

PROCESS PLURALISM, AI AND LEGITIMACY: A SCOPING REVIEW

Talia Schwartz-Maor,* Vera Shikhelman,** Avital Mentovich*** & Orna Rabinovich-Einy****

ABSTRACT

This Article examines how artificial intelligence (AI) shapes perceptions of trust and legitimacy across justice systems and dispute resolution processes. Using a scoping review methodology, we synthesize the growing scholarship on automated decisionmaking (ADM) and other uses of AI in both formal and informal legal contexts. Our review covers thirty-eight studies and identifies three central findings. First, perceptions of AI are shaped by the interaction of task allocation, decisionmaking domain, technical design, and user characteristics. Second, fairness consistently emerges as the dominant evaluative lens, reflecting the influence of procedural justice theory. Yet this emphasis also reveals a gap: pragmatic factors such as access and efficiency receive far less attention. Third, although ADM scholarship is expansive, only a small subset engages with courts and dispute resolution, and that work has tended to focus narrowly on judicial decisionmaking. This emphasis amplifies court-specific concerns while overlooking how attitudes toward AI vary across domains, procedural types, third-party roles, and institutional contexts. Furthermore, such a narrow focus obscures the reality that most disputes today are resolved through plural pathways outside formal adjudication. The article concludes by urging a broader research agenda that situates AI within this diverse dispute resolution landscape and reexamines procedural justice theories in light of the distinctive challenges and opportunities raised by AI-driven processes.

* Post-doctoral fellow, DRA Lab, Faculty of Law, University of Haifa. Orcid ID: <https://orcid.org/0009-0008-2376-312X>

** University of Haifa, DRA Lab, Faculty of Law. Orcid ID: <https://orcid.org/0000-0001-9576-9426>

*** Professor, Faculty of Law, University of Haifa. Orcid ID: <https://orcid.org/0000-0002-1164-7438>

**** Professor, Faculty of Law, University of Haifa. PI, Dispute Resolution Automation Lab at the University of Haifa. Orcid ID: <https://orcid.org/0000-0002-9855-0072>.

This article was funded by the European Union (ERC, 2021-COG, 101044195). Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or the European Research Council. Neither the European Union nor the granting authority can be held responsible for them.

We would like to thank Betty Vudinsky, Yoel Behar, Reut Gilad, Tamar Gur-Ramot, Yaakov Goltzman, Itai Bernstein, Noy Cohen, Vered Pery and Harel Shaked for very helpful research assistance.

I. INTRODUCTION

For centuries, human “third parties” have occupied a central role in the resolution of disputes. Village elders, Roman officers, community leaders, facilitators, mediators, arbitrators, and modern-day judges have all rendered a decision in disputes, or helped the parties reach a consensual resolution.¹ In recent decades, the spread of alternative dispute resolution (ADR), in the form of institutionalized mediation in the courts and the community on the one hand, and the proliferation of judicial conflict resolution practices on the other hand, has created a rich dispute resolution landscape in which formal decisions and informal settlements co-exist.² In fact, the reality of courts has been one in which the formal trial is “vanishing.”³ Most court cases settle, and settle early, with the aid of the judge, or another third party. Often such resolution is preceded by some early stage decisionmaking by the judge, but the ultimate outcome of the case is agreed-upon.⁴ Settlement (as well as other legal outcomes), can now be reached through various procedural options which comprise the legal landscape, a reality famously referred to as “process pluralism.”⁵

How will the introduction of Artificial Intelligence (AI) impact the formal and informal dispute resolution landscape? As in other domains, AI is permeating the legal milieu. The prospect of automated decisionmaking (ADM) by judges and use of AI in other dispute resolution processes employed in the justice system seems unavoidable, and to many, desirable. While debates over AI’s performance in judicial decisionmaking remain prominent,⁶ the question arises: what do we actually

¹ See Book Note, *Justice Without Law?: Resolving Disputes Without Lawyers*, 51 GEO. WASH. L. REV. 791, 792 (1983) (reviewing JEROLD S. AUERBACH, *JUSTICE WITHOUT LAW* (1983)); Laura Nader, *Controlling Processes in the Practice of Law: Hierarchy and Pacification in the Movement to Re-form Dispute Ideology*, 9 OHIO ST. J. ON DISP. RESOL. 1 (1993) (arguing that “harmony ideology,” i.e. “the use of a rhetoric of peace through consensus, finds fertile ground within the legal profession through cultural control”); see generally MARTIN SHAPIRO, *COURTS: A COMPARATIVE AND POLITICAL ANALYSIS* (1981) (proposing a model for the study of courts that emphasizes the different modes of decisionmaking and the multiple political roles that characterize the functioning of courts in different political systems).

² See Michal Alberstein, *Forms of Mediation and Law: Cultures of Dispute Resolution*, 22 OHIO ST. J. ON DISP. RESOL. 321 (2007) (providing “a map of mediation models and analyz[ing] the intellectual context from which they emerge”); Carrie Menkel-Meadow, *When Litigation is Not the Only Way: Consensus Building and Mediation as Public Interest Lawyering*, 10 WASH. U. J.L. & POL’Y 37, 39 (2002) (exploring how alternative dispute resolution “processes that enable the expression and ‘handling’ of conflict may serve the public interest,” even better than “the simplistic Anglo-American conception of adversary justice or public interest litigation”); Nancy A. Welsh, *Making Deals in Court-Connected Mediation: What's Justice Got To Do with It*, 79 WASH. U. L. Q. 787, 791 (2001) (arguing that “particularly within the context of the courts, mediation should be expected to deliver to disputants an experience of [procedural] justice”).

³ Marc Galanter, *The Vanishing Trial: An Examination of Trials and Related Matters in Federal and State Courts*, 1 J. EMPIRICAL LEGAL STUD. 459, 481–83, 506–10, 530 (2004) (finding a decline in the portion of cases that are terminated by trial and a decline in the absolute number of trials in various American judicial fora).

⁴ Ayelet Sela & Limor Gabay-Egozi, *Judicial Procedural Involvement (JPI): A Metric for Judges’ Role in Civil Litigation, Settlement, and Access to Justice*, 47 J.L. & SOC’Y 468, 468 (2020). (exploring the “scope of judicial involvement in settlements, the ratio between judges’ normative public-life function and their problem-solving function, and other pertinent questions”).

⁵ Carrie Menkel-Meadow, *Hybrid and Mixed Dispute Resolution Processes: Integrity of Process Pluralism*, in COMPARATIVE DISPUTE RESOLUTION 405, 416–17 (Maria Federica Moscati et al. eds., 2020).

⁶ See, e.g. Julia Angwin et al., *Machine Bias*, PROPUBLICA (May 23, 2016), <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing> [<https://perma.cc/TXB8-VXK8>] (arguing that the COMPAS system used to predict recidivism is biased against black people); Matthew Dahl et al., *Large Legal Fictions: Profiling Legal*

know about its use beyond judicial rulings? There are many other junctures of legal processes in which AI could play a role and, in some jurisdictions, already does (such as China, Morocco, and Singapore).⁷

Furthermore, some of the prominent debates in the legal domain have tended to focus on the performance of AI outputs, while overlooking the impact of AI on stakeholders' "subjective" perceptions regarding the fairness, trust, and legitimacy of the introduction of automation into the legal realm. Understanding such perceptions is important not only because fairness and trust are key antecedents of the legal system's legitimacy,⁸ but also because they are anchored in inherently human capabilities, namely the ability to establish meaningful interpersonal interactions between the parties and the (human) decisionmaker.⁹ Here, too, the question arises as to what the current literature reveals about perceptions of AI use across different legal pathways.

Therefore, this paper seeks to broaden the lens beyond traditional legal scholarship by conducting a scoping review of empirical studies that examine the antecedents of trust, legitimacy, and fairness in relation to the use of AI across both formal and informal dispute resolution processes. Such a review enables us to consider how perceptions of AI unfold across the wider landscape of dispute resolution, including informal and consensual processes.

The structure of the article is as follows. Section II outlines the methodology employed for data collection and screening in our review. Section III reviews, among others, the methods employed and the patterns observed in the included studies.

Hallucinations in Large Language Models, 16 J. LEGAL ANALYSIS 64, 66 (2024) (showing that LLMs hallucinate at least 58% of the time, struggle to predict their own hallucinations, and often uncritically accept users' incorrect legal assumptions; therefore, the authors caution against the rapid and unsupervised integration of popular LLMs into legal tasks); Neel Guha et al., *LegalBench: A Collaboratively Built Benchmark for Measuring Legal Reasoning in Large Language Models*, in 36 ADVANCES IN NEURAL INFO. PROCESSING SYS. 1, 4–8 (2023) (presenting the LEGALBENCH LLM software and the different legal tasks it can perform).

⁷ Vasily A. Laptev & Daria R. Feyzrakhmanova, *Application of Artificial Intelligence in Justice: Current Trends and Future Prospects*, 4 HUM.-CENTRIC INTEL. SYS. 394, 395–96 (2024) (discussing, among others, the Chinese case); David Uriel Socol De La Osa & Nydia Remolina, *Artificial Intelligence at the Bench: Legal and Ethical Challenges of Informing—or Misinforming—Judicial Decision-Making Through Generative AI*, 6 DATA & POL'Y, e59–2, e59–10, e59–12 (2024) (discussing the case of Singapore); *Artificial Intelligence and Judicial Systems in Africa*, LAWYERS HUB, <https://www.lawyershub.org/news/post/artificial-intelligence-and-judicial-systems-in-africa> [<https://perma.cc/U54Y-QZA2>] (last visited Sept. 10, 2025) (discussing the case of Morocco).

⁸ Jonathan Jackson, *Norms, Normativity, and the Legitimacy of Justice Institutions: International Perspectives*, 14 ANN. REV. L. & SOC. SCI. 145, 145, 152–156 (2018) (finding that procedural justice is the strongest predictor of police legitimacy); Avital Mentovich, J.J. Prescott & Orna Rabinovich-Einy, *Legitimacy and Online Proceedings: Procedural Justice, Access to Justice, and the Role of Income*, 57 LAW & SOC'Y REV. 189, 189 (2023) (finding that "perceptions of procedural justice and access to justice are each separately associated with a litigant's appraisal of system legitimacy"); Jason Sunshine & Tom R. Tyler, *The Role of Procedural Justice and Legitimacy in Shaping Public Support for Policing*, 37 LAW & SOC'Y REV. 513, 521–525 (2003) (discussing different aspects of police legitimacy).

⁹ See Yuen J. Huo et al., *Superordinate Identification, Subgroup Identification, and Justice Concerns: Is Separatism the Problem; Is Assimilation the Answer?*, 7 PSYCH. SCI. 40, 40–45 (1996) (discussing sub-groups in society and decisionmaking); EDGAR ALLAN LIND & TOM R. TYLER, *THE SOCIAL PSYCHOLOGY OF PROCEDURAL JUSTICE* 93, 101–105 (1988) (focusing, among others, on the importance of trust towards the decisionmaker); Tom R. Tyler, *The Psychology of Procedural Justice: A Test of the Group-Value Model*, 57 J. PERSONALITY & SOC. PSYCH. 830, 834 (1989) (showing that that neutrality, trust, and standing are a key input into people's reactions to their experiences with third parties); Tom R. Tyler & Steven L. Blader, *Identity and Cooperative Behavior in Groups*, 4 GRP. PROCESSES & INTERGROUP REL. 207, 212–13, 218–19, 222–23 (2001) (indicating that pride and respect significantly predict cooperative behavior, with status judgments).

Section IV analyzes the broader implications of these findings, and Section V offers concluding remarks.

II. SCOPE AND METHODOLOGY OF THE REVIEW

We employ a scoping review methodology, which offers a structured and systematic synthesis of the existing body of knowledge, relying on a predefined and transparent process.¹⁰ A scoping review is particularly appropriate in novel research contexts where the literature remains limited and fragmented, often lacking coherence in its conceptual foundations, methodological approaches, and findings. This methodology has been applied in the study of automated decisionmaking, though not yet in the context of dispute resolution.¹¹

Data collection and screening

Given our focus on perceptions of trust and legitimacy of ADM and use of AI in formal and informal dispute resolution, we employed the following inclusion criteria for including papers in our scoping review:

- (1) Empirical studies on perceptions of AI in courts and informal dispute resolution;
- (2) Written in English;
- (3) Reporting primary research (excluding meta-analysis);
- (4) Published between 2015-2025;
- (5) Search terms included:
 - a. trust OR fairness AND algorithm AND survey AND “dispute resolution” AND empirical OR experiment OR data OR study;
 - b. trust OR fairness AND algorithm AND survey AND “dispute settlement” AND empirical OR experiment OR data OR study;
 - c. trust OR fairness AND algorithm AND survey AND judge AND empirical OR experiment OR data OR study.

Our screening was comprised of several steps, as shown in Figure 1.

We ran a search on Scopus and Google Scholar (first fifteen pages, or 150 most relevant results) using our inclusion criteria as indicated above. The subsequent screening stage involved manual screening of articles falling outside the scope, which did not meet the inclusion criteria: non-empirical, no AI involvement (purely human decisionmaking), did not deal with perceptions, or was not within dispute resolution or the judicial contexts. Studies on criminal justice for example, or public policy, were therefore screened out, unless they related to judges/courts. We also manually searched for related articles using citation tracking, scanning papers that were within scope (the “snowball” method).

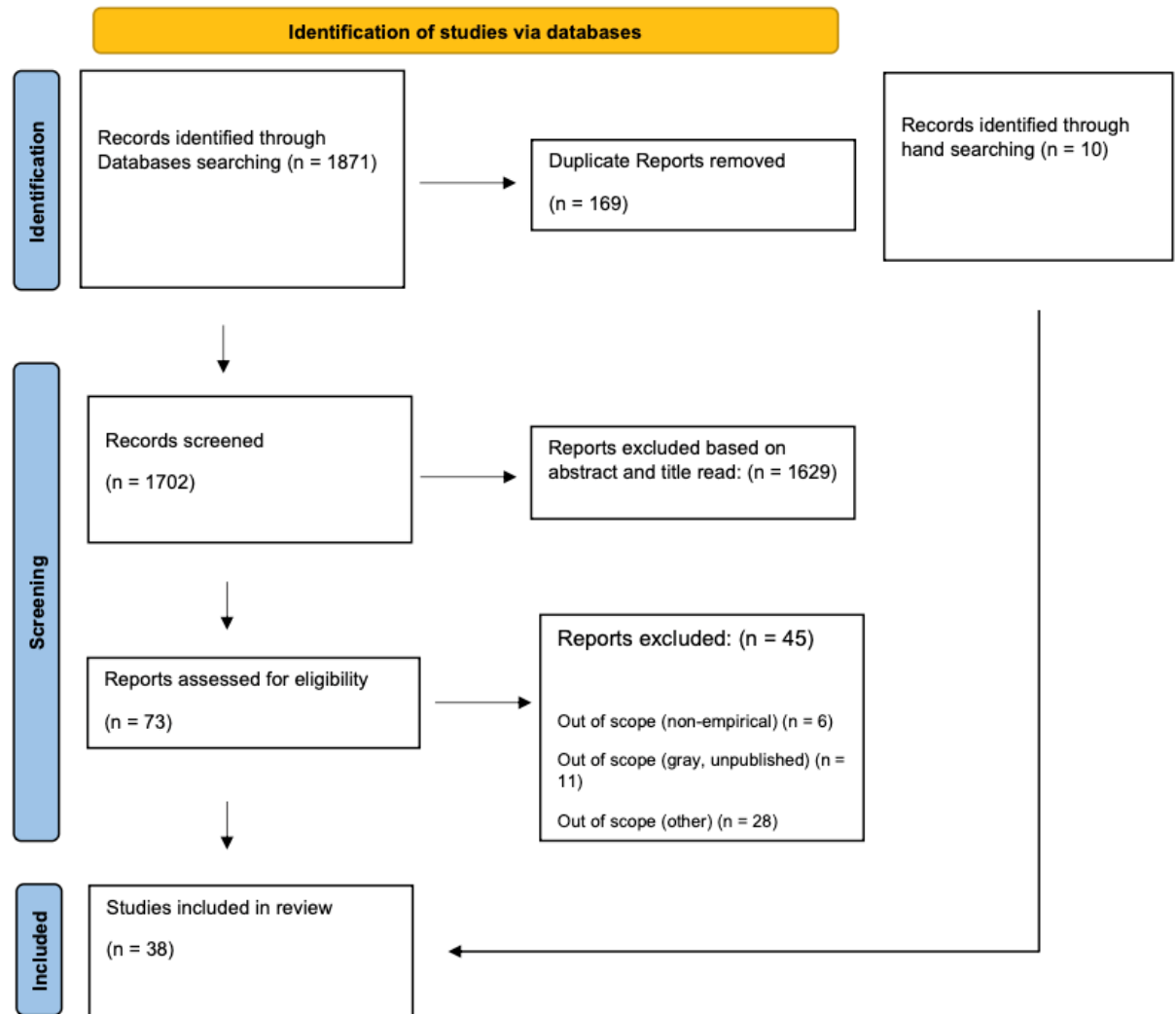
¹⁰ For articles discussing scoping methodology, see generally Hilary Arksey & Lisa O’Malley, *Scoping Studies: Towards a Methodological Framework*, 8 INT’L J. SOC. RSCH. METHODOLOGY 19 (2005) (describing scoping studies as a useful methodology for mapping broad and heterogeneous bodies of literature); David Moher et al., *Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement*, 6 PLOS MED. (2009) (providing reporting guidelines for systematic reviews and evidence synthesis).

¹¹ See Ella Glikson & Anita Williams Woolley, *Human Trust in Artificial Intelligence: Review of Empirical Research*, 14 ACAD. MGMT. ANNALS 627, 629–51 (2020) (reviewing the empirical research on human trust in AI conducted in multiple disciplines over the last twenty years); Christopher Starke et al., *Fairness Perceptions of Algorithmic Decision-Making: A Systematic Review of the Empirical Literature*, 9 BIG DATA & SOC’Y 1, 8–9 (2022) (conducting a systematic literature review examining empirical insights on fairness perceptions in algorithmic decisionmaking across various domains and disciplines).

This process yielded a body of thirty-eight (38) studies that met our criteria (See Table 1 in the Appendix). While modest in size compared to the vast literature on algorithmic decisionmaking in other domains, this corpus provides a valuable window into how questions of fairness, legitimacy, trust, and acceptance have been examined in the context of legal and dispute resolution processes. In what follows, we map the main patterns emerging from these studies, beginning with an overview of their methodological orientations and participant populations, and then turning to the substantive findings on perceptions of AI in judicial and dispute resolution settings.

III. PATTERNS IN THE REVIEWED LITERATURE: EMPIRICAL FINDINGS

Searches in Scopus and Google scholar (first fifteen pages) yielded overall 1870 papers (n=1870), of which 168 were duplicates; of the remaining 1702 papers, 1629 were excluded upon an abstract and title read, following which they were determined as outside the scope of the paper. Of the remaining seventy-three (73) papers, all of which were read in full, fifty-three (53) were excluded for being out of scope. Ten (10) additional papers were identified within scope following a manual search (citation tracking method), resulting in overall thirty-eight (38) papers being included. See Figure 1 for a graphic description of the search process, and Appendix - Table 1 for a summary of all research articles included in the final pool.



From: Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ* 2021;372:n71. doi: 10.1136/bmj.n71

Figure 1. Search strategy.(adapted from Page et al., 2021¹²).

¹² Matthew J. Page et al., *The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews*, *BMJ* (2021), <https://www.bmj.com/content/372/bmj.n71> [<https://perma.cc/NGU5-CNEC>].

A. Participants, Methodology and Constructs in the Reviewed Studies

1. *Studies' Participants*

Below we provide an overview of key features of the study participants in the reviewed literature. Mapping these characteristics, such as sample size, geographic coverage, and demographic composition, is important because they shape the scope of the findings, highlight possible biases, and indicate where further research is needed to build a more complete picture of perceptions of AI in adjudication and dispute resolution.

The studies reviewed considerably vary in scale, with sample sizes ranging from as few as twenty (20),¹³ seventy-seven (77),¹⁴ and eighty-six (86) participants,¹⁵ to much larger surveys of 1,725,¹⁶ 3,971,¹⁷ and 9,030 participants.¹⁸ These differences in size reflect, among other things, the diversity of approaches and methods employed, and they may have implications for generalizability of the findings to the broader population, depending on the research design and context.

Studies' populations vary geographically, though given that English was an inclusion criterion, language, and consequently geography, biases may be present. Approximately ~ ninety-two (92)% of papers report on Western societies (thirty-five (35) out of thirty-eight (38)) – the U.S. or Europe – Lithuania,¹⁹ the Netherlands,²⁰ Portugal,²¹ and Spain.²² One paper focused on multiple countries, including Germany, UK, Brazil, France and Singapore.²³ This imbalance is important to bear in mind, as it suggests that much of what we know about perceptions of AI in legal processes reflects Western legal cultures and may not fully capture the perspectives that would emerge in other legal and social contexts.

¹³ Anna-Katharina Dhungel & Moreen Heine, *Cui Bono? Judicial Decision-Making in the Era of AI: A Qualitative Study on the Expectations of Judges in Germany*, 33 TATUP - ZEITSCHRIFT FÜR TECHNIKFOLGENABSCHÄTZUNG IN THEORIE UND PRAXIS/J. FOR TECH. ASSESSMENT IN THEORY & PRAC. 14, 14 (2024).

¹⁴ Sandra Pérez Domínguez & Pere Simón Castellano, *Attitudes and Perceptions Regarding Algorithmic Judicial Judgement: Barriers to Innovation in the Judicial System?*, 39 REV. DE INTERNET, DERECHO Y POL. 1, 4 (2023).

¹⁵ Ayelet Sela, *Can Computers Be Fair? How Automated and Human-Powered Online Dispute Resolution Affect Procedural Justice in Mediation and Arbitration*, 33 OHIO ST. J. ON DISP. RESOL. 91, 130 (2018).

¹⁶ Ryan P. Kennedy, Philip D. Waggoner & Matthew M. Ward, *The Role of Personality in Trust in Public Policy Algorithms*, 84 J. POL. 1132, 1144 (2022) [hereinafter Kennedy 2022].

¹⁷ Derek E. Bambauer & Michael Risch, *Worse Than Human?*, 53 ARIZ. ST. L.J. 1091, 1117 (2021).

¹⁸ Kirk Bansak & Elisabeth Paulson, *Public Attitudes on Performance for Algorithmic and Human Decision-Makers*, 3 PNAS NEXUS 1,10 (2024).

¹⁹ Dovilė Barysė & Roece Sarel, *Algorithms in the Court: Does It Matter Which Part of the Judicial Decision-Making Is Automated?*, 32 A.I. & L. 117, 126, 134 (2024).

²⁰ Theo Araujo et al., *In AI We Trust? Perceptions About Automated Decision-Making by Artificial Intelligence*, 35 A.I. & SOC'Y 611, 612, 615 (2020).

²¹ Andreia Martinho, *Surveying Judges About Artificial Intelligence: Profession, Judicial Adjudication, and Legal Principles*, 40 A.I. & SOC'Y 569, 570–71, 574 (2024).

²² Domínguez & Castellano, *supra* note 14, at 2–3.

²³ Kathrin Eidenmüller, Conor McLaughlin & Horst Eidenmüller, *Expanding the Shadow of the Law: Designing Efficient Judicial Dispute Resolution Systems in a Digital World—An Empirical Investigation*, 29 HARV. NEGOT. L. REV. 53,66 (2024).

A majority (thirty-one (31) of thirty-eight (38), ~ eighty-one (81)%) of the studies' population is composed of lay-people or a mix of the general population and legal professionals.²⁴ Only a few papers focus exclusively on professionals, such as judges,²⁵ and public policy officials.²⁶ This distribution matters, as it suggests that existing findings may reflect how AI in legal decisionmaking is perceived by the broader public, while the views of professional actors, key actors in sustaining the legitimacy of legal processes, remain relatively underexplored.

In terms of demographics, our review shows that participants' gender (n= thirty-one (31)) and age (n= thirty (30)) were the most common measures, with level of education (n= fifteen (15)) and race/ethnicity of the participants (n= fifteen (15)) somewhat lagging behind, although studies did include race as a condition in vignette experimental studies.²⁷ The relatively marginal significance given to race in the different aspects of research may reflect latent assumptions about the role played by race in shaping attitudes towards technological change, but is nevertheless surprising given previous research findings demonstrating that race and ethnicity play a dominant role in legitimacy perceptions of the justice system.²⁸ Other demographics variables, such as political orientation (n= eight (8)), income (n= four (4)), and employment status (n= seven (7)), were measured in a small number of studies.

In addition, a significant portion (n= thirteen (13)) of the reviewed papers measure individual differences in terms of perceptions of technology. Such measures include: a) past experience with or knowledge of technology (n= nine (9)), and/or b) attitudes regarding the use of technology (n= seven (7)).²⁹ These variables are important because they capture how prior exposure and baseline attitudes toward technology shape receptiveness to AI in legal settings, and may help explain variation that cannot be accounted for by demographics alone.

2. Studies' Methods

²⁴ Barysè & Sarel, *supra* note 19, at 128; Domínguez & Castellano, *supra* note 14, at 4, 7–8.

²⁵ See, e.g., Anna Fine, Stephanie Le & Monica K. Miller, *Content Analysis of Judges' Sentiments Toward Artificial Intelligence Risk Assessment Tools*, 24 CRIMINOLOGY, CRIM. JUST., L. & SOC'Y 31, 33–39 (2023) [hereinafter Fine 2023]; Martinho, *supra* note 21, at 572–582; Dhungel & Heine, *supra* note 13, at 15–19.

²⁶ Michael C. Horowitz & Lauren Kahn, *What Influences Attitudes About Artificial Intelligence Adoption: Evidence from U.S. Local Officials*, 16 PLOS ONE 1, 4–5 (2021).
<https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0257732> [<https://perma.cc/PG5P-4HYT>].

²⁷ See, e.g., Nina Grgić-Hlača et al., *The Case for Process Fairness in Learning: Feature Selection for Fair Decision Making*, in PROC. ON MACH. LEARNING & L. 1, 5, 7, 10–11 (2016); Niels Van Berkel et al., *Crowdsourcing Perceptions of Fair Predictors for Machine Learning: A Recidivism Case Study*, 3 PROC. ACM HUM.-COMPUT. INTERACTION., 1, 6, 9, 11 (2019) [hereinafter Van Berkel 2019]; Ryan Kennedy et al., *Net Versus Relative Impacts in Public Policy Automation: A Conjoint Analysis of Attitudes of Black Americans*, 40 A.I. & SOC'Y 2571, 2576–77, 2579–80 (2024) [hereinafter Kennedy 2024].

²⁸ See, e.g., Jonathan Jackson et al., *Centering Race in Procedural Justice Theory: Structural Racism and the Under- and Over-Policing of Black Communities*, 47 LAW & HUM. BEHAV. 68, 74–78 (2023) (finding that people who believed that Black communities were underpoliced and overpoliced also tended to question the legitimacy of the police, especially if they identified with the Black Lives Matter movement); Avital Mentovich et al., *Policing Alienated Minorities in Divided Cities*, 14 REG. & GOVERNANCE 531, 540–47 (2020) (examining the legal authority among national minorities); Sunshine & Tyler, *supra* note 8, 532–33 (2003) (finding that the model of procedural fairness applies to both minority and non-minority groups).

²⁹ This measurement includes technology attitudes, Innovativeness (personal innovativeness with technology), affinity for technology interaction, and technology acceptance.

In addition to examining study populations, it is also important to consider the research methods employed in the reviewed literature, as methodological choices shape both the kinds of questions asked and the inferences that can be drawn. The majority of studies (twenty-four (24) of thirty-eight (38) ~ sixty-three (63)%) employ vignette-based survey designs, while ten rely on surveys without experimental manipulations, and three use semi-structured interviews.³⁰ Among experimental approaches, one study involved a mock online dispute resolution simulation,³¹ another employed a lab-based incentivized game,³² and a third used an adaptive experiment in which subsequent questions were determined by prior answers.³³ In addition, five (5) studies employed conjoint experiments to measure attribute preferences toward AI-based risk assessment and sentencing tools.³⁴ Overall, nearly half of the reviewed papers (nineteen (19) of thirty-eight (38), fifty (50)%) adopt a comparative design, contrasting human and algorithmic decisionmaking.

3. *Studies' Constructs*

In assessing the state of the literature, one must look beyond the methods used, at the outcomes that scholars choose to measure. In empirical research, these outcomes, often referred to as *dependent variables*, capture the constructs through which perceptions of AI are evaluated.³⁵ The choice of outcome measure is not a neutral design decision: it both shapes the insights that can be generated and reflects which disciplinary traditions are setting the terms of inquiry, leaving other important dimensions underexplored. In other words, constructs such as fairness, trust, legitimacy, or acceptance serve as more than technical indicators; they signal which values are treated as central benchmarks and which remain peripheral. Differences in conceptualization and measurement thus determine not only the comparability of findings across studies, but also the standards by which AI in legal processes is judged, and the questions that remain unasked.

Across the studies reviewed, outcome measures vary considerably. The constructs most frequently examined are fairness (thirteen (13)), trust (nine (9)), preferences (eight (8)), acceptance (seven (7)), and legitimacy (four (4)). Some studies focus more broadly on beliefs or attitudes toward legal AI,³⁶ while others

³⁰ Yeju Choi, *Using AI in My Disputes? Clients' Perception and Acceptance of Using AI in Mediation*, 43 CONFLICT RESOL. Q. 223, 226–27 (2025); Eidenmüller, McLaughlin, & Eidenmüller, *supra* note 23, at 66; Dhungel & Heine, *supra* note 13, at 16.

³¹ Sela, *supra* note 15, at 108.

³² Irene Locci & Sébastien Massoni, *Judged by Robots: Preferences and Perceived Fairness of Algorithmic Versus Human Punishments*, 21 REV. OF L. & ECON. 501, 505 (2024).

³³ Megha Srivastava, Hoda Heidari & Andreas Krause, *Mathematical Notions vs. Human Perception of Fairness: A Descriptive Approach to Fairness for Machine Learning*, in 25 PROC. ACM SIGKDD INT'L CONF. ON KNOWLEDGE DISCOVERY & DATA MINING 2459, 2460 (2019).

³⁴ Kennedy 2024, *supra* note 27, at 2573–76; Amit Haim & Dvir Yogev, *What Do People Want from Algorithms? Public Perceptions of Algorithms in Government*, 49 LAW & HUM. BEHAV. 263, 266–69 (2025); Bansak & Paulson, *supra* note 18, at 2–4; Kennedy 2022, *supra* note 16, at 1136–38; Philip D. Waggoner et al., *Big Data and Trust in Public Policy Automation*, 10 STAT., POL. & POL'Y 115, 119–22 (2019).

³⁵ JOHN W. CRESWELL & J. DAVID CRESWELL, *RESEARCH DESIGN: QUALITATIVE, QUANTITATIVE, AND MIXED METHODS APPROACHES*, 52–53 (5th ed. 2018) (explaining dependent variables as measured outcomes in empirical research).

³⁶ Jennifer Skeem, Nicholas Scurich & John Monahan, *Impact of Risk Assessment on Judges' Fairness in Sentencing Relatively Poor Defendants*, 44 LAW & HUM. BEHAV. 51, 52–53 (2020); Yochanan E. Bigman & Kurt Gray, *People Are Averse to Machines Making Moral Decisions*, 181 COGNITION 21, 23 (2018); Haim & Yogev, *supra* note 34, at 264–72;

address more specific judgments such as fairness,³⁷ trustworthiness,³⁸ or legitimacy.³⁹ Still others explore related dimensions such as blame attribution.⁴⁰

Fairness emerges as the most prevalent outcome measure, with thirteen (13) of thirty-eight (38) studies examining perceptions of fairness or its proxies. Most focus on procedural fairness, typically assessed through single-item agreement scales such as “how fair was the decisionmaking process,”⁴¹ or “how fair was the defendant treated.”⁴² Studies on outcome fairness tend to ask about the fairness of machine-generated outcomes,⁴³ or whether respondents agreed with the outcome.⁴⁴ A few adopt more comprehensive measures, which include fairness, voice, bias, and accuracy.⁴⁵ Others examine fairness perceptions of the AI model itself,⁴⁶ including assessments of discrimination.⁴⁷

Nine (9) studies investigate trust. Some ask directly whether an algorithmic decisionmaker “can be trusted,”⁴⁸ while others use composite measures combining fairness, predictability, bias, and usefulness.⁴⁹ Schiff and co-authors,⁵⁰ for instance, measure government performance through a scale including trust, perceived decision quality, and personal impact. Kennedy and co-authors uniquely rely on a behavioral proxy, examining the weight given to advice from a human versus an algorithm.⁵¹

Taenyun Kim & Wei Peng, *Do We Want AI Judges? The Acceptance of AI Judges’ Judicial Decision-Making on Moral Foundations*, 40 A.I. & SOC’Y 3683, 3684–86, 3691–93 (2025); Domínguez & Castellano, *supra* note 14, at 3; Eiichiro Watamura, Yichen Liu & Tomohiro Ioku, *Judges Versus Artificial Intelligence in Juror Decision-Making in Criminal Trials: Evidence from Two Pre-Registered Experiments*, 20 PLOS ONE 1, 4 (2025) [hereinafter Watamura 2025].

³⁷ Araujo et al., *supra* note 20, at 613–17, 621; Barysè & Sarel, *supra* note 19, at 123, 125, 129, 132–34.

³⁸ Gizem Yalcin et al., *Perceptions of Justice by Algorithms*, 31 A.I. & L. 269, 275, 277, 281 (2022); Anna Fine & Shawn Marsh, *Judicial Leadership Matters (Yet Again): The Association Between Judge and Public Trust for Artificial Intelligence in Courts*, 4 DISCOVER A.I. 1, 5–7, 10, 12 (2024).

³⁹ Ari Waldman & Kirsten Martin, *Governing Algorithmic Decisions: The Role of Decision Importance and Governance on Perceived Legitimacy of Algorithmic Decisions*, 9 BIG DATA & SOC’Y 1, 3–4 (2022); see Fine & Marsh, *supra* note 38, at 6–7, 12.

⁴⁰ Adam L. Ozer, Philip D. Waggoner & Ryan Kennedy, *The Paradox of Algorithms and Blame on Public Decision-Makers*, 26 BUS. & POL. 200, 202–03 (2024).

⁴¹ Araujo et al., *supra* note 20, at 616; Benjamin Minhao Chen, Alexander Stremitzer & Kevin Tobia, *Having Your Day in Robot Court*, 36 HARV. J.L. & TECH. 127, 148 (2022); Anna Fine, Emily R. Berthelot & Shawn Marsh, *Public Perceptions of Judges’ Use of AI Tools in Courtroom Decision-Making: An Examination of Legitimacy, Fairness, Trust, and Procedural Justice*, 15 BEHAV. SCIS. 1, 9 (2025) [hereinafter Fine 2025]; Martinho, *supra* note 21, at 574.

⁴² Ric Simmons, *Big Data, Machine Judges, and the Legitimacy of the Criminal Justice System*, 52 U.C. DAVIS L. REV. 1067, 1102 (2018).

⁴³ Barysè & Sarel, *supra* note 19, at 129; Martinho, *supra* note 21, at 571–72, 580.

⁴⁴ Simmons, *supra* note 42, at 1105–07.

⁴⁵ See e.g., Sela, *supra* note 15, at 125.

⁴⁶ Araujo et al., *supra* note 20, at 617–20; Grgić-Hlača et al., *supra* note 27, at 5–6; Van Berkel 2019, *supra* note 27, at 29–30; Niels van Berkel et al., *Effect of Information Presentation on Fairness Perceptions of Machine Learning Predictors*, PROC. OF THE CHI CONF. ON HUM. FACTORS COMPUTING SYS. 1, 2–3 (2021) [hereinafter Van Berkel 2021].

⁴⁷ Srivastava, Heidari & Krause, *supra* note 33, at 2459, 2461–62; Van Berkel 2019, *supra* note 27, at 29–30.

⁴⁸ See Eiichiro Watamura et al., *Empathetic Robot Judge, We Trust You*, 40 INT’L J. HUM.-COMPUT. INTERACTION 5192, 5195 (2024) [hereinafter Watamura 2023]; Dovilė Barysė, *People’s Attitudes Towards Technologies in Courts*, 11 LAWS 71, 75 (2022).

⁴⁹ Yalcin et al., *supra* note 38, at 275; Araujo et al., *supra* note 20, at 614; Ace Vo & Miloslava Plachkinova, *Investigating the Role of Artificial Intelligence in the U.S. Criminal Justice System*, 21 J. INFO., COMM’N & ETHICS SOCIETY 550, 551 (2023).

⁵⁰ Daniel S. Schiff, Kaylyn Jackson Schiff & Patrick Pierson, *Assessing Public Value Failure in Government Adoption of Artificial Intelligence*, 100 PUB. ADMIN. 653, 658 (2022).

⁵¹ Kennedy 2022, *supra* note 16, at 1133.

Several studies focus on preferences, whether for human versus AI decisionmakers,⁵² judicial methods,⁵³ or specific AI model features, such as COMPAS (Correctional Offender Management Profiling for Alternative Sanctions) system predictions.⁵⁴ Seven (7) studies examine acceptance, often through experimental manipulations. For example, Bigman and Gray test whether identical parole decisions are evaluated differently depending on whether they are made by a human or an algorithm,⁵⁵ Haim and Yogev examine acceptance of ADM across administrative and quasi-judicial domains,⁵⁶ and Kim and Peng analyze acceptance through the lens of moral foundations.⁵⁷

Finally, only four (4) studies explicitly measure legitimacy. Waldman and Martin use a straightforward single-item slider (“decision is legitimate”),⁵⁸ while Fine and co-authors apply a survey-based qualitative text analysis to identify statements implying threats that AI poses to legitimacy of the judiciary or calls for guidance of work with AI.⁵⁹

As we can see, fairness is the most prominent outcome measure, reflecting the strong influence of procedural justice theory. Alongside fairness a wide range of other measures are employed. The heterogeneity of such measures, ranging from single-item perceptions to composite scales and behavioral proxies, complicates comparability across studies and may raise concerns about construct validity.

Furthermore, the dominance of fairness as the primary lens in reviewed studies highlights a gap in how perceptions of AI are examined in legal settings. Evidence from other domains shows that perceptions of algorithmic decisionmaking are strongly influenced by perceptions of performance and accuracy, with perceived utility and effectiveness serving as key drivers of legitimacy and adoption,⁶⁰ with legal decisionmaking being no exception.⁶¹ A narrow focus on fairness risks overstating ethical concerns while underrepresenting the pragmatic factors that shape real-world acceptance.

⁵² Bambauer & Risch, *supra* note 17, at 1093, 1095.

⁵³ Bansak & Paulson, *supra* note 18, at 3.

⁵⁴ Grgić-Hlača et al., *supra* note 27, at 3–6 (focusing on COMPAS predictions); Kennedy 2022, *supra* note 16, at 1139–41 (focusing on criminal justice sentencing); Van Berkel 2019, *supra* note 27, at 29; Van Berkel 2021, *supra* note 46, at 5 (both focusing on COMPAS predictions); Waggoner et al., *supra* note 34, at 117 (focusing on data used by algorithms).

⁵⁵ Bigman & Gray, *supra* note 36, at 23–24.

⁵⁶ Haim & Yogev, *supra* note 34, at 264–66.

⁵⁷ Kim & Peng, *supra* note 36, at 3683–84.

⁵⁸ Waldman & Martin, *supra* note 39, at 6.

⁵⁹ Fine 2023, *supra* note 25, at 31.

⁶⁰ See, e.g., Anne-Marie Nussberger et al., *Public Attitudes Value Interpretability but Prioritize Accuracy in Artificial Intelligence*, 13 NATURE COMM'NS 1, 1 (2022) (finding, inter alia, accuracy to outweigh interpretability when there is a trade-off); Laszlo Horvath et al., *Citizens' Acceptance of Artificial Intelligence in Public Services: Evidence from a Conjoint Experiment About Processing Permit Applications*, 40 GOV'T INFO. Q. 1, 3, 9 (2023) (finding high accuracy of the AI system in the context of public service to be a key feature in shaping both acceptance and perceived fairness); Pascal D. König, Stefan Wurster & Markus B. Siewert, *Consumers Are Willing to Pay a Price for Explainable, But Not for Green AI. Evidence from a Choice-Based Conjoint Analysis*, 9 BIG DATA & SOC'Y 1, 7–8 (2022) (showing that people value cost in the context of AI, often at the expense of other features as transparency and sustainability).

⁶¹ Nina Grgić-Hlača et al., *Human Perceptions of Fairness in Algorithmic Decision Making: A Case Study of Criminal Risk Prediction*, in INT'L WORLD WIDE WEB CONF. COMM., 903, 911 (2018); A.J. Wang, *Procedural Justice and Risk-Assessment Algorithms* 10–12 (Jun. 21, 2018) (unpublished manuscript), <https://dx.doi.org/10.2139/ssrn.3170136> [<https://perma.cc/UGL8-HQCR>].

For a summary of the constructs employed in the reviewed papers, see Appendix - Table 2.

B. Legal Domain and the Role of the Algorithm

A further dimension of analysis concerns the legal domains in which AI is deployed and the roles it is assigned within decisionmaking processes. The studies reviewed span a range of contexts, from general examinations of judicial decisionmaking to specific applications in civil, criminal, and alternative dispute resolution. They also differ in whether algorithms are positioned as direct substitutes for human decisionmakers, as tools shaping particular stages of the legal process, or as components of facilitative dispute resolution.

As defined in our scoping criteria, all of the reviewed studies examine ADM and the adoption of AI within a judicial or dispute resolution context. Four (4) papers analyze AI in the judicial context broadly, without specifying a particular legal domain.⁶² As for the rest, a range of decision domains emerges. Civil use cases include commercial disputes, consumer refund scenarios,⁶³ and divorce proceedings.⁶⁴ Criminal use cases are somewhat more numerous, including sentencing decisions,⁶⁵ minor infractions such as parking tickets,⁶⁶ and the initiation of criminal proceedings on the basis of algorithmic recommendations.⁶⁷ Other studies construct fictitious scenarios, such as a robbery-homicide case,⁶⁸ or examine the criminal justice system more broadly.⁶⁹ The most common applications in this domain involve bail and recidivism prediction tools,⁷⁰ with a subset focusing specifically on the widely used COMPAS model.⁷¹ Finally, three (3) studies analyze alternative dispute resolution settings,⁷² while another three (3) examine the quasi-judicial context of parole decisions.⁷³

Our review also reveals two distinct orientations across the literature. The first category includes studies that explicitly compare algorithmic decisionmaking to that of human legal professionals (n=19). These papers provide direct insights into perceptions of how algorithms perform relative to human actors in legal or quasi-legal contexts. The second category comprises studies that focus on perceptions of automation in legal processes without a comparison to a human-driven equivalent (n=19). Both orientations concentrate on the conditions under which algorithmic tools are regarded as legitimate, trustworthy, or fair.

⁶² Barysè & Sarel, *supra* note 19, at 117; Barysè, *supra* note 48, at 1; Martinho, *supra* note 21, at 569; Locci & Massoni, *supra* note 32, at 501.

⁶³ Chen, Stremitzer & Tobia, *supra* note 41, at 141; Sela, *supra* note 15, at 93.

⁶⁴ Yalcin et al., *supra* note 38, at 275–76.

⁶⁵ Chen, Stremitzer & Tobia, *supra* note 41, at 141; Waggoner et al., *supra* note 34, at 121.

⁶⁶ Araujo et al., *supra* note 20, at 615.

⁶⁷ *Id.*

⁶⁸ Watamura 2023, *supra* note 48, at 5194.

⁶⁹ Vo & Plachkinova, *supra* note 49, at 550.

⁷⁰ Chen, Stremitzer & Tobia, *supra* note 41, at 130; Fine 2025, *supra* note 41, at 2; Kennedy 2022, *supra* note 16, at 1133; Waldman & Martin, *supra* note 37, at 5.

⁷¹ Kennedy 2022, *supra* note 16, at 1139; Grgić-Hlača, *supra* note 61, at 2; Van Berkel 2019, *supra* note 46, at 2.

⁷² Choi, *supra* note 30, at 223; Sela, *supra* note 15, at 92; Eidenmüller, McLaughlin, & Eidenmüller, *supra* note 23, at 79–84.

⁷³ Waldman & Martin, *supra* note 39, at 5; Haim & Yogev, *supra* note 34, at 269; Bigman & Gray, *supra* note 36, at 23.

Accordingly, we organize our findings along these two axes: beginning with studies that evaluate AI in comparison with human legal actors, and then turning to those that focus on the features of AI-based processes as standalone mechanisms. Together, these strands of analysis provide a foundation for assessing the benchmarks against which algorithmic performance is evaluated and the normative expectations that shape its perceived legitimacy.

1. Human vs. AI: Algorithmic Aversion

Half of the reviewed literature directly compares perceptions of algorithmic decisionmaking with those of human legal professionals. At first glance, these studies suggest a consistent pattern: participants generally express greater trust in human legal professionals than in algorithms. Yet, the findings reveal a more nuanced picture. Of the studies reviewed, nine (9) report some form of algorithmic aversion, three indicate a preference for algorithms, five (5) find outcomes dependent on context, and two (2) show no clear preference.

Nine (9) studies point to algorithmic aversion, typically in scenarios where AI is presented as a substitute for human legal professionals in reaching ultimate case outcomes.⁷⁴ This aversion is often linked to the perception that humans possess qualities essential to adjudication such as empathy, deliberation, and the ability to provide voice—qualities that algorithms cannot replicate. For instance, Yalcin and co-authors found human legal professionals to be perceived as more trustworthy, particularly in emotionally complex cases.⁷⁵ Waldman and Martin reported that AI decisionmaking was regarded as less legitimate than human judgment across nearly all decision domains, with legitimacy declining as the stakes increased.⁷⁶

Similarly, Watamura and co-authors showed that human legal professionals were perceived as significantly more empathetic than their robotic counterparts.⁷⁷ Fine and co-authors underscore this point, showing that aversion was rooted in concerns about procedural justice, including deliberation and the opportunity to be heard.⁷⁸

Five (5) studies, however, demonstrate that preferences are highly context-dependent. Bambauer and Risch found that decision domain and stakes shaped whether humans or algorithms were favored.⁷⁹ Sela observed greater support for human adjudication in arbitration,⁸⁰ but also greater openness to algorithms in mediation, where decisionmaking authority rests with the parties. Barysé and Sarel similarly reported a division between technical functions, where AI was preferred, and later stages of judicial decisionmaking, where humans were favored.⁸¹ Locci and Massoni found divergence between laypeople, who tended to prefer algorithms, and legal professionals, who preferred human decisionmaking.⁸² Finally, Waggoner and

⁷⁴ See, e.g., Vo & Plachkinova, *supra* note 49, at 551; Waldman & Martin, *supra* note 39, at 11; Yalcin et al., *supra* note 38, at 269.

⁷⁵ Yalcin et al., *supra* note 38, at 281.

⁷⁶ Waldman & Martin, *supra* note 39, at 2.

⁷⁷ Watamura 2023, *supra* note 48, at 5192.

⁷⁸ Fine 2023, *supra* note 25, at 37.

⁷⁹ Bambauer & Risch, *supra* note 17, at 1094.

⁸⁰ Sela, *supra* note 15, at 134.

⁸¹ Barysé & Sarel, *supra* note 19, at 132–33.

⁸² Locci and Massoni, *supra* note 32, at 503–04.

Kennedy demonstrated that preferences varied according to individual personality traits.⁸³

Interestingly, three (3) studies found a preference for algorithms, all within the criminal law domain—a context usually regarded as especially high-stakes. Kennedy and co-authors reported that participants placed more weight on algorithmic advice in recidivism risk assessments than on human advice, particularly among those already inclined to trust algorithms.⁸⁴ Araujo and co-authors found that respondents perceived AI as fairer than human legal professionals in a scenario involving the initiation of a criminal prosecution.⁸⁵ Simmons, examining bail decisions, found no clear preference in closed questions but noted that respondents in open responses viewed algorithms as enhancing fairness when used alongside human legal professionals.⁸⁶

Two (2) studies were inconclusive. Bansak and Paulson found that in bail contexts participants were more concerned with efficiency than with the identity of the decisionmaker,⁸⁷ while Watamura showed that sentencing outcomes were influenced more by mitigating circumstances than by whether the decision was made by a human legal professional or an algorithm.⁸⁸

Taken together, these findings suggest that “algorithmic aversion” cannot be understood as a uniform phenomenon. While skepticism toward algorithmic adjudication appears strongest when AI is positioned as a substitute for human legal professionals in substantive decisionmaking, attitudes are more favorable in technical or advisory roles, or when algorithms operate alongside human actors. Having considered studies that directly compare human and algorithmic decisionmakers, the next section turns to research that examines perceptions of legal processes employing AI without contrasting them with human-driven alternatives.

2. Perceptions of AI in Legal Settings with No Human Comparison

The studies examined in this section do not assess whether algorithms outperform or align with human judgment; rather, they explore how individuals evaluate the legitimacy and trustworthiness of algorithmic legal processes as standalone mechanisms. A consistent finding across this literature is that perceptions are highly context-dependent. Whether an algorithm is deemed fair, legitimate, or trustworthy depends not only on its technological features, but also on a host of surrounding conditions. Key factors include the function assigned to the algorithm (e.g., providing recommendations versus making binding decisions), its perceived transparency or explainability, and its demonstrated accuracy or error rate.

In addition to these technological attributes, external variables shape perceptions. These include the legal domain in which the algorithm operates (e.g., sentencing versus small claims adjudication) and characteristics of the evaluators themselves, such as demographic background, prior exposure to technology, or

⁸³ See Kennedy 2022, *supra* note 16.

⁸⁴ *Id.* at 1140–41.

⁸⁵ Araujo et al., *supra* note 20, at 617.

⁸⁶ Simmons, *supra* note 42, 1106–07.

⁸⁷ Bansak & Paulson, *supra* note 18, at 1.

⁸⁸ Watamura 2025, *supra* note 36, at 10.

personality traits.⁸⁹ Trust in legal automation, in short, does not arise from the system alone, but is embedded in a broader socio-technical context.

Across this subset of studies, stronger acceptance emerges in relation to technical rather than substantive functions. For instance, Choi found that participants were comfortable with AI assisting mediators in tasks such as scheduling, tracking case details, and summarizing discussions, but far less accepting of AI in co-mediating substantive issues or in tasks that did not directly benefit them, such as training the model.⁹⁰ Fine and Marsh similarly show that trust in AI varied by context,⁹¹ a conclusion echoed in interviews with judges,⁹² surveys among legal professionals,⁹³ and mixed samples of lay and legal actors.⁹⁴ Haim and Yogev likewise demonstrate that acceptance varies by domain, with parole decisions viewed as substantially less acceptable for automation than more administrative functions such as permits.⁹⁵

Other studies isolate particular technological/functional attributes that influence acceptance. Grgić-Hlača and co-authors found that perceptions of fairness were driven primarily by accuracy,⁹⁶ while Schiff and co-authors reported that fairness weighed more heavily than transparency or responsiveness in the context of bail decisions.⁹⁷ Kennedy and co-authors show that participants were willing to tolerate some level of algorithmic bias if the system produced net social benefits.⁹⁸ Srivastava and co-authors similarly found that when stakes were high, as in recidivism assessments, accuracy mattered more to participants than equality.⁹⁹

Taken together, these studies suggest that evaluations of algorithmic legal processes are shaped by a dynamic interplay of technical design, task allocation, decisionmaking domain, and user characteristics. The strongest support for automation arises in technical and efficiency-enhancing functions, while skepticism remains in areas involving core adjudicative judgments or morally weighty decisions. Fairness taken together with accuracy, emerges as the most influential attribute, eclipsing transparency or responsiveness. These findings underscore that legitimacy in legal automation cannot be reduced to the intrinsic properties of the technology; it depends on how the technology is embedded within legal processes, and how those processes are perceived by the individuals they affect. This contextual lens provides a bridge to the next stage of analysis: a deeper examination of the conditions that give rise to algorithmic acceptance towards the use of algorithms in adjudication and dispute resolution as they emerge from the entire pool of articles within our scope.

C. Algorithmic Acceptance Across Categories and Domains

⁸⁹ See, e.g., Haim & Yogev, *supra* note 34, at 272–74; Araujo et al., *supra* note 20, at 618–20; Domínguez & Castellano, *supra* note 14, at 9.

⁹⁰ Choi, *supra* note 30, at 227–28.

⁹¹ Fine & Marsh, *supra* note 38, at 46 (discussing in the contexts of bail decisions and sentencing).

⁹² Dhungel & Heine, *supra* note 13, at 18.

⁹³ Eidenmüller, McLaughlin, & Eidenmüller, *supra* note 23.

⁹⁴ Domínguez & Castellano, *supra* note 14, at 2–3, 9.

⁹⁵ Haim & Yogev, *supra* note 34, at 272–74.

⁹⁶ Grgić-Hlača et al., *supra* note 27, at 3, 8.

⁹⁷ Schiff, Schiff & Jackson, *supra* note 50, at 663.

⁹⁸ Kennedy 2024, *supra* note 27, at 2580.

⁹⁹ Srivastava, Heidari & Krause, *supra* note 33, at 2466.

Building on this mapping of domains and roles, we now turn to the question of what explains variation in acceptance across them. We identify four recurring factors in the reviewed literature: case type, dispute system design, AI design features, and individual characteristics. Each illuminates the conditions under which algorithmic tools are embraced, resisted, or viewed with ambivalence in judicial and dispute resolution settings.

With respect to case type, opposition to AI is lowest in low-stakes or less complex decisions. Araujo and co-authors, for example, found that human decisions to initiate criminal lawsuits were perceived as less fair, riskier, and less useful than algorithmic ones, but that this gap disappeared in minor cases such as parking tickets.¹⁰⁰ Waldman and Martin similarly observed higher legitimacy scores for AI in less consequential decisions, with algorithms rated least fair in parole contexts.¹⁰¹ Yalcin and co-authors examined divorce cases and found that AI use in emotionally complex disputes generated the lowest levels of trust, whereas no significant differences emerged between AI and human decisionmaking in low-emotional or high-technical cases.¹⁰² These findings underscore that “what is at stake,” both in terms of domain and decision complexity, plays a central role in shaping acceptance of AI.

Second, in terms of task or functionality, the literature shows that AI is perceived as more acceptable in advisory or procedural roles than when delivering final decisions. Kennedy and co-authors found that people displayed no aversion when algorithmic advice accompanied a human decisionmaker, and in some cases even preferred algorithmic advice on its own.¹⁰³ Vo and Plachkinova similarly observed no decline in trust when judges relied on AI input, and noted that engagement with AI could increase trust in a human judge.¹⁰⁴ Studies by Barysè and Sarel, and Martinho likewise indicate higher acceptance of AI in earlier trial stages involving routine tasks, as compared to later phases culminating in final judgments.¹⁰⁵ In a related finding, Sela showed that when decisionmaking authority remains with the parties, as in mediation, preference for AI can surpass that for humans.¹⁰⁶ Taken together, these studies suggest that acceptance is closely tied to the design of the dispute system: AI is most readily embraced when it operates in a supportive capacity, particularly in early or advisory stages, rather than as the ultimate decisionmaker.¹⁰⁷

Research shows that attributes of the AI mechanism itself are central in shaping acceptance. Three stand out: accuracy, transparency, and the presence of a human “in the loop.” Accuracy consistently emerges as the most influential factor. Higher accuracy is positively associated with acceptance of AI.¹⁰⁸ When error rates were equal, participants in one study even preferred algorithms over humans.¹⁰⁹ Tradeoff studies further suggest that individuals are willing to sacrifice some degree of

¹⁰⁰ Araujo et al., *supra* note 20, at 615, 617–18.

¹⁰¹ Waldman & Martin, *supra* note 39, at 8–10.

¹⁰² Yalcin et al., *supra* note 38, at 275–84.

¹⁰³ Kennedy 2022, *supra* note 16, at 1144–45.

¹⁰⁴ Vo & Plachkinova, *supra* note 49, at 560–61.

¹⁰⁵ Barysè & Sarel, *supra* note 19, at 133; Martinho, *supra* note 21, at 577.

¹⁰⁶ Sela, *supra* note 15, at 132–33.

¹⁰⁷ *Id.* at 142–43.

¹⁰⁸ Chen, Stremitzer & Tobia, *supra* note 41, at 161.

¹⁰⁹ Bambauer & Risch, *supra* note 17, at 1128.

fairness for gains in accuracy.¹¹⁰ Relatedly, training data size has been shown to shape credibility assessments, often outweighing data relevance,¹¹¹ though participants remain reluctant to share their own data.¹¹² People are also sensitive to inputs perceived as biased: while criminal history or charges were viewed as fair bases for prediction, age, gender, and race were consistently rejected.¹¹³

Transparency also plays an important role. Participants tend to evaluate algorithms as fairer when they understand or can interpret the model's reasoning.¹¹⁴ Experiments show that transparency treatments reduce aversion, sometimes eliminating differences between human and algorithmic decisionmakers.¹¹⁵ Choi found that transparency likewise influences acceptance in mediation.¹¹⁶

Finally, having a human "in the loop" is positively associated with legitimacy and acceptance. Studies show that human oversight of algorithmic outcomes, whether in reviewing or approving decisions, consistently improves evaluations of fairness and legitimacy.¹¹⁷

Studies also examine how individual traits, demographics, and professional background shape attitudes toward AI. Overall, personality traits and prior experience with AI appear more predictive than demographic variables. Most notably, prior experience with AI and digital literacy were positively associated with acceptance across domains and automation levels.¹¹⁸ Moreover, familiarity with AI influenced the reasons for opposition: those inexperienced emphasized preserving human control, while those with AI experience cited concerns about bias.¹¹⁹ A general propensity to trust AI also correlated with greater trust in automated decisionmaking.¹²⁰ Finally, personality traits influence trust: participants with a high need for evaluation personality type trusted algorithms less, while those with a high need for cognition personality type trusted them more, particularly in criminal sentencing.¹²¹

Demographic variables have yielded mixed results. Age effects were inconsistent: some studies reported no association,¹²² while others found younger participants more accepting.¹²³ Findings on gender are similarly split: several studies reported greater aversion among women,¹²⁴ while others found no difference.¹²⁵

¹¹⁰ Grgić-Hlača et al., *supra* note 27, at 7; Simmons, *supra* note 42, at 1077–90; Srivastava, Heidari & Krause, *supra* note 33, at 2466.

¹¹¹ Ozer et al., *supra* note 40, at 131; Kennedy 2022, *supra* note 16, at 1143.

¹¹² Choi, *supra* note 30, at 228.

¹¹³ Grgić-Hlača et al., *supra* note 27, at 5; Van Berkel 2019, *supra* note 27, at 9–10.

¹¹⁴ Van Berkel 2019, *supra* note 27, at 4; Daria Szafran & Ruben L. Bach, *The Human Must Remain the Central Focus: Subjective Fairness Perceptions in Automated Decision Making*, 34 MINDS & MACHS. 1, 1 (2024).

¹¹⁵ See Locci & Massoni, *supra* note 32, at 504.

¹¹⁶ Choi, *supra* note 30, at 228.

¹¹⁷ See Waldman & Martin, *supra* note 39, at 11; Domínguez & Castellano, *supra* note 14, at 9–10; Szafran & Bach, *supra* note 114, at 24.

¹¹⁸ Domínguez & Castellano, *supra* note 14, at 9.

¹¹⁹ Horowitz & Kahn, *supra* note 26, at 1.

¹²⁰ Barysè & Sarel, *supra* note 19, at 1135; Kennedy 2022, *supra* note 16, at 125.

¹²¹ Kennedy 2022, *supra* note 16.

¹²² *Id.*; Domínguez & Castellano, *supra* note 14, at 8; Srivastava, Heidari & Krause, *supra* note 33, at 2464.

¹²³ See Horowitz & Kahn, *supra* note 26, at 4; Araujo et al., *supra* note 20, at 614; Barysè & Sarel, *supra* note 19, at 137.

¹²⁴ See Araujo et al., *supra* note 20, at 617; Bambauer & Risch, *supra* note 17, at 1120; Horowitz & Kahn, *supra* note 26, at 2; Van Berkel 2021, *supra* note 46, at 8–9.

¹²⁵ Barysè & Sarel, *supra* note 19, at 129.

Studies that included race generally found limited effects, though Kennedy and co-authors showed that Black Americans were willing to tolerate algorithmic racial disparities if automation produced net community benefits, such as reduced crime.¹²⁶

Differences between laypeople and professionals are more consistent. While most studies focus on lay participants, six (6) examine legal professionals. These studies show that judges and other professionals exhibit greater algorithmic aversion, especially in contexts like bail or recidivism prediction.¹²⁷ Yet, opposition among professionals also diminishes when AI is confined to early, technical stages of the legal process.¹²⁸

Taken together, these findings suggest that support for AI is shaped less by broad demographic categories than by experience with technology and the context of its use. Accuracy and transparency remain the most valued features, while human oversight mitigates legitimacy concerns. Professionals—those most familiar with legal processes—tend to be more skeptical than laypeople, perhaps reflecting normative concerns of those tasked with safeguarding due process as well as concerns over implications for their professional future.

IV. FROM MAPPING TO MEANING: IMPLICATIONS AND NEXT STEPS

The aim of this scoping review is to provide an overview of existing research on the perceptions of automation in formal and informal legal processes, as well as to uncover the circumstances under which the use of AI in this domain is perceived as trustworthy, legitimate, and fair.

Screening processes started with thousands of research papers dealing with algorithmic involvement in decisionmaking with only thirty-eight (38) of them falling within our defined scope: empirical studies examining perceptions towards AI in the alternative dispute resolution or judicial context. This significant gap shows that while there is a burgeoning interest in AI, its application to the formal and informal dispute resolution sphere is relatively limited. The dearth of research is in stark opposition to the pace at which automation is transforming these arenas, making research on perceptions of such developments all the more necessary.

Our focus on perceptions of AI was driven by the centrality of individual perceptions to the establishment of trust and legitimacy. Research has shown that acceptance of legal proceedings is not typically rooted in objective outcomes but rather in how fair or trustworthy they seem to the public.¹²⁹ The significance of individual perceptions has been recognized not only in the legitimacy literature but also in the dispute resolution field in writing on the need to design dispute systems with stakeholder involvement¹³⁰ and in the technological sphere's commitment to the development of tools that commit to a "user centered design" approach.¹³¹

¹²⁶ Kennedy 2024, *supra* note 27, at 2574.

¹²⁷ Fine 2023, *supra* note 25, at 37; Domínguez & Castellano, *supra* note 14, at 10;

¹²⁸ See Barysè & Sarel, *supra* note 19, at 132; Martinho, *supra* note 21, at 582; Dhungel & Heine, *supra* note 13, at 19.

¹²⁹ See Tom R. Tyler, *Psychological Models of the Justice Motive: Antecedents of Distributive and Procedural Justice*, 65 J. PERSONALITY & SOC. PSYCH. 850, 857–59 (1994); Sunshine & Tyler, *supra* note 8, at 514, 520, 534–36.

¹³⁰ LISA BLOMGREN AMSLER, JANET K. MARTINEZ & STEPHANIE E. SMITH, DISPUTE SYSTEM DESIGN: PREVENTING, MANAGING AND RESOLVING CONFLICT 7, 29–30 (2020).

¹³¹ See Margaret Hagan, *Introduction to Design Thinking for Law*, in LEGAL INFORMATICS (Daniel M. Katz, Ron Dolin & Michael Bommarito eds., 2021) 155, 163; Orna Rabinovich-Einy & Ethan Katsh, *Artificial Intelligence and the Future of*

Our review, like studies in other domains, identifies some degree of algorithmic aversion, expressed in a preference for human decisionmaking. At the same time, the extent of this aversion may be overstated, reflecting the disproportionate attention given to a limited set of judicial functions, while other, more common features of the contemporary dispute resolution landscape receive far less consideration.

Specifically, our scoping review suggests that most studies focus on high-stake legal decisions, such as decisions regarding imprisonment, risk assessment, and bail hearings. This is so perhaps because such cases highlight the gravitas of the legal system and spark the interest and curiosity of the public. In reality, though, a significant portion of the caseload with which the legal system deals has to do with much more mundane cases, many of which are civil, and even within the criminal realm, cases tend to be relatively simple and to involve low stake petty offenses such as minor non-criminal traffic offences.¹³²

As shown in our review, those few studies that do focus on day-to-day, low-stake civil disputes demonstrate that people harbor more positive perceptions towards the introduction of AI into such settings. Indeed, this is the “stuff” that the dispute resolution landscape—formal and informal—is made of, and these are the problems that color people’s lives. A wide-scale, nuanced study of individual perceptions towards use of AI in addressing a broad range of dispute types could generate important lessons as to the acceptability and legitimacy of the adoption of AI tools in a variety of settings, moving beyond broad legal categories and provocative case studies.

Second, our review uncovers an emphasis in the literature on the significance of the adoption of AI in delivering the ultimate outcome of a case. Here again we find that studies do not fully reflect the reality of courts, and in particular the now well-known “vanishing trial” phenomenon, according to which only a very small fraction of cases filed are resolved through a formal judicial verdict following a full-fledged legal process.¹³³ By highlighting attitudes towards the substitution of human decisionmakers by AI “judges,” we not only focus on the least likely use of AI in courts, but—as our scoping review shows—we may in fact trigger algorithmic aversion. Our scoping review demonstrates that the introduction of AI into earlier phases of the trial is not only acceptable, but is even perceived as preferable by individuals,¹³⁴ and judges.¹³⁵

In addition, by focusing on the judicial role, the studies reviewed overlook the reality of process pluralism that exists in modern day courts.¹³⁶ We now have

Dispute Resolution: The Age of AI-DR, in *ONLINE DISPUTE RESOLUTION: THEORY AND PRACTICE* 471, 471 (Mohamed Abdel Wahab, Daniel Rainey & Ethan Katsh eds., 2021).

¹³² Michelle Russell & Ruth Rosenthal, *State Courts Play a Key Role in American Life*, PEW (Oct. 17, 2024), <https://www.pew.org/en/research-and-analysis/issue-briefs/2024/10/state-courts-play-a-key-role-in-american-life> [<https://perma.cc/2NPR-R5BH>](bringing data about US state courts cases: according to the report, more than half of state and local courts cases are traffic related and mostly noncriminal); COURT STATISTICS PROJECT, REPORT ON EXAMINING THE WORK OF STATE COURTS: AN OVERVIEW OF 2015 STATE COURT CASELOADS 9 (2016), <https://ncsc.contentdm.oclc.org/digital/collection/ctadmin/id/2177/> [<https://perma.cc/JSE6-J8TB>](finding that in 2015 traffic cases composed 54% of the state court docket, criminal cases 21%, civil cases 18%, and domestic relations 6%).

¹³³ Galanter, *supra* note 3, at 459–60.

¹³⁴ Barysè & Sarel, *supra* note 19, at 120–21.

¹³⁵ Martinho, *supra* note 21, at 582.

¹³⁶ Menkel-Meadow, *supra* note 2, at 45; Carrie Menkel-Meadow, *From Legal Disputes to Conflict Resolution and Human Problem Solving: Legal Dispute Resolution in a Multidisciplinary Context*, 54 J. LEGAL EDUC. 7, 10 (2004).

judges that employ a myriad of roles as part of “judicial dispute resolution,”¹³⁷ as well as other nonjudicial third parties that operate alongside and within judicial settings, such as mediators and arbitrators, some of whom have decisionmaking authority while others facilitate consensual dispute resolution.¹³⁸ In our scoping review, we found that only one study¹³⁹ explored the implications of facilitative versus adjudicative dispute resolution and uncovered stark differences in perceptions towards the adoption of AI in each of these settings. While not examining it directly, other studies suggest that when AI performs an advisory role (similar to a mediator’s role), no aversion is displayed. To fully understand the impact of AI on our justice system, we need to move beyond formal court processes and examine a plurality of processes that operate “in the shadow” of formal court decisions.¹⁴⁰

Finally, our review suggests that the prominence of algorithmic aversion in the literature may itself be a product of the research design: the large number of studies comparing AI directly with human decisionmakers tend to foreground aversion. By contrast, studies that examine perceptions of AI without comparison to a human actor, across a broader range of contexts, and encompassing different functions, capabilities, and institutional settings reveal a more nuanced and, at times, more favorable picture of algorithmic acceptance. Our scoping review therefore suggests that algorithmic aversion for AI in the judging and dispute resolution context is not an overarching phenomenon but may reflect the particular focus of current studies.

Therefore, in terms of future direction, our review suggests that a more nuanced study of the implications of the introduction of AI, taking into account the nature of the role it is expected to fulfill, the phase of the proceeding into which it is introduced, and various contextual factors relating to the dispute, the parties, procedural design, and the setting would generate a richer understanding of both the opportunities and challenges relating to AI adoption.

In addition, we see a need for broadening the scope of methods used to study AI-related perceptions in this arena. Most studies employed a vignette-based approach, with only one study employing an experiential approach in a simulated setting. The overall preference for human over algorithmic decisionmaking expressed in the studies raises some questions as to the impact of experiencing a dispute resolution system that employs AI on perceptions of its fairness and legitimacy. To what extent are respondents’ attitudes shaped by the research methods employed? Can individuals meaningfully translate information about novel systems with which they have little or no experience into perceptions and attitudes that resemble those formed in real life or simulated encounters? Findings from the healthcare domain suggest that different modes of interaction shape both attitudinal acceptance and actual engagement with AI.¹⁴¹ These insights underscore the need for

¹³⁷ Michal Alberstein, *Judicial Conflict Resolution (JCR): A New Jurisprudence for an Emerging Judicial Practice*, 16 CARDOZO J. CONFLICT RES. 879, 885–86 (2015).

¹³⁸ Carrie Menkel-Meadow, *Regulation of Dispute Resolution in the United States of America: From the Formal to the Informal to the ‘Semi-formal’*, in REGULATING DISPUTE RESOLUTION: ADR AND ACCESS TO JUSTICE AT CROSSROADS 419, 446–47 (Felix Steffek et al. eds., 2013).

¹³⁹ See Sela, *supra* note 15.

¹⁴⁰ See Robert H. Mnookin & Lewis Kornhauser, *Bargaining in the Shadow of the Law: The Case of Divorce*, 88 YALE L.J. 950, 951 (1979).

¹⁴¹ See Sarah Lebovitz, Hila Lifshitz-Assaf & Natalia Levina, *To Engage or Not to Engage with AI for Critical Judgments: How Professionals Deal with Opacity When Using AI for Medical Diagnosis*, 33 ORG. SCI. 1, 14 (2021).

more experiential research in both formal and informal dispute resolution, particularly as such tools become increasingly prevalent.

As with any scoping review, this study has limitations worth noting. First, our selection criteria were restricted to studies published in English, and therefore our findings cannot be taken as representative of empirical work on algorithmic fairness published in other languages. Second, we included only published, peer-reviewed studies, thereby excluding unpublished work and non-peer-reviewed sources. Third, although our search strategy was deliberately broad, the scope of our search terms necessarily limited the range of studies identified, potentially omitting relevant research employing alternative terminology. To mitigate this risk, we conducted supplementary hand searches using snowball sampling and citation network analysis of the papers included in our review. Fourth, given the interdisciplinary nature of the field, the constructs employed across studies varied considerably. In some cases, only a handful of papers, at times a single study, addressed a particular variable, making it difficult to draw firm conclusions regarding the specific factors that shape perceptions of algorithmic fairness and the use of AI in judicial and dispute resolution settings.

Moreover, the methodological constraints of the reviewed literature may themselves influence the overall patterns reflected in our synthesis. Most of the studies rely on vignette-based survey designs, which pose two principal limitations: (1) they capture self-reported perceptions rather than behavioral data, and (2) they present hypothetical scenarios rather than involving real-world dispute resolution systems or actual disputants. Even studies adopting experimental designs typically relied on scenario-based descriptions rather than live or experiential settings.

Taken together, these limitations suggest that while our review offers an important overview of the emerging field, further empirical work, especially research that is grounded in real-world settings and diverse populations, will be essential to refine and extend the insights presented here.

V. CONCLUSION

The significance of this scoping review lies both its findings as well as the gaps it reveals. Courts today are sites of “process pluralism,” employing a wide range of methods and processes for resolving claims, most of which terminate in early settlement. Nevertheless, the scholarship on perceptions of AI has disproportionately focused on whether algorithms might replace the final judicial decision, while devoting far less attention to the broader array of functions in which AI can be, and in some cases already is, deployed.

This narrow emphasis on judicial decisionmaking may help account for the prominent findings of algorithmic aversion and the preference for human adjudication that dominate the literature. By contrast, the relatively limited work on informal dispute resolution and on AI engagement at earlier stages of the legal process points toward more nuanced, and at times more positive, orientation toward AI adoption.

The paucity of research in this domain is particularly striking given the rapid pace at which AI technologies are being integrated into legal practice, and the profound significance of legal outcomes in people’s lives. As the use of AI expands

across both formal and informal avenues for resolving disputes, sustained empirical inquiry will be needed to assess the impact of diverse forms of automation on perceptions of fairness, trust, and legitimacy. Only through such inquiry can the development and deployment of AI in the justice system be guided in ways that preserve, and ideally strengthen, the legitimacy of legal institutions.

APPENDIX

Table 1 – Description of the Reviewed Studies

Author(s) & Year	Methods	Sample size	Recruitment platform	Decision domain(s)	Research question(s)
Araujo et al., 2020	Experimental (vignettes)	N=958	Kantar Public	Media, public health and judicial	The impact of personal characteristics on perceived fairness of ADM
Bambauer & Risch, 2021	Experimental (vignettes)	N=3971	MTurk	Loan approval; inclusion in clinical trial; liability for traffic offense; gift card award	The impact of error rate, input type, cost and speed on preferences for human vs. algorithmic decisionmaking in four domains
Bansak & Paulson, 2024	Conjoint experiment (vignettes)	N=9030	Qualtrics	Loan approval, pretrial release	Relative importance of efficiency and fairness in human vs. algorithmic decisionmaking
Barysé, 2022	Survey	N – 408	Snowball sampling via online networks of legal professionals and lay people	Legal technology acceptance in courts	To what extent does the Technology Acceptance Model (TAM) explain people's attitudes toward legal technologies in courts, and how do these vary across profession, age, gender, and court experience?
Barysé & Sarel, 2024	Survey	N=269	Convenience sampling of lay people and legal professionals	Legal process	The impact of stage of automation of the legal process on perceived fairness of a judicial outcome
Bigman & Gray, 2018	Experimental (vignettes)	Study 2: N = 263	MTurk	Parole	Whether people are averse to machines making moral decisions

Chen et al., 2022	Experimental (vignettes)	N=1710	Lucid Theorem	Consumer refund, bail, sentencing	The role of decisionmaker identity (AI vs human), Interpretability and hearing on perceived fairness of algorithmic decisions
Choi, 2025	Mixed methods Semi structured interviews and survey	Study 1: N=12 Study 2: N=152	Study 1: Listserve and social media Study 2: MTurk	Mediation tasks – administrative and interpersonal	Explores how potential mediation clients perceive and accept mediators using AI in their disputes through the Unified Theory of Acceptance and Use of Technology
Dhungel & Heine, 2024	Structured interviews	N = 20	Email invitations	Judicial decisionmaking	(1) How will court proceedings appear in the year 2040? (2) Implications of increased use of AI on the role of judges. (3) Should AI systems prevail over human judgements if the system arrives at superior verdicts?
Eidenmueller et al., 2024	Mixed methods Structured interviews and survey	Study 1: 24 Study 2: 275	Invited via email	B2B commercial disputes	(1) What are the preferences of businesses as the “customers” of dispute resolution services for the design of court proceedings to resolve B2B commercial disputes? (2) How do businesses conceive of such proceedings against the background of rapid technological advances?
Fine et al., 2023	Mixed methods Survey	N=381	Convenience sampling of National Judicial College	Bail decisions (recidivism predictions)	Judges’ perceptions regarding AI-based risk assessment tools

Fine & Marsh, 2024	Mixed methods Survey	N = 150	Prolific	Bail, Sentencing, Legal Writing	What factors influence public trust in the application of AI in courts
Fine et al., 2025	Experimental (vignettes)	N = 1800	Prolific	Bail decisions & sentencing	How does the public perceive judges who use AI compared to those who rely on their expertise in bail and sentencing decisions, and how do these perceptions differ across racial and ethnic groups?
Grgić-Hlača et al., 2016	Experimental	N=100	MTurk	Bail decisions (COMPAS)	The impact of different types of data input on the perceived fairness of COMPAS automated decisionmaking
Haim & Yogev, 2025	Conjoint experiment (vignettes)	N = 1213	Prolific	Parole decisions, refugee resettlement, unemployment benefits eligibility, building permit approvals, and small business licenses	How do specific attributes of algorithmic decisionmaking tools (ADTs), related to algorithm design and institutional governance affect the public's perceptions of implementing ADTs in government programs
Horowitz & Kahn, 2021	Mixed methods Survey	N=690	CivicPulse Convenience sampling of U.S. officials	Multiple use-cases, including automotous cars, AI-surgery, sentencing, surveillance	The attitudes of local officials in the United States regarding AI-enabled systems in multiple domains

Kennedy et al., 2022	Experimental Conjoint experiment (vignettes)	Study 1: N=1725 Study 2: N=1000 Study 3: N=600 Study 4: (Conjoint) N=439	MTurk and Lucid Theorem	Recidivism prediction	The impact of the source of advice (crowdsourcing, expert, algorithm, hybrid algorithm-expert) on trust placed in advisor and preferences regarding algorithm attributes in a model predicting recidivism
Kennedy et al., 2024	Conjoint experiment (vignettes)	N = 973	Forthright Access Panel	Pretrial detention and traffic enforcement	Do Black Americans support algorithmic public policy interventions that create or maintain disparities, if those algorithms nonetheless produce net benefits for their own community?
Kim & Peng, 2025	Experimental (vignettes)	N = 128	CloudResearch	Judicial decisionmaking	The acceptance of artificial intelligence-based judicial decisionmaking (AI-JDM) as compared to human judges, and whether certain moral domains are considered more appropriate for AI moral decisionmaking than others

Locci & Massoni, 2024	Experimental (lab-incentivized game)	N = 125	ORSEE via LEEL (Laboratoire d'Economie Expérimentale de Paris)	Criminal-like punishment in a public goods setting	Would people prefer to be judged by another person or by a machine? Would judges prefer to make the punishment decision themselves or delegate the decisions to an algorithm? And how would individuals who are punished rate the fairness of the punishment?
Martinho, 2024	Mixed quantitative and qualitative analysis Survey	N=279	Convenience sampling of judges	Adjudication (broadly)	Judges' perceptions on the impact of AI on the legal profession, adjudication, and legal principles
Ozer et al., 2024	Experimental (vignettes)	Study 1: N = 2765 Study 2: N = 1423	Lucid & Amerispeak	Probation	How the use of algorithms in public decisionmaking, specifically in judicial contexts, affects the blame attributed to decisionmakers when errors occur
Pérez & Castellano, 2023	Survey	N=77	Convenience sampling of legal professionals	Penal/criminal justice vs. other such as civil (determination of compensation amounts), legal tasks (analysis of cases; drafting) procedure related tasks (selection of juries; chatbots to answer questions)	The impact of prior knowledge, profession, domain, and automation level on acceptance of AI
Schiff et al., 2022	Experimental (vignettes)	N=1460	MTurk	Child welfare; criminal justice	The impact of decision domain, and value type (fairness vs. transparency vs. responsiveness) on perceptions towards ADM in public policy

Sela, 2018	Mock-up experiment (vignette-based)	N=86	Convenience sampling of students	Commercial dispute	The impact of decisionmaker identity (human vs. automated) and type of process employed (arbitration vs. mediation) impact perceived fairness of dispute resolution systems
Simmons, 2018	Mixed qualitative quantitative Experimental (vignettes)	N= 600	MTurk	Bail decisions	The impact of decisionmaker identity (judge vs. judge assisted by algorithm) and bail amount (low vs. high) on perceived fairness and accuracy of predictive algorithms for bail decisions
Skeem et al., 2020	Experimental (vignettes)	N = 340	Judiciary leaders in 3 U.S. jurisdictions (Eastern, Midwestern, Southwestern)	Sentencing (drug offenses)	If providing judges with algorithmic risk assessment information influences sentencing decisions
Srivastava et al., 2019	Mixed qualitative quantitative Experimental (vignettes)	N=100	MTurk	Criminal and medical risk assessments	The preferences towards accuracy and equity in low vs. high stake decisions
Szafran& Bach, 2024	Experimental (vignette)	N = 3697	German Internet Panel	Banking, criminal justice, hiring, unemployment	Which subjective aspects do individuals consider when assessing the fairness of a decisionmaking process guided by automated decisionmaking
Van Berkel et al., 2019	Mixed quantitative and qualitative Experimental (vignettes)	N=90	MTurk	Bail decisions (COMPAS)	The effect of decisionmaking forum (individual vs. small structured group vs. small unstructured group) on overall perceived fairness of AI models

Van Berkel et al., 2021	Mixed quantitative and qualitative Experimental (vignettes)	N=80	Prolific	Bail decisions (COMPAS), Loan approval	The effect of information visualization techniques on people's perceived fairness of AI models
Vo & Plachkinova, 2023	Survey	N=467	MTurk	Criminal sentencing	The perceptions towards AI integration in federal criminal sentencing and its implications for trust
Waggoner et al., 2019	Mixed qualitative quantitative Conjoint experiment (vignettes)	N=661	MTurk	Criminal sentencing	The impact of various features on people's assessment of judicial criminal sentencing that relies on AI
Waggoner & Kennedy, 2022	Experimental (vignettes)	N = 395	MTurk	Forecasting reoffence probability	The role of major personality inventories – need for cognition, need to evaluate, the “Big 5” – in shaping individuals’ trust in public policy algorithms, specifically dealing with criminal justice sentencing
Waldman & Martin, 2022	Experimental (vignettes)	Study 1: N=294 Study 2: N=305	MTurk	potholes, education, parole, health, policing	Impact of decision importance, outcome-accuracy, input-data and governance procedure on legitimacy of algorithmic public policy decisions
Watamura et al., 2023	Experimental (video clips)	N=531	Surveroid	Criminal	The impact of judge identity (human vs. algorithm), perceived empathy and trust on judgment evaluation and acceptance of judgment

Watanabe et al., 2025	Experimental (vignettes)	Study 1: N = 1735 Study 2: N = 1731	Japanese internet panel via commercial firm	Criminal sentencing	Do jurors show greater deference to sentencing decisions made by human judges versus AI systems, particularly in cases involving mitigating circumstances in which human-like reasoning may be valued?
Yalcin et al., 2023	Experimental (vignettes)	Study 1: N=608 Study 2: N=1,214	MTurk	Divorce cases	The role of decisionmaker type (human judge vs. AI) and case complexity (low vs. high-technical vs high-emotional) in shaping perceived legitimacy of a judicial decision

Table 2 – Constructs Employed in the Reviewed Papers

[illegible]

Ozer et al., 2024											1
Pérez & Castellano, 2023						1					
Schiff et al., 2022			1								
Sela, 2018		1									
Simmons, 2018	1										
Skeem et al., 2020						1					
Srivastava et al., 2019	1										
Szafran & Bach, 2024	1										
Van Berkel et al., 2019	1										
Van Berkel et al., 2021	1										
Vo & Plachkinova, 2023			1								
Waggoner et al., 2019				1							
Waggoner & Kennedy, 2022			1								
Waldman & Martin, 2022		1									
Watamura et al., 2023			1			1					
Watamura et al., 2025						1					
Yalcin et al., 2023	1										
	13	4	9	8	3	7	2	1	2	1	1