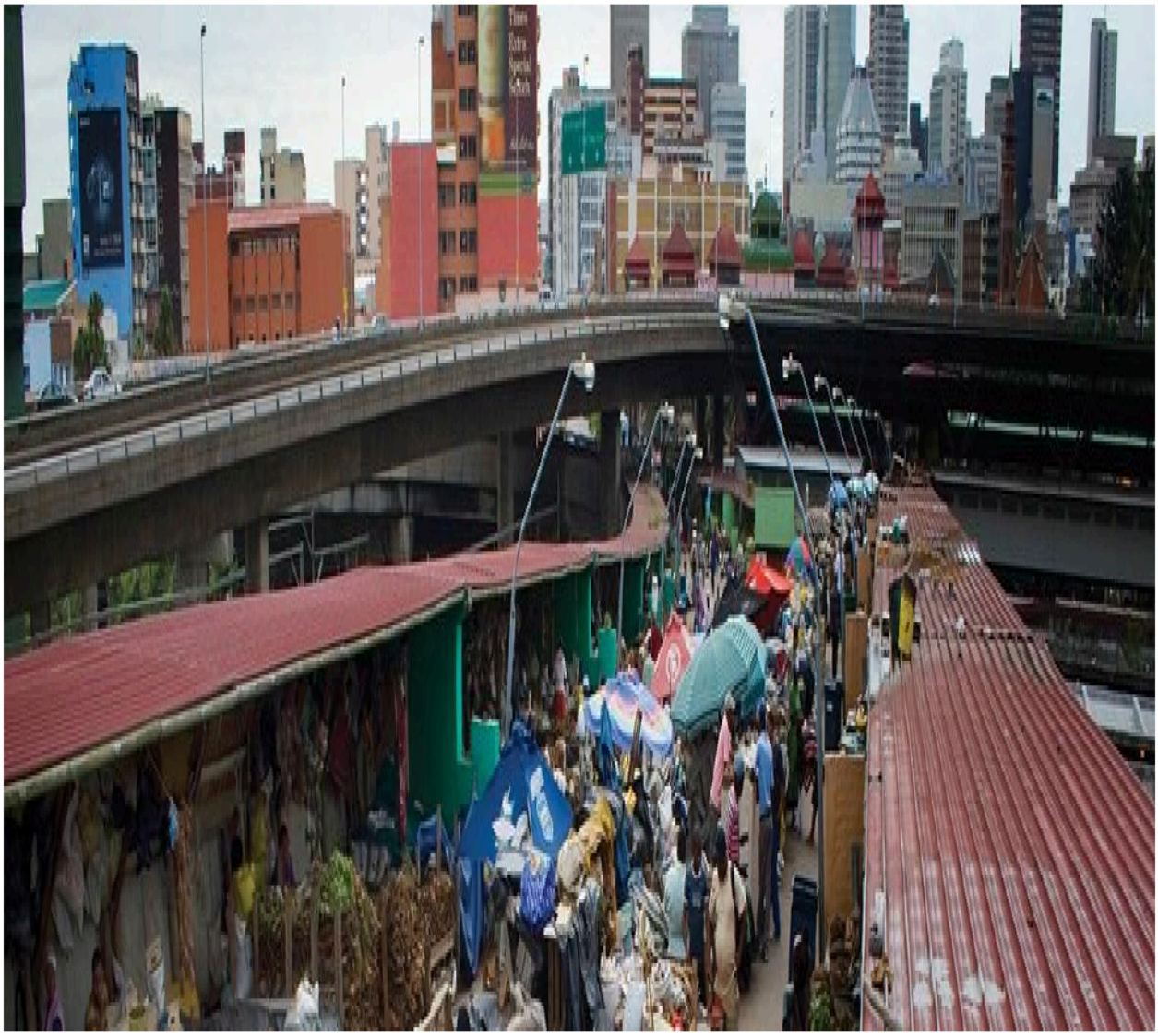
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Awareness of Algorithmic Manipulation and Intention to Seek Consumer Redress in Bangladesh

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Algorithmic manipulation raises a consumer-protection question beyond recognition of persuasive design: whether awareness is associated with readiness to document harm and seek redress. This study examines that question through an exploratory analysis of 385 numerical questionnaire records from a Bangladesh AI and law research project. A theory-informed framework distinguishes concern about exploitation, perceived recognition, evidence-preservation intention and the belief that complaint mechanisms strengthen trust. Because internal consistency did not support reflective block scores, the analysis uses individual indicators. A proportional-odds model estimates associations with redress intention, supplemented by paired endorsement analysis, multiplicity adjustment, specification checks and repeated cross-validation. Redress intention was endorsed in 310 records (80.5%), compared with evidence preservation in 264 (68.6%). The paired difference was 11.9 percentage points (bootstrap 95% CI 6.2-17.7), with 91 records endorsing redress but not evidence preservation. Adjusted associations were uncertain for recognition (OR 1.248, 95% CI 0.986-1.580), evidence preservation (OR 1.118, 0.884-1.413), concern (OR 1.008, 0.785-1.294) and complaint-linked trust (OR 1.285, 0.979-1.687); none showed a clear adjusted association after Holm correction. Cross-validated ranked probability loss was 0.1965 against 0.1941 for a training-frequency baseline. The analysis distinguishes endorsement of redress from preparedness and predictive discrimination. Implications concern evidence-oriented consumer education and accessible complaint procedures, rather than a demonstrated causal effect of awareness. Interpretation is limited by single-item measurement, incomplete recruitment documentation and unresolved numerical-data provenance.

Keywords: algorithmic manipulation; consumer redress; evidence preservation; deceptive design; ordinal regression; persuasion knowledge; Bangladesh

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1 Introduction

Digital commerce connects consumers to information, recommendations and service interfaces that can shape decisions. Influence is not automatically manipulation. A recommendation can reduce search effort, while a misleading urgency cue or obstructive cancellation route can interfere with a considered choice. The analytical challenge is to distinguish a consumer's concern about these possibilities from recognition of a specific practice and willingness to respond. Research on dark commercial patterns provides a foundation for examining this distinction without assuming that every automated recommendation is harmful.[1]

The use of artificial intelligence adds a further question about personalisation and the credibility of communication. Consumers may encounter apparently helpful interactions that also promote commercial objectives. However, a questionnaire about algorithmic manipulation cannot establish the technical architecture of a platform or demonstrate that an individual transaction involved AI. This article studies endorsement of statements about manipulation and redress. It does not classify interfaces as unlawful, identify perpetrators or estimate the prevalence of particular technologies in Bangladesh.

The consumer-protection relevance extends beyond avoiding an initial purchase. After suspected harm, a person may need to retain a transaction record, identify an appropriate recipient and explain the problem. A stated willingness to complain does not guarantee that these steps will be undertaken. Complaint scholarship has long distinguished intentions and different forms of response.[2] Evidence preservation is therefore treated here as a separate preparatory intention rather than folded into a general awareness or redress scale.

Awareness is often assumed to provide a pathway from recognising risk to asserting consumer rights. That assumption contains several distinct propositions. A person can be concerned about exploitation without recognising manipulative design accurately. Someone who recognises a practice may prefer to avoid the platform rather than complain. A person willing to complain may not preserve the records needed to explain a transaction. Studying these differences requires measures that do not build the expected relationship into a single score.

The Algorithmic Manipulation and Redress questionnaire block contains distinct statements about concern, perceived recognition, evidence preservation, complaint intention and the belief that rights

[1] OECD, ‘Dark Commercial Patterns’ (2022) OECD Digital Economy Papers No 336, doi:10.1787/44f5e846-en; Colin M Gray and others, ‘The Dark (Patterns) Side of UX Design’ in Proceedings of CHI 2018 (ACM 2018), doi:10.1145/3173574.3174108; Arunesh Mathur and others, ‘Dark Patterns at Scale: Findings from a Crawl of 11K Shopping Websites’ (2019) 3 Proceedings of the ACM on Human-Computer Interaction, article 81, doi:10.1145/3359183; Arunesh Mathur, Mihir Kshirsagar and Jonathan Mayer, ‘What Makes a Dark Pattern... Dark? Design Attributes, Normative Considerations, and Measurement Methods’ in Proceedings of CHI 2021 (ACM 2021), doi:10.1145/3411764.3445610.

[2] Jagdip Singh, ‘Consumer Complaint Intentions and Behavior: Definitional and Taxonomical Issues’ (1988) 52 Journal of Marketing 93–107, doi:10.1177/002224298805200108.

awareness increases redress intention. Their content requires separate assessment before aggregation. A composite containing both recognition and complaint intention would blur the antecedent–outcome distinction. Content mapping and measurement diagnostics therefore guide the item-level analysis.

Consumer decision research describes how people interpret persuasion attempts, while planned-behaviour theory separates intention from its antecedents and from subsequent action.[3] Trust research and complaint-handling scholarship additionally direct attention to the institutions through which consumers respond.[4] Together, these perspectives motivate a narrower question than whether people generally support consumer rights: do concern, perceived recognition, preparation and complaint-related beliefs distinguish stronger redress intention within the available records?

Bangladesh provides the context for the study. The Consumers' Right Protection Act 2009 establishes a national consumer-protection framework, and the Directorate of National Consumers' Right Protection provides complaint information. The analysis examines stated orientation towards redress within this institutional context. It does not assess statutory coverage of particular algorithmic practices or the performance of complaint-handling authorities.[5]

The study addresses four principal objectives. It assesses the distribution of recognition, concern, preparation and redress statements; compares evidence-preservation and redress endorsement within records; estimates adjusted ordinal associations with redress intention; and evaluates whether the selected predictors improve prediction relative to an unconditional baseline. Robustness checks additionally assess response-category coding, sample restriction and predictor specification. The analysis is exploratory and was not preregistered.

The distinctive contribution is a separation of descriptive endorsement, preparation-related discordance, conditional association and predictive utility. These are different questions and can produce different conclusions. A sample can strongly endorse redress while an awareness model has little ability to distinguish whose intention is stronger. A statistically identifiable difference between two item margins can coexist with weak individual-level association between them. Reporting these distinctions avoids turning a general educational recommendation into an unsupported causal or predictive claim.

[3] Icek Ajzen, ‘The Theory of Planned Behavior’ (1991) 50 Organizational Behavior and Human Decision Processes 179–211, doi:10.1016/0749-5978(91)90020-T; Marian Friestad and Peter Wright, ‘The Persuasion Knowledge Model: How People Cope with Persuasion Attempts’ (1994) 21 Journal of Consumer Research 1–31, doi:10.1086/209380.

[4] Roger C Mayer, James H Davis and F David Schoorman, ‘An Integrative Model of Organizational Trust’ (1995) 20 Academy of Management Review 709–734, doi:10.5465/amr.1995.9508080335; Stephen S Tax, Stephen W Brown and Murali Chandrashekaran, ‘Customer Evaluations of Service Complaint Experiences: Implications for Relationship Marketing’ (1998) 62 Journal of Marketing 60–76, doi:10.1177/002224299806200205; Moshe Davidow, ‘Organizational Responses to Customer Complaints: What Works and What Doesn’t’ (2003) 5 Journal of Service Research 225–250, doi:10.1177/1094670502238917.

[5] The Consumers’ Right Protection Act 2009 (Bangladesh), Act No 26 of 2009, authentic English text published under SRO No 08-Law/2014, Bangladesh Gazette Extraordinary (29 January 2014) 1491–1521; Directorate of National Consumers’ Right Protection, ‘The Consumers’ Right Protection Act, 2009’ and official complaint information, https://dncrp.gov.bd/ and https://dncrp.gov.bd/pages/static-pages/6922dd11933eb65569e13607 (accessed 17 October 2026).

The study uses an existing numerical questionnaire database. Its inferential scope is conditional association within the available records, rather than nationally representative prevalence or causal identification. The optional contextual-text field is excluded. Data-origin and recruitment limitations are specified in Section 3.2 and considered when interpreting the findings.

2 Literature Review and Theoretical Foundation

The framework links consumer decision-making to redress while keeping each measured statement within its actual content. It draws on planned-behaviour theory, persuasion knowledge and complaint-related trust. It does not equate the available questions with a complete operationalisation of any one theory. Literature informs the expectations; the database determines which relationships can be estimated.

2.1 Algorithmic manipulation and deceptive design

Dark-pattern research examines design choices that can undermine a user's ability to choose in accordance with their interests. Taxonomic work identifies recurring interface practices, and large-scale website research demonstrates methods for locating such practices.[6] Conceptual analysis further asks which design attributes and normative considerations make a pattern problematic.[7] This literature establishes a research domain; it does not supply a universal rule that personalisation is deceptive. An empirical study must identify the behaviour and harm under investigation rather than infer manipulation from automation alone.

Legal and experimental scholarship provides complementary evidence. Luguri and Strahilevitz examine responses to experimentally presented dark patterns, while Susser, Roessler and Nissenbaum analyse the conditions under which online influence becomes manipulation.[8] These contributions support distinguishing an experienced intervention from a respondent's belief about manipulation. The current questionnaire contains no randomised interface exposure, transaction trace or technical inspection. Its recognition item

[6] Gray and others, ‘The Dark (Patterns) Side of UX Design’ (n 1); Mathur and others, ‘Dark Patterns at Scale’ (n 1).

[7] Mathur, Kshirsagar and Mayer, ‘What Makes a Dark Pattern... Dark?’ (n 1).

[8] Jamie Luguri and Lior Jacob Strahilevitz, ‘Shining a Light on Dark Patterns’ (2021) 13 Journal of Legal Analysis 43–109, doi:10.1093/jla/laaa006; Daniel Susser, Beate Roessler and Helen Nissenbaum, ‘Online Manipulation: Hidden Influences in a Digital World’ (2019) 4 Georgetown Law Technology Review 1–45, https://georgetownlawtechreview.org/online-manipulation-hidden-influences-in-a-digital-world/GLTR-01-2020/.

therefore measures perceived capability, not demonstrated resistance to a deceptive interface.

Recent work extends the discussion to interventions, vulnerability and regulatory framing. Lu and colleagues investigate end-user empowerment interventions, and Rossi and colleagues discuss the multidimensional nature of digital vulnerability.[9] Trzaskowski examines manipulation by design, while Yi and Li map scholarship connecting legal and human-computer interaction perspectives.[10] These developments motivate research that connects recognition to usable responses. They also caution against treating awareness education as sufficient protection when the design and accessibility of commercial systems remain consequential.

2.2 Theory of planned behaviour and redress intention

The Theory of Planned Behaviour treats behavioural intention as conceptually distinct from behaviour and relates intention to attitudes, subjective norms and perceived control.[11] This distinction fits the dependent variable: AMR4 asks whether a person would consider a complaint or redress mechanism after harmful manipulation. It does not ask whether a complaint was filed, resolved or compensated. The response is also conditional on a hypothetical harmful situation. It cannot establish the strength of intention under the practical constraints of a real dispute.

The instrument does not contain validated multi-item measures of the theory's principal components. Concern about exploitation is not a complete attitude-towards-complaining measure, recognition is not procedural control, and evidence preservation is not a direct measure of behavioural intention to file a complaint. The model is consequently theory-informed rather than a full test of planned-behaviour theory. This matters for interpreting uncertain coefficients: failure to distinguish redress responses using these items cannot be presented as a rejection of the broader theory.

A useful future extension would specify the target action, setting and time horizon. For example, intention to submit a documented complaint to a named route after a defined

[9] Yuwen Lu, Chao Zhang, Yuewen Yang, Yaxing Yao and Toby Jia-Jun Li, 'From Awareness to Action: Exploring End-User Empowerment Interventions for Dark Patterns in UX' (2024) 8 Proceedings of the ACM on Human-Computer Interaction, article 59, doi:10.1145/3637336; Arianna Rossi and others, 'Who Is Vulnerable to Deceptive Design Patterns? A Transdisciplinary Perspective on the Multi-Dimensional Nature of Digital Vulnerability' (2024) 55 Computer Law & Security Review 106031, doi:10.1016/j.clsr.2024.106031.

[10] Jan Trzaskowski, 'Manipulation by Design' (2024) 34 Electronic Markets, article 14, doi:10.1007/s12525-024-00699-y; Weiwei Yi and Zihao Li, 'Mapping the Scholarship of the Regulation of Dark Patterns: A Systematic Review of Concepts, Regulatory Paradigms, and Solutions from Law and HCI Perspectives' (2025) 59 Computer Law & Security Review 106225, doi:10.1016/j.clsr.2025.106225.

[11] Ajzen, 'The Theory of Planned Behavior' (n 3).

transaction problem is more precise than willingness to consider any mechanism. Such precision would permit direct measures of perceived procedural ability, expected costs and social support. These mechanisms motivate the discussion but are not assigned numerical values in the current analysis.

2.3 Persuasion knowledge and perceived recognition

The Persuasion Knowledge Model focuses attention on how people understand and cope with persuasion attempts.[12] For this article, its relevance lies in distinguishing recognition of a commercial tactic from general concern about exploitation. AMR2 asks whether a respondent can recognise some manipulative design or personalised pressure. Agreement indicates perceived recognition capability. It does not show that the person can discriminate manipulative and legitimate designs in a task with known answers.

Recognition could be associated with redress intention because a person who can name the practice may find it easier to explain a grievance. Yet recognition may also lead to avoidance, scepticism or private switching. A complaint is only one possible response. The conceptual connection is therefore directional but uncertain, especially when the outcome refers broadly to considering a mechanism rather than committing to a specific action. This reasoning motivates the recognition hypothesis without assuming that awareness necessarily produces formal mobilisation.

Concern about vulnerability is treated separately. AMR1 expresses concern that algorithms can exploit consumer vulnerabilities. Vulnerability scholarship emphasises situational and contextual conditions rather than reducing vulnerability to a fixed characteristic of a group.[13] A high concern response is not proof that the respondent has experienced harm. Concern might increase motivation to seek redress, but it could also coexist with perceived helplessness. The instrument does not contain the measures needed to distinguish these alternatives.

2.4 Consumer complaint behaviour and evidence preparation

Consumer complaint research distinguishes forms of response and identifies complaint handling as a relational and organisational process.[14] The current study separates evidence-preservation intention from redress intention for that reason. AMR3 concerns retaining evidence after believing that an AI-enabled platform has misled the person. AMR4 concerns considering a complaint mechanism after harmful manipulation. These items refer to related but non-identical conditions, so their comparison should be interpreted as response-pattern discordance rather than a measured transition from one stage to another.

[12] Friestad and Wright, ‘The Persuasion Knowledge Model’ (n 3).

[13] Stacey Menzel Baker, James W Gentry and Terri L Rittenburg, ‘Building Understanding of the Domain of Consumer Vulnerability’ (2005) 25 Journal of Macromarketing 128–139, doi:10.1177/0276146705280622.

[14] Singh, ‘Consumer Complaint Intentions and Behavior’ (n 2); Tax, Brown and Chandrashekaran, ‘Customer Evaluations of Service Complaint Experiences’ (n 4); Davidow, ‘Organizational Responses to Customer Complaints’ (n 4).

Evidence preparation may matter because a complaint normally involves describing what occurred. A record of the offer, payment, communication or interface could help that description, depending on the applicable process. However, the dataset contains no completed complaint or assessment of evidence quality. Endorsement of preserving evidence is therefore a preparatory intention, not demonstrated evidentiary competence, legal admissibility or successful access to remedy. No mediation model is estimated because contemporaneous statements cannot establish that preparation transmits an awareness effect into subsequent redress.

Complaint-handling research also shows why an individual-only explanation is incomplete. Organisational responses, procedures and prior experiences belong to the environment in which a person acts.[15] In this dataset, those conditions are largely unmeasured. Weak prediction from awareness questions may therefore reflect omitted processes as well as measurement limitations. It cannot determine that those processes account for the unexplained variation; they remain hypotheses for subsequent study.

2.5 Complaint mechanisms and trust

Trust is not a single interchangeable attitude. Foundational trust models distinguish the construct from related beliefs, while e-commerce research develops separate measures of trust-relevant dimensions.[16] CTP5 states that clear complaint mechanisms increase trust in AI-enabled commerce. The item is best described here as a complaint-trust linkage belief. It does not directly measure confidence that an existing institution will deliver a favourable outcome, the quality of a particular platform's complaints process or general trust in chatbots.

The expectation is that endorsing the value of complaint mechanisms may be associated with stronger willingness to consider using one. However, the two statements overlap conceptually, and an association would remain vulnerable to shared wording and response style. Conversely, a weak association would not show that accessible procedures are unimportant. The item is retained because it makes the institutional component of the research brief more specific, while its interpretation is bounded by its conditional wording.

International consumer-policy instruments place accessible dispute resolution and redress within the protection of consumers in electronic commerce.[17] They provide a policy reference for designing usable routes. They are not evidence that the surveyed

[15] Tax, Brown and Chandrashekaran, ‘Customer Evaluations of Service Complaint Experiences’ (n 4); Davidow, ‘Organizational Responses to Customer Complaints’ (n 4).

[16] Mayer, Davis and Schoorman, ‘An Integrative Model of Organizational Trust’ (n 4); D Harrison McKnight, Vivek Choudhury and Charles Kacmar, ‘Developing and Validating Trust Measures for e-Commerce: An Integrative Typology’ (2002) 13 Information Systems Research 334–359, doi:10.1287/isre.13.3.334.81.

[17] OECD, Recommendation of the Council on Consumer Dispute Resolution and Redress (2007), OECD/LEGAL/0356, https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0356; OECD, Recommendation of the Council on Consumer Protection in E-commerce (2016), OECD/LEGAL/0422, https://legalinstruments.oecd.org/en/instruments/336.

records document institutional access or that the recommendations constitute applicable Bangladesh law. This article uses them to frame prospective implications, rather than to infer statutory duties from questionnaire endorsement.

2.6 Hypotheses and framework

Four exploratory hypotheses concern stronger ordinal redress intention. H1 proposes a positive association with concern about algorithmic exploitation. H2 proposes a positive association with perceived recognition of manipulative design. H3 proposes a positive association with evidence-preservation intention. H4 proposes a positive association with the complaint-trust linkage belief. All are conditional associations, adjusted for two knowledge items, training exposure, daily AI use and recorded student status.

AIL1 concerns plausible but inaccurate AI output, and AIL3 concerns bias or incomplete information. These enter separately as knowledge-oriented controls. Training combines short orientation and course/certified exposure; daily use contrasts daily or almost daily use with all other categories. Neither variable identifies an intervention effect. Student status distinguishes the largest recorded group from other current-status categories without treating those groups as equivalent. The model does not estimate differences among all professional categories.

Figure 1 presents the four focal associations and the analytical distinction between preparation and complaint intention. The paired endorsement comparison is a separate descriptive component. It is not an extra causal path. Predictive evaluation subsequently asks whether the entire model improves ordinal probability forecasts, which is different from testing an individual coefficient. This separation follows the distinction between explanation and prediction in statistical modelling.[18]

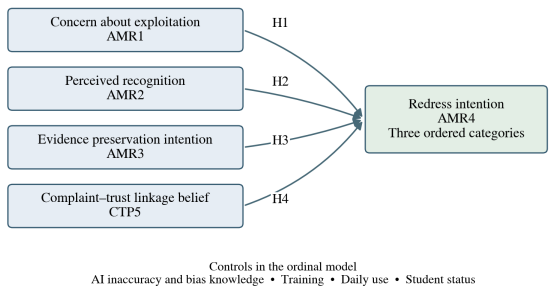


Figure 1. Proposed analytical framework

Arrows denote exploratory conditional associations. The preparation-redress paired comparison is analysed separately and does not establish a causal sequence.

3 Methodology

The study combines content assessment, descriptive analysis, paired-response comparison, ordinal modelling and internal predictive validation. Model complexity is constrained by the measures and the response distribution. The numerical database remains unchanged throughout the analysis. Content distinctions, measurement diagnostics and the response distribution guide the exploratory specification.

[18] Galit Shmueli, 'To Explain or to Predict?' (2010) 25 Statistical Science 289–310, doi:10.1214/10-STS330.

3.1 Data source and population scope

The source is Group-7-Law-SDG-Database.xlsx and its companion research plan and questionnaire. The Data sheet contains 385 rows and 35 variables. Background fields cover age, gender, current status, education, location, AI experience, use frequency and training. The instrument contains five AIL, five CRA, five CTP and five AMR items on a five-point agreement scale. The project describes a Bangladesh context, but national coverage and selection probabilities are not documented.

The primary analysis uses all 385 numerical records because the research title concerns consumer redress rather than a student-only population. Recorded current status comprises 232 law students, 68 law graduates, 51 advocates or legal professionals and 34 other relevant respondents. The resulting scope is law-oriented and mixed-status. It is not a representative sample of all consumers. A student-only analysis examines sensitivity to the dominant status group and is not treated as a direct replication in a new sample.

3.2 Data provenance and sampling considerations

The codebook describes Respondent_ID as a Synthetic respondent sequence and F3_Optional_Comment as a Synthetic contextual comment. These descriptions are retained accurately. The contextual comments are excluded from quantitative and qualitative interpretation. The identifier label may describe anonymised numbering, but the available documentation does not establish the origin of the numerical answers. Accordingly, the analysis is reported as an exploratory examination of the database; verified human-participant provenance is not assumed.

The sampling frame, recruitment log, contact denominator, survey mode, fieldwork dates and full institutional coverage are not documented in the analytical materials. A response rate and probability-based national margin of error cannot therefore be estimated. Cochran's sample-planning formula, $n = 1.96^2 \times 0.50 \times 0.50 / 0.05^2 = 384.16$, rounds upward to 385. This calculation describes the planning benchmark and does not establish a probability sampling design.[19]

[19] William G Cochran, Sampling Techniques (3rd edn, Wiley 1977).

3.3 Measurement mapping

Table 1 identifies the analytical role of each selected statement. AMR4 is the outcome. AMR1, AMR2, AMR3 and CTP5 are the focal predictors. AIL1 and AIL3 are distinct controls rather than a combined AI-literacy score. AMR5 is descriptive because it states that rights awareness increases redress intention; using it as evidence of that same effect would blur a belief about a relationship with an independently estimated association. Other CRA and CTP items remain outside the focal model, apart from a specified CRA4 sensitivity check.

Table 1. Item roles and measurement boundaries

Role	Indicator	Meaning
Outcome	AMR4	Considering a complaint or redress mechanism
Concern	AMR1	Concern that algorithms exploit vulnerabilities
Recognition	AMR2	Perceived recognition of manipulative design
Preparation	AMR3	Intention to preserve evidence
Complaint-linked trust	CTP5	Clear mechanisms would strengthen trust
Knowledge controls	AIL1; AIL3	AI inaccuracy; bias or incomplete data
Training control	Any training	Orientation or course/certification versus none
Use control	Daily use	Daily or almost daily versus all other frequency
Status control	Student	Law student versus other recorded status
Descriptive only	AMR5	Belief that awareness increases intention

The primary outcome pools responses one to three into no agreement, retaining agree and strongly agree as two higher ordered categories. Only three AMR4 records select disagree and none selects strongly disagree; the pooling avoids estimating a threshold from this sparse lower category. It does not imply that neutrality and disagreement have the same psychological meaning. A model retaining the four observed original categories assesses sensitivity to this choice. Predictor items retain their one-to-five scores, with categorical recognition coding examined separately.

3.4 Screening and measurement diagnostics

All 20 agreement variables are complete and within the one-to-five range. Respondent identifiers are unique, complete item vectors have no exact duplicates, and no record selects one identical category across all 20 statements. These checks address selected data-quality features, not authenticity or independent participation. All 385 records contain affirmative consent, adult-eligibility and relevant-AI-awareness fields. Such recorded fields do not independently verify how consent or recruitment occurred.

Cronbach's alpha is calculated for the four five-item blocks as a diagnostic of the proposed composite interpretation.[20] Content distinctions and observed consistency do not support treating them as reflective scales. A reflective measurement

[20] Lee J Cronbach, ‘Coefficient Alpha and the Internal Structure of Tests’ (1951) 16 Psychometrika 297–334, doi:10.1007/BF02310555.

model and latent mediation effects are not estimated. Separate observed statements retain their specific meanings. Measurement-model specification research supports making the intended construct-indicator relationship explicit before choosing an estimator.[21] Single-item error remains unresolved by this choice.

3.5 Ordinal regression and multiplicity

The primary proportional-odds model uses logit $Pr(Y > k) = \alpha k + X\beta$ for the two cumulative thresholds, where higher Y indicates stronger redress endorsement.[22] Odds ratios are $\exp(\beta)$ for a one-point item increase or the specified binary contrast. Maximum-likelihood estimates use model-based Wald intervals and two-sided p values. The nine slopes comprise four focal predictors and five controls. Variance inflation factors assess linear redundancy. This model describes associations; it does not control all potential confounding.

The four focal p values form one family for Holm adjustment. The controls are interpreted descriptively. A stacked cumulative-binary logistic diagnostic tests whether the nine slopes differ across the two thresholds, using a respondent-cluster sandwich covariance because each record contributes twice. The joint interaction test evaluates the proportional-odds restriction. The diagnostic evaluates consistency of the estimated slopes across outcome thresholds. Institutional clustering cannot be assessed because institution identifiers are unavailable.[23]

3.6 Paired endorsement and uncertainty

Evidence preservation and redress are separately dichotomised at agree or strongly agree for a paired descriptive comparison. The cross-tabulation identifies concordant and discordant endorsement patterns. An exact two-sided McNemar test compares the two margins.[24] The redress-minus-preservation difference receives a percentile interval from 10,000 paired-record bootstrap resamples with seed 20261017. Resampling keeps each record's two responses together. It quantifies conditional sampling uncertainty within the dataset and does not account for an unknown recruitment process.

[21] Scott B MacKenzie, Philip M Podsakoff and Cheryl Burke Jarvis, 'The Problem of Measurement Model Misspecification in Behavioral and Organizational Research and Some Recommended Solutions' (2005) 90 Journal of Applied Psychology 710–730, doi:10.1037/0021-9010.90.4.710.

[22] Peter McCullagh, 'Regression Models for Ordinal Data' (1980) 42 Journal of the Royal Statistical Society Series B 109–127, doi:10.1111/j.2517-6161.1980.tb01109.x.

[23] Sture Holm, 'A Simple Sequentially Rejective Multiple Test Procedure' (1979) 6 Scandinavian Journal of Statistics 65–70; Ralf Bender and Stefan Lange, 'Adjusting for Multiple Testing—When and How?' (2001) 54 Journal of Clinical Epidemiology 343–349, doi:10.1016/S0895-4356(00)00314-0.

[24] Quinn McNemar, 'Note on the Sampling Error of the Difference Between Correlated Proportions or Percentages' (1947) 12 Psychometrika 153–157, doi:10.1007/BF02295996.

3.7 Predictive and specification checks

The ordinal model is refitted in five-fold stratified cross-validation repeated five times, yielding 25 held-out evaluations. The baseline uses category frequencies estimated only from each training fold. Normalised ranked probability score averages squared cumulative-probability errors across the two thresholds; logarithmic loss evaluates the probability assigned to the observed category. Lower values indicate better performance. Proper-score evaluation and separation of fitting from held-out assessment are important safeguards against overstating predictive utility.[25]

Sensitivity analyses retain the original outcome categories, restrict to students, omit AMR3, replace the two general knowledge controls with CRA4, and code recognition as agree/strongly agree indicators relative to no agreement. Binary logistic fits at thresholds four and five provide another diagnostic. These are exploratory specifications, not independent confirmatory tests. Confidence intervals, specification stability and predictive comparisons take priority over declaring findings on one side of a conventional p-value threshold.[26]

3.8 Ethics and research integrity

The questionnaire describes academic purpose, voluntary participation, anonymity, aggregate reporting and the option to stop. The analytical file contains coded identifiers and categorical backgrounds rather than participant names or account credentials. Original consent documentation and a formal ethical approval or exemption determination were unavailable for this analysis. Recorded consent and eligibility fields are therefore distinguished from independent verification of the collection process. No independent ethics clearance or exemption is claimed.

This analysis involved no new participant recruitment. Optional comments were excluded, numerical responses were retained in their recorded form, and estimates and uncertainty are reported transparently. The ethical account remains limited by the unavailable collection documentation and unresolved numerical-data provenance described in Section 3.2.

4 Results

The findings distinguish item distributions, within-record discordance, adjusted ordinal associations and held-out predictive performance. Counts are exact summaries of the numerical database. Inferential quantities are conditional on the analytical model and do not establish national population prevalence or respondent authenticity.

[25] Tilmann Gneiting and Adrian E Raftery, ‘Strictly Proper Scoring Rules, Prediction, and Estimation’ (2007) 102 Journal of the American Statistical Association 359–378, doi:10.1198/016214506000001437; Gavin C Cawley and Nicola LC Talbot, ‘On Over-fitting in Model Selection and Subsequent Selection Bias in Performance Evaluation’ (2010) 11 Journal of Machine Learning Research 2079–2107, https://www.jmlr.org/papers/v11/cawley10a.html.

[26] Ronald L Wasserstein, Allen L Schirm and Nicole A Lazar, ‘Moving to a World Beyond p < 0.05’ (2019) 73 The American Statistician Supplement 1, 1–19, doi:10.1080/00031305.2019.1583913.

4.1 Record profile

The recorded sample has equal male and female counts, 188 each; five records prefer not to disclose gender and four select other. Ages 21-23 account for 162 rows, followed by 24-26 with 83 and 18-20 with 60. Dhaka accounts for 160 records. Law students constitute 60.3% of the database, and the remaining records describe graduates, legal professionals and other respondents. Table 2 summarises the main background categories.

Table 2. Recorded sample profile

Variable	Category	n	%
Age	21-23	162	42.1
Age	24-26	83	21.6
Age	18-20	60	15.6
Age	27-30	41	10.6
Age	31+	39	10.1
Gender	Male	188	48.8
Gender	Female	188	48.8
Gender	Prefer not to say	5	1.3
Gender	Other	4	1.0
Current status	Law student	232	60.3
Current status	Law graduate	68	17.7
Current status	Advocate or legal professional	51	13.2
Current status	Other relevant respondent	34	8.8
Location	Dhaka	160	41.6
Location	Other city corporation	82	21.3
Location	District town	70	18.2
Location	Upazila-rural area	64	16.6
Location	Other	9	2.3
Training	No	222	57.7
Training	Yes, short orientation	117	30.4
Training	Yes, course or certified training	46	11.9

Training is recorded in 163 rows, including 117 short orientations and 46 courses or certifications. Daily or almost daily use is recorded in 106 rows, compared with 166 weekly users. These are general AI-exposure descriptors; neither identifies consumer-redress instruction or experience in pursuing a complaint. The mixture of locations and statuses broadens the recorded profile but does not demonstrate balanced or representative recruitment.

4.2 Distributions and reliability

Concern about exploitation has mean 3.862, perceived recognition 3.834 and evidence-preservation intention 3.842. The redress item has mean 4.161, while the complaint-trust linkage has mean 4.226. Agreement counts are 267 for concern, 258 for recognition, 264 for evidence preservation, 310 for redress and 326 for complaint-linked trust. Table 3 presents the selected item statistics, with the two AI knowledge controls and the descriptive AMR5 item.

Table 3. Selected item statistics and agreement

Item	Mean	SD	Agree n	Agree %
AMR1	3.862	0.777	267	69.4
AMR2	3.834	0.799	258	67.0
AMR3	3.842	0.822	264	68.6
AMR4	4.161	0.747	310	80.5
AMR5	3.813	0.811	251	65.2
CTP5	4.226	0.731	326	84.7
AIL1	3.574	0.823	214	55.6
AIL3	4.135	0.720	316	82.1

For the redress outcome, 75 records fall in the pooled no-agreement category, 170 select agree and 140 strongly agree. The distribution is concentrated towards endorsement. A high endorsement proportion does not imply that actual complaints are common or that individual differences will be well predicted. Spearman associations with redress are small: 0.057 for

concern, 0.099 for recognition, 0.063 for preservation and 0.113 for complaint-linked trust.

Block alphas are 0.201 for AIL, 0.186 for CRA, 0.158 for CTP and 0.197 for AMR. Together with the content differences, these values do not support the proposed reflective composites. Table 4 reports the diagnostics and resulting analytical decisions. Item-level modelling is therefore retained. This does not establish that each single item is a reliable complete measure of a wider construct; it keeps the estimates tied to explicit questionnaire wording.

Table 4. Block reliability diagnostics

Block	Items	Alpha	Analytical decision
AIL	5	0.201	Separate indicators
CRA	5	0.186	Separate indicators
CTP	5	0.158	Separate indicators
AMR	5	0.197	Separate indicators

4.3 Evidence preservation and redress endorsement

Table 5 shows 219 records endorsing both intentions and 30 endorsing neither. Ninety-one endorse redress without endorsing evidence preservation, while 45 endorse preservation without endorsing redress. Thus, the larger marginal endorsement of redress is not simply a uniform elevation across identical response patterns. The full ordinal correlation between the two items is small, with Spearman $\rho = 0.063$ and $p = 0.214$.

Table 5. Paired evidence-preservation and redress endorsement

Evidence preservation	Redress not endorsed	Redress endorsed	Total
Not endorsed	30	91	121
Endorsed	45	219	264
Total	75	310	385

Endorsement = response 4 or 5. The discordant counts are 91 and 45. Redress minus preservation = 11.9 percentage points, bootstrap 95% CI 6.2-17.7; exact McNemar $p < 0.001$.

The paired redress-minus-preservation difference is 0.1195, or 11.9 percentage points, with a percentile bootstrap 95% interval from 6.2 to 17.7 points. The exact McNemar p value is below 0.001. The direction is clear within the recorded responses, but the contrast concerns two differently worded hypothetical statements. It is not an estimated loss of consumers between sequential complaint stages, evidence of procedural failure or a demonstrated population-level preparedness deficit.

4.4 Adjusted ordinal associations

The primary model estimates are shown in Table 6 and Figure 2. Concern has OR 1.008, with 95% CI 0.785-1.294 and unadjusted $p = 0.951$. Recognition has OR 1.248, with interval 0.986-1.580 and $p = 0.065$. Evidence preservation has OR 1.118, with interval 0.884-1.413 and $p = 0.353$. Complaint-linked trust has OR 1.285, with interval 0.979-1.687 and $p = 0.071$. All four intervals include one.

Table 6. Primary proportional-odds model

Predictor	OR	95% CI	Raw p	Holm p
Concern	1.008	0.785-1.294	0.951	0.951
Recognition	1.248	0.986-1.580	0.065	0.260
Evidence preservation	1.118	0.884-1.413	0.353	0.706
Complaint-linked trust	1.285	0.979-1.687	0.071	0.260
Inaccuracy knowledge	1.046	0.828-1.321	0.704	—
Bias knowledge	0.956	0.732-1.248	0.739	—
Any training	0.921	0.625-1.357	0.677	—
Daily use	1.390	0.900-2.146	0.138	—
Law student	1.078	0.731-1.588	0.706	—

n = 385. Positive coefficients indicate stronger redress endorsement. Item contrasts are per one response point. Holm correction covers the four focal predictors only.

After Holm adjustment, the p values are 0.951 for concern, 0.260 for recognition, 0.706 for preservation and 0.260 for complaint-linked trust. H1-H4 do not receive multiplicity-adjusted support. The positive recognition and trust estimates remain compatible with potentially relevant associations as well as values close to no association. The results should not be described as proof of exact null effects or as statistically established positive relationships.

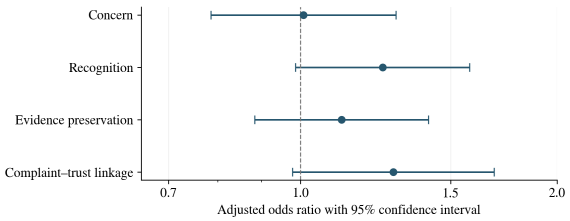


Figure 2. Focal ordinal associations with redress intention

Model-based 95% intervals; n = 385. All focal intervals include an odds ratio of one.

The control estimates are also uncertain: OR 1.046 for AI inaccuracy knowledge, 0.956 for bias knowledge, 0.921 for recorded training, 1.390 for daily use and 1.078 for student status. Their intervals all include one. These coefficients do not evaluate training effectiveness or the causal influence of AI use. The student indicator contrasts students with a heterogeneous nonstudent group rather than estimating every professional-status difference.

4.5 Model adequacy and predictive utility

The likelihood-ratio comparison against the category-frequency null gives $\chi^2(9) = 12.256$, $p = 0.199$. McFadden pseudo-R^2 is 0.0152 and AIC is 816.287. Pseudo-R^2 is a likelihood-based index, not a percentage of observed intention variance explained. Variance inflation factors range from 1.017 to 1.080, indicating little linear redundancy. The stacked cumulative-logit diagnostic gives $\chi^2(9) = 2.136$, $p = 0.989$, providing no detected slope heterogeneity across the two thresholds. This does not prove the proportional-odds assumption.

Table 7. Held-out prediction compared with a training-frequency baseline

Metric	Ordinal model	Baseline	Interpretation
Ranked probability loss	0.1965	0.1941	Lower is better
Logarithmic loss	1.0567	1.0475	Lower is better

Five stratified folds repeated five times. The baseline is estimated inside each training fold. Ranked-probability skill = –0.0121. Fold results are not independent replications.

Across the 25 held-out evaluations, the model's normalised ranked probability loss is 0.1965, compared with 0.1941 for the training-frequency baseline. Mean logarithmic loss is 1.0567 against 1.0475. Both criteria therefore favour the simpler baseline in this internal validation. The ranked-probability skill score is −0.0121, equivalent to approximately 1.2% worse loss relative to the baseline. These overlapping folds are not independent replications, and no significance test across fold scores is claimed.

4.6 Sensitivity and overall pattern

Table 8 summarises the focal coefficients under alternative specifications. Retaining the four observed response categories yields recognition OR 1.244 and complaint-linked trust OR 1.287, with intervals still spanning one. Omitting preservation produces recognition OR 1.240 and trust OR 1.297. Replacing the two general knowledge covariates with CRA4 gives recognition OR 1.245 and trust OR 1.298. These changes do not establish a clear adjusted association in the full numerical sample.

Table 8. Sensitivity estimates for focal associations

Specification	n	Concern	Recognition	Preservation	Trust linkage
Original categories	385	1.01 (0.79-1.29)	1.24 (0.98-1.57)	1.12 (0.89-1.41)	1.29 (0.98-1.69)
Students only	232	0.84 (0.61-1.17)	1.38 (1.00-1.90)	1.09 (0.81-1.47)	1.15 (0.81-1.65)
Without preservation	385	1.01 (0.78-1.29)	1.24 (0.98-1.57)	Omitted	1.30 (0.99-1.70)
CRA4 knowledge control	385	1.02 (0.79-1.30)	1.24 (0.98-1.57)	1.12 (0.89-1.42)	1.30 (0.99-1.70)

Entries are odds ratios with model-based 95% intervals. Student recognition has raw p = 0.047 and Holm-adjusted p = 0.188 within that specification. No between-status interaction is estimated.

In the 232-record student restriction, recognition has OR 1.381, 95% CI 1.004-1.900 and unadjusted p = 0.047. Its within-specification Holm-adjusted p value is 0.188. This exploratory subgroup result therefore does not provide multiplicity-adjusted support, and no formal student-versus-nonstudent interaction is claimed. Categorical recognition estimates are OR 1.490 for agree and 1.587 for strongly agree relative to no agreement; both intervals span one. The overall pattern combines high redress endorsement, a clear paired marginal contrast and limited explanatory and predictive discrimination.

5 Discussion

The findings distinguish redress endorsement, evidence preparation and the ability of the model to discriminate stronger intention. The paired contrast and the ordinal estimates address different aspects of this question. Results remain exploratory, with interpretation bounded by the measurement and documentation limitations described in the methodology. The discussion develops plausible mechanisms and priorities for prospective testing rather than causal explanations.

5.1 Intention and preparation are distinct responses

The paired comparison shows more endorsement of considering redress than preserving evidence. That result supports treating the two questions separately. It does not establish a causal sequence because both are measured at the same occasion and describe somewhat different hypothetical circumstances. A respondent may imagine that a platform or complaint body will retrieve the relevant record, while another may save evidence without wanting to complain. These are possible interpretations, not documented motivations.

Complaint theory helps explain why a preparatory step and a redress decision need not coincide.[27] Nevertheless, the present comparison cannot distinguish private complaints, public reviews, regulatory contact, litigation or platform-based resolution. The generic phrase complaint or redress mechanism may invite different mental scenarios. A subsequent instrument should ask about a specified route and a defined transaction problem. That would make it possible to examine whether particular preparation steps are associated with intention and eventual use of that route.

The discordant responses identify patterns for further investigation. Ninety-one records endorse redress without evidence preservation, while 45 endorse preservation without redress. These patterns do not establish deficiencies in an individual's competence, procedural exclusion or actual complaint completion. Scenario-based and longitudinal research could examine the circumstances underlying each pattern.

5.2 Recognition shows a possible but unresolved association

Recognition has a positive adjusted point estimate but an interval that includes one. The student-only model produces a somewhat larger estimate with a conventional unadjusted p value just below 0.05, yet the adjustment and subgroup context limit that observation. A difference in significance across specifications is not evidence that the underlying associations differ between populations. It may reflect sampling variation, composition or model sensitivity. The article therefore treats recognition as a candidate relationship for replication rather than a confirmed subgroup mechanism.

[27] Singh, ‘Consumer Complaint Intentions and Behavior’ (n 2); Tax, Brown and Chandrashekaran, ‘Customer Evaluations of Service Complaint Experiences’ (n 4); Davidow, ‘Organizational Responses to Customer Complaints’ (n 4).

Persuasion knowledge supplies a plausible reason why identifying a tactic could help someone formulate a grievance.[28] It also allows coping responses other than complaint. Recognising a design could prompt avoidance, advice seeking or switching, none of which the outcome captures. Future work should measure these alternatives alongside complaint intention and use an objective recognition task. A self-assessed capability item cannot resolve whether confidence is accurate or whether particular tactics are recognised.

5.3 Concern and redress discrimination

The concern estimate is close to one, with uncertainty spanning both lower and higher odds of stronger intention. The measured concern item therefore contributes little discrimination in this specification. Its general reference to exploitation of consumer vulnerabilities differs from personal vulnerability, perceived control and experience of a specific event. The result remains specific to that operationalisation.

Vulnerability research helps keep interpretation focused on the interaction between people and circumstances.[29] The available data do not measure interface constraints, financial stakes, time pressure, confidence in institutions or prior unsuccessful complaints. A person can express high concern while perceiving few effective options. Another can be less concerned in general but willing to challenge a specific harm. Testing such explanations requires additional measures; assigning them as established mediators would be speculative.

5.4 Complaint-linked trust and institutional interpretation

The trust-related item is strongly endorsed but only weakly associated with redress intensity after adjustment. Its wording values clear complaint mechanisms as a source of trust. It does not ask whether the respondent trusts a particular mechanism or expects success. The estimate should therefore not be presented as the effect of institutional trust. This distinction is consistent with research that differentiates trust constructs and complaint-handling evaluations.[30]

The result also avoids a circular policy claim. Respondents' endorsement that a clear mechanism would strengthen trust cannot independently demonstrate that a redesigned mechanism will increase complaint participation. A field experiment or documented implementation study would be needed. The present evidence motivates measuring clarity, procedural burden, perceived fairness and expected response separately, then examining how those characteristics relate to observed use.

[28] Friestad and Wright, ‘The Persuasion Knowledge Model’ (n 3).

[29] Rossi and others, ‘Who Is Vulnerable to Deceptive Design Patterns?’ (n 9); Baker, Gentry and Rittenburg, ‘Building Understanding of the Domain of Consumer Vulnerability’ (n 13).

[30] Mayer, Davis and Schoorman, ‘An Integrative Model of Organizational Trust’ (n 4); Tax, Brown and Chandrashekaran, ‘Customer Evaluations of Service Complaint Experiences’ (n 4); Davidow, ‘Organizational Responses to Customer Complaints’ (n 4); McKnight, Choudhury and Kacmar, ‘Developing and Validating Trust Measures for e-Commerce’ (n 16).

5.5 Endorsement and predictive performance

The ordinal model does not improve held-out probability forecasts relative to the category-frequency baseline. The baseline already reflects the concentration of responses towards agreement. Additional predictors introduce estimation uncertainty without demonstrating a corresponding predictive gain. This pattern is consistent with the modest likelihood-based fit and the uncertain coefficient estimates. The validation results provide no evidence of practical targeting utility for the current specification.

The distinction between explanation and prediction is important here.[31] A model can be useful for expressing a research question without being suitable for identifying which consumers need support. The present model should not be used to rank individuals for intervention or predict actual complaint filing. Such use would add a different outcome, external validity requirements and potential fairness concerns that have not been evaluated. Internal cross-validation does not compensate for uncertain recruitment or prove transportability.

5.6 Measurement structure and evidentiary scope

The low block alphas show that the questionnaire's thematic organisation should not be mistaken for validated reflective measurement. Each block contains statements about different domains, and the AMR block in particular blends concern, capability, two intentions and a relationship belief. Keeping these items separate avoids an ambiguous composite but leaves single-item error unresolved. A future study should develop multiple indicators for each narrowly defined concept and assess their structure in an independent sample.

Data-quality checks establish features of the numerical file but cannot independently authenticate its collection process. The codebook descriptions and unavailable recruitment records therefore remain relevant to empirical interpretation. The contribution is a reproducible, theory-informed analysis of the available database, with generalisation restricted by those evidentiary limits.

6 Theoretical and Practical Implications

The implications concern research design and prospective consumer-support interventions. They follow from the separation of measured concepts and the limits of predictive performance. None of the proposed interventions was evaluated in this dataset, and recommendations should be tested rather than presented as causal consequences of the reported associations.

[31] Shmueli, ‘To Explain or to Predict?’ (n 18); Gneiting and Raftery, ‘Strictly Proper Scoring Rules’ (n 25); Cawley and Talbot, ‘On Over-fitting in Model Selection’ (n 25).

6.1 Theoretical implications

First, recognition, concern, preparation and redress intensity require separate operationalisation. Their shared topic does not imply a common reflective trait. The study's specification preserves distinctions that a general manipulation-awareness score could conceal. A stronger theory test would measure attitudes towards a specified complaint, norms, procedural control, expected response and actual subsequent action. It would then examine whether recognition contributes beyond these more proximal determinants.

Second, the paired comparison demonstrates why marginal endorsement and individual association answer different questions. Redress is endorsed more often than evidence preservation, but the two ordinal responses are only weakly associated. Neither fact establishes a sequential process. Consumer-redress models should distinguish the distribution of a disposition from the ordering of actions and from the practical ability to complete them. Longitudinal observations would be required to connect these components as a process.

Third, the baseline comparison distinguishes theoretical relevance from demonstrated predictive utility. Conceptual plausibility, conditional associations and forecast performance require separate evaluation. The present results delimit the information provided by the selected measures rather than establish a general failure of planned-behaviour, trust or persuasion-knowledge theory. This distinction guides more focused measurement and external validation.

6.2 Educational and platform implications

Consumer education could connect the recognition of a suspicious practice to a concrete, safe response. Exercises might ask participants to identify the disputed claim, retain a transaction confirmation and produce a concise account of what occurred. Performance should be assessed using scenarios and a clearly defined rubric rather than agreement that evidence preservation is desirable. This would address the preparation component without assuming that all consumers who endorse redress can already carry it out.

Platforms could evaluate whether complaint interfaces make records accessible and permit a user to explain the problem without unnecessary navigation. A proposed design could offer a readable transaction summary, a route to human assistance and an acknowledgement containing a complaint identifier. These are prospective design features, not requirements established by the present statistical results. Testing should assess usability, disclosure risk and completion, including for users with different levels of literacy and access.

International consumer-policy guidance supports considering accessible dispute resolution as part of effective e-commerce protection.[32] Local implementation should use the applicable Bangladesh institutional framework and current official guidance. The study does not establish a legal right to a particular technical feature or determine

[32] OECD, Recommendation on Consumer Dispute Resolution and Redress (n 17); OECD, Recommendation on Consumer Protection in E-commerce (n 17).

which authority has jurisdiction over a hypothetical AI practice. Consumer-support materials should make such distinctions explicit.

6.3 Policy and evaluation implications

Evaluation should record whether assistance improves a defined response, such as preserving the relevant transaction information or completing a complaint form correctly. It should also examine burdens created by the process itself. A programme may increase confidence without improving completion, or improve completion without changing general awareness. These different outcomes require separate indicators.

A documented pilot and independent validation sample are needed to evaluate an awareness-based prediction tool before operational use. The present baseline comparison does not support consumer screening with this model. Clear provenance, meaningful consent and a data dictionary distinguishing empirical answers from contextual examples are also necessary for evaluating future programmes.

7 Conclusion Limitations and Future Research

This article examined algorithmic-manipulation awareness and redress intention using 385 numerical questionnaire records associated with a Bangladesh research project. A paired endorsement comparison, proportional-odds model and internal predictive validation yielded complementary findings. Redress intention received greater endorsement than evidence preservation, while adjusted associations involving concern, recognition, preparation and complaint-linked trust remained uncertain. The ordinal model did not improve held-out forecasts against training-fold category frequencies.

The central contribution is to distinguish willingness to consider redress from preparation, conditional association and prediction. The study identifies priorities for measurement development and prospective evaluation. It does not estimate causal effects of education or evidence preparation, and population-level interpretation remains conditional on clarification of numerical-data provenance.

Data provenance and sampling documentation are central limitations. The codebook labels the identifier sequence and contextual comments as synthetic, while the origin of the numerical answers is not independently documented. Contextual comments are excluded. Sampling probabilities, fieldwork dates, response rates and complete institutional coverage cannot be assessed. These uncertainties, together with the mixed law-oriented profile, restrict generalisation to consumers across

Bangladesh.

Measurement is cross-sectional, self-reported and restricted to single indicators. The outcome concerns considering a mechanism after hypothetical harm, not filing or obtaining redress. Predictors omit procedural knowledge, complaint experience and observed costs. Score-based item predictors assume equal log-odds increments, with recognition-category checks offering only a partial sensitivity assessment. Institutional dependence cannot be evaluated. Model-based intervals and internal resampling do not incorporate provenance uncertainty or unknown selection bias.

Future research should document the numerical-data origin, population, sampling frame, contact denominator, consent process and review arrangements. Cognitive interviews could distinguish recognition confidence from demonstrated skill and clarify the meaning of complaint mechanisms. A documented pilot could then evaluate separate measures of concern, capability, procedural control and preparation.

A prospective design could follow responses to a defined transaction scenario through recognition, evidence retention, mechanism selection and complaint completion. Experiments could compare recognition-only information with preparation-oriented assistance, using ethically designed tasks. External validation should evaluate whether a model improves proper probability scores and useful decisions over simple baselines. Related analyses from a common project should disclose their shared data source while maintaining distinct questions and outcomes.

Declarations

Ethics and consent

No new participant recruitment was undertaken for this numerical analysis. The questionnaire describes voluntary participation, anonymity and the option to stop, and all records contain affirmative consent and adult-eligibility fields. The codebook's provenance labels require clarification before publication as an empirical human-participant study.

Data availability

The analysis uses the numerical Group 7 database, excluding optional contextual comments. Aggregate results and analytical specifications are reported in the article and appendices. Access to row-level records is subject to confirmation of data origin, ownership, confidentiality obligations and applicable participant permissions.

Author contributions

Santa Ahamed: Lead authorship; development of the topic-specific research argument; manuscript preparation. The work was developed under the supervision of Prof. Dr Kazi Abdul Mannan.

Kazi Abdul Mannan: Supervision; conceptual and methodological guidance; interpretation of findings; critical review and editing of the manuscript.

Generative AI disclosure

Generative AI assisted literature organisation, manuscript drafting, language editing and analytical coding. Numerical estimates were computed programmatically from the database. The authors remain responsible for the accuracy of the analysis, interpretation and reporting.

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Appendix A Selected questionnaire items

AIL1. I understand that generative AI can produce plausible but inaccurate information.

AIL3. I understand that AI outputs may reflect bias or incomplete data.

CTP5. Clear complaint mechanisms increase my trust in AI-enabled digital commerce.

AMR1. I am concerned that algorithms can exploit consumer vulnerabilities.

AMR2. I can recognize some forms of manipulative online design or personalized pressure.

AMR3. I would preserve evidence if I believed an AI-enabled platform had misled me.

AMR4. I would consider using a complaint or redress mechanism after harmful algorithmic manipulation.

AMR5. Awareness of consumer rights increases my intention to seek redress.

Scale: 1 = strongly disagree; 2 = disagree; 3 = neutral; 4 = agree; 5 = strongly agree.

Appendix B Reproducibility specification

The primary outcome is AMR4 recoded to three ordered categories: responses at or below three, response four, and response five. Predictors are AMR1, AMR2, AMR3, CTP5, AIL1, AIL3, any recorded training, daily or almost daily AI use, and current status Law student. The ordered-logit model contains no separate intercept because threshold parameters provide the location structure. The proportional-odds diagnostic uses two stacked cumulative binary outcomes with threshold-specific slope interactions and a covariance clustered on record identity. This diagnostic clustering accounts for duplicated contributions in the stack, not institution-level dependence.

The paired analysis defines endorsement as four or five for AMR3 and AMR4. Bootstrap resampling preserves each row's paired responses. The 10,000-resample seed and cross-validation seed are 20261017. Predictive validation uses five stratified folds repeated five times, refitting the model in each training set. The category-frequency baseline is estimated from the same training set. For three outcome categories, the normalised ranked probability loss is one half of the sum of squared errors between the first two cumulative predicted probabilities and their observed-category indicators. Logarithmic loss is the negative log probability assigned to the observed category.

Table B1. Additional threshold and recognition-category checks

Specification	Predictor	OR	95% CI	Raw p
Agreement threshold	AMR1	1.046	0.767-1.428	0.775
Agreement threshold	AMR2	1.254	0.924-1.702	0.146
Agreement threshold	AMR3	1.189	0.857-1.649	0.301
Agreement threshold	CTP5	1.227	0.840-1.791	0.290
Strong-agreement threshold	AMR1	1.005	0.755-1.337	0.974
Strong-agreement threshold	AMR2	1.257	0.968-1.632	0.086
Strong-agreement threshold	AMR3	1.073	0.834-1.381	0.583
Strong-agreement threshold	CTP5	1.285	0.937-1.762	0.120
Recognition agree	vs no agreement	1.490	0.955-2.323	0.079
Recognition strongly agree	vs no agreement	1.587	0.935-2.696	0.087

Binary-threshold models use HC3 sandwich inference. Categorical-recognition estimates use ordinal maximum-likelihood inference. These checks are exploratory. Software: statsmodels 0.15.0; scikit-learn 1.8.0; NumPy 2.3.5; pandas 2.2.3.