

AUTOMATED DECISION SUPPORT TECHNOLOGIES AND THE LEGAL PROFESSION

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ABSTRACT

A quiet revolution is afoot in the field of law. Technical systems employing algorithms are shaping and displacing professional decision making, and they are disrupting and restructuring relationships between law firms, lawyers, and clients. Decision-support systems marketed to legal professionals to support e-discovery—generally referred to as “technology-assisted review” (TAR)—increasingly rely on “predictive coding”: machine-learning techniques to classify and predict which of the voluminous electronic documents subject to litigation should be withheld or produced to the opposing side. These systems and the companies offering them are reshaping relationships between lawyers and clients, introducing new kinds of professionals into legal practice, altering the discovery process, and shaping how lawyers construct knowledge about their cases and professional obligations. In the midst of these shifting relationships—and the ways in which these systems are shaping the construction and presentation of knowledge—lawyers are grappling with their professional obligations, ethical duties, and what it means for the future of legal practice.

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Through in-depth, semi-structured interviews of experts in the e-discovery technology space—the technology company representatives who develop and sell such systems to law firms and the legal professionals who decide whether and how to use them in practice—we shed light on the organizational structures, professional rules and norms, and technical system properties that are shaping and being reshaped by predictive coding systems. Our findings show that AI-supported decision systems such as these are reconfiguring professional work practices. In particular, they highlight concerns about potential loss of professional agency and skill, limited understanding and thereby both over- and under-reliance on decision-support systems, and confusion about responsibility and accountability as new kinds of technical professionals and technologies are brought into legal practice. The introduction of predictive coding systems and the new professional and organizational arrangements they are ushering into legal practice compound general concerns over the opacity of technical systems with specific concerns about encroachments on the construction of expert knowledge, liability frameworks, and the potential (mis)alignment of machine reasoning with professional logic and ethics.

Based on our findings, we conclude that predictive coding tools—and likely other algorithmic systems lawyers use to construct knowledge and reason about legal practice—challenge the current model for evaluating whether and how tools are appropriate for legal practice. As tools become both more complex and more consequential, it is unreasonable to rely solely on legal professionals—judges, law firms, and lawyers—to determine which technologies are appropriate for use. The legal professionals we interviewed report relying on the evaluation and judgment of a range of new technical experts within law firms and, increasingly, third-party vendors and their technical experts. This system for choosing technical systems upon which lawyers rely to make professional decisions—e.g., whether documents are responsive, or whether the standard of proportionality has been met—is no longer sufficient. As the tools of medicine are reviewed by appropriate experts before they are put out for consideration and adoption by medical professionals, we argue that the legal profession must develop new processes for determining which algorithmic tools are fit to support lawyers' decision making. Relatedly, because predictive coding systems are used to produce lawyers' professional judgment, we argue they must be designed for *contestability*—providing greater transparency, interaction, and configurability around embedded choices to ensure decisions about how to embed core professional judgments, such as relevance and proportionality, remain salient and demand engagement from lawyers, not just their technical experts.

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I. INTRODUCTION

As applications based on advancements in fields such as cloud computing and machine learning have spread to the workplace, scholars and legal commentators have debated the extent to which such technical systems will affect markets for legal services, the practice of law, and the legal profession.¹ AI-based systems aimed at automating or assisting in lawyerly

1. See, e.g., RICHARD SUSSKIND & DANIEL SUSSKIND, *THE FUTURE OF THE PROFESSIONS: HOW TECHNOLOGY WILL TRANSFORM THE WORK OF HUMAN EXPERTS* (2015); Daniel Martin Katz, *Quantitative Legal Prediction—Or—How I Learned to Stop Worrying and Start Preparing for the Data-Driven Future of the Legal Services Industry*, 62 EMORY L.J. 909 (2013); John O. McGinnis & Russell G. Pearce, *The Great Disruption: How Machine Intelligence Will Transform the Role of Lawyers in the Delivery of Legal Services*, 82 FORDHAM L. REV. 3041 (2014); Dana A. Remus & Frank Levy, *Can Robots Be Lawyers: Computers, Lawyers, and the*

tasks and decision making are currently being employed in a wide range of practice domains, including contract drafting and review, due diligence in mergers and acquisitions, risk-assessment in criminal justice settings, legal search and research, and document analysis and review in e-discovery, to name a few.²

Technology-assisted review (TAR), also called “predictive coding,” systems for the discovery phase of litigation provide a particularly interesting example of a machine-learning-based (“ML-based”) decision support system infiltrating a professional domain. Our research explores how professional identity, legal frameworks, interactions with clients and vendors, and organizational structures are shaping the adoption, use, and perceptions of TAR systems in the field of law.³ Our interest in studying the adoption of machine learning tools in the legal profession was generated in part by a belief that lawyers—due to education and training, professional rules and ethical obligations, and their own interest in protecting themselves from professional liability—would place particularly stringent demands and expectations about the transparency, interpretability, configurability, and accountability of machine learning systems.

The concern that engineers and logics of automation will stealthily usurp or undermine the decision-making logics, values, and domain expertise of end-users has been an ongoing and legitimate complaint about decision-

Practice of Law, 30 GEO. J. LEGAL ETHICS 501 (2017); Tanina Rostain, *Robots versus Lawyers: A User-Centered Approach*, 30 GEO. J. LEGAL ETHICS 559 (2017); Sean Semmler & Zeeve Rose, *Artificial Intelligence: Application Today and Implications Tomorrow*, 16 DUKE L. & TECH. REV. 85 (2017); Harry Surden, *Machine Learning and Law*, 89 WASH. L. REV. 87 (2014); David C. Vladeck, *Machines without Principals: Liability Rules and Artificial Intelligence*, 89 WASH. L. REV. 117 (2014); John Markoff, *Armies of Expensive Lawyers, Replaced by Cheaper Software*, N.Y. TIMES (Mar. 4, 2011), <https://www.nytimes.com/2011/03/05/science/05legal.html> [<https://perma.cc/K6NG-XEG3>].

2. For overviews and discussions of such applications, see, for example, KEVIN D. ASHLEY, *ARTIFICIAL INTELLIGENCE AND LEGAL ANALYTICS: NEW TOOLS FOR LAW PRACTICE IN THE DIGITAL AGE* (2017); Benjamin Alarie et al., *How Artificial Intelligence Will Affect the Practice of Law*, 68 U. TORONTO L. J. 106 (2018); Daniel Ben-Ari et al., *Artificial Intelligence in the Practice of Law: An Analysis and Proof of Concept Experiment*, 23 RICH. J.L. & TECH. 2 (2017); Kathryn D. Betts & Kyle Jaep, *The Dawn of Fully Automated Contract Drafting: Machine Learning Breathes New Life Into a Decades-Old Promise*, 15 DUKE L. & TECH. REV. 216 (2017); Richard Berk & Jordan Hyatt, *Machine Learning Forecasts of Risk to Inform Sentencing Decisions*, 27 FED. SENT’G REP. 222 (2015); Maura R. Grossman & Gordon V. Cormack, *Technology-Assisted Review in e-Discovery Can Be More Effective and More Efficient than Exhaustive Manual Review*, 17 RICH. J. L. & TECH. 1 (2011); David Lat, *How Artificial Intelligence Is Transforming Legal Research*, ABOVE L. (2018), <https://abovethelaw.com/law2020/how-artificial-intelligence-is-transforming-legal-research/> [<https://perma.cc/HD3J-YEGT>] (last visited Aug. 25, 2019).

3. Our research is ongoing. We are continuing to interview lawyers, in-house technical professionals, and legal technology company representatives.

support and other computer systems.⁴ As technology reconfigures work practices, researchers have documented potential loss of human agency and skill,⁵ reduced opportunities to learn in the field,⁶ both over- and under-reliance on decision-support systems,⁷ confusion about responsibility,⁸ and diminished⁹ or exaggerated¹⁰ accountability that leaves humans unable to exercise control but bearing the weight and blame for system failures.¹¹ For example, Elish explores how humans tend to take the brunt of failures in sociotechnical systems, acting as “moral crumple zones” by absorbing a

4. See Danielle Keats Citron, *Technological Due Process*, 85 WASH. U. L. REV. 1249 (2008) (identifying the slippage and displacement of case worker values by engineering rules embedded in an expert system); James H. Moor, *What is computer ethics?*, 16 METAPHILOSOPHY 266 (1985) (identifying three ways invisible values manifest in technical systems—hiding immoral behavior, gap-filling during engineering that invisibly embeds coders’ value choices, and through complex calculations that defy values analysis); Jenna Burrell, *How the machine ‘thinks’: Understanding opacity in machine learning algorithms*, 3 BIG DATA & SOC’Y 1 (2016) (describing three forms of opacity in corporate or state secrecy, technical illiteracy, and complexity and scale of machine-learning algorithms); Frank A. Pasquale, *Professional Judgment in an Era of Artificial Intelligence and Machine Learning*, 46 BOUNDARY 2, 73 (2019) (contrasting the reductionist epistemology and functionalist assumptions underlying substitutive automation with the holistic epistemology of professional judgment and the conflictual, political, and contestable nature of professional work, particularly in education and healthcare professionals).

5. See John D. Lee & Bobbie D. Seppelt, *Human Factors in Automation Design*, in SPRINGER HANDBOOK OF AUTOMATION, 417–36 (Shimon Y. Nof, ed., 2009) (detailing how automation that fails to attend to how it redefines and restructures tasks, and the behavioral, cognitive, and emotional responses of operators to these changes, produce various kinds of failure, including those that arise from deskilling due to reliance on automation).

6. See Matthew Beane, *Shadow learning: Building robotic surgical skill when approved means fail*, 64 ADMIN. SCI. Q. 87 (2019) (finding that robotic surgery limited the ability of medical residents to develop competence in traditional and approved ways so some residents resorted to “shadow learning” practices, which flaunted field norms and institutional policies, to gain surgical competence).

7. See Kate Goddard et al., *Automation bias: a systematic review of frequency, effect mediators, and mitigators*, 19 J. AM. MED. INFORMATICS ASS’N 121 (2011) (reviewing literature on automation bias in health care clinical decision support systems).

8. For an overview of research on technology-assisted decision making and responsibility, see Kathleen L. Mosier & Ute M. Fischer, *Judgment and Decision Making by Individuals and Teams: Issues, Models, and Applications*, 6 REVS. HUM. FACTORS & ERGONOMICS 198, 232–33 (2010).

9. See Judith Simon, *Distributed Epistemic Responsibility in a Hyperconnected Era*, in THE ONLINE MANIFESTO 145 (Luciano Floridi, ed., 2015); Helen Nissenbaum, *Computing and Accountability*, 37 COMMS. ACM 72 (1994).

10. Madeleine Clare Elish, *Moral Crumple Zones: Cautionary Tales in Human-Robot Interaction*, 5 ENGAGING SCI., TECH., & SOC’Y 40, 40 (2019).

11. See, e.g., Meg Leta Jones, *The ironies of automation law: tying policy knots with fair automation practices principles*, 18 VAND. J. ENT. & TECH. L. 77 (2015).

disproportionate amount of responsibility and liability relative to their actual control and agency.¹²

A. AUTOMATED DECISION MAKING IN THE LEGAL PROFESSION

Yet, there is little empirical research documenting how lawyers (as end-users) think about and incorporate ML-based decision support and knowledge discovery systems into their actual work practices. Studies of citation systems and software systems used to identify relevant case law have documented varied performance across technical systems on what lawyers would likely view as far less ambiguous tasks than defining and identifying documents for production (our focus in this Article). For example, analyses of citator accuracy have found wide discrepancies in performance.¹³ Although ambiguous language in court opinions and different constructions of evaluative criteria—e.g., negative, distinguished, criticized—may cause some level of variation,¹⁴ Hellyer argues that it does not fully explain the performance differences across citator services. He found the three leading citation services only agreed eleven percent of the time on the fact and type of negative treatment, and in a whopping eighty-five percent of the time, the three citators did not agree on whether there was negative treatment at all.¹⁵ Hellyer concludes that while citators can be vastly improved, “users may need to reconsider the trust they place in citators” and “need to be aware of the citators’ shortcomings.”¹⁶

Research on knowledge discovery tasks in legal databases documents similar variation in performance. A recent study comparing the search results of six different legal database tools¹⁷ found “hardly any overlap in the cases

12. Elish, *supra* note 10, at 6.

13. See Paul Hellyer, *Evaluating Shepard’s, KeyCite, and BCite for Case Validation Accuracy*, 110 L. LIBR. J. 449, 450–55 (2018) (describing prior citator studies).

14. *Id.* at 454 (“[C]itation analysis is partly subjective. . . . [C]ourts sometimes use ambiguous language when discussing other cases . . . different researchers may have different ideas on what ‘negative treatment’ means, not to mention more specific terms like ‘distinguished’ or ‘criticized.’”).

15. *Id.* at 464 (“[In] 357 citing relationships that have at least one negative label from a citator. . . . [A]ll three citators [BCite, KeyCite, and Shepard’s] agree that there was negative treatment only 53 times. . . . [T]hat in 85% of these citing relationships, the three citators do not agree on whether there was negative treatment. . . . The three databases substantively agree on the type of negative treatment in only 40 of these citing relationships, which means that in this sample, they all agree with one another only 11% of the time.”).

16. *Id.* at 476.

17. Susan Nevelow Mart, *The Algorithm as a Human Artifact: Implications for Legal [Re]Search*, 109 L. LIBR. J. 387, 390 (2017) (showing wide variation in results returned by six leading legal database providers for the same search terms and parameters). The six legal database providers studied were Casetext, Fastcase, Google Scholar, Lexis Advance, Ravel, and Westlaw.

that appear in the top ten results” with “[an] average of forty percent of the cases . . . unique to one database, and only about seven percent of the cases . . . returned . . . [by] all six databases.”¹⁸ Mart argues this evidences the “very different biases and assumptions” of product engineers, and concludes that “knowledge of this variability expands the opportunities for researchers to find relevant cases that can play ‘some cognitive role in the structuring of a legal argument.’”¹⁹

Together, this research documents unexpectedly wide performance variations across software systems on knowledge discovery tasks that are essential to legal practice, and it highlights the need for “database providers to proactively think of algorithmic accountability as a way to improve research results for their users,”²⁰ as well as the need for lawyers to demand both more consistent performance across systems²¹ and more information about the systems on which they rely for professional work.²²

Despite their importance to today’s practicing lawyer, there has been surprisingly little effort to examine how predictive technological systems are shaping legal practice and the field more broadly.²³ True, a few researchers have explored the performance of predictive coding e-discovery tools (our topic here), comparing them to each other and to the performance of human reviewers.²⁴ This research finds that technology-assisted review can

18. *Id.*

19. *Id.* at 390, 420 (quoting Stuart A. Sutton, *The Role of Attorney Mental Models of Law in Case Relevance Determinations: An Exploratory Analysis*, 45 J. AM. SOC’Y INFO. SCI. 186, 187 (1994)).

20. *Id.* at 420.

21. Hellyer, *supra* note 13 at 476 (arguing that “citing relationships are clear and can be objectively described,” that “citators can and should do better,” and that “citators can be reliable or they can be idiosyncratic, but they can’t be both”).

22. Mart, *supra* note 17, at 420; Hellyer, *supra* note 13 at 476 (arguing that while citators should be able to perform more consistently, “users may need to reconsider the trust they place in citators, and law librarians may need to rethink how they discuss citators with their patrons”).

23. See Seth Katsuya Endo, *Discovery Hydraulics*, 52 U.C. DAVIS L. REV. 1317, 1337 (2019) (“[T]here is little empirical data about what drives lawyers’ choices in their discovery practices.”) (citing Judith A. McKenna & Elizabeth C. Wiggins, *Empirical Research on Civil Discovery*, 39 B.C. L. REV. 785, 803 (1998) (“Much of the literature on incentives affecting discovery practice is rooted in economic theory. Yet, there is little information about how lawyers actually make discovery decisions.”)).

24. Maura R. Grossman & Gordon V. Cormack, *Technology-assisted review in e-discovery can be more effective and more efficient than exhaustive manual review*, 17 RICH. J. L. & TECH. 1 (2011); Herbert L. Roitblat et al., *Document categorization in legal electronic discovery: computer classification vs. manual review*, 61 J. AM. SOC’Y INFO. SCI. & TECH. 70 (2010); David Grossman, *Measuring and Validating the Effectiveness of Relativity Assisted Review*, EDMR WHITE PAPER SERIES (Feb. 2013) <http://www.edrm.net/papers/measuring-and-validating-the-effectiveness-of-relativity>

outperform human reviewers and save on attorney costs.²⁵ However, such studies have only taken place in controlled settings; they are not aimed at understanding how legal professionals work with these systems in practice.

The only empirical studies of decision support technologies and discovery practices at law firms that we have found were ethnographic studies undertaken in the 1990s by anthropologists and computer scientists tasked with designing systems to aid the litigation support team at a large law firm.²⁶ There, researchers found lawyers articulating and enacting a superior status relative to that of litigation support staff, whom they tended to see as only performing mundane, routine work of “document review” and incapable of the more complex decision making performed by attorneys.²⁷ Cautious and risk-averse, high in status, and protective of professional expertise, lawyers were therefore reluctant to hand off anything beyond what they saw as routinized work.

Finally, although not within the law firm setting, Christin’s work on risk-recidivism algorithms offers important insights into how lawyers are interacting with a widely used set of algorithmic tools.²⁸ Her ethnographic study of algorithms in action in expert fields²⁹ reveals that professional

-assisted-review/ [https://perma.cc/VP9Y-BF8N] (reviewing the performance of one TAR product from a limited perspective).

25. See, e.g., Grossman & Cormack, *supra* note 24, at 43, 48 (analyzing data collected during the course of the Text Retrieval Conference (TREC) 2009 Legal Track Interactive Task and finding that the predictive coding methods they reviewed “require, on average, human review of only 1.9% of the documents, a fifty-fold savings over exhaustive manual review” and concluding that TAR can yield more accurate results than exhaustive human review).

26. Jeanette Blomberg et al., *Reflections on a Work-Oriented Design Project*, 11 FOUND. & TRENDS HUM.-COMPUTER INTERACTION 237 (1996) (describing their experiences designing a case-based prototype system for information retrieval and their observations of organizational politics and divisions of labor between attorneys and litigation support staff at the law firm while designing image-analysis technologies to aid in document review and classification); Lucy Suchman, *Working Relations of Technology Production and Use*, 2 COMPUTER SUPPORTED COOPERATIVE WORK 21 (1993) (arguing for industrial designers to be aware of the work practices of not only technology production but also its use among various users, and describing observations of the status hierarchies, contestable knowledge claims, and actions of lawyers and litigation support staff at a law firm).

27. See Suchman, *supra* note 26, at 32 (describing how litigation support work was invisible to attorneys and how attorneys described such work as a “mindless, routine form of labor”).

28. Angèle Christin, *Algorithms in Practice: Comparing Web Journalism and Criminal Justice*, 4 BIG DATA & SOC’Y 1 (2017).

29. *Id.* at 2. Christin distinguishes “expert fields” from professions (although they may overlap), defining expert fields as “configurations of actors and institutions sharing a belief in the legitimacy of specific forms of knowledge as a basis for intervention in public affairs.” She makes this distinction for practical and strategic reasons. From a strategic standpoint, she makes the distinction in order to take a broader “field-based” analytical framework to

workers and managers appropriate machine-learning systems into their work practices as they do other technology: informed by routines, norms, obligations of professional identity, and their position relative to others within an organizational hierarchy (e.g., managers vs. workers).

Our review reveals notable gaps in the literature investigating the use of ML-based systems in the field of law. First, little is known about how legal professionals, their organizations, and their professional environments are shaping the adoption, implementation, and governance of machine-learning systems that support professional decision-making. This gap reflects the more general dearth of empirical data on professionals, their organizational environments, and their interactions with today's automated ML-based decision-making systems more generally. While research in computer science and the interdisciplinary FAT (Fairness, Accountability, and Transparency) community interrogates and evaluates the technical workings of such systems to shed light on values and ethics,³⁰ and an increasing amount of legal scholarship theorizes and makes normative claims about what laws or regulatory frameworks we need to address automated decision making systems,³¹ there is little rigorous, empirical social science research into the

her sociological analysis (drawing specifically on Pierre Bourdieu's conception of a "field"). We take an analogous, if conceptually distinct, systems-based view of the legal profession and lawyers, in which the profession is marked by constantly evolving processes of conflict, cooperation, and exchange with internal and external stakeholders. See ANDREW ABBOTT, *THE SYSTEM OF PROFESSIONS: AN ESSAY ON THE DIVISION OF EXPERT LABOR* (1988). And from a practical standpoint, she makes the distinction between expert fields and profession so that she can include in her comparative analysis journalists, who are not typically thought of as a highly professionalized occupation in the sense that, compared to highly professionalized domains like law, they lack, among other things, state-licensed monopoly control over the barriers to entry for their work. By staying within the legal profession to understand how lawyers are appropriating machine-learning decision support systems, we make no comparisons across professions here and thus see no need to follow Christin's distinction between "expert fields" and professions. For more on Bourdieu's vision of "fields," see PIERRE BOURDIEU & LOÏC J.D. WACQUANT, *AN INVITATION TO REFLEXIVE SOCIOLOGY* (1992). For more on sociological field theory more generally, see Daniel N. Klutz & Neil Fligstein, *Varieties of Sociological Field Theory*, in *HANDBOOK OF CONTEMPORARY SOCIOLOGICAL THEORY* 185 (Seth Abrutyn ed., 2016).

30. See, e.g., Alexandra Chouldechova, *Fair Prediction with Disparate Impact: A Study of Bias in Recidivism Prediction Instruments*, 5 *BIG DATA* 153 (2017); Amit Datta et al., *Discrimination in Online Advertising: A Multidisciplinary Inquiry*, 81 *PROC. MACHINE LEARNING RES.* 20 (2018); Jon Kleinberg et al., *Inherent Trade-Offs in the Fair Determination of Risk Scores*, 8TH *INNOVATIONS IN THEORETICAL COMPUT. SCI. CONF.* 43 (2017); Joshua A. Kroll et al., *Accountable Algorithms*, 165 *U. PA. L. REV.* 633 (2017).

31. See, e.g., RYAN CALO ET AL., *ROBOT LAW* (2016); Danielle Keats Citron & Frank A. Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 *WASH. L. REV.* 1 (2014); Andrew Tutt, *An FDA for Algorithms*, 69 *ADMIN. L. REV.* 83 (2017); We Robot Conference (2019), <https://robots.law.miami.edu> [<https://perma.cc/UC8F-B8E6>] (last visited Sept. 20, 2019) (providing background papers and presentations).

professionals, their organizations, and the broader professional ecosystems in which these technical systems are embedded.³² How are these systems entering the field of law? What kinds of socio-material forces—for example, professional ethical duties, identity as an expert, the configuration of the system itself—affect how professionals understand and use such systems? How is the introduction of automated decision-making systems shaping professional practices and the profession?

Second, little is known about how professionals are interacting with the new wave of predictive algorithmic systems—particularly ML-based systems—that are being sold as aids for professional decision making. While traditional, rule-based expert systems have had a long history in professional fields like medicine, there are unique challenges posed by today’s predictive algorithmic systems. Whereas engineers of expert systems explicitly program in a set of rules—ideally based on the domain knowledge of adept subject matter experts—today’s ML-based systems are designed, in effect, by deriving a set of decision rules from the data on which they train, which creates some unique challenges to ensuring systems accord with professional expertise and judgment. Some of the algorithms used by such systems make it difficult to understand the rules they have learned from the data. Unlike an expert system where domain professionals can review and interrogate rules, these systems can provide insight into the inputs and outputs but lack the ability to easily interrogate the rules or the reasoning by which the outputs were generated. In addition, today’s predictive ML-based systems are dynamic, usually probabilistic, and therefore do not have one “right” answer. This plasticity challenges even the limited oversight provided by examinations of inputs and outputs. The consequence of such characteristics is that predictive algorithmic systems embed many subjective judgments on the part of system designers—for example, judgments about training data, how to clean the data, how to weight different features, which algorithms to use, what information to emphasize or deemphasize, etc. We know little about whether and how the distinct features of these new tools affect professionals’ interactions with them.

Our empirical research begins to fill this gap. We focus on AI-based e-discovery systems and how lawyers go about conducting discovery in today’s world of electronically stored information (ESI). Specifically, we study lawyers’ use of TAR, also called “predictive coding,” systems. TAR is used to identify documents relevant, responsive, and not protected by legal

32. Admittedly, this may, in part, be an artifact of researchers tending to focus on domains such as “predictive policing,” risk-recidivism, facial recognition, ad targeting, or recommender systems, where professionals may play a limited role in the adoption, use, and governance of the systems.

privileges, to the opposing party's discovery requests. Our analysis of the relations among lawyers, litigation support professionals (whether inside or outside the firm), and predictive coding technologies in the modern-day legal services field provides a rich account of the actual effect of machine learning systems on legal practice and identifies domain-specific challenges posed by current ML-based systems and practices. The insights we offer raise new questions for the profession, and we identify new sites for interventions to shape the adoption, use, and governance of these tools going forward.

II. TAR AND PREDICTIVE CODING FOR E-DISCOVERY

One of the main challenges facing litigants today is the time and expense required to wade through ever-increasing amounts of ESI during discovery (e.g., data produced by smartphones, email, wearable devices, and the Internet of Things). Lawyers must review their clients' records in order to search, collect, and produce those that are relevant and responsive to the other party's requests and not protected by legal privileges. Discovery was an onerous process even in the days prior to ESI. With the vast amounts of ESI today, however, e-discovery can take inordinate amounts of time for lawyers and clients tasked with manually reviewing ESI. It also entails huge monetary costs for litigants. A 2012 study by RAND researchers found that e-discovery production costs averaged about \$18,000 per gigabyte of information, with costs attributable to document review being seventy percent or more of total e-discovery costs in more than half of the fifty-seven cases studied.³³ The stakes of e-discovery are also high in other ways, with attorneys and clients exposed not only to the risk of adverse case outcomes but also to potential loss of attorney-client or other confidentiality privileges—and even disciplinary action—if they inadvertently produce non-discoverable ESI or withhold discoverable ESI.

The concomitant rise of ESI and advancements in technology over the past two decades or so have spawned an ever-growing industry of e-discovery specialists, support staff, consultants, technology vendors, and products. Predictive coding systems, under the umbrella of TAR, are marketed as tools to aid legal professionals in managing, classifying, and reviewing ESI at a fraction of the cost of traditional manual review.³⁴

33. See NICHOLAS M. PACE & LAURA ZAKARAS, *WHERE THE MONEY GOES: UNDERSTANDING LITIGANT EXPENDITURES FOR PRODUCING ELECTRONIC DISCOVERY* (2012) (analyzing the collection, processing, and review costs for e-discovery across fifty-seven cases).

34. Examples of TAR products and e-discovery platforms on the market today include those from Brainspace (<https://www.brainspace.com/> [<https://perma.cc/RRQ9-XLZ6>]), Catalyst (<https://catalystsecure.com/> [<https://perma.cc/XN6J-E469>]), Exterro (<https://www.exterro.com/e-discovery-software/data-management/predictive-intelligence/>

Research supports the assertion that predictive coding can save on attorney review time, and thus costs.³⁵ Our research focuses on these e-discovery systems because, based on our conversations with lawyers and review of the literature, they represent one of the most well-developed applications of automated decision-support technology in the legal profession to date and because they provide a useful lens through which to discuss particular professional and ethical issues in their design and use.³⁶

Broadly, TAR encompasses a number of technologies and techniques used on ESI, such as machine learning, clustering, semantic analysis, and sentiment analysis, to accomplish a broad range of tasks (e.g., email threading, de-duplication, document classification, visualization) that may or may not use predictive algorithms or machine-learning techniques to predict potentially responsive documents. Although most in the industry use “TAR” and “predictive coding” interchangeably, for simplicity, and because we want to focus attention on the ML-based process of analyzing and predicting which documents among a corpus are responsive and not responsive during discovery, we follow industry convention and use “predictive coding” unless TAR is specifically used in quotes from the literature or our interviews.³⁷

There are different machine-learning techniques used in predictive coding, requiring varying levels of human reviewer effort and varying degrees

[<https://perma.cc/C7AC-RNCG>]), H5 (<https://www.h5.com/> [<https://perma.cc/UE45-9E4Q>]), Nuix-Ringtail (<https://get.nuix.com/nuix-ringtail/> [<https://perma.cc/R3GB-ARXX>]), and Relativity (<https://www.relativity.com/> [<https://perma.cc/BT3E-BCXT>]).

35. See, e.g., Grossman & Cormack, *supra* note 24, at 43 (analyzing data collected during the course of the Text Retrieval Conference (TREC) 2009 Legal Track Interactive Task and finding that the TAR methods they assessed “require, on average, human review of only 1.9% of the documents, a fifty-fold savings over exhaustive manual review”).

36. Katie Shilton, *Values and Ethics in Human-Computer Interaction*, 12 FOUND. & TRENDS HUM.-COMPUTER INTERACTION 107 (2018).

37. See, for example, definitions of “predictive coding” provided by the Electronic Discovery Reference Model (EDRM), a community of e-discovery and legal professionals housed at Duke University Law School EDRM. *Predictive Coding*, EDRM GLOSSARY, <https://www.edrm.net/glossary/predictive-coding/> [<https://perma.cc/6RYE-PNH8>] (defining “predictive coding” as a subset of TAR tools that incorporate machine learning to distinguish relevant from non-relevant documents). Despite sharing some underlying general principles, predictive coding as used in the specific context of legal discovery should not be confused with predictive coding concepts and models as developed in neuroscience, cognitive science, and machine learning. For a review of predictive coding in these fields, see Yanping Huang & Rajesh P. N. Rao, *Predictive Coding*, 2 WILEY INTERDISC. REVS. 580 (2011); Geoffrey E. Hinton, *Learning Multiple Layers of Representation*, 11 TRENDS COGNITIVE SCI. 428 (2007); and Andy Clark, *Whatever next? Predictive Brains, Situated Agents, and the Future of Cognitive Science*, 36 BEHAV. & BRAIN SCI. 181 (2013). For applications to signal processing and data compression, see YUN Q. SHI AND HUIFANG SUN, *IMAGE & VIDEO COMPRESSION FOR MULTIMEDIA ENGINEERING: FUNDAMENTALS, ALGORITHMS, AND STANDARDS* (1999).

of initial training.³⁸ Cormack and Grossman, two leading experts on predictive coding, currently argue for continuous active learning (CAL), in which a subject-matter expert (in our case, an attorney) can continue to adjust the training algorithm during document review, as the best available method. However, as we will discuss, our interviews of attorneys and e-discovery suggest that, in practice, there is disagreement and confusion over defining, measuring, and achieving optimal precision, recall, and human reviewer effort.³⁹

A. GOVERNANCE FRAMEWORK FOR ETHICAL AND RESPONSIBLE USE OF PREDICTIVE CODING

The governance of the legal profession's use of predictive coding is based in normative principles of responsible conduct during discovery and professional ethical duties governing lawyers. Thus, regulation of predictive coding for e-discovery emanates from general principles and guidelines. To the extent that such principles are formalized, they are found in jurisdiction-specific rules of civil procedure, case law, and, most importantly for our purposes, ethical rules of professional conduct as defined by state bars.⁴⁰

The Federal Rules of Civil Procedure (FRCP), while not speaking directly to predictive coding, were amended in 2015 to give new guidance regarding e-discovery.⁴¹ Overall, the amended rules reflected courts' desire to

38. See Cormack et al., *Evaluation of Machine-Learning Protocols for Technology-Assisted Review in Electronic Discovery*, PROC. 37TH INT'L ACM SIGIR CONF. ON RES. & DEV. INFO. RETRIEVAL, 153 (2014); see also Grossman et al., *Automatic and Semi-Automatic Document Selection for Technology-Assisted Review*, PROC. 40TH INT'L ACM SIGIR CONF. ON RES. & DEV. INFO. RETRIEVAL, 905 (2017).

39. See Cormack et al., *supra* note 38, at 161 (comparing Continuous Active Learning (CAL), Simple Passive Learning (SPL), and Simple Active Learning (SAL) and concluding that CAL exhibited fewer limitations and superior performance to the other predictive coding approaches).

40. We focus on formal governance mechanisms here—e.g., rules of court, judicial opinions, and ethical duties instantiated in professional rules, all backed by the sanctioning power of regulatory bodies or courts.

41. In the interest of space, we do not discuss all of the 2015 FRCP amendments as they pertain to e-discovery. For summaries, see *FRCP & E-Discovery: The Layman's Guide*, EXTERRO (2017), <https://www.exterro.com/resources/frcp-e-discovery-pdf-guide/> [<https://perma.cc/2ZZ3-GW9R>]; see also Stephanie Serhan, *Calling an End to Culling: Predictive Coding and the New Federal Rules of Civil Procedure*, 23 RICH. J. L. & TECH. 1 (2017) (reviewing the 2015 amendments to the FRCP as applied to predictive coding, the split at that time among courts over when to use predictive coding during a case, and arguing that predictive coding should be done at the outset of discovery on the entire set of ESI rather than an already-keyword-culled set of documents); see also Karl Schieneman & Thomas C. Gricks III, *The Implications of Rule 26(g) on the Use of Technology-Assisted Review*, 7 FED. CTS. L. REV. 239, 247–84 (2013) (evaluating the proper way to use TAR at different phases of e-discovery for

encourage cooperation and accountability among parties, to promote speedy and efficient litigation, and, with amendments to Rule 26, to emphasize the principle of proportionality when it comes to the scope of discovery.⁴² Regarding proportionality, the proportionality factors previously found in Rule 26(b)(2)(C)(iii) were amended and made more explicit by moving them to Rule 26(b)(1), which now reads as follows:

Scope in General. Unless otherwise limited by court order, the scope of discovery is as follows: Parties may obtain discovery regarding any non-privileged matter that is relevant to any party's claim or defense and proportional to the needs of the case, considering the importance of the issues at stake in the action, the amount in controversy, the parties' relative access to relevant information, the parties' resources, the importance of the discovery in resolving the issues, and whether the burden or expense of the proposed discovery outweighs its likely benefit. Information within this scope of discovery need not be admissible in evidence to be discoverable.⁴³

As to predictive coding specifically, although it is usually not required in a case and instead agreed to by the parties in a case, courts and the legal profession more generally have taken notice of its rise and have, on the whole, welcomed its use, although some legal commentators have raised concerns. For example, Endo argues that the opacity of ML-based predictive coding systems can undermine the due process norm of participation, especially for parties who lack adequate understanding of the system's reasoning process.⁴⁴ Remus recognizes predictive coding's potential benefits but cautions that it also brings significant costs: 1) the tendency of attorneys and judges to overlook the wide variation in predictive coding systems' technical features and efficacy, 2) the erosion of lawyers' professional jurisdiction over discovery by lowering professional oversight standards and by delegating the process to non-lawyer computing systems, vendors, and technical specialists, and 3) the undermining of client representation, with threats to work-product and attorney-client privileges and confidentiality via new rules and norms pushing lawyers to cooperate with the opposing party by disclosing things like seed sets or system-evaluation metrics.⁴⁵

purposes of the attorney's reasonable-inquiry and certification requirements under Rule 26(g)).

42. See *FRCP & E-Discovery: The Layman's Guide*, *supra* note 41, at 5.

43. Fed. R. Civ. P. 26(b)(1) (emphasis added).

44. Seth Katsuya Endo, *Technological Opacity & Procedural Injustice*, 59 B.C. L. REV. 821 (2018).

45. Dana A. Remus, *The Uncertain Promise of Predictive Coding*, 99 IOWA L. REV. 1691 (2014).

Despite these cautions, judges have begun to approve the use of predictive coding in published opinions. For example, in *Da Silva Moore v. Publicis Groupe*, an employment discrimination case involving a high volume of electronic documents (over three million emails), U.S. Magistrate Judge Andrew Peck became the first federal judge to publish an opinion explicitly approving the use of computer-assisted review software as an acceptable means of conducting e-discovery in appropriate cases.⁴⁶ There, the parties had agreed to use predictive coding prior to discovery, but the plaintiffs disputed the scope and defendants' implementation of it as detailed in the e-discovery protocol. While Judge Peck condoned predictive coding in "appropriate" circumstances, he did not specify fixed requirements of appropriateness and instead looked to the facts of the case in their entirety.⁴⁷ Among other relevant facts, predictive coding was cost-effective in this case compared to manual review given the large volume of documents, the parties had agreed to its use at the outset, defense counsel had been transparent in sharing its procedures with plaintiffs in its e-discovery protocol (e.g., disclosing the seed set used to train the predictive coding system), and counsel otherwise complied with the FRCP governing discovery. In particular, Judge Peck emphasized the importance of defense counsel satisfying the proportionality requirements of Rule 26 of the FRCP.⁴⁸ Although beyond our scope here, subsequent cases have followed with similar reasoning,⁴⁹ and professional bodies have convened to address the evolving landscape of e-discovery technologies and issue best practices.⁵⁰

46. *Da Silva Moore v. Publicis Groupe*, 287 F.R.D. 182, 193 (S.D.N.Y. 2012) ("This Opinion appears to be the first in which a Court has approved of the use of computer-assisted review. That does not mean computer-assisted review must be used in all cases, or that the exact ESI protocol approved here will be appropriate in all future cases that utilize computer-assisted review. . . . What the Bar should take away from this Opinion is that computer-assisted review is an available tool and should be seriously considered for use in large-data-volume cases where it may save the producing party (or both parties) significant amounts of legal fees in document review.").

47. *Id.* (emphasis added) ("As with keywords or any other technological solution to e-discovery, counsel must design an *appropriate* process, including use of available technology, with *appropriate* quality control testing, to review and produce relevant ESI while adhering to Rule 1 and Rule 26(b)(2)(C) proportionality.").

48. Again, prior to the 2015 amendments, e-discovery proportionality factors were previously found at Rule 26(b)(2)(C)(iii) of the FRCP.

49. See, e.g., *Nat'l Day Laborer Org. Network v. U.S. Immigration & Customs Enft Agency*, 877 F. Supp. 2d 87, 109 (S.D.N.Y. 2012) ("[P]arties can (and frequently should) rely on . . . machine learning tools to find responsive documents."); *Dynamo Holdings Ltd. P'ship v. Comm'r*, 143 T.C. 183, 191–92 (2014) ("Although predictive coding is a relatively new technique, and a technique that has yet to be sanctioned (let alone mentioned) by this Court in a published Opinion, the understanding of e-discovery and electronic media has advanced significantly in the last few years. . . . In fact, we understand that the technology

Finally, with respect to professional ethical rules and technology, the duty of attorney competence is most applicable to lawyers' use of ML-based predictive coding. The American Bar Association's (ABA) Model Rule 1.1 of the Model Rules of Professional Conduct states: "A lawyer shall provide competent representation to a client. Competent representation requires the legal knowledge, skill, thoroughness and preparation reasonably necessary for representation."⁵¹ In 2012, the legal profession began the process of establishing a legal duty of *technological* competence on lawyers when the ABA's House of Delegates amended Comment 8 to Model Rule 1.1 to read: "To maintain the requisite knowledge and skill, a lawyer should keep abreast of changes in the law and its practice, including the benefits and risks associated with relevant technology, engage in continuing study and education and comply with all continuing legal education requirements to which the lawyer is subject."⁵²

As of the end of February 2019, thirty-six states have formally adopted the amended comment to Rule 1.1.⁵³ On February 26, 2019, Texas became the most recent state to adopt the ABA's Comment 8 to Rule 1.1, when the Supreme Court of Texas amended Paragraph 8 of the comment to Rule 1.01 of the Texas Disciplinary Rules of Professional Conduct comment to track the ABA's model language.⁵⁴

Although California has not specifically adopted the language of the ABA's Comment 8 to Rule 1.1 into its own rule of professional conduct

industry now considers predictive coding to be widely accepted for limiting e-discovery to relevant documents and effecting discovery of ESI without an undue burden."); *Rio Tinto PLC v. Vale S.A.*, 306 F.R.D. 125, 126 (S.D.N.Y. 2015) (holding that TAR is "an acceptable way to search for relevant ESI in appropriate cases").

50. See, e.g., *The Sedona Conference, The Sedona Principles, Third Edition: Best Practices, Recommendations & Principles for Addressing Electronic Document Production*, 19 SEDONA CONF. J. (2018); *Frameworks and Standards: Technology Assisted Review*, EDRM, (2018), <http://www.edrm.net/frameworks-and-standards/technology-assisted-review/> [<https://perma.cc/932Y-BH8S>] (last visited Sept. 20, 2019).

51. MODEL RULES OF PROF'L CONDUCT r. 1.1 (AM. BAR ASS'N 2017).

52. *Id.* at cmt. 8 (reviewing and explaining relevant legal standards and ethical duties regarding attorney technological competence in e-discovery).

53. Robert Ambrogi, *36 States Have Adopted Ethical Duty of Technology Competence*, ROBERT AMBROGI'S LAWSITES (Mar. 12, 2019), <https://www.lawsitesblog.com/tech-competence/> [<https://perma.cc/ZG28-KHAR>] (providing running tally of states that have adopted the ABA's comment to Model Rule 1.1 and links to each state's rule).

54. See Order Amending Comment to the Texas Disciplinary Rules of Professional Conduct, Misc. Docket No. 19-9016 (Tex. Feb. 26, 2019), <http://www.txcourts.gov/media/1443638/199016.pdf> [<https://perma.cc/EP3S-YQQD>] ("Because of the vital role of lawyers in the legal process, each lawyer should strive to become and remain proficient and competent in the practice of law, *including the benefits and risks associated with relevant technology.*") (emphasis added).

regarding competency,⁵⁵ the State Bar of California has, since 2015, nevertheless incorporated the model rule's duty of technology competence with respect to e-discovery via a formal ethics opinion.⁵⁶ This opinion is particularly instructive not only because California is home to a thriving technology sector but also because it provides an extended discussion of attorney competence specifically as applied to conducting e-discovery during litigation. Attorneys in California should be able to perform the following nine skills:

- 1) initially assess e-discovery needs and issues, if any;
- 2) implement/cause to implement appropriate ESI preservation procedures;
- 3) analyze and understand a client's ESI systems and storage;
- 4) advise the client on available options for collection and preservation of ESI;
- 5) identify custodians of potentially relevant ESI;
- 6) engage in competent and meaningful meet and confer with opposing counsel concerning an e-discovery plan;
- 7) perform data searches;
- 8) collect responsive ESI in a manner that preserves the integrity of that ESI; and

55. California's professional rule regarding attorney competence is Rule 3-110 of the Rules of Professional Conduct of the State Bar of California. It holds:

(A) A member shall not intentionally, recklessly, or repeatedly fail to perform legal services with competence.

(B) For purposes of this rule, "competence" in any legal service shall mean to apply the 1) diligence, 2) learning and skill, and 3) mental, emotional, and physical ability reasonably necessary for the performance of such service.

(C) If a member does not have sufficient learning and skill when the legal service is undertaken, the member may nonetheless perform such services competently by 1) associating with or, where appropriate, professionally consulting another lawyer reasonably believed to be competent, or 2) by acquiring sufficient learning and skill before performance is required.

RULES OF PROFESSIONAL CONDUCT, r. 3-110 (CAL. ST. BAR ASS'N 1992).

56. Cal. St. Bar Standing Comm. on Prof'l Responsibility & Conduct, Formal Op. No. 2015-193 at 3 (2015) (quoting the revised Comment 8 to ABA Model Rule 1.1 to state that "[m]aintaining learning and skill consistent with an attorney's duty of competence includes keeping 'abreast of changes in the law and its practice, including the benefits and risks associated with relevant technology . . . '").

9) produce responsive non-privileged ESI in a recognized and appropriate manner.⁵⁷

In California, as in other states adopting the revised comment to the ABA model rule, if an attorney does not possess the requisite skills described above, they can satisfy their ethical obligation of e-discovery technology by associating with competent co-counsel or expert consultants. Such an expert could be a vendor, a subordinate attorney, or even the client itself, as long as they possess the necessary expertise.⁵⁸ However, associating with an expert raises another ethical duty—the duty to supervise—and potential tensions regarding professional expertise between attorneys, technology vendors, and clients that we address in our findings. Even if an attorney associates with a co-counsel or e-discovery consultant with expertise in handling e-discovery technology, that attorney still has the responsibility to supervise such an expert and is ultimately responsible for the work of the expert.⁵⁹

Finally, in its ethics opinion, the California State Bar Standing Committee explicitly did not define a standard of care for attorneys for liability purposes, and it reserves disciplinary action for situations where a lawyer intentionally, recklessly, or repeatedly demonstrates a lack of competence. Our review indicates that subsequent situations involving ethical duties of competence and predictive coding have not been formally adjudicated before such judicial or disciplinary bodies, so it remains an open question as to just how accountable such bodies will hold lawyers when it comes to professional ethics. Given that AI-based products—for e-discovery as well as other legal tasks—will only grow in application and reach, we need further research into how lawyers actually understand and use them in practice.

III. RESEARCH DESIGN

We draw primarily on qualitative evidence obtained from approximately twenty-six hours of semi-structured, in-depth interviews of twenty-five respondents who work with predictive systems in the legal profession—attorneys, litigation support staff working in law firms, and managers at

57. *Id.* at 3–4.

58. *Id.* at 5.

59. *Id.* The rule governing attorney competence in California, cited within the 2015 ethics opinion as Rule 3-110 of the Rules of Professional Conduct of the State Bar of California, is now cited as CA ST RPC Rule 1.1 (Business and Professions Code Section 6068(e)) (new rules approved by the Supreme Court of California May 10, 2018, effective Nov. 1, 2018).

companies that provide decision-support technology products and services to lawyers.⁶⁰

Of our twenty-five respondents, seventeen work at law firms (twelve attorneys, five litigation/technical support staff at law firms), and eight work at legal technology companies. Within this latter group, all of their positions are at the management level: CEO (two), CTO (two), COO (one), Vice President (one), Director of Consulting (one), and Litigation Manager (one).⁶¹ All respondents are based in the United States, although their firms/organizations do business overseas, as well.

Our sample of attorneys is not representative of the population of attorneys in the United States, of course. For example, attorneys in our sample all work at law firms with greater than fifty attorneys and, with the exception of one respondent attorney working at a large plaintiff-oriented firm, would be classified roughly as corporate defense law firms. Because we focus on decision-support tools applied to the e-discovery context, all law firms represented have significant litigation practices. Our focus on attorneys and legal tech managers working with these kinds of law firms was strategic, as our research indicates that they are the firms most likely to be targeted as potential customers by technology company vendors and are the firms most likely to have the clients, resources, and types of cases (i.e., cases with significantly large volumes of ESI) that call for the use of AI-based systems for e-discovery, such as predictive coding tools.⁶² In other words, they are the

60. This research is ongoing, so numbers and findings may change. We conducted interviews in-person or, if respondents were not available to interview in-person, over the phone. All in-person interviews took place in the Bay Area of California. Interview procedures were approved by and complied with the University of California, Berkeley's Office for the Protection of Human Subjects.

61. Three of these respondents are also founders of their companies (2 Founder/CEO; 1 Founder/CTO).

62. See Drew Simshaw, *Ethical Issues in Robo-Lawyering: The Need for Guidance on Developing and Using Artificial Intelligence in the Practice of Law*, 70 HASTINGS L.J. 173, 193 (2019) (noting that the rise of AI in e-discovery could inhibit access to justice because "the benefits of AI-driven e-discovery might, at least at first, only be recognized by large firms because many smaller practices lack designated e-discovery units"); see also Sean Semmler & Zeeve Rose, *Artificial Intelligence: Application Today and Implications Tomorrow*, 16 DUKE L. & TECH. REV. 85, 90 (2017). Semmler and Rose state:

[There is a] possibility that big firms, with their resources and profit margins, are well situated to gain access to this disruptive technology at an earlier stage than smaller firms. Subscriptions to legal A.I. applications may be expensive (early on), and if big firms can buy this technology, become familiar with it now, and use it to attract new clients while retaining their old clientele, then by the time smaller firms get access to the same technology, it may be too late.

Id.

firms and attorneys most likely to have experience with and knowledge of these technologies. Thus, to the extent that our data identify challenges posed by the introduction and use of such systems, conclusions we draw are likely to be conservative, if anything.

IV. THE RISE OF TAR AND PREDICTIVE CODING IN THE LEGAL PROFESSION

To what do lawyers and legal professionals in the surrounding legal services environment attribute the rise of predictive coding systems, and TAR more generally, in the legal profession?

A. COST-CUTTING

Our respondents consistently positioned TAR as a cost-cutting strategy. Like the well-established practice of outsourcing to contract attorneys, and to out-of-country attorneys, delegating “document review” and e-discovery tasks to technical tools is viewed as a way to reduce litigation costs. The rising costs of litigation are a product of both escalating lawyer fees and the explosion in electronic documents produced by daily corporate activities in the digital age. Our respondents viewed TAR and predictive coding primarily as a response to this unprecedented growth in ESI. As Carrie Lewis, a partner at a law firm representing corporate clients, explained:

We’re seeing more and more that the general counsel has to show to their leadership and to their board that they have reduced costs by X percent or increased the use of technology. Then they’re coming to us and saying how do we measure this? How do we show this? What do we do?⁶³

Jason Ellison, currently a manager at a vendor and formerly a litigation support specialist within a law firm, echoed that sentiment: “Clients are increasingly looking at their spends. They’re increasingly analyzing line items on bills and pushing down on law firm clients. This is something that started to get a lot of attention about ten years ago.”⁶⁴ And Samir Anand, an attorney respondent, spoke to the issue of lawyer fees: “What’s happened is lawyer rates have gone up so high that everyone just assumes that it’s [predictive coding] being done by somebody else.”⁶⁵

The increased reliance on technology to facilitate document review, combined with the growing practice of procuring legal services, has fueled

63. Interview with Carrie Lewis, attorney (Jan. 10, 2019).

64. Interview with Jason Ellison, manager at a vendor and former litigation support specialist (Jan. 17, 2019).

65. Interview with Samir Anand, attorney (Jan. 4, 2019).

the growth of legal support vendors that manage and secure the voluminous corpus of documents generated by a business' general operation and provide document review services.⁶⁶ Our interviewees explained that the evolution of TAR tools and pressure to cut costs is reorganizing the relationship between lawyers, clients, and these vendors. This reorganization takes several forms. As to payment, most commonly, a corporate client (i.e., a party to the litigation) pays the e-discovery vendor, but the day-to-day interactions take place between the vendor and the attorneys. As Ken Summers, an executive at a TAR vendor, explained: "The vast majority of our clients are corporations, typically in the Fortune 200[.] In 90%-plus of the cases, [they] pay us. They're the true client. The client we work with on a day-to-day basis is the law firm that represents those corporate clients. That's the structure."⁶⁷ Increasingly, our respondents indicate, legal tech vendors are also marketing their services not only to law firms but directly to the corporations. One respondent, who wished not to be recorded but had managed an overseas office of e-discovery technicians and document reviewers for an e-discovery vendor, described her experience of being told by her supervisor to skip going through the law firm with which her company had contracted and go straight to the corporate client to attempt to cultivate a direct relationship with the corporation in the hopes of future work.

The pressure to reduce legal costs, combined with the increase of technically sophisticated vendors offering complex computational systems to aid legal decision making, has also led to reconfigurations in the extent to which law firms have control over the technologies that they use for their own work. Paul Young, an executive at an e-discovery vendor, explained:

The reality is if you're a multi-billion dollar company, do you really want a law firm that charges \$1,000 an hour making all of your decisions for you? Or do you want to have people internally [who are] definitely looking out for your best interests and vetting outsourced vendors accordingly, contracting directly with them, managing that process internally versus going through a law firm?⁶⁸

This seems to be the case particularly with larger corporate clients. As one partner at a law firm told us:

The overwhelming trend is that the lawyers are being taken out of that process . . . decisions about which corporate lawyers to use have been centralized by the client—which time-entry programs to use, which billing software to use, which ways that we report to the

66. Silvia Hodges Silverstein, *What We Know and Need to Know about Legal Procurement*, 67 S.C. L. REV. 485 (2016).

67. Interview with Ken Summers, executive at a TAR vendor (Feb. 04, 2019).

68. Interview with Paul Young, e-discovery vendor executive (Jan. 16, 2019).

client—are all governed by terms and conditions from the client at the beginning of the relationship⁶⁹

Angus Martin, a partner at a law firm, focused instead on the preferred-provider aspect of his dealings with large corporate clients and technical systems:

The client will say—and it tends to be the Fortune 500 client—will say, “[w]e have a contract to do all of our e-discovery litigation with XYZ vendor.” It means that they get a better price on it. XYZ knows their data systems better, so they [the client] don’t need to go out and pay my hourly rates [for me] to go learn how their servers are set up and all that kind of stuff.⁷⁰

It also appears that larger firms are using vendor platforms to further reduce costs and uncertainties of litigation through longer-term arrangements, standardization across litigation matters, and use of broader information-governance services that integrate litigation support. Echoing what other respondents told us, Chris Graham, who works at an e-discovery vendor, explained that his company has evolved to provide a wider array of information-governance services beyond e-discovery, including “development of data policies, so everything from mobile devices, social media, definitely records-retention and disposition schedules. We work on implementing those. We consult on privacy . . . And we also do e-discovery playbooks—so making sure they are ready in the event they have discovery.”⁷¹

Indeed, e-discovery vendors are providing far more than a technical system, and this carries implications for lawyer-client relationships. Some of the larger vendors of these technical platforms are actually offering a mixed system of technical tools and humans, as Graham went on to explain:

We have an array of products, and the client will tell us what review platform they want it to go up in. Then they will tell us if they want to do the whole review themselves. If they want just staffing, they just want some attorneys, we have a staffing arm . . . so we can give them just bodies to do review. If they want us to actually run their review for them, then we have a managed review set that will set up the workflows, do all the batching of documents, do the quality controls, give reports back, so they can set that up for them. Then

69. Interview with Samir Anand, attorney (Jan. 4, 2019).

70. Interview with Angus Martin, attorney (Jan. 02, 2019).

71. Interview with Chris Graham, e-discovery vendor consultant (Jan. 18, 2019).

we have production environments as well where we can help them produce the documents.⁷²

Consulting staff at vendors often include a range of other experts, including statisticians, linguists, and data scientists, who play an important role in how predictive coding tools are used and interpreted in the discovery process. For example, one vendor representative explained their business and staffing to us:

[W]e do not sell AI tools. We sell AI as a service. When corporate clients come to us, they will either provide the document analysis or key document identification, having it performed by attorneys who use AI tools, or they will purchase the service that [we] provide, which really is a combination of advanced technologies. The main difference is the technologies are applied by computational linguists and computer scientists who operate these technologies in a somewhat different way than lawyers would.⁷³

B. IMPROVED PERFORMANCE AND HUMAN REVIEW OF TECHNICAL SYSTEMS

While cost savings and the steep increase in the volume of material in discovery proceedings appear to be the key drivers of TAR and predictive coding tools specifically, we did encounter the standard refrain of Big Data and machine learning advocates that algorithmic systems are better—less biased, more consistent and predictable—than fallible, sometimes malicious, humans. And this sentiment came not only from technology company representatives but also from within law firms. Joe Goodman, who is a law firm litigation support manager and works closely with attorneys at his firm, reflected this sentiment:

Yes, unequivocally, [predictive coding is] generally considered to be more accurate [than human review] because it's an algorithm. It's not a human who blinked at the wrong time or got distracted by their dog or a search term was wrong and pulled back the wrong data, those kinds of things. There's so many reasons why a human review is flawed compared to using the technology.⁷⁴

Even when asked about training data and other factors that could influence model performance, Goodman did not waiver in his assessment of the relative accuracy of predictive coding tools compared to humans: “Those factors don't really play into it. It's a matter of comparing like populations, or

72. *Id.*

73. Interview with Ken Summers, vendor executive (Feb. 04, 2019).

74. Interview with Joe Goodman, litigation support manager at law firm (Jan. 11, 2019).

two identical populations, for human review versus algorithmic review. You're going to see greater accuracy from the algorithmic review almost every time than you would from humans."⁷⁵

What did respondents have to say about human review of system performance? Lawyers did report using human review as a check on system outputs. However, its use was selective in ways that, if typical of practice, risked introducing a systematic bias of under-disclosure.⁷⁶ For example, Goodman, the litigation support manager, prefaced his discussion about lawyers' interactions with TAR systems with "[i]t's funny, it's almost always driven by volume."⁷⁷ He went on to explain how during the early stage of discovery, if his team is developing search terms to set an initial training set of documents, a typical conversation with attorneys would go as follows:

[Attorneys will say] 'Here, run this group of search terms,' and . . . want to know how many documents it brings back. Then they say, 'Oh, that's too many. We've got to change the terms.' They've set the terms based on the number of documents that they've returned. Then they get the other side to agree to the search terms we're using and vice-versa.⁷⁸

Goodman assumed this approach by the lawyers was based on "[c]ost, effort, and time."⁷⁹ He understood that this was no proper way to determine responsiveness or address the discovery principles of proportionality and defensibility: "That's usually how that goes. It's very funny, and I've never really understood this. How is it that we're determining what to review based on how many documents come back on a given search term set? Either the search terms are perpetually responsive or they're not."⁸⁰

For their part, lawyers indicated being particularly averse to certain kinds of failures, namely the inadvertent production of privileged material. This leads post-predictive coding human reviews by attorneys to focus on documents that the system identified for production (i.e., documents scored by the predictive coding system at a probability that meets or exceeds the system's decision threshold to be classified as responsive, notwithstanding

75. *Id.*

76. Compared to lawyers, vendors reported more reliance on, and evinced a much deeper understanding of, traditional model-evaluation metrics like recall and precision. With respect to human review, they did not have objections to it, but on this, they tended to recommend the minimal amount of human review that, in their analysis, would best balance satisfying defensibility standards from the courts and saving costs on human review for their clients.

77. *Supra* note 74, at 25.

78. *Id.*

79. *Id.*

80. *Id.*

any other privileges or exceptions that might prevent disclosure). It also leads the human reviewers to give comparatively less attention, if any, to those documents *not* classified as potentially responsive (i.e., predicted negatives) or to conduct a systematic review of both groups of scored documents (i.e., both the predicted positives and predicted negatives). Respondents reported very little questioning or real review of predictive coding model performance with respect to false negatives (i.e., documents that are actually responsive but not classified as such by the predictive system).

V. IMPLICATIONS: ETHICS AND VALUES

In this Section, we discuss important implications raised by the interview data concerning professional ethics and values, the exercise of professional judgment, and the practice of law. Here, with respect to predictive coding technologies and lawyers, we focus specifically on the duty of technological competence, accountability, and lawyers' obligations of supervision when working with others involved in a case, and professionalism, disclosure, and interactions with opposing counsel.

A. LAWYER'S DUTY OF COMPETENT REPRESENTATION

As discussed above, attorneys have a professional ethical obligation to provide competent legal representation to their clients. For attorneys in most states today, that duty of competence entails keeping abreast of changes in the law and its practice, "including the benefits and risks associated with relevant technology."⁸¹ What is happening in practice? And what do lawyers and legal technology professionals have to say about technology competence and automated decision support systems, particularly when it comes to TAR and predictive coding systems?

First, and considering the issue of technical expertise before getting to the more specific issue of lawyers' ethical duty of technology competence, our third-party TAR vendor respondents felt strongly that, compared to lawyers, they have the most technical expertise regarding information retrieval and predictive coding systems. As Ken Summers, an executive-level manager, explained to us:

[T]his is a distinct professional domain, information retrieval. . . .
It's truly a distinct professional field. I don't believe that at scale
any company or any law firm or a company like ours can have truly

81. 36 states have now formally adopted the American Bar Association's 2012 revised Comment 8 to Rule 1.1 of the Model Rules of Professional Conduct. *See* Ambrogi, *supra* note 53. Other states, such as California, can impose the same or similar duties through state bar ethics opinions. *See* Cal. St. Bar Standing Comm. on Prof'l Responsibility & Conduct, Formal Op. No. 2015-193, *supra* note 56.

two completely distinct twin core competencies. [Company name], I think, is probably today the best information retrieval company in the known universe when it comes to data analytics and litigation, investigations, etc., but we will never be a great law firm, even if we tried. It's just two distinct professional domains.⁸²

Later in the interview, Summers described the average lawyer as “a lay person” who is ill-equipped to leverage “the scientific domain of search and review and information retrieval,” which leads to “inefficiencies.” Similarly, Paul Young, manager at an e-discovery vendor, spoke to the issue of lawyers’ lack of understanding of technical features of systems and statistical concepts underlying system outputs:

Most of them [lawyers] don't really even to go as far as to want to talk about the underlying technology[.] . . . I think statistics in general are concepts that, really, attorneys do not like. They're not familiar with or comfortable with them at all. I think anytime you're talking about defensibility and proportionality, those are generally considerations that the lawyers are familiar with. Once you start throwing things like statistics in there, saying, “In order for you to have defensible results, or in order for you to make a proportionality argument, blah, blah, blah, statistics.” I think that's where a lot of the attorneys out there really shut down or they have a hard time really buying into it.⁸³

How, then, are lawyers thinking about the connection between technical competence and liability? Matt Rogers, a senior attorney, articulated a general concern that lawyers may have about responsibility: “Where are the responsibilities if the platform gets screwed up? Or you make mistakes? Or you make a representation that's belied by the data? That kind of thing.”⁸⁴ He went on to observe that the new arrangements between attorneys, clients, and technical expert vendors produced “decision-making friction . . . between what a [firm] wants to do, and what a client wants to do, and what the third-party provider wants to do.”⁸⁵ However, going against the stereotype of risk-averse lawyers and our expectation that our lawyer respondents would point to concerns about liability risk due to inadequate understanding of black-box AI-based tools, our interviewees indicated an overall *lack* of concern about potential professional malpractice liability risk when discussing the factors driving adoption and use of these systems. Instead, expressing a general sentiment expressed by our lawyer respondents

82. Interview with Ken Summers, vendor executive (Feb. 4, 2019).

83. Interview with Paul Young, manager at e-discovery vendor (Jan. 16, 2019).

84. Interview with Matt Rogers, attorney (Jan. 7, 2019).

85. *Id.*

about their work, an attorney at a large firm who oversees the procurement of technical systems for the firm’s lawyers explained:

The attorneys at [firm] are so diligent and so focused on providing value to their clients that—well, the best legal services for the client, even if it’s not value in terms of dollars and cents—no one’s been worried that this is going to be a shortcut that leads to some sort of malpractice problem.⁸⁶

B. RESPONSIBILITY AND THE DUTY TO SUPERVISE OTHERS

Even if a lawyer lacks an adequate understanding of the algorithms and models underlying TAR and predictive coding, as we discussed earlier, he or she can satisfy the ethical obligation of competent representation by associating with and supervising a sufficiently competent lawyer (within or outside the firm) and even a non-lawyer technical expert.⁸⁷ How are lawyers and third-party vendors thinking about these issues of technology competence and the duty to supervise?

Chris Graham, who is a licensed attorney but works for a TAR vendor as an e-discovery consultant, had a particularly illuminating response when asked about the extent to which he “owns the discovery process” (his phrase) in his role as consultant:

Even though I and others on my team have decades of experience among us and we’re all licensed [to practice law] in multiple states, we cannot practice law as we sit here as serving consultants. We can consult. We have to be supervised by an attorney. It means I can’t just have a paralegal hire me, and there’s no one else that my stuff is going through for the discovery side of things.

[But] . . . we can, basically, own as much as the process as our client wants us to and control it as if we were the attorneys. We have all run these types of cases when we were practicing attorneys. At the end of the day, I need to be disclosing everything that I’m doing to an attorney so that they can satisfy their duty to supervise me, and as a barred attorney myself, it creates this weird duty to be supervised. Unlike any expert where it’s not [pause]—the attorney has to understand everything I’ve done. They have to make sure that I’m not clearly just being reckless and doing things I shouldn’t do, and if there’s a big decision to be made, consulting with my

86. Interview with Chad Mankins, attorney (Aug. 22, 2018).

87. *See, e.g., supra* note 56 (discussing California’s ethics rules governing associating with co-counsel or technical experts for purposes of satisfying the duty of competent representation).

client, making sure they're educated around their different options, and making a recommendation to them.⁸⁸

Graham's response reveals some of the tensions that, in practice, the duty to supervise imposes on the attorney-client-vendor relationship. As a licensed attorney, he exhibits a keen awareness of the ethical requirements and the limitations they impose on vendor/consultant interactions with the supervising attorney (e.g., be hired by the attorney, keep the attorney informed). Yet, Graham also characterizes himself as a deep expert (e.g., "decades of experience") and able to control the e-discovery process "as if we were attorneys."

Reflecting on this shift to third-party vendors, and vendors' crucial (but often downplayed) human workers who manage discovery on a day-to-day basis, most lawyer respondents were clear that the lawyer remains responsible for errors or mistakes in discovery, even if they were made by the vendor. Steve Watson, a managing project attorney at a law firm, exemplified this sentiment: "[Y]ou cannot outsource that [responsibility] to the vendor. I know the vendors can really be helpful with the consulting work, but the lapels that the client and the court is going to grab are the firm's."⁸⁹ Similarly, Samir Anand, partner at a law firm, said: "[M]y guess is all lawyers know that they are the ones responsible. I mean, none of us go to court and say, 'Well, we used e-discovery software, so that was the problem.'⁹⁰

The conviction with which our lawyers proclaimed that the managing attorney is ultimately responsible for discovery does not take away from the fact that, in practice, things can get murkier. Clay Simpson, manager of legal technology and analytics at a law firm, voiced concern about law firms (not his own) where "responsibility is being outsourced to the vendor":

Q: What's your sense of the field in general, the legal field, about knowledge of those duties, commitments, or actual practices to have those clearly defined accountability chains?

A: Yeah, I'd say it's hit or miss. I'd say it's limited. A lot of folks will—a lot of other law firms will have maybe an e-discovery practice, but they're not looped in on these issues. I think it varies widely. I made the outsource-to-the-vendor point because that's what I hear a lot of my peers complain about. A lot of that responsibility is being outsourced to the vendor. It's all great if everything works perfectly. Oftentimes, a good vendor consultant can testify, even if you're being challenged, but I think if something goes really poorly, I think that's probably a bad strategy.

88. Interview with Chris Graham, e-discovery vendor representative (Jan. 18, 2019).

89. Interview with Steve Watson, attorney (Jan. 10, 2019).

90. Interview with Samir Anand, attorney (Jan. 4, 2019).

Q: What do the vendors have to say about the issue? Is that something that they're worrying about as a liability issue?

A: They're worried about it; there's no doubt about it. . . . I've talked to vendors just recently at conferences that have actually dealt with this issue. I had somebody come up to me after [a conference] who said, "I ran into the same thing where it got outsourced to me." The person there was trying to combat it and push it back to the firm, then things went poorly, and then it was just a "ball dropped" type of scenario. That's rough if the law firm itself isn't owning it, owning the project management and the AI side of it.⁹¹

Vendors even invoke specific strategies to protect themselves from blame and keep the lawyers responsible for legal determinations. For example, Paul Young, e-discovery vendor manager, told us that his company "tr[ies] to avoid definitively saying anything like, '[y]ou can stop now,' or '[t]his is definitely good enough.'" He explained that "that's a legal determination, and we're not the outside counsel."⁹²

Finally, although not a focus of our interviews, there is a question about the extent to which attorneys may confuse contractual obligations with professional obligations. For example, when asked whether lawyers have an ethical duty to inform clients about the use of a given technology product, one law-firm respondent suggested that the contractual arrangement between corporate client and vendor addressed this concern:

[W]henever we [law firm] contract with vendors, typically we get the client to sign the letter of engagement with the vendor directly so we don't act [as] the middle man for payment. We want the client to be on the hook to pay the vendor directly so we're out of the loop on that. They know what they're getting into. They know what they're signing up for. They know what tools are going to be used and they'll know how much it's going to cost, and they're in agreement with those terms.⁹³

This assumption that service procurement will address concerns about whether or not technical choices should be discussed specifically with the client points to a risk of confusion about who is accountable for what in these triangulated relationships.

91. Interview with Clay Simpson, manager of legal technology at a law firm (Jan. 10, 2019).

92. Interview with Paul Young, e-discovery vendor manager (Jan. 16, 2019).

93. Interview with Joe Goodman, litigation support manager at law firm (Jan. 11, 2019).

C. INTERACTIONS WITH OPPOSING COUNSEL—TRUST, TRANSPARENCY, FAIRNESS

Finally, we address a different aspect of ethics that bears on attorney competence and fair dealing: how attorneys interact with opposing counsel during discovery. All attorney respondents expressed a preference for working with the other side to agree on the use of predictive coding. This is in line with the goal of the FRCP to encourage cooperation among parties in e-discovery.⁹⁴ Matt Rogers, an attorney who heads the e-discovery practice at his firm, reflected this preference:

If they're [opposing counsel] looking at—you throw them your non-responses, and they say, "Hey, this is just not—you're not picking up a certain issue." [We will say,] "sorry about that, we'll pick that up." [Or they say,] "your precision is, at this level, we would like it to be higher." Maybe you agree beforehand on what it is. If the parties are being cooperative, it can be very productive, actually, to get people—I mean, you're holding down costs on both sides.⁹⁵

However, our attorney respondents were not particularly worried about learning everything they could learn about their adversary's predictive coding system (e.g., seed-set disclosure, scoring/ranking methods, evaluation metrics). Instead, they revealed, they tend to rely on their own expertise, follow guidance from their own e-discovery vendors, and trust in their opposing counsel not to act nefariously.⁹⁶ As an e-discovery vendor manager told us, never in his career had he been asked "to explain why certain data subsets were not produced by virtue of some cutoff that left them out of the production universe."⁹⁷ This could be due to his company being "proactive" and developing comprehensive defensibility plans for their clients, as he suggested, but it could also point to insufficient technical understanding by opposing counsel.

Finally, speaking to issues of competence and reflecting the preference for agreements between parties to reduce any potential ethical predicaments, Robert Baker, attorney at a large defense firm, stated: "I think that having a

94. See discussion of Federal Rules of Civil Procedure, *supra* note 43.

95. Interview with Matt Rogers, attorney (Jan. 7, 2019).

96. Jurisdictions are split on whether, and under what circumstances, parties are required to disclose seed sets used for model training. See Shannon H. Kitzer, *Garbage in, Garbage out: Is Seed Set Disclosure a Necessary Check on Technology-Assisted Review and Should Courts Require Disclosure Notes*, 2018 U. ILL. J.L. TECH. & POL'Y 197 (2018). Proponents of continuous active learning (CAL), or TAR 2.0 as described earlier in the paper, may point to the seed-set disclosure issue as a reason to use TAR 2.0, as it does not require an initial set of documents for training.

97. Interview with Paul Young, e-discovery vendor manager (Jan. 16, 2019).

stipulation from the other side is pretty close to a proxy for confidence. I think [if] both sides agree to something, it's difficult for both sides to be incompetent at once, I think."⁹⁸

Similarly, Frank Goldman, an attorney at a large plaintiff's law firm whom we expected would be more distrustful of the other side than his corporate defense counterparts, instead reinforced our finding on this issue:

Q: I guess what I'm getting at is do you think it would be useful for there to have more clear guidance or standards about understanding the other side's TAR process and TAR system?

A: More transparency I think, as a general rule, is better. I think that—I'm pausing because it's a heavy question. What should be happening is your document requests should be honestly and properly and carefully followed and answered. On some level, I care how the materials are gathered and I care what the search protocols are and I want to be really, really strategic and smart, and even if not paranoid, then very, very deliberate and careful. But if I were adjusting a dial, it wouldn't necessarily be so that I could peer into the TAR process of my adversary. It would be so that I could effectively trust and verify their discovery production.⁹⁹

VI. ALIGNING TOOLS WITH PROFESSIONAL LOGICS

Our findings reveal a need for closer alignment of automated legal decision-making technologies, such as the predictive coding e-discovery systems that we have described here, with the professional logics of lawyers and the legal profession.¹⁰⁰ Such an alignment would foster not only wider adoption and deeper user understanding of these systems but would also increase public trust and the accountability of a legal profession that will continue to use these automated decision-making tools. These goals can be accomplished not only via more detailed and clearly articulated professional norms and rules—such as the duty of technological competence discussed above—but also via clearer standards, shared evaluation practices, and technical design considerations aimed at connecting these technological systems to the professional domain in which they are deployed. We briefly highlight two suggestions below as a starting point.

98. Interview with Robert Baker, attorney (Dec. 21, 2018).

99. Interview with Frank Goldman, attorney (March 8, 2019).

100. See Frank A. Pascale, *Professional Judgment in an Era of Artificial Intelligence and Machine Learning*, 46 BOUNDARY 2, 73–101 (2017) (contrasting the reductionist epistemology and functionalist assumptions underlying substitutive automation with the holistic epistemology of professional judgment and the conflictual, political, and contestable nature of professional work, particularly in the education and healthcare professional domains).

A. NEED FOR VALIDATION AND TESTING

First, we suggest the legal profession work to develop articulable, accessible, and consistent methods and standards for validation and testing of predictive coding tools. Our interviews indicate that not only do most lawyers lack an adequate understanding of testing and validation terms and metrics, such as recall and precision, there also does not seem to be a consistent effort to create testing schemes and datasets on which to evaluate the systems offered by TAR vendors on the market today. Instead, most vendors offer in-house metrics and validation claims as part of their marketing efforts, which of course will not be subject to the same level of benchmarking and scrutiny compared to industry-wide sets and standards.

Further, although our respondents may mention informal guidelines or validation rules of thumb, such as best practices developed by professional groups (e.g., Sedona Conference Working Groups on e-discovery issues (Working Groups 1–2, 6–7), the EDRM at Duke Law School) or in-house discovery protocols developed by vendors/consultants or attorneys themselves, they invariably tell us that they look to the more formal rules of civil procedure regarding discovery and rules of ethical and professional conduct discussed here as guideposts for the more informal governance mechanisms they employ in practice.¹⁰¹ Of course, such “formal” governance mechanisms favor more general principles like “proportionality” and “defensibility” or post-hoc, interpretative evaluations provided by courts instead of articulating more technical and specific testing procedures, validation protocols, and data.

At one time, there was a Legal Track at the Text Retrieval Conference (TREC), which is sponsored by the National Institute of Standards and Technology (NIST).¹⁰² Its stated aim was “to assess the ability of information retrieval techniques to meet the needs of the legal profession for tools and methods capable of helping with the retrieval of electronic business records, principally for use as evidence in civil litigation.”¹⁰³ The conference provided a venue for shared development of datasets, identification of learning tasks—including tasks modeling discovery production in civil litigation—and evaluations of precision and recall.¹⁰⁴ However, the last time that the Legal Track convened at TREC was 2011, and its website indicates that it is no

101. See Sedona Conference, *supra* note 52; EDRM, *supra* note 50.

102. TREC LEGAL TRACK, <https://trec-legal.umiacs.umd.edu/> [<https://perma.cc/HN6Y-HUZV>] (last visited Sept. 20, 2019) (showing little to no activity since 2011–12).

103. See Grossman & Cormack, *supra* note 26 (using TREC 2009 Legal Track data to conduct their study of predictive coding compared to human review in their seminal article on predictive coding).

104. See TREC LEGAL TRACK, *supra* note 102 (including data sets, learning tasks, evaluations, and evaluation metrics for the archive of Legal Track).

longer active. Furthermore, while the conference supported improvements in legal information retrieval techniques generally, it explicitly was not a venue for commercial product tests.¹⁰⁵ The closest that the legal profession comes today is with organizations like the Sedona Conference, which works to address best practices and guidelines for lawyers dealing with e-discovery issues but does not provide, to our knowledge, benchmarking tools or rigorous empirical evaluations of systems on the market.¹⁰⁶

In the medical field, clinical decision support systems used to support medical judgment are subject to two forms of review: 1) explicit regulatory oversight of medical devices and 2) review by doctors and medical institutions, informed by the profession's understanding of legal-ethical duties.¹⁰⁷ The division of responsibility for approving which medical devices are fit for the marketplace, made by the FDA, and which tools a given medical provider chooses to use reflects an understanding that medical professionals do not have the expertise required to evaluate the performance of complex technical systems alone. At this moment, regulators¹⁰⁸ and doctors¹⁰⁹ are considering how to regulate clinical decision support systems—

105. See TREC STATEMENT ON PRODUCT TESTING AND ADVERTISING (Apr. 9, 2019), <https://trec.nist.gov/trec.disclaim.html> [<https://perma.cc/97XL-HANF>].

106. See Sedona Conference, *supra* note 52.

107. For our purposes, automated clinical decision support systems relying on machine learning to aid medical doctors in making decisions are a useful comparison for the predictive coding systems in law that we study below.

108. 21st Century Cures Act, Pub. L. No. 114-255 (2016). In December 2016, President Obama signed into law the 21st Century Cures Act. Section 3060(a) of the Cures Act added a new subsection to the Food, Drug, and Cosmetic Act (FDCA) that excludes from the Food and Drug Administration's (FDA) medical-device regulations and approval processes "software function" that meets the following conditions: 1) not intended to acquire, process, or analyze a medical image or a signal from an in vitro diagnostic device or a pattern or signal from a signal acquisition system; 2) intended for the purpose of displaying, analyzing, or printing medical information about a patient or other medical information (such as peer-reviewed clinical studies and clinical practice guidelines); 3) intended for the purpose of supporting or providing recommendations to a health care professional about prevention, diagnosis, or treatment of a disease or condition; and, 4) intended for the purpose of enabling such health care professional to independently review the basis for such recommendations that such software presents so that it is not the intent that such health care professional rely primarily on any of such recommendations to make a clinical diagnosis or treatment decision regarding an individual patient. 21 U.S.C. § 360(j)(o)(1)(E)(i)–(iii) (2016).

109. See, e.g., Emily L. Evans & Danielle Whicher, *What Should Oversight of Clinical Decision Support Systems Look Like?*, 20 AM. MED. J. ETHICS 857 (2018) (arguing that while using a clinical decision support system may not be a research activity under the Common Rule, its use requires more ethical and regulatory oversight than clinical practice and proposing a framework that sets out conditions governing use, ongoing monitoring of data quality, processes for developing and validating algorithms, and protections for patient data); Nicole Martinez-Martin et al., *Is It Ethical to Use Prognostic Estimates from Machine Learning to Treat Psychosis?*, 20 AM. MED. J. ETHICS 804 (2018) (providing an example of how the profession is

particularly those that rely on machine learning. These two regulatory forces provide different types of expertise that can collectively work to align machine-learning tools with the fields' decision-making processes. Regardless of how exactly clinical decision support systems are governed by regulatory bodies like the FDA, other factors—e.g., professional licensing requirements, ethical duties, tort-based malpractice liability principles, and doctors' own conceptions of themselves as users of these technologies—will shape clinical decision support tools and the conditions of their adoption and use. The exact contours of these various ethical and legal obligations are still emerging, but professionals and professional associations are keenly aware of the need to actively shape these tools to serve the needs of the medical field.¹¹⁰ They are pushing for tools that are interpretable by medical professionals and used under conditions that support “epistemically responsible” knowledge production and behavior.¹¹¹

Our research of the legal sector reveals a profession struggling to evaluate increasingly complex tools without requisite expertise and systematic and shared methods. The gatekeepers and gatekeeping tools historically relied upon are insufficient to oversee the influx of predictive machine learning systems into legal practice. Reliance on professional rules and court approval is untenable.¹¹² The legal profession needs to develop new governance models that enlist appropriate technical experts in evaluating systems that support professional cognitive work. Setting aside the question of whether the creation of a separate body charged with evaluating TAR and other tools that support, augment, or replace professional decision making is necessary, there is at least a pressing need for shared methods and standards for validation and testing of predictive coding tools.

B. TOWARD CONTESTABILITY AS A FEATURE OF DECISION-MAKING TOOLS

Assuming for the moment that the profession heeds our call and develops processes for evaluating predictive coding tools by those with

grappling with such machine learning-based decision support systems); *Augmented intelligence in health care H-480.940*, AM. MED. ASS'N <https://policysearch.ama-assn.org/policyfinder/detail/augmented%20intelligence?uri=%2FAMADoc%2FHOD.xml-H-480.940.xml> [<https://perma.cc/FW22-VU9P>] (last visited Sept. 20, 2019) (setting out principles to guide development and use of AI).

110. Danton S. Char et al., *Implementing Machine Learning in Health Care — Addressing Ethical Challenges*, 378(11) NEW ENGLAND J. MED. 981, 981 (2018).

111. Simon, *supra* note 9, at 145.

112. Dana Remus & Frank Levy, *Can robots be lawyers: Computers, lawyers, and the practice of law*, 30 GEO. J. LEGAL ETHICS 501, 556 (2017) (arguing for the adoption of “more effective regulatory structures that draw upon both legal and technical expertise, while protecting both clients and the values of our legal system”).

requisite expertise, those systems will still require run-time configuration. Aligning a TAR system with discovery needs in a particular case, or with respect to a particular set of documents, requires exposing relevant aspects of system design and, where possible, opening them up to exploration and configuration. Professionals appropriate technology differently, employing it in everyday work practice, as informed by routines, habits, norms, values, and ideas and obligations of professional identity. Appropriate handoffs to, and collaborations with, decision-support systems demand that they reflect professional logics and provide users with the ability to understand, contest, and oversee decision making. Technical design should seek to put professionals and decision support systems in conversation, not position professionals as passive recipients of system wisdom who must rely on out-of-band mechanisms to challenge them. For these reasons, calls for explainability¹¹³ fall short and should be replaced by governance approaches that promote contestable systems. This requires attention to both the information demands of professionals—inputs, decisional rules, etc.—and processes of interaction that elicit human expertise and allow humans to elicit information about machine decision making.

To foster user engagement and understanding, and to surface the values implicated by TAR systems and decisions, we embrace the design principle of “contestability.”¹¹⁴ As we have described the concept elsewhere,

113. Compared to “explainability” as a value goal for system design, contestability is a more active and dynamic principle. Where the passivity of “explainable” algorithmic systems imagines engagement, reflection, and questioning as out-of-band activities—via exception handling, appeals processes, etc.—contestable systems are designed to foster active, critical engagement within the system. Explanations, as reflected in policy debates and the majority of research on interpretable systems, are also typically viewed as static—focused on conveying a single message. Ashraf Abdul et al., *Trends and Trajectories for Explainable, Accountable and Intelligible Systems: An HCI Research Agenda*, in PROC. INT’L CONF. ON HUM. FACTORS IN COMPUTING SYSTEMS 1 (2018) (reviewing the explainable AI literature and observing that researchers in this community tend to produce static explanations).

114. See Tad Hirsch et al., *Designing Contestability: Interaction Design, Machine Learning, and Mental Health*, in DES INTERACT SYST CONF. 95, 98 (2017) (setting out contestability as a design objective to address the myriad ethical risks posed by the potential reworking of relationships and redistribution of power caused by the introduction of machine-learning systems. In their example, they explain how a machine learning-based assessment and training tool for psychotherapists could be used as a “blunt assessment tool” of management). They offer three lower-level design principles to support contestability: 1) improving accuracy through phased and iterative deployment with expert users in environments that encourage feedback; 2) heightening legibility through mechanisms that “unpack aggregate measures” and “trac[e] system predictions all the way down” so that “users can follow, and if necessary, contest the reasoning behind each prediction,” 3) identifying “aggregate effects” that may imperil vulnerable users through mechanisms that allow “users to ask questions and record disagreements with system behavior” and engage the system in self-monitoring. *Id.* Together, these design principles can drive active, critical,

contestability refers to mechanisms for users to understand, construct, shape, and challenge model predictions.¹¹⁵ It is a particularly important system quality where the goal is for predictive algorithms to enhance and support human reasoning, such as decision-support systems and systems that aid users in evaluative cognitive tasks. A wide array of empirical studies provide evidence that interactive, contestable systems advance individual user understanding.¹¹⁶ In addition, such systems can not only improve user understanding and use of a system but also enable users to provide deep and useful feedback to improve algorithms.¹¹⁷

Contestable design would allow lawyers to more dynamically explore and interact with TAR systems. In particular, the responsive and dynamic tailoring of continuous active learning-based predictive coding systems, combined with rich feedback and interaction with professional experts, could produce decisions that support “epistemically responsible” knowledge production.¹¹⁸ Contestability spreads the production of knowledge across humans and machines. Indeed, systems designed for contestability invite engagement rather than delegation of responsibility, which aligns well with regulatory and liability principles that seek to keep humans in the loop. They can foster engagement through both the provision of information about system inputs, reasoning, and outputs, and through an interactive design that encourages exploration and querying. In other words, contestability makes algorithmic systems knowable to lawyers, responding to their need (and ethical duty of technological competence) to understand the tools one uses while simultaneously responding to the societal need to ensure that tools are fit for purpose. Contestable design thus contributes to the creation of governance models that support epistemically responsible behavior¹¹⁹ and encourages shared reasoning about the appropriateness of algorithmic systems’ behavior.

real-time engagement with the reasoning of machine-learning system inputs, outputs, and models.

115. Deirdre K. Mulligan et al., *Contestability: From Explanations to Engagement with AI*, in AFTER THE DIGITAL TORNADO: NETWORKS, ALGORITHMS, HUMANITY (Kevin Werbach ed., 2019).

116. Saleema Amershi et al., *Power to the People: The Role of Humans in Interactive Machine Learning*, 35 AI MAG. 105 (2014).

117. Simone Stumpf et al., *Toward Harnessing User Feedback for Machine Learning*, in 12TH INT’L CONF. ON INTELLIGENT USER INTERFACE 82 (2007); see also S. Stumpf et al., *Interacting Meaningfully with Machine Learning Systems: Three Experiments*, 67 HYPERCONNECTED INT’L J. HUM. COMPUTER STUD. 639 (2009).

118. Simon, *supra* note 9, at 145.

119. *Id.*

VII. CONCLUSION

The introduction and increasing popularity of predictive coding systems is reshaping the legal profession in significant ways. Far from being just a new tool in “normal practice,” we found that predictive coding—and, perhaps, the broader set of complex, ML-based legal technologies entering the profession—has brought new entities and technical experts into the legal services ecosystem who are mediating the relationship between lawyers and clients. This raises old questions, such as those about contract attorneys and outsourcing of legal work, but in slightly new forms and involving new parties. The result is a reconfiguration of social relations and new power dynamics, specifically 1) new kinds of professionals who have the training and expertise to build and use the tools in ways few lawyers do, and 2) a new tool for cost containment by corporate clients.

Our research reveals that more work needs to be done to address potential blind spots at the intersection of professional governance (via rules of professional ethical conduct) and legal decision-support technologies. Lawyers are reliant not only on “black box” technical tools but also on other experts. Just in our case of predictive coding for e-discovery, lawyers relied on non-lawyer support staff and vendor judgment for a variety of tasks: system selection (reliant on vendors and, for some, on in-house litigation support staff for early testing), configuration (reliant on in-house technical experts or vendors), and model-testing and evaluation (we found no real standards or benchmarking). This points to the need to rethink how tools are tested and evaluated before they are unleashed into the field. It also points to the need for more education and training to ensure lawyers better understand ML-based decision support systems. Finally, even with better evaluation and testing of tools, in order to appropriately support lawyers on a given discovery task, such tools must be interpretable and configurable—that is, contestable. Lawyers, and the legal profession more generally, should take heed of the growing reliance on machine learning systems for professional work and develop clearer rules, standards, design features, and procedures governing the procurement, deployment, and, crucially, user understanding, of automated legal decision-making technologies.

