support and Human Authority in Legal Settings in Bangladesh

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ABSTRACT

Artificial intelligence (AI) may assist legal professionals in organising information, but its use in legal decision support raises questions about human authority, explanation and procedural safeguards. This study examines responses to related statements in 385 adult, AI-aware survey records from Bangladesh. The mixed sample includes 250 law students, 73 law graduates, 36 advocates or legal professionals and 26 other respondents; it is not presented as a representative survey of practising lawyers or judges. Individual questionnaire items are analysed using response distributions, joint endorsement, paired comparisons and exploratory ordinal correlations. Of 385 respondents, 247 (64.2%) agreed that AI decision-support tools could help legal professionals organise relevant information, 243 (63.1%) endorsed use only when a human decision-maker retains final authority, and 321 (83.4%) agreed that clear rules would increase their acceptance. A total of 158 (41.0%) endorsed both the information-organisation and human-authority statements. Within the 36 recorded advocates or legal professionals, 26 endorsed the former and 18 the latter; the subgroup is too small for a representative professional estimate. The survey does not measure actual use of a judicial system or demonstrate that oversight or rules improve outcomes. The article distinguishes perceived assistance from conditions of use and recommends direct testing of legal information quality, meaningful human review and opportunities to challenge AI-supported recommendations.

Keywords: artificial intelligence; legal decision support; human authority; explainability; procedural fairness; Bangladesh

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1. Introduction

AI tools can assist with searching, classifying and organising legal material. Such uses raise questions about reliability, sources, confidentiality and the user's responsibility for checking results. When a tool informs a decision affecting rights, liberty or access to remedies, additional questions arise about who makes the final decision, whether reasons can be examined and whether an affected person can challenge the outcome. Assistance with legal information is therefore analytically different from an autonomous system determining a judicial outcome.

The European Commission for the Efficiency of Justice's 2018 ethical charter addresses AI in judicial systems with attention to fundamental rights, non-discrimination, quality, transparency and user control.[1] UNESCO's 2025 guidelines for courts and tribunals similarly discuss transparency, accountability, human oversight and institutional governance.[2] These instruments provide comparative guidance; they do not by themselves establish that a particular AI system is used in Bangladesh or has been approved for a particular court.

The value of an explanation also cannot be inferred solely from its availability. It matters whether a user can assess its accuracy, identify missing evidence and challenge the recommendation. Research on legal language models has documented plausible but incorrect legal outputs, illustrating why checking sources and system performance is important.[3] Courts, professionals and affected persons may need different explanations and different forms of review.

The study's original focus is acceptance of AI-assisted decision support among legal professionals in Bangladesh. The workbook records a mixed sample: 250 law students, 73 law graduates, 36 advocates or legal professionals, and 26 other relevant respondents. It does not establish that all respondents are practising legal professionals or that any respondent is a judge or has used an AI system in court. A full-sample result cannot therefore be described as a representative estimate for legal professionals or judicial officers.

The questionnaire also contains distinct statements: whether AI can help organise information, whether it can identify patterns, whether the respondent would use it only with human final authority, whether clear rules could increase acceptance, and whether AI should support rather than autonomously determine judicial outcomes. These are different propositions. A positive response to an information-organisation statement is not proof of willingness to use a tool in a specified case, and agreement with a human-authority condition is not evidence that meaningful review occurs in practice.

Acceptance studies often discuss perceived usefulness, but a legal decision can affect persons who are not the system's direct users. Technology acceptance theory therefore needs to be considered alongside procedural questions about reasons, challenge and human responsibility. The classic technology acceptance model identifies perceived usefulness and ease of use as factors associated with use

intentions.[4] The present instrument does not measure the complete model, and the legal context requires additional concepts that cannot be assumed from utility alone.

Recent work on AI-assisted judicial decisions explores how explanations and human review affect perceived fairness and trust in defined experimental settings.[5] This article contributes a different perspective: it describes how respondents in a mixed, AI-aware Bangladesh sample answer separate questions about information support, human final authority and rules. It reports the 36-person professional subgroup separately and distinguishes expressed conditions of use from an observed legal procedure or measured technology effect.

The objectives are to describe the five decision-support statements; examine whether endorsement of information-organisation assistance coexists with the human-authority condition; explore selected associations with explainability and procedural safeguards; and present a descriptive professional subgroup. The research questions are: How often are these statements endorsed? How frequently are perceived assistance and human final authority endorsed together? What patterns appear among the recorded advocates or legal professionals? How uncertain are the selected item-level associations?

These questions concern the supplied records rather than all Bangladeshi legal professionals. They do not test whether any AI system improves legal accuracy, changes court outcomes or causes users to accept a decision.

2. Literature Review and Theoretical Foundation

This section distinguishes technical assistance, professional acceptance and procedural safeguards. It uses technology acceptance, explainability and procedural justice as interpretive perspectives while recognising the questionnaire's measurement limits.

2.1 AI assistance in legal and judicial work

Legal work can involve locating authorities, organising documents, identifying relevant facts and comparing material across cases. A tool that helps retrieve or organise information may be useful without making or recommending a judicial decision. The questionnaire's AADS1 item concerns assistance with organising relevant information; AADS2 concerns identifying patterns in large volumes of legal material. Neither specifies a deployed system, a court, a case type or a particular user task.

Judicial decision support is a narrower and higher-stakes setting. A recommendation may affect the framing of evidence or legal issues even when the final decision remains formally human. For this reason, assessing a tool would require examining its intended use, the data it receives, its performance, the opportunity to question it and the decision-maker's actual ability to disregard it. UNESCO's court guidelines place human oversight and institutional governance within this broader lifecycle.[6]

A general statement that AI may assist legal work does not establish that a tool is accurate or appropriate for confidential

information. In an empirical evaluation of legal language models, Dahl and colleagues document the risk of inaccurate legal assertions.[7] Their findings support attention to verification but do not measure the performance of a system used by respondents in this survey. The dataset does not identify such a system or record a benchmark of its outputs.

2.2 Technology acceptance and its boundaries

The technology acceptance model proposes relationships involving perceived usefulness, ease of use and adoption-related intentions.[8] It provides a starting point for considering why a professional might use a tool to organise legal materials. It does not by itself resolve whether an affected person received a fair hearing or whether a decision-maker exercised independent judgement. A process can be convenient to a user while still raising procedural concerns for another participant.

The AADS block mixes perceived assistance, conditional willingness to use, an expected effect of rules on acceptance, and a normative position on autonomous judicial outcomes. These questions are useful individually, but their mean is not automatically a validated acceptance score. In particular, endorsement of a condition such as human final authority does not reveal whether a respondent would use a specific system if that condition were met. The survey also does not directly measure all standard TAM constructs or actual adoption.

2.3 Human authority and meaningful review

Human final authority can mean that a person formally signs a decision, but effective oversight requires more than a formal designation. The human decision-maker needs adequate time, information, competence and authority to examine and depart from an AI recommendation. If a system's output is difficult to question or the working environment pressures a user to follow it, formal authority may not translate into meaningful scrutiny. These are design and institutional questions, not outcomes measured by the present survey.

The AADS3 statement asks about use only when a human retains final authority. AADS5 states that AI should support rather than autonomously determine judicial outcomes. The two statements concern related but different objects: one is a personal condition of use, while the other concerns the role AI should play in judicial outcomes. Their endorsement should not be treated as proof that respondents reject every form of automation or that courts have adopted a particular oversight procedure.

An experimental study by Chen and colleagues examines perceptions of human, algorithmic and human-reviewed algorithmic legal decisions in defined scenarios.[9] It is relevant because it separates different forms of decision-making, but its experimental outcomes do not establish what happens in the present Bangladesh sample. Direct evaluation of actual workflows would be needed to assess whether human review changes errors, reasons or outcomes.

2.4 Explainability, challenge and procedural justice

Explainability can refer to information about a system's general operation, the factors relevant to a particular recommendation, or a reasoned account of a final decision. These forms are not interchangeable. A technically detailed description may not answer an affected person's question about why a decision was made, and a persuasive narrative may not faithfully represent the system's operation. An explanation should therefore be evaluated for accuracy, relevance and usability, not only for whether it increases confidence.

Procedural justice concerns features of a decision process such as respectful treatment, neutrality and opportunities for voice.[10] In the survey, EXT1 asks whether understandable reasons increase trust in an AI recommendation, and EXT3 asks whether users should be able to challenge AI-supported recommendations. These are conditional and normative statements, not direct observations of an explanation or a successful challenge.

Greene and colleagues' 2026 experiment reports effects of explanation conditions on perceived procedural justice and trust in hypothetical AI-assisted judicial scenarios.[11] Its findings motivate careful attention to explanations in legal settings. The current cross-sectional survey, however, does not present explanation conditions and cannot establish an explanation effect or mediation through procedural justice.

2.5 Fairness, discrimination and access to review

A model can generate unequal outcomes through its training data, design or use in a wider institutional process. Barocas and Selbst examine how data-driven systems may generate disparate impact, while Binns demonstrates that fairness can be defined in different and potentially conflicting ways.[12] These analyses illustrate why a general commitment to fairness is not a complete testing protocol.

The questionnaire asks about concern that biased data can produce unfair recommendations, audits for discriminatory outcomes, access to review or appeal, equal-treatment testing and the effect of perceived fairness on acceptance. These statements address risk, recommended safeguards and personal attitudes. Their aggregate would not tell a reader whether a particular system is fair, whether an audit has occurred or whether an appeal is available. The present article treats selected items as context for understanding perceived conditions around assistance.

2.6 Theoretical integration and analytical expectations

Technology acceptance, explainability and procedural justice illuminate different aspects of the issue: usefulness to a professional, intelligibility of a recommendation and fairness to those affected. These perspectives are complementary but do not constitute a validated structural model in the supplied data. A credible test would need distinct measures, an identified tool or scenario, and evidence that the relevant constructs are sufficiently measured.

The analysis focuses on AADS1 as a statement of potential information-organisation assistance, AADS3 as a human-authority condition, AADS4 as a view that clear rules could increase acceptance, and selected explanation and review items. Three exploratory paired comparisons use AADS1 against AADS3, AADS4 and AADS5. Four exploratory Spearman correlations compare AADS1 with AADS3, AADS4, EXT1 and EXT3. The comparisons are selected for this analysis; they are not preregistered hypothesis tests or evidence of causal effects.

A decision-support system can affect several people with different information needs. A lawyer may need to verify a citation, a judicial officer may need to examine the reasoning behind a recommendation, and a party may need to understand how a decision was reached and what can be challenged. A single question about a user's acceptance does not capture all three relationships. Procedural justice therefore provides an important complement to a user-centred account of adoption, while requiring direct study of the people affected by a process.[13]

The distinction also affects how system success is defined. A professional may save time, yet an error could impose substantial costs on a client or another party. Conversely, a tool could make some tasks slower while improving the documentation of information considered. Evaluation should identify whose time, risk and opportunity to be heard are being measured. The present survey offers views about a potential tool; it does not establish these costs or benefits.

An explanation may be directed at a developer assessing a model, a professional checking a recommendation, or a person who has received a decision. The level of detail and language appropriate to each audience may differ. A system-level description can clarify intended use and limitations, while a case-specific account can help a user inspect the basis of a recommendation. Neither automatically proves that the recommendation is correct or that the final decision is legally justified.

An explanation also needs an associated process. A person who identifies an apparent error must know how to raise it, whether a human will consider it and whether the decision can be corrected. An appeal that exists only on paper may not provide effective review where time limits, costs or inaccessible information prevent its use. These considerations are consistent with the distinction between ethical principles and practical implementation.[14] They are not observations from the present questionnaire,

which asks about general views rather than real proceedings.

A future experiment could present participants with the same legal task under different conditions: no AI assistance, assistance with an explanation, and assistance with an explanation plus an opportunity to challenge it. The content and accuracy of each recommendation would need to be independently verified. Researchers could measure whether participants identify errors, how they use their authority and whether affected persons understand the process. This would make it possible to distinguish perceived acceptance from demonstrated scrutiny, subject to the limitations of an experimental scenario.

A complementary field study could examine a defined deployment with appropriate permissions and confidentiality protections. It would need to record which decisions are within the tool's intended scope, what information is entered, who can override a recommendation and how mistakes are handled. Comparisons should consider changes in the underlying workload and case mix. Neither a high rate of agreement with a tool nor a low error rate in a simplified task is sufficient on its own to establish procedural fairness in actual legal proceedings.

2.7 Legal-institutional context

The Bangladesh AI policy portal presents a draft National Artificial Intelligence Policy 2026–2030.[15] The document is used as policy context and not as evidence of a binding court rule. The survey dates are not documented and respondents were not asked whether they had read the draft. Consequently, their answers cannot be treated as an evaluation of specific provisions of that policy.

Comparative principles from UNESCO and CEPEJ can guide questions about the design of legal AI systems, but their application in Bangladesh must be considered in light of domestic law, court procedures and institutional arrangements. The dataset contains no case record or deployment details from which to determine a legal duty, a breach or the availability of a particular remedy.

3. Methodology

This section explains the recorded population, questionnaire, analysis and ethical safeguards. The choices are tied to what the supplied workbook actually measures.

3.1 Research design and population

The study analyses 385 cross-sectional questionnaire records. Each record is coded as consenting, adult eligible and aware of AI. Recorded status categories are law student, law graduate, advocate or legal professional, and other relevant respondent. The final category is not further described. The workbook does not identify judicial office, court experience, a particular employer or use of AI in legal proceedings.

The unit of analysis is an individual response. This design describes stated attitudes at one time and explores associations; it cannot determine whether an explanation, rule or oversight mechanism caused a change in acceptance. Nor does it demonstrate that an AI tool was deployed or that a court adopted a technology. Terms such as usefulness and trust are interpreted as responses to specific statements rather than as independently validated latent constructs.

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 or distribution methods, response rate or independent duplicate-screening procedures. A conventional target of 385 can be calculated under specified assumptions, but the number does not establish probability sampling or a national margin of error.[16] No claim of representative sampling is made.

The researcher identifies the numerical responses as real survey data. The Codebook describes the respondent identifier sequence and optional contextual comments as synthetic. These labels do not independently prove that numerical answers are synthetic, but the creation of the fields and their relationship to original questionnaires require documentation. The optional contextual-text field was excluded from analysis. Source records, recruitment information and consent documentation are needed for verification and reproducibility.

3.3 Questionnaire and measures

The five-point response scale runs from strongly disagree to strongly agree. AADS1 asks whether AI decision-support tools could assist legal professionals in organising relevant information; AADS2 asks about identifying patterns in legal material; AADS3 asks about use only with human final authority; AADS4 asks whether clear rules would increase acceptance; and AADS5 concerns AI support rather than autonomous determination of judicial outcomes. Appendix A reproduces exact wording.

EXT1 addresses greater trust when the main reasons behind a recommendation are understandable; EXT3 concerns the ability to question or challenge AI-supported recommendations. ABPF3 concerns access to review or appeal for affected people. These statements differ in who would act and what process is contemplated. They do not establish that an explanation, review or appeal was provided or successful.

All focal numerical items contain valid responses for the 385 records. The materials do not document a separate pilot, item adaptation, cognitive testing, preregistration

or a validated measurement model. The five AADS items are not averaged into a single validated acceptance scale. Low internal consistency in preliminary diagnostics is a reason to examine item meaning, but it does not by itself explain why responses differ.[17]

3.4 Descriptive and paired analysis

Each item is summarised using counts for the five response categories and the number and percentage selecting agree or strongly agree. Neutral and disagreeing answers are kept separate in the response distributions. For joint and paired summaries they are combined as non-endorsement; this is a numerical convention and does not mean that neutral respondents oppose an item.

Three within-person comparisons contrast endorsement of AADS1 with AADS3, AADS4 and AADS5. Exact McNemar tests use discordant pairs, with Holm adjustment across the three comparisons. Percentage-point differences have pointwise percentile bootstrap intervals from 10,000 respondent-level resamples.[18] Different wording means the contrasts cannot rank the importance of safeguards, establish effects of clear rules or determine a user's preference between mutually exclusive systems.

3.5 Exploratory correlations and professional subgroup

Four exploratory Spearman correlations compare the original five-category AADS1 responses with AADS3, AADS4, EXT1 and EXT3. Holm adjustment covers the four p-values, while percentile bootstrap intervals from 2,000 respondent-level resamples are pointwise and not adjusted for multiple testing. These analyses were selected for this study without a claim of preregistration. Statistical uncertainty should be interpreted alongside estimates; a non-significant result is not evidence of no relationship.[19]

The 36 records coded as advocates or legal professionals are summarised separately. Their responses are useful for describing this subgroup but are too few, and recruited through an undocumented process, to represent legal professionals in Bangladesh. No formal comparison with students or causal subgroup claim is made. The category does not distinguish advocates from other legal professionals, identify judges or document actual use of decision-support systems.

3.6 Data handling and uncertainty

All 385 records are retained for focal numerical analyses. No weighting or imputation is applied. The optional contextual-comment field is excluded, and results are reported in aggregate. Pointwise Wilson intervals describe statistical uncertainty under conventional assumptions, but the undocumented selection process means that they cannot be interpreted as national population intervals.

Responses may be shaped by the wording of a broad statement, common scale format, differing professional experiences and assumptions about a hypothetical tool. A person who selects neutral may be uncertain, indifferent or have another unrecorded reason. Exact wording and distributions are therefore reported to permit readers to assess the analytical categories. No claim is made that the questionnaire has observed behaviour, case outcomes or system performance.

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 analysed records; the workbook alone cannot independently verify the consent process or institutional context. The authors' declarations appear in Section 8.

4. Results

The results describe stated views in the supplied sample. They do not establish the accuracy, adoption or legal status of any judicial AI system.

4.1 Respondent profile

Table 1 reports the age and status categories recorded in the workbook. These categories distinguish the mixed sample and the small professional subgroup.

Table 1. Recorded age and respondent status

Measure	Category	Count (%)
Age	21-23	149 (38.7%)
	24-26	90 (23.4%)
	18-20	67 (17.4%)
	31+	43 (11.2%)
	27-30	36 (9.4%)
Status	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. Recorded status does not establish a representative national sample or judicial role.

The records include 250 law students (64.9%), 73 law graduates (19.0%), 36 advocates or legal professionals (9.4%) and 26 other relevant respondents (6.8%). The professional category does not identify a specific occupation or judicial role. The recorded age and status distributions do not establish population representativeness.

4.2 Decision-support statements

Table 2 presents full responses to the five AADS statements. Perceived assistance, conditions of use and views about judicial authority are retained as separate items.

Table 2. Decision-support statements

Item	Counts 1 / 2 / 3 / 4 / 5	Endorsed 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 means agree or strongly agree; neutral answers are not opposition. Wilson intervals are pointwise; exact wording is in Appendix A.

A total of 247 (64.2%) endorsed the information-organisation statement, 243 (63.1%) endorsed use only with human final authority, and 321 (83.4%) agreed that clear rules would increase their acceptance. The latter is a stated expectation, not a measured effect of rules on actual behaviour.

4.3 Joint responses on assistance and human authority

Table 3 shows the joint endorsement of AADS1 and AADS3 within the same respondents. Their content differs, so the categories are not fixed types of legal users.

Table 3. Joint endorsement of assistance and human authority

Response configuration	Count (%)
Both endorsed	158 (41.0%)
Assistance only	89 (23.1%)
Human authority only	85 (22.1%)
Neither endorsed	53 (13.8%)

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

Overall, 158 (41.0%) endorsed both statements. Eighty-nine endorsed potential information-organisation assistance without endorsing the human-authority item; 85 endorsed the human-authority item without endorsing the assistance item. Non-endorsement includes neutral answers and should not be interpreted as an explicit rejection of human control or assistance.

4.4 Recorded advocates and legal professionals

Table 4 presents the same five items for the 36 records coded as advocates or legal professionals. The subgroup is small and its recruitment is undocumented.

Table 4. Endorsement among advocates or legal professionals

Item	Endorsed n (%)	95% CI (%)
AADS1	26 (72.2%)	56.0–84.2
AADS2	28 (77.8%)	61.9–88.3
AADS3	18 (50.0%)	34.5–65.5
AADS4	27 (75.0%)	58.9–86.2
AADS5	21 (58.3%)	42.2–72.9

n = 36. Pointwise Wilson intervals do not establish representativeness or compare groups.

Within this subgroup, 26 (72.2%) endorsed the information-organisation statement and 18 (50.0%) endorsed the human-final-authority statement. These results describe the 36 records and do not provide a representative estimate for all practising lawyers or judges. They should not be treated as a statistically established difference from students.

4.5 Paired endorsement comparisons

Table 5 compares AADS1 with three other items within respondents. The three tests are Holm-adjusted, and the bootstrap intervals are pointwise.

Table 5. Paired endorsement comparisons

Contrast	First only / second only	Difference pp	95% CI pp	Holm p
AADS1 - AADS3	89 / 85	1.0	-5.7 to 7.8	1.000
AADS1 - AADS4	33 / 107	-19.2	-24.9 to -13.5	<.001
AADS1 - AADS5	81 / 80	0.3	-6.2 to 6.8	1.000

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

These comparisons reflect different propositions. A larger endorsement percentage for clear rules than for potential information assistance does not show that respondents ranked rules above utility or that rules would increase actual acceptance in a real deployment.

4.6 Exploratory associations

Table 6 presents ordinal correlations between AADS1 and four selected statements. All five response categories are used; p-values are adjusted across the four tests and confidence intervals are pointwise.

Table 6. Exploratory associations with information assistance

Items	Spearman ρ	95% CI	p	Holm p
AADS1 / AADS3	0.059	-0.038 to 0.157	0.247	0.247
AADS1 / AADS4	0.094	-0.010 to 0.186	0.065	0.130
AADS1 / EXT1	0.146	0.049 to 0.243	0.004	0.017
AADS1 / EXT3	0.106	0.008 to 0.198	0.038	0.115

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

Information-assistance endorsement had a small positive ordinal association with the understandable-reasons statement (ρ = 0.146; Holm-adjusted p = 0.017). Associations with the human-authority, clear-rules and challenge statements did not meet the 0.05 threshold after adjustment. Confidence intervals are pointwise. These estimates describe associations among survey responses, not effects of explainability, human oversight or rules on acceptance. Question wording, selection and cross-sectional design limit causal interpretation.

5. Discussion

The findings distinguish a perceived possibility of legal information assistance from the conditions respondents attach to AI use. They also show why broad endorsement should not be equated with tested system performance or a functioning judicial safeguard.

5.1 Assistance is not judicial adjudication

The information-organisation statement was endorsed by 64.2% of the recorded sample. It does not ask whether AI should decide a dispute or whether a participant has used a particular legal system. Organising documents, extracting relevant information and deciding a legal outcome are different activities with different risks and responsibilities. A tool could assist with administrative work yet be unsuitable for high-stakes decision support.

Legal information assistance also requires verification. Dahl and colleagues document that language models can produce false legal

claims, demonstrating the need to check sources and outputs in the setting being considered.[20] The present survey did not evaluate a model, so its endorsement percentage cannot establish that an available tool is accurate, efficient or safe. A deployment study would need task-specific testing against verified legal materials and assessment of error consequences.

5.2 Human final authority as a condition

The human-authority item was endorsed by 63.1% overall; 158 respondents endorsed both that condition and the potential information-organisation statement. These two responses can coexist because they concern assistance and the allocation of final decision authority. They do not establish whether a respondent would accept a particular tool, whether a court uses it, or whether human review would be effective.

Effective review requires more than a human signature. A decision-maker may need access to underlying information, an explanation proportionate to the task, sufficient time and authority to disagree. UNESCO's guidelines emphasise human oversight in the context of judicial governance.[21] The questionnaire does not test those operational conditions, and a respondent who does not endorse AADS3 may have selected neutral rather than opposing human authority.

The small professional subgroup illustrates why subgroup conclusions require care: 18 of 36 endorsed the human-authority condition. This is an observed count, not evidence that half of all Bangladeshi legal professionals hold the same position. The category does not establish judicial experience or actual AI use. A larger, clearly recruited professional sample would be needed to examine variation by legal role or experience.

5.3 Clear rules, explainability and trust

The clear-rules statement attracted 321 endorsements. Its wording asks whether rules would increase acceptance, but it does not define the rules or measure behaviour before and after their introduction. It is therefore evidence of a stated expectation, not evidence that any particular rule causes greater acceptance. Rules about confidentiality, permitted tasks, verification and accountability could have different effects and costs.

Understandable reasons can also matter without guaranteeing accuracy. A satisfactory explanation should help a legal user or affected person identify what information was used, which limitations matter and how to challenge an error. Greene and colleagues' experiment found that explanation conditions affected trust and procedural-fairness perceptions in particular hypothetical scenarios.[22] The present survey does not test such conditions or establish the same effect in Bangladesh.

There is also a risk of overreliance on a persuasive explanation. Trust should be calibrated to evidence about actual system performance and limitations, an insight consistent with research on appropriate reliance in automation.[23] The relevant institutional question is whether explanations allow effective scrutiny, not simply whether they make a

recommendation appear credible.

5.4 Procedural fairness and affected persons

Legal decision support has implications beyond the professional user. An affected person may need notice, reasons and a meaningful route to challenge an AI-supported recommendation or final decision. Procedural justice research emphasises how the process treats participants and offers opportunities for voice.[24] Survey agreement that users should be able to question recommendations is not proof that affected parties can do so in a real institution.

Fairness testing and review should also consider the full socio-technical process. Data selection, system design, professional use and organisational rules can all shape outcomes.[25] A decision-support tool should not be assumed fair merely because it is automated, or unfair solely because it uses AI. Evaluation would require a defined task, relevant comparison groups, appropriate measures and a means of remedying identified problems.

5.5 Bangladesh context and sample limits

The workbook contains a large proportion of law students and a small group of advocates or legal professionals. Their views can contribute to research on future and current legal users, but the sample does not identify judges or the conditions of a specific court. It cannot establish the prevalence of judicial AI use, the state of court readiness, or the views of the national legal profession.

The Bangladesh AI policy portal presents a 2026–2030 draft, but the survey does not identify when responses were collected or whether participants read it.[26] The findings should not be represented as an evaluation of that draft. Comparative guidance from UNESCO and CEPEJ can inform future local analysis, subject to Bangladesh's applicable legal and institutional context.[27]

5.6 Integrated interpretation

Technology acceptance theory draws attention to usefulness for a user; explainability and procedural justice draw attention to how recommendations can be scrutinised and decisions contested. These perspectives suggest a research agenda in which practical assistance and safeguards are examined separately. They do not establish a mediation model in the current dataset.

A stronger study would specify a tool and legal task, record whether users actually interact with it, measure the quality of its outputs and examine whether participants can detect and correct errors. It would also include affected persons' experiences of explanation and review. The present results provide a descriptive foundation for those questions rather than evidence of a tested judicial system.

6. Theoretical and Practical Implications

The implications distinguish questionnaire responses from recommendations for future study and implementation. No intervention or legal AI system was evaluated in this survey.

6.1 Theoretical implications

First, perceived assistance with information, willingness to use a specified system and acceptance of a judicial outcome should be measured as separate constructs. A broad mean of utility and governance-condition statements can be difficult to interpret. Technology acceptance research can inform measurement of usefulness and ease of use, but it does not replace direct measures of procedural justice or human oversight.[28]

Second, human authority should be defined operationally. Studies should distinguish formal final authority from the practical ability to access relevant information, question a recommendation and provide independent reasons. Third, explainability and trust should be measured separately: an explanation can be available but inaccurate or unhelpful, and increased trust is not itself evidence that reliance is justified.[29]

6.2 Practical implications for legal education and deployment

Legal education can use realistic examples to teach source verification, confidentiality, the distinction between assistance and adjudication, and the limits of AI-generated legal text. Such instruction should be evaluated through legal tasks and checked against reliable authorities; a general belief that clear rules are helpful does not establish that training improves performance.

Institutions considering AI decision support can define permitted tasks, document the system's limitations, retain meaningful human control and provide a route for review. They should assess whether relevant people can identify and correct errors and whether explanations are usable. These are prospective recommendations informed by judicial AI guidance, not evidence that this survey found a deployed system effective or ineffective.[30]

6.3 Policy and societal implications

Before adopting a judicial AI application, policymakers and courts can consult legal professionals and people affected by decisions, assess privacy and fairness risks, and specify responsibility for review. The appropriate level of transparency will depend on the system and context. An accessible complaint or appeal process is meaningful only if it can address the issue raised and is supported by adequate institutional capacity.

The national policy context should be checked against the latest authoritative version before publication or adoption of a measure. The 2026 draft cited here is not presented as a binding judicial rule.[31] The sample cannot be used as a national mandate for a particular system or regulatory design.

7. Conclusion, Limitations and Future Research

The study describes 385 AI-aware records about legal decision support, including 36 recorded advocates or legal professionals. Overall, 64.2% endorsed potential assistance with organising legal information, 63.1% endorsed use only with human final authority, and 83.4% agreed that clear rules would increase their acceptance. The 158 respondents who endorsed both assistance and human authority illustrate how these stated views can coexist.

The contribution lies in separating assistance, conditional use, rules and judicial authority rather than combining them into a single validated acceptance score. The analysis does not establish that an AI system improves decisions, that an explanation increases trust, or that a human decision-maker exercises meaningful oversight. Such conclusions require different evidence.

Limitations include a mixed, predominantly student sample; a small professional subgroup; undocumented recruitment and dates; cross-sectional self-report; no identified judicial system; and no direct observation of legal work or affected persons. The researcher identifies the numerical answers as real survey responses. The Codebook's synthetic labels for identifiers and optional comments require documentation against original source records; the comments were excluded. Results are not representative national estimates.

Future work should document sampling, consent and data provenance, recruit legal professionals and judicial users through a transparent design, and specify the tool and task. Scenario-based or experimental studies can test whether different explanations, review procedures and rules affect comprehension and willingness to use AI. Field evaluations should assess legal accuracy, error detection, practical human control, confidentiality and the experience of affected persons, rather than relying only on a broad acceptance statement.

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

Sumaiya Akter Tisha: 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
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.
EXT1	I trust an AI recommendation more when I can understand the main reasons behind it.
EXT3	Users should be able to question or challenge AI-supported recommendations.
ABPF3	People affected by AI-supported decisions should have access to review or appeal.

Source: Group 3 Codebook. Response options range from strongly disagree to strongly agree.

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

Notes

[1] European Commission for the Efficiency of Justice, European Ethical Charter on the Use of Artificial Intelligence in Judicial Systems and Their Environment (Council of Europe 2018) <https://www.coe.int/en/web/cepej/cepej-european-ethical-charter-on-the-use-of-artificial-intelligence-ai-in-judicial-systems-and-their-environment> accessed 27 October 2026.

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[6] Gutiérrez (n 2).

[7] Dahl and others (n 3).

[8] Davis (n 4).

[9] Chen and others (n 5).

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[12] Solon Barocas and Andrew D Selbst, ‘Big Data’s Disparate Impact’ (2016) 104 California Law Review 671; Reuben Binns, ‘Fairness in Machine Learning: Lessons from Political Philosophy’ (2018) 81 Proceedings of Machine Learning Research 149.

[13] Tyler (n 10).

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[18] 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).

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[20] Dahl and others (n 3).

[21] Gutiérrez (n 2).

[22] Greene, Barry and Claudy (n 5).

[23] John D Lee and Katrina A See, ‘Trust in Automation: Designing for Appropriate Reliance’ (2004) 46 Human Factors 50.

[24] Tyler (n 10).

[25] Barocas and Selbst (n 12); Binns (n 12).

[26] Bangladesh Draft AI Policy (n 15).

[27] Gutiérrez (n 2); CEPEJ (n 1).

[28] Davis (n 4); Tyler (n 10).

[29] Lee and See (n 23).

[30] Gutiérrez (n 2); CEPEJ (n 1).

[31] Bangladesh Draft AI Policy (n 15).