

**American Bar Association
42nd Annual Forum on Franchising**

**ARTIFICIAL INTELLIGENCE, E-DISCOVERY, AND THE NEXT
FRONTIERS OF DISCOVERY IN FRANCHISE LITIGATION**

**Theo S. Arnold
Money Mailer
Cypress, California**

and

**John M. Doroghazi
Wiggin and Dana LLP
New Haven, Connecticut**

**October 16-18, 2019
Denver, Colorado**

TABLE OF CONTENTS

I. INTRODUCTION: SMART MACHINES KNOW YOU ARE PREGNANT <u>AND</u> CAN HELP WITH LITIGATION	1
II. A BRIEF HISTORY OF AI: SEARCHING FOR BOBBY FISCHERBOT	2
A. Rise of The Chess Machines	2
B. Artificial Neural Networks Learn How to Learn	4
C. I'll Take Computer Gameshow Contestants for \$2000, Alex	6
III. AN OVERVIEW OF DISCOVERY AND OTHER RULES RELATED TO ELECTRONICALLY STORED INFORMATION	7
A. Federal Rules of Civil Procedure	7
B. Ethical Rules Require Litigators to Understand Technology	11
IV. DISCOVERY USING AI	12
A. Common Types of Electronic Documents	12
B. Document Review Using AI	16
V. TAR: THE NUTS AND BOLTS OF AI DISCOVERY	19
A. How It Works	19
B. Errors and Issues	19
VI. HOW HAVE COURTS REACTED TO AI AND TAR	22
A. <i>Da Silva Moore v. Pubicilis Groupe</i> is First Opinion to Approve of TAR	22
B. Requiring the Use of TAR	23
C. Coupling TAR with other Review Techniques	24
D. Disclosure Requirements	25
E. Local and International Rules Addressing Technology Assisted Review	26
F. Notable Commentaries	27
G. Franchise Specific Cases	28
VII. WELCOMING OUR NEW COMPUTER OVERLORDS: ON BEYOND DISCOVERY! ...	28

VIII. CONCLUSION	30
------------------------	----

Biographies.....	32
------------------	----

88888888\2806\4818-5245-2515.v1

I. INTRODUCTION: SMART MACHINES KNOW YOU ARE PREGNANT AND CAN HELP WITH LITIGATION

People are brand-loyal almost by habit: they have a typical store or set of stores where they go for everyday purchases, use products that they know or like, and, as a result, buy the same brands from those stores essentially on autopilot. However, when people go through a major life event, like graduation, a new job, or a move, their shopping habits frequently change: they become open to disrupting brand preference habits that may have remained static for years, and they suddenly begin purchasing new brands or product lines.¹ After the major life event, customers' product preferences likely will return to a static state, but a new product will be the beneficiary of the shoppers' habits. In other words, a correctly-timed advertisement can drive years of repeat consumer purchases.

The birth of a child is an especially disruptive event, both for a new-parent's personal life and for the parent's buying habits. New parents buy a lot of stuff, made up mostly of new products and new brands they've never had to purchase before. Marketing to new parents has a great return on investment, and is typically easy, as birth records are generally public.² But therein lies the rub: because every retailer has access to public birth records, new parents are inundated by product and service advertisements as soon as the child arrives.

Moreover, the shift in buying habits for new parents does not begin at the birth of the child but several months earlier. By the second trimester, pregnant women shift their buying habits to start purchasing, among other items, prenatal vitamins, purses or bags large enough to hold diapers and other supplies, and unscented versions of lotions and hygiene products.³ The challenge to marketers is two-faceted: they need to learn of a woman's pregnancy before the birth not only to beat competitors to the punch but also to capture buying habit changes that occur during the pregnancy itself.

In 2012, an irate man walked into a Target outside Minneapolis with a stack of coupons in his hand, having seen first-hand the fruits of Target's attention to this marketing problem. He demanded to know why the store manager thought it was appropriate to send his high-school aged daughter a mailer full of coupons for maternity items, baby clothes, and cribs, and asked if Target was trying to encourage the girl to get pregnant. When the manager called to follow up and apologize again a few days later, the father's tone was conciliatory. His daughter was due in August.⁴

But how did Target know?

Target knew because of a predictive coding model it had developed for anticipating pregnancies. It started by working backwards: it provided its predictive model with birth registry announcements and birth records, then cross-referenced the mother's names against Target's records to find what mothers were its customers. Target then looked at everything these customers had bought at Target before giving birth. The model looked for patterns in behavior

¹ Charles Duhigg, *How Companies Learn Your Secrets*, N.Y. Times Mag., Feb. 16, 2012, <https://www.nytimes.com/2012/02/19/magazine/shopping-habits.html>.

² *Id.*

³ *Id.*

⁴ *Id.*

and started learning from the data entered into it. After it had received a sufficient amount of data, it began churning out predictive indices of pregnancy that could eventually determine a woman's pregnancy status and even due date based on her purchases and purchase timing of key products. The model could then suggest other products responsive to the woman's probable buying habits going forward.⁵

Target had hit the jackpot, but too well. When the company started shipping pregnancy-related advertisements to customers identified by its predictive model, the customers complained. Many found it intrusive and unsettling that Target could determine they were pregnant without being told.⁶

So what do pregnant women, Target, and data analytics have to do with being a lawyer? As it turns out, data analytic technologies can be used for more than simply instigating family drama or inducing brand switches in beer and toilet paper. They can also significantly aid in litigation discovery and other potential legal service applications. This paper will provide a brief history of machine learning and discovery in litigation. It will then explain how machine learning is used in discovery, the pros and cons of the technologies, how courts have reacted to the new technology, and how this topic can be applied in the franchise context.

II. A BRIEF HISTORY OF AI: SEARCHING FOR BOBBY FISCHERBOT

A. Rise Of The Chess Machines

The history of artificial intelligence ("AI") has largely been written on the chessboard. Chess, which requires significant mental cognition and ingenuity to play well, has long been the favored test subject for machine learning.⁷

Initial explorations into building a machine that could think for itself took place in the 1770s, when an inventor named Wolfgang von Kempelen introduced Vienna's royal court to a then-modern wonder of the world: a machine that could play chess against a human opponent.⁸ This machine was in the shape of a man sitting at a table in front of a chess board, and was soon nicknamed the Turk because of its clothing and overall outward appearance. Before each game, von Kempelen would make a grand display of opening the Turk to show the eager onlookers the inside compartment, with the hopes of dispelling any notions of trickery and proving that the machine thought and decided on its own while playing.⁹ Following this routine, the crowds watched in amazement as The Turk played chess against a human being and clearly thought out each move as it played, responding as needed to the completely unpredictable move the player

⁵ *Id.*

⁶ *Id.* Target solved the creepiness problem by simply adding more non-pregnancy ads into the mailer to mask the pregnancy ads; pregnant women considered an ad mailer consisting solely of pregnancy ads "creepy," but were excited to find the same pregnancy ads in a mailer surrounded by unrelated ads. The latter scenario did not trigger the idea that they were being tracked, but merely left them with the sense that Target had some products that were useful to them.

⁷ See, e.g., FENG-HSIUNG HSU, BEHIND DEEP BLUE: BUILDING THE COMPUTER THAT DEFEATED THE WORLD CHESS CHAMPION, 32 (2002) (explaining that building a chess machine that could defeat a World Champion was the "holy grail" of computer science).

⁸ See *The Turk*, Wikipedia, https://en.wikipedia.org/wiki/The_Turk (last visited Aug. 2, 2019); see also TOM STANDAGE, THE LIFE AND TIMES OF THE FAMOUS EIGHTEENTH-CENTURY CHESS-PLAYING MACHINE (2002).

⁹ *Id.*

had made just moments prior.¹⁰ The Turk would even know if its opponent cheated, and would delicately move the offending piece back to signal its awareness.¹¹ No one could understand how this machine was able to replicate human cognition; many theorized on how von Kempelen tricked the audience, but at the time none could prove he was a fraud.

In reality, the Turk was a cheat. Hardly the example of artificial intelligence it purported to be, the Turk simply concealed a man hidden inside the body of the machine that played for him,¹² defeating such patzers¹³ as Napoleon and Edgar Allen Poe. However, the Turk's emergence during the Industrial Revolution prompted a new line of scientific inquiry: what if, instead of simply creating a machine to perform repeated physical tasks, we could teach one to think?

In 1912, Spanish civil engineer and mathematician Leonardo Torres y Quevedo built an automaton called El Ajedrecista, which was capable of playing a simplified chess endgame with three pieces.¹⁴ El Ajedrecista played the white king and rook against a human playing the black king, won by checkmate every time regardless of the human player's moves, and was capable of detecting illegal moves through its rudimentary algorithm.¹⁵ The device used electromagnetic mesh circuitry that encoded the positions of each piece on the board. It was eventually upgraded by Quevedo's son to include a voice recording announcing "checkmate" when the machine won.¹⁶

As the power of computing and imagination into what it could achieve blossomed, so did computer scientists' explorations into digital chess. The mid-Twentieth Century saw computing luminaries such as Alan Turing, whose "theory of computation" suggested that a machine could simulate any process of formal reasoning by algorithm,¹⁷ and John McCarthy, the MIT scientist who coined the term "artificial intelligence" in the 1950s, both writing early computer chess programs.¹⁸ McCarthy's "Kotok-McCarthy" program, considered the first chess program to play convincingly, bears the ignominious distinction of becoming the first chess program to *lose* a match between two computer players. The M-2 at the Moscow Institute for Theoretical and Experimental Physics, a project advised by three-time world chess champion and computer scientist Mikhail Botvinnik, defeated Kotok-McCarthy 3-1.¹⁹

¹⁰ *Id.*

¹¹ *Id.*

¹² *Id.*

¹³ A chess term for a low level or poor chess player. From the German *patzen*, "to bungle" or "to blunder." *Patzer*, MERRIAM-WEBSTER DICTIONARY (online ed., available at: <https://www.merriam-webster.com/dictionary/patzer>).

¹⁴ See *El Ajedrecista*, Wikipedia, https://en.wikipedia.org/wiki/El_Ajedrecista (last visited Aug. 2, 2019); see also ANDREW WILLIAMS, HISTORY OF DIGITAL GAMES: DEVELOPMENTS IN ART, DESIGN AND INTERACTION, 30-31 (2017).

¹⁵ *El Ajedrecista*, Wikipedia, *supra* note 14; WILLIAMS, *supra* note 14 at 30-31.

¹⁶ *El Ajedrecista*, Wikipedia, *supra* note 14; WILLIAMS, *supra* note 14 at 30-31.

¹⁷ Alan Turing, *Digital Computers Applied To Games* (1953), <http://www.turingarchive.org/browse.php/B/7>; see also *Computer Chess*, Wikipedia, https://en.wikipedia.org/wiki/Computer_chess (last visited Aug. 2, 2019).

¹⁸ *Id.*; see also *Kotok-McCarthy*, Wikipedia, <https://en.wikipedia.org/wiki/Kotok-McCarthy> (last visited Aug. 2, 2019); Alan Kotok, A Chess Playing Program for the IBM 7090 (June 1962) (Massachusetts Institute of Technology Department of Electrical Engineering Thesis) (available at: <https://dspace.mit.edu/handle/1721.1/17406>) (last visited Aug. 2, 2019).

¹⁹ *Kotok-McCarthy*, Wikipedia, *supra* note 18.

By 1970, there was a World Computer Chess Championship, initially dominated by the “Chess” program developed by Larry Atkin and David Slate at Northwestern University.²⁰ Within the decade, Chess Version 4.5 won a human Class B tournament (~1700 Elo rating),²¹ and by the early 1980s some programs were playing at Master levels.²² From there, computers rapidly ascended the chess ranks, collectively improving at a rate of about forty Elo points per year.²³ (The corresponding rise in human performance over the same timeframe was a paltry two points per year.)²⁴ In 1996, IBM’s supercomputer named Deep Blue beat Garry Kasparov, the undisputed best human chess player at the time, in a single game, but lost the overall match; the next year, artificial intelligence came into its own, as Deep(er) Blue won the rematch 3.5-2.5.²⁵

These computers used modified brute force search methods: they simply ran through millions of moves and countermoves and analyzed the resulting positions.²⁶ The increases in playing strength were largely the result of more computing power, along with more carefully mapped pruning and extension strategies.²⁷ Pruning and extension strategies are the ability of the program to stop looking at obviously bad options (like countermoves that provide no strategic benefit) or to further explore interesting or potentially beneficial options (like unconventional, but strategically advantageous moves).²⁸

B. Artificial Neural Networks Learn How To Learn

More recently, chess computers have crossed the line from pure analysis to actual learning. One of the most powerful chess engines today, the AlphaZero, trained itself to play Chess with only the rules of Chess provided to it; it had no other initial instructions, opening books,

²⁰ *Chess (Northwestern University)*, Wikipedia, [https://en.wikipedia.org/wiki/Chess_\(Northwestern_University\)](https://en.wikipedia.org/wiki/Chess_(Northwestern_University)) (last visited Aug. 2, 2019).

²¹ The Elo rating is a method for calculating relative skill in zero-sum games. Originally developed for chess by Arpad Elo, a Hungarian-American physics professor and master chess player, it has been used in a wide variety of competitive games and forms the main statistical predictor behind sports prediction rankings such as Sagarin’s college football ratings or those of fivethirtyeight.com, the politics and sports website run by Nate Silver. The difference in Elo scores between two players gives a predicted likelihood of success for the higher-ranked player. Evenly-matched opponents can expect to win 50% of games against each other. A player 100 points above an opponent can expect to win 64% of games; 200 points, 76% of games. In general, a beginner player is around an 800 Elo score; a mid-level player around 1600; a professional player around 2400; and an elite professional around 2800. See *Elo Rating System*, Wikipedia, https://en.wikipedia.org/wiki/Elo_rating_system (last visited Aug. 2, 2019); ARPAD ELO, *THE RATING OF CHESSPLAYERS, PAST & PRESENT* § 8.4 (1978); Mark Glickman, *Approximating Formulas for the USCF Rating System*, Feb. 22, 2001, <http://math.bu.edu/people/mg/ratings/approx/approx.html> (last visited Aug. 2, 2019).

²² Fred Hapgood, *Computer Chess Bad-Human Chess Worse*, *New Scientist*, Dec. 23 1982, at 827–30; see also *Belle (chess machine)*, Wikipedia, [https://en.wikipedia.org/wiki/Belle_\(chess_machine\)](https://en.wikipedia.org/wiki/Belle_(chess_machine)) (last visited Aug. 2, 2019).

²³ L. Stephen Coles, *Computer Chess: The Drosophila of AI*, Oct. 30, 2002, <http://www.drdobbs.com/parallel/computer-chess-the-drosophila-of-ai/184405171> (last visited Aug. 2, 2019).

²⁴ *Id.*

²⁵ Hsu, *supra* note 7; *Deep Blue*, IBM, <https://www.ibm.com/ibm/history/ibm100/us/en/icons/deepblue/> (last visited Aug. 2, 2019).

²⁶ *Computer Chess*, Wikipedia, https://en.wikipedia.org/wiki/Computer_chess (last visited Aug. 2, 2019).

²⁷ *Id.*

²⁸ *Id.*

or endgame tables.²⁹ AlphaZero simply played games against itself until it developed its own algorithms for finding worthwhile moves.³⁰ In other words, given a simple starting condition (win = 1, loss = 0) and time to explore, AlphaZero was able to derive its own rules for analyzing the strength of individual moves.³¹

AlphaZero relies on an “artificial neural network” to improve. An artificial neural network is a group of linked logical nodes designed to predict an output value for sets of input values.³² These can be chess moves, like the prediction that a player will be up nine points in relative strength for a move that captures the opponent’s queen³³ without additional loss, or they can be just about anything else.

The power and value of artificial neural networks and machine learning is illustrated by a relatively simple hypothetical. Suppose I have a puss-cat.³⁴ Not just any puss-cat, but a particularly photogenic and cute puss-cat. I have hilarious pictures of my puss-cat in amusing and unique situations that I want to use to start a new meme that will bring me internet fame and riches. But there’s a problem. I have thousands of pictures to sort through to find the ones of my puss-cat behaving desirably, and other people also occasionally take funny pictures of my puss-cat as he wanders the neighborhood. I do not have the time or ability to consistently sort through the pictures, tag my puss-cat, and upload the correct images to my social media accounts. So the question becomes, how can I find the pictures to make myself rich?

The solution to the problem is to use an artificial neural network. To do so, a system is needed with at least three sets of layers: an input layer, which pictures are fed into; a hidden layer, which performs calculations; and an output layer, which returns a positive value if the puss-cat is in the picture and a negative value if the picture is of anything else.³⁵

The newborn neural network is then provided a variety of pictures, including some of the puss-cat. The system looks at many aspects of data in the pictures – the locations and color of pixels, the shapes created by high-contrast edges such as the outlines of bodies or objects, image metadata embedded in the picture file, etc. – and spits out a guess as to whether each picture is of my puss-cat, or of something else entirely.³⁶ Once it arrives at an output value, the machine

²⁹ *AlphaZero*, Wikipedia, <https://en.wikipedia.org/wiki/AlphaZero> (last visited Aug. 2, 2019); Sarah Knapton & Leon Watson, *Entire Human Chess Knowledge Learned and Surpassed by DeepMind’s AlphaZero in Four Hours*, The Telegraph (Dec. 6, 2017), <https://www.telegraph.co.uk/science/2017/12/06/entire-human-chess-knowledge-learned-surpassed-deepminds-alphazero/>.

³⁰ *Id.*

³¹ *Id.*

³² *Id.*

³³ In chess, the relative strength of a position is often analyzed numerically as a predictive score of victory. Pawns are worth one point, knights and bishops three, rooks five, and the queen nine. Thus, capturing your opponent’s queen is “worth” nine points. *Chess Piece Relative Value*, Wikipedia, https://en.wikipedia.org/wiki/Chess_piece_relative_value (last visited Aug. 2, 2019); see also *Chess Pieces Value*, Chess.com, <https://www.chess.com/article/view/chess-piece-value> (last visited Aug. 2, 2019).

³⁴ A recurring verbatim introduction to, and subject of, property law hypotheticals from Professor A. W. Brian Simpson (1931-2010). Professor Simpson taught Mr. Arnold’s property law class at the University of Michigan Law School.

³⁵ *A Beginner’s Guide to Neural Networks and Deep Learning*, Skymind, <https://skymind.ai/wiki/neural-network> (last visited Aug. 2, 2019); Paul King, *How Do Artificial Neural Networks Work?*, Quora.com, Apr. 17, 2016, <https://www.quora.com/How-do-artificial-neural-networks-work>.

³⁶ *Skymind*, *supra* note 35; King, *supra* note 35.

performs a crucial step: it “backpropagates for error” by comparing the output to the known inputs.³⁷ In other words, it asks itself whether it accurately identified the pictures of the puss-cat by looking at its previous answers. It then adjusts the weights it gives to various aspects of the data, perhaps assigning more importance to the color of particular pixels and less to the time of day the picture was taken, in an effort to minimize the error rate.³⁸ Finally, the network runs this process as an iterative loop until it fine-tunes its puss-cat detection algorithm and can successfully pick out the photos of the puss-cat each time it runs.³⁹

C. I’ll Take Computer Gameshow Contestants For \$2000, Alex

Another example of modern AI processing – and perhaps the one most related to e-discovery work – is Watson, the IBM natural language processing computer built to compete on Jeopardy! against human players.⁴⁰ Watson grew out of the computer chess world; IBM took up the idea of competing on a Jeopardy! competition after Deep(er) Blue’s 1997 defeat of Garry Kasparov.⁴¹

A quiz show is a trickier undertaking than chess. Especially Jeopardy! Chess is perfectly logical, semantically straightforward, and follows a series of set rules. By contrast, Jeopardy! makes intentional use of the ambiguities of natural language, and the clues given tease and dance around the specific information sought, employing allusion and connotation to point toward the desired result. To be effective, Watson would have to approximate understanding of natural language; it would have to surpass answering straightforward questions, like “This breed of puss-cat is native to Thailand and featured in the Disney movie *Lady and the Tramp*,” to handling the allusive or esoteric, like “We are, ‘if you please,’ this type of slender fur baby.”⁴²

Originally, Watson approached the natural language problem not by developing its own algorithm, but by running more than 100 algorithms simultaneously and comparing the results.⁴³ Essentially, Watson is a massive database that thinks in probabilities; IBM seeded the computer with approximately 200 million pages of content, including the full text of the 2011 version of Wikipedia, and let it loose to run its algorithms on each instance of input data.⁴⁴ Watson then constructed a confidence interval from the answers. The more algorithms that agreed on an answer, and the more robust those algorithms were at parsing the input given, the higher

³⁷ *Id.*

³⁸ *Id.*

³⁹ *Id.*

⁴⁰ Clive Thompson, *What Is Watson?* N.Y. Times Mag., June 16, 2010, <https://www.nytimes.com/2010/06/20/magazine/20Computer-t.html>.

⁴¹ *Id.*

⁴² *Id.*; see also Peggy Lee, *The Siamese Cat Song*, from *LADY AND THE TRAMP* (Walt Disney 1955).

⁴³ Thompson, *supra* note 40.

⁴⁴ *Id.*; Joab Jackson, *IBM Watson Vanquishes Human Jeopardy Foes*, PC World, Feb. 17, 2011, https://www.pcworld.com/article/219893/ibm_watson_vanquishes_human_jeopardy_foes.html; Ben Zimmer, *Is It Time to Welcome Our New Computer Overlords?*, The Atlantic, Feb. 17, 2011, <https://www.theatlantic.com/technology/archive/2011/02/is-it-time-to-welcome-our-new-computer-overlords/71388/>.

probability that the answer was correct.⁴⁵ Once a response surpassed the confidence threshold the researchers set, Watson would buzz in and answer the question.⁴⁶

In the words of Ken Jennings, the Jeopardy! superstar champion who lost to Watson in a million-dollar challenge match, Watson “thought” much like a human player did:

The computer's techniques for unravelling Jeopardy! clues sounded just like mine. That machine zeroes in on keywords in a clue then combs its memory (in Watson's case, a 15-terabyte databank of human knowledge) for clusters of associations with those words. It rigorously checks the top hits against all the contextual information it can muster: the category name; the kind of answer being sought; the time, place, and gender hinted at in the clue; and so on. And when it feels “sure” enough, it decides to buzz. This is all an instant, intuitive process for a human Jeopardy! player, but I felt convinced that under the hood my brain was doing more or less the same thing.⁴⁷

In a way, Watson's original configuration represented a hybrid of human and artificial intelligence that approximates the artificial neural network: IBM scientists tested out various language algorithms with Watson and tweaked the algorithms themselves in the lab iteratively to arrive at better answers.⁴⁸ Later versions of Watson, which IBM has been developing for uses ranging from clinical medical diagnosis to water conservation to jewelry purchases, have added neural network capabilities to learn from earlier errors, much like AlphaZero taught itself to play chess.⁴⁹ Now for the good news: the same functions that can teach a computer to play chess, beat humans at Jeopardy!, and recognize puss-cat pictures can also teach a computer to assist lawyers with discovery in litigation.

III. AN OVERVIEW OF DISCOVERY AND OTHER RULES RELATED TO ELECTRONICALLY STORED INFORMATION

Before addressing AI in discovery, it is necessary to set out the basic rules of the road that exist in discovery.⁵⁰ This section will briefly outline the general discovery rules found in the Federal Rules of Civil Procedure, basic ethics issues in discovery, and some of the recent changes to the Federal Rules.

A. Federal Rules of Civil Procedure

⁴⁵ Thompson, *supra* note 40.

⁴⁶ This was Watson's true advantage. In Jeopardy!, the buzzers are locked until immediately after Alex Trebek finishes reading the clue. A series of lights flashes on the sides of the game board indicating the contestants can buzz in. Human contestants must see and react to the lights, which takes tenths of a second. Watson, electronically notified that the floor was open, could operate its buzzer in about eight milliseconds. Ken Jennings, *My Puny Human Brain*, Slate.com, Feb. 6, 2011, <https://slate.com/culture/2011/02/watson-jeopardy-computer-ken-jennings-describes-what-it-s-like-to-play-against-a-machine.html>.

⁴⁷ *Id.*

⁴⁸ Thompson, *supra* note 40.

⁴⁹ *Watson*, Wikipedia, [https://en.wikipedia.org/wiki/Watson_\(computer\)](https://en.wikipedia.org/wiki/Watson_(computer)) (last visited August 2, 2019).

⁵⁰ This paper focuses on the Federal Rules of Civil Procedure and does not attempt to address the procedural rules of each state.

The Federal Rules of Civil Procedure address discovery by providing a general framework for case management, overarching discovery principles, and detailed instructions on how parties are supposed to use specific discovery tools—which are mainly interrogatories, depositions, requests to admit, and document discovery, both on parties and non-parties.⁵¹

1. Rule 26

To address case management, the Federal Rules call for the entry of a case scheduling order after consultation among the parties or receiving what is referred to as the Rule 26(f) report.⁵² Absent good cause, the scheduling order must occur within the earlier of sixty days of any defendant's appearance or ninety days of the service of process on any defendant.⁵³ The scheduling order must address the time for joining parties, amending pleadings, completing discovery, and filing motions.⁵⁴ The scheduling order may (and usually does) address other issues, such as setting a trial or pre-trial date; establishing procedures for addressing discovery disputes without court intervention; setting the scope of discovery; discussing the handling of disclosure, discovery, or preservation of electronically stored information; and setting forth agreements of the parties for asserting privilege.⁵⁵ Rule 16 works in tandem with Rule 26(f), which requires the parties to meet for the purpose of proposing a discovery plan. The exact contents of the plan and Rule 26(f) report to the court vary by federal court district (as most districts have customized requirements).⁵⁶ However, the report virtually always includes the parties' views and proposals regarding: the timing of various deadlines; the possibility of settlement; anticipated issues on topics like preservation or production of electronically stored information; and privilege issues.⁵⁷ Finally, Rule 26 also contains various provisions setting default rules regarding the timing of disclosure for various types of information about witnesses and trial exhibits.⁵⁸

⁵¹ It is important to understand the evolution of those rules as technology has evolved. When the Federal Rules were first adopted, computers did not exist. In 1970, the Rules started recognizing the importance of electronic data. That year, Rule 34 was amended to make clear that Rule 34 applies to electronic data compilations. Fed. R. Civ. P. 34 (1970). In 2006, several major amendments were made to more closely tie the rules to modern technology and the electronic documents created by it. Fed. R. Civ. P. (2006). Rule 26(a)(1)(B) was amended to parallel Rule 34(a) by recognizing that a party must disclose electronically stored information as well as documents that it may use to support its claims or defenses. See Fed. R. Civ. P. 26 and adv. comm. note (2006). Rule 16 was similarly amended to include discussion of electronically stored information. *Id.* The committee notes to Rule 16 highlighted that the inclusion of electronically stored information to the rule as designed to alert the court to the possible need to address the handling of discovery of electronically stored information early in the litigation if such discovery is expected to occur. *Id.* Ultimately, the amendments were meant to elevate electronically stored information to the same level as physical documents for discovery purposes, while still recognizing the new complexities associated with them.

⁵² FED. R. CIV. P. 16(b)(1).

⁵³ FED. R. CIV. P. 16(b)(2).

⁵⁴ FED. R. CIV. P. 16(b)(3)(A).

⁵⁵ FED. R. CIV. P. 16(b)(3)(B)(i-v).

⁵⁶ For example, compare the District of Connecticut Form 26(f) report form, available at <http://ctd.uscourts.gov/sites/default/files/Revised-Local-Rules-07-24-2019.pdf> with the Western District of Washington's model ESI Agreement and Local Rule 26(f), available at <https://www.wawd.uscourts.gov/sites/wawd/files/WAWDAIILocalCivilRules.pdf>.

⁵⁷ FED. R. CIV. P. 26(f)(3).

⁵⁸ FED. R. CIV. P. 26(a)(1) (setting forth required, mandatory initial disclosures); 26(a)(2) (setting forth required disclosures about expert witnesses, including timing of disclosures); 26(a)(3) (setting forth timing of required disclosures).

Next, Rule 26 outlines a set of general parameters about the scope of discovery. The basic standard is that “unless otherwise limited by the Court,” the parties

may obtain discovery regarding any nonprivileged 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.⁵⁹

This version of Rule 26(b) was put into place at the end of 2015 in response to concerns that the parties and courts had drifted away from the Rule's intent of having discovery that was proportional to the needs of particular case.⁶⁰ As a protection against overly broad, embarrassing, unduly burdensome, or otherwise improper discovery requests (particularly given the potential scope of electronic discovery), the Rules allow a party to seek a protective order, through which the court may disallow, limit, or otherwise condition discovery.⁶¹

2. Rule 34

As previously stated, the Rules set forth a number of specific discovery devices. Most of those devices—such as depositions, requests to admit, interrogatories, and requests for physical examination—have little relevance to the use of AI in discovery. Rather, the primary focus of AI in discovery is on requests for production of documents pursuant to Rule 34. Rule 34 permits a party to serve an opposing party a request to produce and permit for inspection designated documents, tangible items, or electronically stored information.⁶² Any objections to production requests must be made with specificity to the particular request, and the objection must state whether any responsive documents are being withheld on the basis of the objection.⁶³ In addition, being specific in objections matters. It is not enough under the Rules to simply say a request is burdensome; instead, the objection must spell out how and why a request is burdensome.

For electronically stored information, the Rules contain additional details. First, production of electronic documents is only required from sources that the parties can obtain “either directly or, if necessary, after translation by the responding party into a reasonably usable form.”⁶⁴ As a corollary, the Rules further state that “[a] party need not provide discovery of electronically stored information from sources that the party identifies as not reasonably accessible because of undue

of information about trial exhibits and witnesses); 26(d) (explaining that discovery requests served before the Rule 26(f) conference are deemed served as of the date of the conference).

⁵⁹ Fed. R. Civ. P. 26(b)(1).

⁶⁰ Fed. R. Civ. P. 26(b)(1) advisory committee's note to 2015 amendment.

⁶¹ Fed. R. Civ. P. 26(c).

⁶² Fed. R. Civ. P. 34(a).

⁶³ Fed. R. Civ. P. 34(b)(2)(B).

⁶⁴ Fed. R. Civ. P. 34(a)(1)(A).

burden or cost.”⁶⁵ The Rules also provide that electronically stored data may be produced “in a form or forms in which it is ordinarily maintained or in a reasonably usable form or forms” and that the same electronically stored data need not be produced in more than one form.⁶⁶

Also relevant to the use of AI in discovery is that discovery is not generally allowed into information and documents protected by the attorney work product and attorney-client privilege.⁶⁷ When such claims are made the withholding party must describe the nature of the documents, communications, or tangible things not produced in a manner that will enable the other party to assess the claim.⁶⁸ If information produced in discovery is subject to a claim of privilege or protection, the party making the claim may notify any party that received the information of the claim and the basis for it.⁶⁹ After being notified, a party must promptly return or destroy the specified information and any copies it has.⁷⁰

3. Rule 37

Finally, Rule 37 addresses how courts are to handle discovery disputes. Aside from procedures for motions to compel⁷¹ and sanctions for violations,⁷² Rule 37 specifically addresses the problem of the potential failure to preserve or produce ESI.⁷³ The prior version of Rule 37(e) provided that “absent exception circumstances, a court may not impose sanctions under these rules on a party for failing to provide electronically stored information lost as a result of the routine, good faith operation of an electronic information system.”⁷⁴ Rule 37(e) currently provides that “[i]f electronically stored information that should have been preserved in the anticipation or conduct of litigation is lost because a party failed to take reasonable steps to preserve it, and it cannot be restored or replaced through additional discovery” then, upon finding prejudice, the court may take steps no greater than necessary to cure the prejudice.⁷⁵ If the loss was intentional, then the court may take greater steps, such as enter adverse inferences or default the destroying party.⁷⁶ This 2015 amendment to Rule 37(e) requires significant sanctions only when the four elements of the new Rule have been met: (a) ESI has been lost; (b) ESI should have been preserved; (c) the party failed to take reasonable steps to preserve ESI; and (d) ESI cannot be restored or

⁶⁵ FED. R. CIV. P. 26(b)(2)(B).

⁶⁶ FED. R. CIV. P. 34(b)(2)(D), (b)(2)(E).

⁶⁷ FED. R. CIV. P. 26(b)(3).

⁶⁸ FED. R. CIV. P. 26(b)(5)(A)(ii).

⁶⁹ FED. R. CIV. P. 26(b)(5)(B).

⁷⁰ *Id.*

⁷¹ FED. R. CIV. P. 37(a).

⁷² FED. R. CIV. P. 37(b).

⁷³ FED. R. CIV. P. 37(e).

⁷⁴ FED. R. CIV. P. 37(e) (amended 2006).

⁷⁵ *Id.*

⁷⁶ *Id.*

replaced through other discovery.⁷⁷ The committee notes make clear that this change was because the large volume of electronically stored information usually involved in cases and the many devices that generate such information make perfection in preserving all relevant ESI often impossible. Thus "reasonable steps" to preserve suffice.⁷⁸

Consistent with the changes to the Rules, it is critical to take steps to preserve documents. The baseline step is to institute a litigation hold, which is the sending of a communication that alerts all document custodians of relevant information and that the information must be preserved. Simply sending a litigation hold, without any other efforts is not enough because "[a] party to a lawsuit, and its agents, have an affirmative responsibility to preserve relevant evidence. A [party] . . . is not relieved of this responsibility merely because the [party] did not itself act in bad faith and a third party to whom [the party] entrusted the evidence was the one who discarded or lost it."⁷⁹ Thus, the best practice is both to send a litigation hold and take other steps, such as requiring proof of receipt, conducting witness interviews, and confirming that auto-delete functions have been turned off. Preservation efforts should be instituted "[w]hen an organization is on notice of a credible probability that it will become involved in litigation."⁸⁰ Further, "[t]he future litigation must be 'probable,' which has been held to mean 'more than a possibility.'"⁸¹

In short, the Federal Rules provide the framework upon which all discovery efforts must be built.

B. Ethical Rules Require Litigators to Understand Technology

Like virtually all other parts of the legal profession, ethics play a role in the use of AI in discovery. The first rule of ethics is competence. The ABA Model Rules requires that "[a] lawyer shall provide competent representation to a client. Competent representation requires the legal knowledge, skill, thoroughness and preparation reasonably necessary for the representation."⁸² The Model Rules include commentary which states "[t]o 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."⁸³ Although not all jurisdictions have adopted the Model Rules, most have issued rules or guidance that are similar to the Model Rules. For example, the comments to New York's rules are more explicit in addressing technological competence: "To maintain the requisite knowledge and skill, a lawyer should (i) keep abreast of changes in substantive and procedural law relevant to the lawyer's practice, [and] (ii) keep abreast of the benefits and risks associated with technology the lawyer uses to provide services to clients or to store or transmit confidential information."⁸⁴

⁷⁷ FED. R. CIV. P. 37(e) (amended 2015).

⁷⁸ *Id.* and associated advisory committee notes to 2015 amendments.

⁷⁹ *Goodman v. Praxair Services, Inc.*, 632 F. Supp. 2d 494, 522 n. 16 (D. Md. 2009).

⁸⁰ *Sedona Conference Commentary on Legal Holds: The Trigger & The Process*, 11 Sedona Conf. J. 265, 271 (2010).

⁸¹ *In re Napster, Inc. Copyright Litig.*, 462 F. Supp. 2d 1060, 1068 (N.D. Cal. 2006).

⁸² MODEL CODE OF PROF'L RESPONSIBILITY CANON 1 (AM. BAR ASS'N 2016).

⁸³ *Id.* at comment 8.

⁸⁴ NEW YORK R. OF PROF'L CONDUCT, 1.1 comment [8] (2018).

Staying abreast of the relevant technology means that litigators must understand electronic documents and how to manage them. Litigators must be aware of all the potential sources of relevant electronic documents, including social media, websites, slack chats, text messages, databases, and metadata. Litigators must understand how data is stored, how long it is saved for, and how it can be collected and deleted. Litigators also must manage the large volume of documents for review and production in a way that protects the client's interests (and confidentiality) and is cost-effective.

IV. DISCOVERY USING AI

The document review process in discovery is meant to sort through documents and identify nonprivileged, responsive documents. But technological advancement has resulted in a swell in documents to review. This has often led to disputes about various kinds of electronic documents. While a deep dive into the disputes regarding each is beyond this paper, the section below sets out some of the pertinent caselaw regarding common types of electronic documents: email, social media, and ephemeral documents. Following that, the paper sets out the advantages and disadvantages of AI assisted discovery.

A. Common Types of Electronic Documents

1. Email

Emails were one of the earliest forms of electronic storage that courts were forced to address. First and foremost, courts have made clear that email is discoverable.⁸⁵ In *Rowe Entertainment, Inc. v. William Morris Agency, Inc.*, the defendants moved for a protective order relieving them of the alleged burden and high expense of producing emails that could contain information relevant to the plaintiffs' discovery requests.⁸⁶ The court concluded that emails are discoverable, despite claims of burden.⁸⁷ And while email can be voluminous,⁸⁸ courts have since consistently held that this burden, without more, is not an impediment to emails being produced in discovery.⁸⁹

Second, courts have made clear that parties must take active steps to preserve email once a litigation hold obligation comes into effect. Failure to preserve and produce email can result in serious sanctions. In *Klipsch Group, Inc. v. ePRO E-Commerce*, the court sanctioned the defendant \$2.7 million for e-discovery failures.⁹⁰ There, the defendant failed to place adequate legal holds on electronic data, including emails, did not disclose relevant documents, and

⁸⁵ *Rowe Entm't, Inc. v. Wm. Morris Agency, Inc.*, 205 F.R.D. 421 (S.D.N.Y. 2002).

⁸⁶ *Id.* at 423-24.

⁸⁷ *Id.* at 428 (finding that plaintiffs demonstrated that discovery sought was relevant and holding that electronic documents are discoverable).

⁸⁸ Even in 2003, somewhat early in terms of email usage, it was "projected that there will be 105 million email users in the United States, who will send over 1.5 billion email messages a day, or approximately 547.5 billion email messages per year--nearly as many messages in a day as the U.S. Postal Service handles in a year." *The Sedona Principles: Best Practices Recommendations & Principles for Addressing Electronic Document Production*, The Sedona Conference, 3 (2003).

⁸⁹ See *Zubulake v. UBS Warburg, LLC*, 217 F.R.D. 309, 311 (S.D.N.Y. 2003).

⁹⁰ No. 16-3637, slip op. (2d Cir. Jan. 25, 2018).

manually deleted thousands of files and emails.⁹¹ The court held “[c]ompliance is not optional or negotiable; rather, the integrity of our civil litigation process requires that the parties before us, although adversarial to one another, carry out their duties to maintain and disclose the relevant information in their possession in good faith.”⁹²

Third, courts do recognize the potentially significant burden of having to search through the emails of multiple custodians’ email inboxes. Thus, so long as a party can adequately establish the burden and offer a reasonable solution, courts are willing to limit email reviews by time and custodian⁹³ and through the use of de-duplication and de-threading.⁹⁴ Courts are also willing to consider cost-shifting, especially where one party cannot afford to undertake a significant review or where the documents sought are only of a potential marginal relevance.⁹⁵ When email is sought from a third-party by subpoena, counsel should not ignore that Rule 45 specifically instructs that a subpoena should not cause a third-party to incur an undue expense and should aggressively seek cost-shifting.⁹⁶ In some contexts, courts will begin shifting costs when a subpoena imposes even \$10,000 of costs on the responding party.⁹⁷

2. Social Media

As of January 2019, 79% of the United States population has at least one social media profile.⁹⁸ As a result, social networking platforms like Facebook, Instagram, and Twitter have increasingly become litigation resources, providing a wealth of statements and images to contradict the claims and defenses of the opposing party.

Social media content and communications are discoverable. In *Thompson v. Autoliv ASP, Inc.*, a federal district court granted the defendant’s motion to compel unredacted content from the plaintiff’s Facebook page.⁹⁹ The case arose from an automobile accident in which the plaintiff

⁹¹ *Id.*

⁹² *Id.*

⁹³ *Nat. Alternatives Int’l, Inc. v. Hi-Tech Pharm., Inc.*, No. 16-CV-02343-H-AGS, 2017 WL 3668738, at *2 (S.D. Cal. May 8, 2017) (“Email production requests will identify the custodian, search terms, and time frame”); *see also generally Hickman v. Taylor*, 329 U.S. 495, 507 (1947) (noting that discovery does have “ultimate and necessary boundaries”); *Coleman v. American Red Cross*, 23 F.3d 1091, 1096 (6th Cir.1994) (“it is well established that the scope of discovery is within the sound discretion of the trial court”).

⁹⁴ *Medtronic Sofamor Danek, Inc. v. Michelson*, 229 F.R.D. 550, 553 (W.D. Tenn. 2003).

⁹⁵ *Id.* at 555; *see also* Institute for the Advancement of the American Legal System, *Electronic Discovery: A View from the Front Lines*, 1-27, http://iaals.du.edu/sites/default/files/documents/publications/ediscovery_view_front_lines2007.pdf (last visited Aug. 2, 2019).

⁹⁶ Fed. R. Civ. P. 45(d)(1).

⁹⁷ *See, e.g., Legal Voice v. Stormans Inc.*, 738 F.3d 1178, 1185 (9th Cir. 2013) (Fed. R. Civ. P. 45 makes cost-shifting mandatory and \$20,000 is a significant expense); *Linder v. Calero-Portocarrero*, 251 F.3d 178, 182-83 (D.C. Cir. 2001).

⁹⁸ *Percentage of U.S. Population with a Social Media Profile from 2008 to 2019*, Statista, <https://www.statista.com/statistics/273476/percentage-of-us-population-with-a-social-network-profile/> (last visited June 3, 2019). Some Americans even set up social media profiles for their pets; Mr. Arnold’s pet snake, for instance, has an Instagram of his own at @satchelthepython.

⁹⁹ No. 09-cv-01375-PMP-VCF, 2012 WL 2342928 (D. Nev. 2012).

claimed injuries caused by a defective seatbelt.¹⁰⁰ The injuries alleged are too numerous to list here, but they consisted of several permanent conditions, lost opportunities (such as the ability to attend college or play violin), and emotional distress.¹⁰¹ The defendant filed a motion to compel the plaintiff to produce “complete and un-redacted copies of the plaintiff’s Facebook and other social networking site accounts” including wall posts, messages, and photos.¹⁰² The plaintiff, in response, argued that the defendant had not made a sufficient showing that the material was reasonably calculated to lead to the discovery of admissible evidence, and was otherwise irrelevant.¹⁰³ The court found that social media data may produce evidence relating to the plaintiff’s physical capabilities and social activities, both of which were relevant to the plaintiff’s claims, and thus discoverable.¹⁰⁴ The one caveat the court included was that, to balance the plaintiff’s privacy interests, the production was to be monitored and expedited, ensuring no copies of the data be made.¹⁰⁵

Although social media content and communications are discoverable, such discovery is not limitless. In *Howell v. Buckeye Ranch, Inc.*, a federal district court denied a motion to compel the username and password of social media accounts held by the plaintiff.¹⁰⁶ This case involved a sexual harassment claim made by the plaintiff against her coworkers which she claimed resulted in mental anguish and decreased social contact.¹⁰⁷ The court opened its opinion by noting that the “[r]elevant information in the private section of a social media account is discoverable.”¹⁰⁸ The court went on to explain that “[content on one’s social media account] is not privileged nor protected from production by a common law right of privacy But a litigant has no right to serve overbroad discovery requests that seek irrelevant information.”¹⁰⁹ The court found that unfettered access to the plaintiff’s social media accounts would permit access to relevant and irrelevant data, and instead instructed the requesting party to serve interrogatories and document requests seeking relevant information from the accounts.¹¹⁰

Information held within a social media account is discoverable so long as the request conforms to the general discovery rules. However, courts are sensitive to the fact that social media may contain a significant amount of private and potentially unflattering or embarrassing information. As such, the courts have tended to favor limited discovery of social media information.

¹⁰⁰ *Id.* at *1.

¹⁰¹ *Id.* at *1-2.

¹⁰² *Id.* at *2 (the request was limited in time).

¹⁰³ *Id.* at *4 (the defendant was able to access the accounts publicly briefly before the accounts were changed to private. This access had resulted in evidence of Plaintiff’s social activities, mental state, and rehabilitative progress).

¹⁰⁴ *Id.*

¹⁰⁵ *Id.* at *5.

¹⁰⁶ No. 2:11-cv-1014, 2012 WL 5265170 (S.D. Ohio 2012).

¹⁰⁷ *Id.* at *1.

¹⁰⁸ *Id.* (citing *Glazer v. Fireman’s Fund Ins. Co.*, 2012 WL 1197167, at *3-4 (S.D.N.Y. 2012)).

¹⁰⁹ *Id.* (citing *Tompkins v. Detroit Metropolitan Airport*, 278 F.R.D. 387, 388 (E.D. Mich. 2012)).

¹¹⁰ *Id.*

3. Ephemeral Technologies

While technology continues to capture and retain more data, technologies have also been developed to avoid retention. Ephemeral technologies are those that “self-destruct” after the recipient views them (such as Snapchat or intraoffice instant messaging platforms), and can be compared to conversation, a medium of communication familiar and similarly ephemeral. The primary concerns with these technologies are retrieval and retention. How do lawyers handle the preservation and production of documents that are designed not be preserved, i.e. that have a self-executing destruction policy? While the conversation analogy may be appropriate in understanding the basic contours of ephemeral technologies, it falls short in preservation requirements in litigation. Unlike face-to-face communications, a tangible physical form is produced, even if only temporarily. Of concern is whether messages exchanged through ephemeral applications must be preserved for discovery.

As noted above, under the Federal Rules of Civil Procedure, the duty to preserve attaches when litigation is reasonably anticipated or foreseeable.¹¹¹ The fact that self-destructing messages have the potential to deprive adversaries and the court of relevant evidence does not, in and of itself, make their use inherently unlawful or unethical.¹¹² Instead, how and when the technologies are used is of concern.

The first major case allowing discovery of ephemeral electronically stored information (EESI) was *Columbia Pictures, Inc. v. Bunnell*.¹¹³ There, the court held that data stored in RAM (a temporary housing unit on a computer for the purpose of quick deletion) is EESI subject to discovery.¹¹⁴ Specifically, the court noted that “RAM is a tangible medium, sufficiently permanent to permit reproduction,” and dismissed claims that “RAM holds data for such a short duration that it is not stored subject to later access and retrieval.”¹¹⁵ Although this case does reach ephemeral technologies in the literal sense, it differs from modern ephemeral technologies in that RAM data is not intentionally composed by the user. Even though this case occurred before the 2015 amendments to the Federal Rules of Civil Procedure, it implies that ephemeral messages may be discoverable for litigation.

A more recent case addressing this issue is *Waymo, LLC v. Uber Tech., Inc.*¹¹⁶ There, Waymo, a self-driving vehicle software company, accused Uber, the ride share application, of intentional spoliation because Uber instructed its employees to use the ephemeral messaging app Wickr.¹¹⁷ In a pretrial order, the court declined to order an adverse inference or sanctions, but noted that Waymo may admit evidence of Uber’s use of ephemeral messaging “to explain gaps in Waymo’s proof that Uber misappropriated trade secrets or to supply proof that is part of the res

¹¹¹ FED. R. CIV. P. 37(e) advisory committee’s notes to 2015 amendment.

¹¹² Text messages, the non-ephemeral technology these self-destructing messages aim to replace, have been found discoverable. See, e.g., *Flagg v. City of Detroit*, 268 F.R.D. 279, 288 (E.D. Mich. 2010) (text messages were a proper subject of discovery).

¹¹³ 245 F.R.D. 443 (C.D. Cal. 2007).

¹¹⁴ *Id.* at 447-48.

¹¹⁵ *Id.* at 448.

¹¹⁶ No. C 17-00939 WHA, 2018 WL 646701 (N.D. Cal. Jan. 30, 2018).

¹¹⁷ *Id.* at *19.

gestae of the case”¹¹⁸ The court also cautioned that Waymo could not use ephemeral messaging evidence in a way that is cumulative, speculative, or distracting.¹¹⁹ Further, Uber was allowed to present evidence that “its use of ephemeral communications shows no wrongdoing, including by pointing out Waymo’s own use of ephemeral communications.”¹²⁰ Notably, the court cautioned that Waymo could not attempt to vilify Uber by virtue of its decision to use ephemeral messaging in general.¹²¹ It is important to note that the case addressed “anticipated litigation” rather than regular business practices. Unfortunately, the case settled before producing any firm discovery precedent.

As already discussed, the civil discovery process is designed to allow broad access to information before trial so that fairness can be maintained in an adversarial justice system; but discovery is not limitless.¹²² Where litigation is neither pending nor anticipated, a party is permitted to exploit auto-deletion of content.¹²³ Similarly, courts have held that the decision to store data in inaccessible formats, rather than accessible ones, is not in and of itself sanctionable.¹²⁴ The Sedona Principles,¹²⁵ citing *Convolve, Inc. v. Compaq Computer Corp.*,¹²⁶ state that the preservation obligation for ephemeral data should not impose “heroic or unduly burdensome requirements.”¹²⁷

Ultimately, it is still too early to distill a pattern courts follow when reviewing discovery issues related to ephemeral technologies. Based on the case law cited above, it would appear that regular use of ephemeral applications, unrelated to actual or pending litigation, is permissible. When litigation is threatened, the best practice is to terminate use of such applications, or preserve messages sent through the application.

B. Document Review Using AI

Once a party has instituted its litigation hold, engaged in the case management process, and determined what documents it will produce, it must actually collect and produce documents. While parties could forgo a review of documents, very few parties are interested in turning over unfiltered access to their records to an opposing party. And some courts consider “data” dumps

¹¹⁸ *Id.*

¹¹⁹ *Id.*

¹²⁰ *Id.* at *21.

¹²¹ *Id.* at *3.

¹²² See *Hickman*, 329 U.S. at 501.

¹²³ *William T. Thompson Co. v. Gen. Nutrition Corp.*, 593 F. Supp. 1443, 1448 (C. D. Cal. 1984).

¹²⁴ See *Quinby v. WestLB AG*, No. 04-Civ.-7406 (WHP) (JBP), 2005 WL 3453908 (S.D.N.Y. Dec. 15, 2005).

¹²⁵ The Sedona Conference, author of the Sedona Principles, is a nonpartisan, nonprofit 501(c)(3) research and educational institute dedicated to the advanced study of law and policy.

¹²⁶ 223 F.R.D. 162, 177 (S.D.N.Y. 2004).

¹²⁷ *The Sedona Principles, Third Edition: Best Practices, Recommendations & Principles for Addressing Electronic Document Production*, 19 Sedona Conf. J. 1, 108 (2018).

to be an improper discovery technique.¹²⁸ In addition, such an approach can waive privilege.¹²⁹ As such, parties must undertake some review of documents to produce them. On the flip side, a party must review the documents that are produced to it. After all, if produced documents are never reviewed, then there was no purpose to seeking the discovery in the first place.

The traditional method of reviewing large amounts of electronic documents is to limit the universe of documents by 1) deduplicating and dethreading documents¹³⁰; 2) using search terms to identify potentially relevant documents; and 3) then using a team of lawyers to review the remaining documents for relevance and privilege.

A party using AI-based discovery tools to review documents has several potential advantages over the traditional approach. (As explained later in this section and in Section 5B below, AI assisted review is not a substitute for human review in many situations and works best for augmenting or replacing contract reviewers in a first level review in a large document case). The largest advantage is cost: by “outsourcing” the most labor-intensive discovery task to a computer, fewer man-hours are needed to review documents for production or to review documents received. Depending on the number of lawyers needed to review documents, the cost of a human based review can total hundreds or thousands of dollars per hour. Instead of incurring the cost of lawyer time to sift through a large document production, the AI-equipped litigant can pay an upfront fee by buying equipment, hiring a vendor, or purchasing a software license, and then have the machine perform the task at the marginal cost of the energy required to operate the necessary computer(s). The attorney’s role will be limited to seeding the machine with responsive and nonresponsive documents and reviewing the results the computer identifies.

The second major advantage is speed. A reasonable average pace for attorneys to review documents produced in discovery appears to be around forty to fifty documents per hour.¹³¹ Watson, by contrast, can scan its library of ~200 million pages of content in the several seconds it takes to hear a Jeopardy! clue.¹³² In addition, humans also must eat, go to the bathroom, and sleep. That means that human document reviewers can only reasonably be expected to spend, at the very extremes, twelve to fourteen hours per day reviewing documents. Humans will also usually demand some time off for weekends or holidays. To have a document review going all day, every day with humans will, as a practical matter, require two or three full shifts of reviewers. That would be essentially cost-prohibitive in all but a handful of cases throughout the country. On

¹²⁸ *ReedHycalog UK, Ltd. v. United Diamond Drilling Servs.*, No. 6:07–CV–251, 2008 U.S. Dist. LEXIS 93177, at *9 (E.D. Tex. Oct. 3, 2008) (“Thus, a producing party may not bury those relevant documents in the hope that opposing counsel will overlook the proverbial ‘smoking gun’ as he wades through an ocean of production.”).

¹²⁹ See *Arconic, Inc. v. Novelis, Inc.*, Civil Action 17-1434, 2019 WL 911417 (W.D. Pa. Feb. 26, 2019). The Sedona Conference also “cautioned that a Rule 502(d) order [(which permits parties to draft their own clawback agreements)] should not be used as a cost-shifting tool allowing the producing party to make a ‘data dump’ and requiring the requesting party to identify privileged documents.”

¹³⁰ Deduplicating refers to the practice of comparing whether documents are identical and removing multiple copies of the same document from a review database. Dethreading is the similar practice of only having the top email in thread of emails appear in a review database. The theory is that all of the prior emails are captured in the thread. These approaches can reduce the size of a review considerably, but also create a greater risk that relevant documents will not be found because instead of a relevant document appearing multiple times, it only appears once.

¹³¹ See, e.g., *Answering Your Questions on Document review*, BIA, <https://www.biaprotect.com/resources/resource/answering-your-questions-on-document-review> (last visited Aug. 2, 2019). The authors confirm from their experience that while it can vary by review or batch of documents, 40-50 documents per hour is a reasonable average speed.

¹³² Jackson, *supra* note 44.

the other hand, computers can work for twenty-four hours per day, seven days per week so long as they have power and, if necessary, internet access. Even a computer with significantly less processing power—and less build cost—than Watson will vastly outstrip the speed of your team of contract attorneys or junior associates in analyzing documents for production or for relevancy.

The third advantage to AI discovery is consistency. Humans are fallible. We have good days and bad days, days where we catch every detail in front of us and days where we half-sleepwalk through the work hours. The AI discovery machine, on the other hand, can't be bargained with. It can't be reasoned with. It doesn't feel pity, or remorse, or fear! And it absolutely will not stop, ever, until the production is fully analyzed.¹³³ The machine will consistently identify the same documents, twenty-four hours a day and seven days a week, that it is seeded or learns to recognize as responsive.

Of course, AI discovery tools also have disadvantages. With the potential exception of further development in neural network capabilities, it may not be able to teach itself what is useful in a case, as the ultimate goal of litigation is only tangentially related to whether a document is responsive in discovery. Consequently, the AI discovery machine has the same flaw built into it as human discovery: it is only as adept as the lawyers seeding it. An AI machine may be able to flag responsive documents, but it cannot accurately assess the reliability or relatibility of witnesses, emotionally connect with judges and jurors, or craft a compelling narrative around its client's experiences – the humanization of legal practice so crucial to obtaining a favorable result. This is one of the reasons that AI discovery tools, at least currently, are rarely used for anything beyond a first level review of documents in high document volume cases.

AI has historically involved more upfront cost to build and seed than human discovery methods, but this may be slackening. Watson, for instance, cost approximately \$3 million just in hardware,¹³⁴ and the Google tensor processing units used by engines such as AlphaZero are estimated at \$35-100 million in production costs each. However, Google now offers cloud-based subscription time on the TPUs from \$24 per hour,¹³⁵ and is selling miniature "edge TPU" machines targeted at low-powered home devices for \$75-150.¹³⁶ These may not be currently robust enough to run legal document discovery needs, but the direction of change is inevitably tending towards cheaper computing power.

Practically speaking, most attorneys will not directly incur hardware computing costs to use AI discovery, but will opt for third-party software solutions instead. The costs of such software vary wildly, with some estimates ranging between \$75-350 per gigabyte (3,000-5,000 text-based documents) or \$40 per month for cloud-based solutions.¹³⁷ The same estimates peg building an in-house hardware system at around \$750,000 per year when amortized over 3 years.¹³⁸

¹³³ See *THE TERMINATOR* (Orion Pictures 1984).

¹³⁴ Lucas Mearian, *Can Anyone Afford An IBM Watson Supercomputer? (Yes)*, Computerworld, Feb. 21, 2011, <https://www.computerworld.com/article/2513312/can-anyone-afford-an-ibm-watson-supercomputer---yes-.html?page=2>.

¹³⁵ *Google Cloud Pricing*, GOOGLE, <https://cloud.google.com/tpu/docs/pricing>.

¹³⁶ *Coral Beta*, GOOGLE, <https://coral.withgoogle.com/products/dev-board/>.

¹³⁷ *How Much Does eDiscovery Cost?*, Logickull, <https://www.logickull.com/public/files/How-Much-Does-eDiscovery-Cost.pdf> (last visited Aug. 2, 2019).

¹³⁸ *Id.*

The other increased cost of AI discovery is training. Most lawyers already understand how to review documents. Moving the process to an AI-based solution will require these attorneys to learn to use the AI software, which may be difficult for some.

V. TAR: THE NUTS AND BOLTS OF AI DISCOVERY

A. How it Works

The most obvious role for AI discovery, occasionally called “technology assisted review” (“TAR”) is in document review, which is estimated to make up 60-70% of the total cost of discovery.¹³⁹ In document reviews, AI-based discovery is designed to do the following:

- Take in a large number of discovery responses.
- Eliminate irrelevant documents.
- Rank the relevant documents from most to least helpful.

The process begins by identifying the universe of documents for the technology-assisted review engine to review and loading it into the computer. Once the document set is loaded, two steps occur: the computer itself begins to index the documents by running algorithms, and the reviewing attorneys seed the computer by picking out responsive and non-responsive documents to teach the machine to sort.¹⁴⁰ The algorithms used by most AI discovery programs are most similar to those employed by Watson: they are natural-language algorithms that analyze the relationships between words and phrases in the documents and spit out probabilistic scores of the documents’ relevance to a particular query.¹⁴¹ Also like Watson, this algorithmic method largely tracks the human review process. Just like people reviewing documents, the algorithms quickly scan documents for key words or phrases, using contextual language cues to determine how relevant the document is to the overall case.¹⁴²

After the machine makes a first-pass review and codes the documents in the discovery database as either responsive or nonresponsive, the attorneys review samples of both categories.¹⁴³ These samples are used to check the computer’s work and refine the algorithms, effectively backpropagating the machine for error as described above.

Another use for the AI discovery engine is the suggestion of new terms or phrases to search. Because natural language algorithms find relationships between terms or phrases that occur with some regularity, the machine may be able to identify salient terms that human reviewers overlooked. In this case, the machine is performing the role of Target’s pregnancy-sensing algorithms, or the search autocomplete algorithm used by Google, Yahoo!, et. al. – it is finding links between snippets of data based on statistical correlations that might not be immediately apparent to the human eye. These suggestions can inform another pass through a document review from a new perspective, or they can prompt terms, phrases, or document

¹³⁹ See Bolch Judicial Institute, *Technology Assisted Review Guidelines* (Jan. 2019), <https://www.consilio.com/wp-content/uploads/2019/03/TAR-Guidelines-January-2019.pdf>.

¹⁴⁰ *Id.*

¹⁴¹ *Id.*

¹⁴² *Id.*

¹⁴³ *Id.*

categories for follow up discovery requests. For instance, the AI discovery engine may suggest “financial performance” or “sales figures” because of its association with “Item 19” or “FDD.”

B. Errors and Issues

Like the human review process, the electronic review process is prone to error. Current AI discovery whitepapers suggest that both human and AI-based reviews have similar error rates, catching approximately 75-85% of responsive documents.¹⁴⁴

These errors can appear in several different forms. False positive errors are where the reviewer codes a worthless document as responsive, causing overinclusion.¹⁴⁵ False positive errors are common in real life examples, especially when machines are calibrated as a failsafe or with high sensitivity. For example: smoke alarms that go off due to smoke from cooking, railroad gates that close with no train approaching, or credit card fraud alerts when you take a vacation to a new location for the first time. However, the system in these cases intentionally errs towards sensitivity, because the burden of the false positive (the annoying siren, additional waits on the commute, calling the credit card company) is outweighed by the consequences of a false negative (house fire, train wreck, monetary fraud).

False negative errors in the AI discovery context occur when a responsive document is coded as nonresponsive and not included in the attorney’s resulting set.¹⁴⁶ Like real world false negatives, this can be disastrous: the document sought could be the smoking gun that wins the case for the side reviewing the discovery. This is especially true given the theorized limits of human cognition; some psychological research suggests that jurors can only receive, process, and remember five to nine documents in a trial.¹⁴⁷ If the falsely disposed document was one of your five to nine, you are giving up far too much!

Finally, a third, and perhaps more insidious error can creep up: the false equivalence error. This error catches responsive documents correctly, but misses distinctions between highly relevant documents and marginally relevant documents.¹⁴⁸ Given the limits of human cognition just discussed, this error could be potentially the worst error of all; it could prompt poor trial strategy through the attorneys’ focus on the wrong five to nine key documents. At a minimum, a false equivalence error would require a thorough second-pass search by human reviewers to rank the machine’s “responsive” output.

The goal of the supervising attorney is to optimize the tradeoffs between correct categorization of the documents and cost—in short, finding the balance between being

¹⁴⁴ *Id.* at 23. These errors likely result from different issues. For humans, errors are often the result of inattention or review fatigue. For computers, the errors are usually a result of imperfections in the algorithm because of a less than perfect seed set or unexpected uses of language in the documents.

¹⁴⁵ See Ralph Losey, *Elusion Random Sample Test Ordered Under Rule 26(g) In a Keyword Search Based Discovery Plan*, e-Discovery Team, <https://e-discoveryteam.com/2018/08/26/elusion-random-sample-test-ordered-under-rule-26g-in-a-keyword-search-based-discovery-plan/>.

¹⁴⁶ *Id.*

¹⁴⁷ George A. Miller, *The Magical Number Seven, Plus or Minus Two*, 63:2 *Psychological Rev.* 81–97 (1956).

¹⁴⁸ Ralph Losey, *Secrets of Search, Part III*, e-Discovery Team, <https://e-discoveryteam.com/2011/12/29/secrets-of-search-part-iii/> (last visited Aug. 2, 2019).

overinclusive versus underinclusive. In statistical theory, the elimination of both false positive and false negative errors is considered impossible.¹⁴⁹

AI discovery may also fall short in several other avenues. First, it is best suited to text-based documents with semantic content such as emails, Word documents, PDFs, or text-heavy PowerPoint slides. Data without semantic content, such as audio, image, or video files, will likely fall outside the capabilities of current AI discovery technologies.¹⁵⁰ Although significant advances are being made in photographic, audio, and video recognition—or we would be unable to use AI technology to monetize our puss-cat pictures—AI is not yet able to glean situational context from the analyzed files. For instance, an AI machine used to sift through prosecution evidence may be unable to tell between homemade videos of a defendant posing with a gun in front of a hunting trophy (not evidence of guilt) and surveillance footage of the same defendant holding a gun during an armed robbery of a franchised restaurant (evidence of guilt). Similarly, an AI machine may be able to recognize pictures of a franchise location but will have a harder time distinguishing between a benign picture of the storefront operating normally and the “smoking gun” picture of the franchise operating as a holdover or in a nonconforming manner to the terms of the franchise agreement. It may, in the absence of other metadata, be unable to distinguish between different storefronts of a particular franchise. In this sense, AI use in non-semantic discovery is akin to a simple email header search: it can tell the supervising attorney that the videos and pictures it found involves a particular person, much like an email header search can identify all the emails sent by a particular sender, but it has difficulty parsing the value of the content within from a probative standpoint.

Second, AI discovery falls short of human review for privilege and work product protection. While AI discovery can review documents for privilege, it tends to “struggle to properly categorize documents as privileged or nonprivileged.”¹⁵¹ Privilege standards are highly variable, context-specific, and require significant nuance. For example, a general counsel may communicate with his or her company in a legal or in a business role, often about similar topics. Documents reflecting or memorializing these communications are likely to lack any data about the context in which they were created, making it impossible to categorize them as privileged or nonprivileged without direct input from the attorney responsible. There also will be significantly fewer privileged documents than unprivileged documents in a given review, posing the risk of lacking a “rich” enough set of privileged documents to seed the machine. Without enough data to properly run through the algorithms and backpropagate, the predictive model of AI discovery suffers.

Third, AI cannot determine the admissibility of documents. The question of evidentiary admissibility is well beyond the scope of this paper, but most attorneys familiar with trial litigation will recognize some fundamental limitations of discovery review – the review process does not itself take into account whether a document needs foundation testimony, will be unduly prejudicial, or will constitute hearsay outside a recognized exception. More pressingly, the admissibility of a responsive document may depend on the foundation laid by a nonresponsive document, which the AI engine would reject! These issues must still be analyzed individually by the attorney after the review process, which may involve revisiting documents previously discarded by the AI engine.

¹⁴⁹ *Type I and Type II errors*, Wikipedia, https://en.wikipedia.org/wiki/Type_I_and_type_II_errors (last visited Aug. 2, 2019).

¹⁵⁰ TAR Guidelines, *supra* note 139, at 38.

¹⁵¹ *Id.* at 32.

Finally, the AI discovery process is not a replacement for case strategy – at least not yet. Although AI discovery review may identify documents that are statistically responsive to discovery requests, it is not yet so advanced that it can rethink the relevance of discovery material where the theory of the case is fluid or as new information comes to light. Submitting a discovery dump to an AI engine also may rob the attorney of useful information: much like writing notes rather than viewing slides helps material stick in memory,¹⁵² the act of sifting through discovery and seeing good and bad responses may itself be instructive to an attorney. Ultimately, the task of turning evidence into a coherent argument falls upon the attorney and not the machine. An attorney that has waded through responsive and nonresponsive discovery alike may have a much deeper understanding of the case than an attorney who simply receives an electronically-curated platter of responsive documents, and may be better able to articulate that case in court.

VI. HOW HAVE COURTS REACTED TO AI AND TAR

As noted above in Section III, the federal rules only offer general guidance on ESI and do not specify any particular technology. This is a double-edged sword: it allows counsel to try and use technology to remediate the discovery issues created by new technology. Conversely, courts are left to determine whether the technological solutions pass muster. This circumstance results in a significant period of uncertainty until a critical mass of courts agree on an approach. The jurisprudence regarding AI and TAR is not entirely developed, with a number of unresolved issues present. But one thing is certain: courts are generally open to any method that will limit the burden of electronic discovery.

A. *Da Silva Moore v. Publicis Groupe* is First Opinion to Approve of TAR

The first published opinion recognizing TAR as an “acceptable way to search for relevant ESI in appropriate cases” was *Da Silva Moore v. Publicis Groupe*.¹⁵³ There, Magistrate Judge Andrew Peck took the opportunity to broadly approve TAR. In the opinion, he wrote “[w]hat the Bar should take away from this Opinion is that [TAR] 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.”¹⁵⁴ The case itself was unusual in that the parties had extensively cooperated in electronic discovery. Specifically, the parties agreed in principle to the defendant’s use of TAR, some aspects of the protocol including the composition of the seed set, and that the defendant would share the training and quality-control sets (except for privileged documents).¹⁵⁵ The dispute was principally about whether training of the computer would consist solely of seven “iterative rounds,” and whether the quality-control process would be adequate.¹⁵⁶ The court found such concerns were premature, and concluded the defendant’s use of TAR was appropriate, considering the following factors:

1. the parties’ agreement to use TAR;

¹⁵² See, e.g., S.A. Beeson, *The Effect of Writing after Reading on College Nursing Students’ Factual Knowledge and Synthesis of Knowledge*, 35(6) J. of Nursing Educ. 258–63 (1996); Kenneth A. Kiewra, et al., *Effects of Repetition on Recall and Note-Taking: Strategies for Learning from Lectures*, 83 J. of Ed. Psych. 120 (1991).

¹⁵³ 287 F.R.D. 182, 183 (S.D.N.Y. 2012).

¹⁵⁴ *Id.* at 193.

¹⁵⁵ *Id.* at 191-92.

¹⁵⁶ *Id.* at 187-88.

2. the vast amount of ESI to be reviewed (over three million documents);
3. the superiority of [TAR] to the available alternatives (i.e., linear manual review or keyword searches);
4. the need for “cost effectiveness and proportionality” under Federal Rule of Civil Procedure 26(b)(2)(C); and
5. the transparent process proposed by [the defendant].¹⁵⁷

Although the language of praise and approval was broad, it was not absolute. The court emphasized that its opinion “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.”¹⁵⁸

Since *Da Silva Moore* was decided and recognized TAR as an acceptable search tool in discovery, many other courts have commented on its use. The same court, shortly after *Da Silva Moore* was decided, wrote in another opinion regarding freedom of information requests that “parties can (and frequently should) rely on latent semantic indexing, statistical probability models, and machine learning tools to find responsive documents.”¹⁵⁹ Courts have since consistently recognized the efficiency and lower costs associated with TAR.¹⁶⁰

The concern of machine error was also addressed in *Da Silva Moore*, when the court explained: “while some lawyers still consider manual review the ‘gold standard,’ that is a myth, . . . [TAR] ‘can (and does) yield more accurate results than exhaustive manual review, with much lower effort.’”¹⁶¹ In all discovery, regardless of review method, perfection is not required. But, while general usage seemingly is permissible in discovery, courts are not in agreement when addressing other issues, such as whether use of TAR is required; whether TAR may be used in tandem with keyword searches; and whether the training coding must be disclosed to the opposing party.

B. Requiring the Use of TAR

¹⁵⁷ *Id.* at 192.

¹⁵⁸ *Id.* at 193.

¹⁵⁹ *Nat’l Day Laborer Org. Network v. U.S. Immigration & Customs Enft Agency*, 877 F. Supp. 2d 87, 109 (S.D.N.Y. 2012).

¹⁶⁰ See *Harris v. Subcontracting Concepts, LLC*, No. 1:12-MC-82, 2013 WL 951336, at *5 (S.D.N.Y. Mar. 11, 2013) (“[w]ith the advent of software, predictive coding, spreadsheets and similar advances, the time and cost to produce large reams of documents can be dramatically reduced”); *Chevron Corp. v. Donziger*, No. 11-Civ.-0691, 2013 WL 1087236, at *32 n.255 (S.D.N.Y. Mar. 15, 2013) (“predictive coding is an automated method that credible sources say has been demonstrated to result in more accurate searches at a fraction of the cost of human reviewers”); *In re Domestic Drywall Antitrust Litig.*, 300 F.R.D. 228, 233 (E.D. Pa. 2014); *Malone v. Kantner Ingredients, Inc.*, No. 4:12-CV-3190, 2015 WL 1470334, at *3 n.7 (D. Neb. Mar. 31, 2015) (“[p]redictive coding is now promoted (and gaining acceptance) as not only a more efficient and cost effective method of ESI review, but a more accurate one”).

¹⁶¹ 287 F.R.D. at 190 (citing 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. 43 (2011)).

The same year *Da Silva Moore* was decided, another case addressed a party's attempt to require the opposing party's use of TAR. In *Kleen Products LLC v. Packaging Corporation of America*, a consolidated antitrust action, the defendants had already completed a large portion of their document review using keyword searches, which cost them over \$1 million.¹⁶² The court, over the plaintiff's objection, declined to require the defendants to redo their discovery using TAR and instead insisted the parties meet and confer about modifying the existing search.¹⁶³ The court emphasized that "[r]esponding parties are best situated to evaluate the procedures, methodologies, and technologies appropriate for preserving and producing their own electronically stored information."¹⁶⁴

More recently, Magistrate Judge Peck, who decided *Da Silva Moore*, concluded in another case that even where parties had not begun the discovery process, one party could not compel the other to use TAR. In *Hyles v. New York City*, he acknowledged that while "in general, TAR is cheaper, more efficient and superior to keyword searching,"¹⁶⁵ an opposing party cannot be forced to review in a manner they do not agree with.¹⁶⁶ "[I]t is not up to the Court, or the requesting party, to force the [defendant] . . . to use TAR when it prefers to use keyword searching. While [Plaintiff] may well be correct that production using keywords may not be as complete as it would if TAR were used, the standard is not perfection, or using the 'best' tool, but whether the search results are reasonable and proportional."¹⁶⁷ Of note, he wrote that there "may come a time when TAR is so widely used that it might be unreasonable for a party to decline to use TAR," but "[w]e are not there yet."¹⁶⁸

Although some courts have flatly denied requests by parties to compel the opposing party to conduct discovery with TAR, others have not been so assertive. In *FDIC v. Bowden*, the court ordered the parties to "consider the use of predictive coding."¹⁶⁹ In *Aurora Cooperative Elevator Co. v. Aventine Renewable Energy*, the court ordered the parties to "consult with a computer forensic expert to create search protocols. . . ."¹⁷⁰ Similarly, in *Independent Living Center v. City of Los Angeles*, the Court ordered the use of TAR to search more than two million documents.¹⁷¹ The takeaway from these cases is that courts approve of TAR as a discovery tool and could be moving in a direction that TAR could be required in cases requiring the review of a large volume of documents.

¹⁶² No. 10-cv-5711, 2012 WL 4498465, at *4 (N.D. Ill. Sept. 28, 2012).

¹⁶³ *Id.* at *5.

¹⁶⁴ *Id.* at *5 (citing The Sedona Conference, *The Sedona Conference Best Practices Commentary on the Use of Search and Information Retrieval Methods in E-Discovery*, 8 Sedona Conf. J. 189, 193 (Fall 2007)).

¹⁶⁵ No.10 Civ. 3119, 2016 WL 4077114, at *2 (S.D.N.Y. Aug. 1, 2016).

¹⁶⁶ *Id.* at *1.

¹⁶⁷ *Id.* at *3.

¹⁶⁸ *Id.* at *3.

¹⁶⁹ No. 4:13-cv-245, 2014 WL 2548137, at *13 (S.D. Ga. June 6, 2014).

¹⁷⁰ No. 4:12-cv-230, 2014 WL 11199118, at *1 (D. Neb. Mar. 10, 2014).

¹⁷¹ No. 2:12-cv-00551, slip op.at 1-2 (C.D. Cal. June 26, 2014).

C. Coupling TAR with other Review Techniques

Where the universe of documents to review is extremely large, coupling TAR with other review techniques such as keyword searches or deduplication may be preferred by the reviewing party to any one technique employed on its own. Decisions have ranged from permitting such procedures, to criticizing and denying them. In *In re Biomet M2A Magnum Hip Implant Products Liability Litigation*,¹⁷² the defendant narrowed the population of possible documents from 19.5 million to less than 4 million using keywords and then utilized TAR on that smaller population of documents. The plaintiff argued such procedure tainted the results, but the court held that the methodology satisfied the standard of reasonableness set forth in the Federal Rules of Civil Procedure.¹⁷³

In *Rio Tinto PLC v. Vales S.A.*,¹⁷⁴ yet another decision by Magistrate Judge Peck, the court permitted the use of keyword culling prior to TAR because the parties agreed to such a procedure. Cooperation and transparency were the central tenets of the decision. But it seems that Magistrate Judge Peck may not have approved this approach if deciding on a clean slate. Specifically, he commented that “[t]he Court itself felt bound by the parties’ protocol, such as to allow keyword culling before running TAR, even though such pre-culling should not occur in a perfect world.”¹⁷⁵

Finally, in *Progressive Casualty Insurance Company v. Delaney*,¹⁷⁶ the court denied a request to switch from search terms and manual review to TAR. This case is not exactly parallel due to timing concerns related to the request¹⁷⁷. However, the court did criticize the plan to apply TAR to the limited document population that was responsive to the word search.¹⁷⁸

Based on this case law, it appears that courts believe that the parties must pick an approach and stick with it, as opposed to mixing and matching approaches during the course of discovery.

D. Disclosure Requirements

The most divisive and potentially relevant divide among courts is the issue surrounding the disclosure of seed, training, and validation sets. Such information may consist of irrelevant documents and attorney work product. In general, courts appear to favor disclosure—with most courts encouraging disclosure and others requiring disclosure.

¹⁷² No. 3:12-MD-2391, 2013 WL 1729682 (N.D. Ind. Apr. 18, 2013).

¹⁷³ *Id.* at *3.

¹⁷⁴ 306 F.R.D. 125, 128-29 (S.D.N.Y. 2015).

¹⁷⁵ *Rio Tinto PLC v. Vales S.A.*, No. 14 CIV. 3042 RMB AJP, 2015 WL 4367250, at *1 (S.D.N.Y. July 15, 2015).

¹⁷⁶ No. 2:11-cv-00678, 2014 WL 3563467 (D. Nev. July 18, 2014).

¹⁷⁷ Progressive had already run the search terms to cull the documents and begun manual review lasting more than a month before the motion was filed. *Id.* at *7. The review protocol was negotiated between the parties and adopted by the court almost a year prior. *Id.* at *9. The motion before the court would have allowed Progressive to relieve itself of the burden it previously agreed to and use predictive coding on a smaller subset of the universe of ESI collected. *Id.* at *10. The court was unwilling to allow Progressive to skirt its prior agreement. *Id.*

¹⁷⁸ *Id.* at *11.

In the *Biomet* case discussed above, the court held that it does not have the “authority to compel discovery of information not made discoverable by the Federal Rules.”¹⁷⁹ Because the seed set includes irrelevant documents used to code the machine, such documents are not discoverable.¹⁸⁰ Despite this acknowledgment, the court also “urge[d] [the defendant] to re-think its refusal.”¹⁸¹ This insistence was founded on the “spirit” of cooperation endorsed by the Sedona Conference.¹⁸² Even where parties voluntarily provide seed data and training, courts still highlight the importance of cooperation and transparency. In *Da Silva Moore*, the court noted that it “highly recommends that counsel in future cases be willing to at least discuss, if not agree to, such transparency in the [TAR] process.”¹⁸³

But, some courts have taken a different approach and required disclosure of seed sets and training techniques. In *Independent Living Center v. City of Los Angeles*,¹⁸⁴ the court ordered that the plaintiff “be involved in and play an active role” in the training process, including making “relevance determinations” in the training documents. In *Winfield v. City of New York*,¹⁸⁵ the court ordered the defendant to both utilize TAR and provide an *in camera* review of the coding process.

Courts have even denied the use of TAR in part due to non-disclosure. In *Progressive Casualty Insurance Company v. Delaney*,¹⁸⁶ the court criticized the plaintiff’s unwillingness in its proposed TAR protocol to share with opposing counsel the irrelevant documents used to train the TAR tool. As noted above, this case was plagued with other concerns as well. But if nothing else, it illustrates that transparency can be a factor in the court’s calculus of determining whether or not to permit TAR.

E. Local and International Rules Addressing Technology Assisted Review

Only one state, New York, has addressed TAR in its court rules. In an amendment which became effective on October 1, 2018, a new rule of the New York Supreme Court Commercial Division¹⁸⁷ encourages litigants to use TAR as a means of reviewing electronically stored information. Specifically, the rule provides “parties are encouraged to use the most efficient means to review documents, including electronically stored information, that is consistent with the parties’ disclosure obligations . . . and proportional to the needs of the case. Such means may

¹⁷⁹ *In re Biomet M2a Magnum Hip Implant Prod. Liab. Litig.*, No. 3:12-MD-2391, 2013 WL 6405156, at *2 (N.D. Ind. Aug. 21, 2013).

¹⁸⁰ *Id.*

¹⁸¹ *Id.*

¹⁸² *Id.*

¹⁸³ *Da Silva Moore*, 287 F.R.D. at 192.

¹⁸⁴ No. 2:12-cv-00551, slip op. at 1-2 (C.D. Cal. June 26, 2014).

¹⁸⁵ No. 15-cv-05236, 2017 WL 5664852, at *10 (S.D.N.Y. Nov. 27, 2017).

¹⁸⁶ No. 2:11-cv-00678, 2014 WL 3563467, at *10 (D. Nev. July 18, 2014).

¹⁸⁷ The Commercial Division is a division of the New York Supreme Courts that hear complicated cases. For a case to be heard in the Commercial Division, it must meet a specific threshold for the amount in dispute. See *Commercial Division-NY Supreme Court*, <http://www.nycourts.gov/courts/comdiv/ny/newyork.shtml>.

include technology-assisted review, including predictive coding, in appropriate cases.”¹⁸⁸ Despite the encouragement provided by the rule, the Advisory Council Memoranda prepared when the rule was published still emphasized that the producing party is best situated to determine its needs in discovery.¹⁸⁹

International jurisdictions have similarly adopted the use of TAR as an option in eDiscovery but have not mandated its use. Ireland,¹⁹⁰ England,¹⁹¹ and Australia¹⁹² all have rulings approving a party’s usage of TAR.

Finally, TAR can certainly be used in arbitration, whether domestic or international, if appropriate. However, the rules of the major arbitral bodies do not specifically address its use.¹⁹³ That is not surprising; arbitration is a creature of contract and often meant to be a more expeditious forum than traditional, in-court litigation. As such, discovery in arbitration is usually more limited. That, in turn, means that there are less likely to be disputes in arbitration that would require discovery into such a broad universe of documents as to require the use of TAR. Similarly, international arbitration generally does not require the disclosure of documents on the same scale as domestic litigation, further lessening the need for TAR in that forum.¹⁹⁴

F. Notable Commentaries

Magistrate Judge Peck has also published a few articles on the topic of TAR. In fact, the leading article on predictive coding is attributable to Magistrate Judge Peck.¹⁹⁵ The article generally discusses the mechanics of predictive coding and the shortcomings of manual review and of keyword searches.¹⁹⁶ This article was adopted shortly after it was published by the court in *Da Silva Moore*.¹⁹⁷

¹⁸⁸ 22 NYCRR § 202.70(g); N.Y. ct. rules § 202.70(g) (Rule 11-e of the Uniform Rules for the Supreme Court and the County Court).

¹⁸⁹ See Unified Court System, John W. McConnell, Memorandum, p. 1, Ex. A p. 2 (Mar. 8, 2018), <https://www.nycourts.gov/rules/comments/index.shtml>.

¹⁹⁰ See *Irish Bank Resol. Corp. v. Quinn*, [2015] IEHC 175 (H. Ct.) (Ir.), upheld by the Irish Court of Appeal.

¹⁹¹ *Pyrho Inv. Ltd. v. MWB Prop. Ltd.*, [2016] EWHC (Ch) 256 (Eng.).

¹⁹² *Money Max Int’l Pty Ltd. (Tr.) v. QBE Ins. Grp. Ltd.* [2016] FCAFC 148 at 3-4 (Austl.).

¹⁹³ See generally AMERICAN ARBITRATION ASSOCIATION: COMMERCIAL ARBITRATION RULES AND MEDIATION PROCEDURES (2013); JAMS COMPREHENSIVE ARBITRATION RULES & PROCEDURES (2014); INTERNATIONAL CENTRE FOR DISPUTE RESOLUTION: INTERNATIONAL DISPUTE RESOLUTION PROCEDURES (2014) INTERNATIONAL CHAMBER OF COMMERCE: ARBITRATION RULES (2017).

¹⁹⁴ Compare INTERNATIONAL CHAMBER OF COMMERCE: ARBITRATION RULES (2017) with AMERICAN ARBITRATION ASSOCIATION: COMMERCIAL ARBITRATION RULES AND MEDIATION PROCEDURES (2013).

¹⁹⁵ See Andrew Peck, *Search, Forward: Will Manual Document Review and Keyboard Searches be Replaced by Computer-Assisted Coding?*, L. Tech. News (Oct. 2011).

¹⁹⁶ *Id.* at 29.

¹⁹⁷ *Da Silva Moore*, 287 F.R.D. at 182. As noted above, the case was decided by Magistrate Judge Peck, thus this reference may have cemented the article’s popularity in the TAR literature.

Since then, TAR has continued to develop and so has the literature. State law journals and practice series have focused heavily on TAR in discovery.¹⁹⁸ The Sedona Conference has published explicitly on the issue, highlighting continued concerns.¹⁹⁹ All the publications point to the same conclusion: TAR is here, and it is here to stay. The Sedona Conference recognizes that the technology only will continue to improve, which may mean one day TAR will become the predominant discovery method.²⁰⁰

G. Franchise Specific Cases

Despite extensive searching, the authors could not locate any published cases relating to the use of TAR and AI in franchise disputes. The authors believe that there is a dearth of franchise specific case law for at least two reasons. First, many franchise systems include arbitration clauses in the franchise agreement. This approach results in a significant percentage of franchise disputes moving forward in arbitration, where TAR is unnecessary or not contemplated, as discussed above. Second, absent challenges to system wide practices, franchise disputes are largely limited to a disagreement about a specific franchise location or group of locations. These kinds of disputes, by their very nature, have a more limited universe of documents.

That said, when it comes to discovery, franchise disputes are fundamentally the same as other commercial litigation and should be covered by the same rules and principles. Thus, TAR would be appropriate to use in a franchise dispute so long as the scale of the case justified its use. For example, TAR would be useful in cases that challenge a system-wide practice or in class or mass actions brought by consumers or franchisees.

VII. WELCOMING OUR NEW COMPUTER OVERLORDS: ON BEYOND DISCOVERY!

Although discovery is the most practical and most widely-used case for AI at the moment, the AI review process can assist attorneys in other legal contexts as well. Before entering litigation, AI engines can perform early case evaluations. The TAR Guidelines published by the Bolch Judicial Institute at Duke Law School suggest that early evaluation is useful to “get a high-level view of the overall makeup of documents” in a case to “better assist with legal strategy,” although this is a fairly limited view of what AI-based early evaluation could provide.²⁰¹ With the right seed information drawn from public records like verdicts and settlements, it is conceivable that AI engines could predict likely outcomes of litigation based on a combination of document content, case location, jury behavior and viewpoints, judicial attitudes, trends in public sentiment, or any other correlated data. Much like Google Maps or Waze predicts traffic patterns and drive time based on analytic models, an AI case evaluator may tell a franchisor that a lawsuit is likely to result in a higher settlement amount for the franchisee when filing suit in Georgia as opposed to filing suit in New York or Delaware.

¹⁹⁸ See, e.g., *Technology-assisted review: Predictive Coding*, 3 N.Y.Prac., Com. Litig. in New York State Courts § 27:41, at 2 (4th ed.); Randy L. Dryer, *Technology & Ethics: Teaching Old Dogs New Tricks or Legal Luddites Are No Longer Welcome in Utah*, Utah B.J., May/June 2015, at 12; Charles Yablon and Nick Landsman-Roos, *Predictive Coding: Emerging Questions and Concerns*, 64 S. C. L. Rev. 633, 647 (Spring 2013).

¹⁹⁹ *The Sedona Conference TAR Case Law Primer*, 18 Sedona Conf. J. 1 (2017).

²⁰⁰ *Id.* at 48.

²⁰¹ TAR Guidelines, *supra* note 139 at 30.

The TAR Guidelines also suggest that AI review is an excellent tool for deposition and trial witness preparation.²⁰² AI discovery review can identify holes in document collections or witness narratives, find and categorize critical documents, and rank documents by their relevance to the case at large or to specific witnesses.²⁰³ It can also tie documents to key dates, assisting the trial attorney in creating a testimony outline. Also, because witnesses may use “code” terms in describing documents or events, AI review may figure those codes out based on their statistical correlation to known terms. Documents in the witness’s “code” may elude a term-based search, but have a greater chance of being caught by natural language algorithms.

On the corporate side, AI engines may be used in internal document management situations such as corporate investigations and data segregation. For instance, an unhappy franchisee may claim that a franchisor’s sales staff made financial performance representations to the franchisee outside an Item 19 disclosure, in which case an internal investigation will reveal whether the sales staff made representations or comments that crossed ethical lines. Companies may conduct investigations into their directors to uncover breaches of fiduciary duty, or into their own systems to determine sources of data breaches. In any of these situations, AI engines may review internal documents in lieu of human forensic research.

In an internal corporate investigation, company data and metadata are searched to retrieve information relevant to the requested investigation. An AI-assisted investigation is designed to rely primarily on data, with the goal of finding quick answers, or at least a quick roadmap of second steps to explore, based on the company’s internal document records. Given that companies tend to have central servers and rely on email for a substantial portion of communications, AI review may prove an excellent tool for narrowing the scope of inquiry into documents responsive to the search. Meanwhile, in data segregation cases, AI engines may be pressed into identifying personally identifying information, medical records, consumer or employment records, or other sensitive data. The TAR Guidelines suggest this may be accomplished by pattern-based searches around credit card numbers, bank accounts, dates of birth, or other content that follows a similar pattern.²⁰⁴ It may be especially useful for the growing number of medical franchises, which face the simultaneous struggle of an exponentially growing amount of electronic documentation plus strengthening privacy regulations. AI-identified private data may then be quarantined, or stored securely.

Corporate transactions could end up being the greatest beneficiary of AI engines. As many corporate lawyers know, one of the most time consuming and expensive processes in a corporate transaction is due diligence. This process usually results in an army of attorneys reviewing vast quantities of documents to see if the target corporation has skeletons in the closet or any unusual obligations or risks. Moreover, most corporate attorneys know that even the most complicated of contracts contain a significant amount of boilerplate. In essence, due diligence is a process of looking for what is different or non-standard.

Although in its infancy relative to AI discovery, contract analysis software can perform due diligence for basic transactions. One provider, LawGeex, claims to have run a study showing that its due diligence software found loopholes and other risks in five nondisclosure agreements at a higher rate of accuracy – and, of course, much faster – than the group of trained corporate attorneys it went up against.²⁰⁵ The company claims that its product can produce better results

²⁰² *Id.* at 34-35.

²⁰³ *Id.*

²⁰⁴ *Id.* at 36.

²⁰⁵ *The Lawstars Blog*, LAWGEEX, <https://blog.lawgeex.com/ai-more-accurate-than-lawyers/> (last visited Aug. 2, 2019).

than human attorneys for simple contract terms within a defined acceptable template. If true, this may be the foremost application for the franchise context: AI engines can review FDDs for compliance with FTC and state regulations, or for uniformity/reasonableness with financial representations or cost forecasts. They could also review franchise agreements for term uniformity, state-specific addenda, or clauses that can vary by jurisdiction, like post-term noncompete provisions. Finally, AI could be used to examine financial statements for unusual line items or ratios that are outside of desired parameters.

Intellectual property law is also a potential target of disruption by AI engines, with startup companies devoted to searching trademark and patent databases for clearance²⁰⁶ and patent prosecution.²⁰⁷ These are interesting applications, but it is unlikely that companies will abandon the tried and true methods anytime soon. For many modern companies, much of their value derives from their patents and intellectual property. It is unlikely that many executives and boards will be willing to place the protection of their intellectual property in the hands of machines until the technology is very advanced or there is a critical mass of others in the industry who are using it.

Although this list is neither exhaustive nor established enough to be in many attorneys' common vernacular, attorneys should not be surprised to see AI heavily featured in their practices in the future.

VIII. CONCLUSION

AI-assisted review is not a flash in the pan. Instead, it likely represents the next evolution in the practice of law for litigation with a significant amount of documents in dispute. Firms and attorneys who adopt this technology will place themselves at a competitive advantage over other firms. With in-house counsel increasingly focused on cost-effectiveness, counsel will likely be expected to make use of this technology in future litigation.

²⁰⁶ TrademarkNow, <https://www.trademarknow.com/> (last visited Aug. 2, 2019).

²⁰⁷ ANAQUA, <http://www.anaqua.com/iam-solutions/ip-management-software/patent-management.html> (last visited Aug. 2, 2019).

88888888\2806\4827-8227-7539.v1

THEO S. ARNOLD

Theo S. Arnold is Vice President and General Counsel of Money Mailer, a franchisor in Orange County, California. Theo has spent his entire legal career in the franchise field, representing both franchisors and franchisees in transactions, regulatory matters, and litigation. He is certified as a specialist in franchise and distribution law by the State Bar of California, sits on the California Lawyers' Association's Franchise Law committee, and was selected as a 2019 Franchise Times Legal Eagle.

Theo is the author of a 2018 *Franchise Law Journal* article on California competition law in franchise disputes, which he believes is the only article in the publication's history to include a comprehensive footnote on the legal misfortunes of the San Diego Chicken. He routinely challenges J. Michael Dady for supremacy on the unofficial annual ranking of most outlandishly dressed Forum participants.

Theo graduated from the University of California, San Diego and received his J.D., cum laude, from the University of Michigan. Go Blue.

JOHN M. DOROGHAZI

John M. Doroghazi is a litigation partner in the New Haven, Connecticut office of Wiggin and Dana LLP and is a member of the firm's Franchise and Distribution, Class Action, and Consumer Protection Practice Groups. Aside from defending franchisors in all types of franchise-related litigation and arbitration, he routinely represents franchisors and others, including hospitals, banks, insurance companies, and online travel retailers, in various types of consumer class actions, including Telephone Consumer Protection Act cases, in courts across the country.

John is an Article Editor for the Franchise Law Journal and is the co-author of the Connecticut chapter in the current edition of the *Franchise Desk Book*. John has also authored numerous articles for the *Franchise Law Journal* and previously presented at the Forum on Franchising. John has been recognized by numerous publications, including being named a Legal Eagle by The Franchise Times, an "Up and Coming Practitioner" for Franchise Law-Nationwide by Chambers, and a "Future Star" and to its "Under 40 Hot-List" by Benchmark Litigation.

John graduated magna cum laude from Boston College and received his J.D., Order of the Coif, from Washington University School of Law. After law school, he was a law clerk to the Honorable Jean C. Hamilton, United States District Judge for the Eastern District of Missouri. John has not yet appeared on the rankings of most outlandishly dressed Forum participants, but maybe this is his year.