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The Longitudinal Impact of IT Self-Efficacy and Interest on Intent to Major

Qinhui Wang
Oklahoma State University, qinhui.wang@okstate.edu

Andy Luse
Oklahoma State University, andyluse@okstate.edu

Julie Rursch
Iowa State University, jrursch@iastate.edu

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AI Developments and Technology-Assisted Review

Brian Almquist

I. Introduction

Technology-Assisted Review (TAR) has become accepted as a valid tool for easing costs when litigants are faced with discovery requests that cover large scale collections of electronic documents and other forms of data. The discovery of electronically stored information (DESI)—or e-Discovery—can be a lengthy process, especially since the producing party has a vested interest in minimizing potential external exposure of information that is not necessarily relevant to a given discovery request. TAR has been implemented by dozens of vendors using standardized protocols, including active learning systems where machine learning algorithms use feedback from human subject matter experts to construct models of document responsiveness. As these models are applied to the remaining documents in the collection, non-responsive documents become smaller portions of the documents requiring review, saving many hours of expensive human labor.

There is a distinction between machine learning document classifiers and what is popularly referred to as "artificial intelligence" in today's discussions of business and technology, particularly the attention-grabbing generative tools using large language models that are being deployed to help white-collar workers spend less time on mundane intellectual tasks. Already, as documented by Armour, Parnham, & Sako (2022) these tools are seen as helping lawyers with putting together the structures of briefs and assisting with contract analysis, billing and utilization decision-making, and even legal research. This article will address some of the possible ways that these tools may also have an impact on some of the tasks involved in e-Discovery.

Given the business structures present and the cultural value placed on legal skills, it is likely that generative AI technologies are likely to "augment" existing human resources if they are present at all in the e-Discovery application space. It is unlikely to take a replacement role given the existing vulnerabilities and weaknesses for TAR, many of which may be exacerbated by the design characteristics and features of popular commercial AI systems.

II. Overview of the Problem

ESI and Information Governance

As regulatory concerns have created burdens on organizations requiring that data be carefully managed, similar challenges are faced over the need to manage information. In a broad sense. Like data governance, information governance includes defining policies that cover the creation, organization, storage, retention and disposal of information. Here, we remember that information is, essentially, data that has been processed and so used to create documents and other forms of value.

Often, information governance is considered an overhead task and a cost centre. Executives do not find investing in it attractive, and it is seen as a defensive business activity, to hold regulators and lawyers at bay. Organizations such as AIIM seek to tie information governance to customer experience management and placing valuable information into the hands of those that can use it profitably. As machine learning and AI tools are used to organize, code (or classify) and generate metadata for information, this moves the burden away from the information creator and improves the adaptation of information governance practices.

A particularly ominous aspect lawsuits and investigations is the potential for "discovery," a legal process that might compel an organization to provide sensitive information to either investigators or the court. As Volonino (2003) points out, organizations are aware that their electronically stored information (ESI), in the form of traditional business records and regular communications, are subject to regulation and discovery, subpoenas, or even search warrants. Companies must now plan to retain electronic records to remain in compliance with laws and exchange regulations.

The process of discovery looms large in popular culture. Legal dramas on popular media frequently feature a sequence where a noxious defendant, forced to hand over their files, delivers mountainous stacks of unsorted document boxes to understaffed teams of plucky young plaintiff's attorneys. In the subsequent montage, the "smoking bullet" is found by the exhausted protagonist and justice is delivered in short order. (An example of this scenario can be found in the feature film, *Class Action,* Apted (1991)) The reality of ESI is that this scene is obsolete. As businesses moved to electronic storage of documents for convenience and cost-reasons, the laws and regulations for retention and delivery of legally pertinent business documents have adjusted to reflect the potential for rapid search and document duplication. More recent popular imaginings of "discovery" might follow from media consumers of political news, looking forward to pending lawsuits in which hidden or embarrassing information will be revealed to the public through "discovery." For one example, in a recent "tweet," Elon Musk "Can't wait for discovery to start" against organizations he dislikes. (Musk, 2023) These imaginings do not reflect the vast volume of information that must be processed, nor the intense negotiations over the parameters of which documents must be "produced" or turned over to opposing litigants.

Discovery Procedure

Before a legal proceeding reaches trial, each side has the right to "discover" as much as possible about their opponent's case. Discovery requests are made for any information that is relevant to the facts that lead to litigation. Since parties are required to provide this information in a readable format by a specific date, industry best-practice ESI management strategies can prevent unnecessarily giving the courts the impression that an organization is attempting to obstruct justice. In turn, poorly managed ESI can lead to expensive processes involving the location, restoration, sorting and review of long-forgotten documents. Given the size and storage technology used, along with the circumstances of a given discovery request, Volonino argues that the time and effort involved in producing relevant evidence for a legal proceeding can reach millions of dollars. Companies with comprehensive and "systemic" policies and procedures for review, retention and destruction of documents produced as part of business operations may find themselves better positioned to respond effectively and at less expense when facing legal obligations—a situation that may be inevitable depending on the organization's industry sector.

Of course, "relevance" is often a source of contentious discussion between parties. Because the process of discovery can be expensive, discussions of "relevance", "responsiveness" and "privilege" can be subject to negotiations between both parties to a suit. In many cases, the results of these negotiations can be formatted in a structured manner that resembles the Boolean search term queries used for several research databases, a format that many lawyers will have familiarized themselves with through their training searching for appropriate precedents in case law databases. (Baron, Lewis, & Oard, 2006; Blair & Maron, 1985) As search technology has improved, strategies for managing document collections have adjusted, and the question of "relevance" has moved beyond the presence of Boolean search terms in a document and more towards the paper-trail idea of "who communicated what to whom, when, and, to the extent possible, why." (Ashley & Bridewell, 2010; Conrad, 2010) Just as documents that are relevant must be found and turned over to a requesting party, subsets of documents are excluded from production to the requesting party. Similar techniques to those used to identify relevant documents in a collection may also be used to identify (and thus withhold from production) those documents that represent work product or privileged communications.

In general, e-Discovery is seen as an early and the most obvious entry point for AI – or more particularly, machine-learning – into the legal industry. In terms of low-hanging fruit, discovery processes could generate up to a quarter of the costs of major litigation. The tasks involve large-scale datasets, and, further, human-generated feedback improves results immensely. (Armour et al., 2022) The main limitation of AI in terms of discovery was that models could only be trained for each case, and so could not be used again. This itself was mitigated by the scale of eDiscovery tasks so that implementation would usually provide a return within the scope of a single project. In contrast, most AI-projects involve training a model that can be applied multiple cases. Training a model to find documents relevant for mergers and acquisitions activities, as Armour et al. contrast, would be transferrable because the relevant terms would be similar across instances.

A Background on eDiscovery and It's Limitations

Term searches (Boolean)

Early attempts at handling ESI involved manual review of voluminous documentation. For many collections, Boolean filters requiring the presence of certain words in a document, would reduce the scope of the collection that needed to be reviewed. Since discovery is a legal procedure, legal teams from both sides of a given case would be involved in careful negotiations over the exact form of the Boolean query. Meanwhile, the Boolean query will return every document that meets the established filtering criteria without prioritization. Every qualifying document qualifies equally.

Probabilistic models for information retrieval would allow for estimating the likelihood that a given document was relevant to the inquiry. Information (such as other statistically unusual co-occurring terms) gleaned from the presumably most relevant documents could be used to build new, more expansive queries. Replacing the assumption of the relevance of high-scoring documents with feedback from a subject matter expert would improve future queries and ranking of results. It is from here that we step to Technology-Assisted Review (TAR), a system where models of documents are more abstracted, but the process of using human feedback to improve query results is still in place. Some systems distinguish between single passes with the reviewer, and others submit batches of documents for review in a cycle of continuous active learning until the system no longer returns relevant documents.

It is important to understand that, in discovery, while cost-savings comes from accurate predictions of document relevance, a simple system could generate outstanding accuracy scores by simply predicting that none of the documents in a collection are relevant. A document collection where only 0.5% of the documents are relevant to a case would still generate an outstanding 99.5% precision mark. Thus, the goal for any discovery system is to maximize recall (percentage of documents found) while retrieving the least number of documents.

Machine-learning techniques used for e-Discovery to this date fall largely in the space of classifiers, where, given an item, the algorithm assigns a label to the item based on the items features. Classification models range from a set of explicit rules to complicated probabilistic estimations, depending on the training algorithm.

This is not the generative AI based on large language models that is currently under popular scrutiny. The question of the impact of these newer machine learning systems, especially in e-Discovery, has largely been unexplored in the literature. Those technologies are largely seen as having an impact by augmenting the capabilities of lawyers by reducing time and effort spent on tedious or mundane tasks. (Armour et al., 2022)

Expert-based feedback for secondary searches

The development of TAR has expanded along the lines of the capabilities of the learning technologies. Early procedures involved developing a model of what constituted a relevant, or "responsive," document. The model would be developed with feedback information from a subject matter expert, who might indicate whether a sample document was relevant or not, and what features of the document were pertinent to this distinction. Under this Simple Learning environment, the model is applied to the remaining document collection to select documents that would be subject to human review.

Within Simple Learning, there was a moderate distinction in procedure. The early training sample might be randomly selected, or specifically chosen to include clearly relevant and non-relevant documents. In both cases, after feedback from the subject matter expert, a new sample set would be generated, and the process would iterate until the model was generating results that met specific quality criteria (e.g., "80% recall is sufficient"). (Galvin, 2021; Guha, Henderson, & Zambrano, 2022) Under the latter format, the model would train on documents that would increasingly fall into a "gray area", so that it would become more sophisticated in its classifications.

Guha, et al., also identify ways that the discovery process can be abused, what is specifically required to abuse a TAR system, and, importantly, what differentiates between gamesmanship and clear-cut abuse examples. Gamesmanship might be considered behaviour where one side is less than collegial, but the behaviour is considered unsanctionable. Gamesmanship might include:

- Last-minute document dumps
- Insisting on expensive reviews that drains opponents resources
- Anything else that imposes costs, delays, or other harassment to the detriment of finding relevant evidence but does not violate clearly established boundaries of illegal activity.

When considering the risks and benefits of any given artificial intelligence system, one must consider how an adversary may attempt to manipulate results. Given the naturally adversarial environment established for resolving legal disputes, one would want to consider the potential for both deliberate and inadvertent activities that may distort or obfuscate the results of e-Discovery tools.

Guha, et al., identify what would be necessary to manipulate TAR results. For instance, intentionally removing relevant records from a training set that would lead the TAR system to documents their owner would prefer not be discovered. Or, modifying the properties of the relevant records, again to misdirect the TAR system.

The second major development in technology-assisted review, sometimes known as TAR 2.0, reflects the modification to the procedure where learning continues after the model is initially created. As the actual human review proceeds, the model is updated with new feedback data, new documents are selected for review, and the process iterates until the review is complete. This has been found to generate greater recall (more relevant documents found) while requiring less human reviewer time. In ideal circumstances, this is where the value in these systems lie: less labour expenses with presumably better results.

Generally, TAR 2.0 offers better results and better efficiency for most scenarios. TAR 1.0 may be more useful when it needs to be done cheaply and quickly with no care for quality, when mandated, or negotiations between opposing parties over discovery have broken down. But, as Guha at al., warn, the use of TAR 1.0 procedures may expose practitioners to additional liability from the use of seed collections combined with the potential for the system to learn a relevance model that does not reflect negotiated parameters.

TAR's Weaknesses and Remedies

Guha, et al., into much greater detail about the possibilities for both intentional and unintentional problems with TAR. Since there are weaknesses—and some of them are tied to proprietary algorithms—it makes sense that TAR technology vendors would not advertise their presence. While some abuses of TAR are clearly intentional and would be subject to sanction, there is a trickier space that falls under the category of "gamesmanship." This is where behaviour, especially on the producer's side, can lead to making unfairly advantageous but defensible choices. This is comparable to "data dumping"—delivering truck loads of documents to the requesting side for manual review just before an upcoming hearing. The producer starts off with an asymmetrical level of knowledge about the document collection. This potentially allows them to specify parameters for a particular TAR process that may help to obscure damning documents. This might entail choosing "stop words" (common words that are not indexed and are thus ignored), picking an advantageous "stopping point" threshold for reviewing documents, or even defining a misleading set of features that would cause a TAR system to misidentify actual responsive documents. Complicating this is the fact that the more plausible responses that the opposing party could make to prevent this behaviour would involve either unacceptable levels of transparency, or partitioning of the dataset that would make the TAR process linearly more expensive.

Seed Set Problems

The seed set is an initial set of labeled documents used to initiate the TAR process. Guha points out that while negotiations over seed sets and how they are constructed or reviewed are a big part of discovery-based litigation, most of these discussions do not reflect recent understandings of biased datasets and their impacts. Biased datasets aren't necessarily intentional, but it is also possible to maliciously insert data into a training set to encourage faulty decision-making on the part of a classifier. The fact that active learning systems are also susceptible to these types of manipulations means that seed sets and evaluation sets (used for validation) should be reviewed for potential bias.

Randomized sampling to build the seed set is probably one of the better approaches, but apparently many attorneys prefer to craft the parameters around how such a seed set is created. In such cases, it may be possible for an attorney to create bogus documents in the seed set to lead the algorithm astray. Randomized sampling can also be defeated by artificially inflating some types of documents by including unnecessary duplicates in both the seed and the dataset.

One of the many interesting solutions to this problem is to break up the training data into different subsets, and then retrain the system on the subsets with the worst performance. Opposing counsel may also ask to review the seed set, but this approach risks exposing privileged information. Finally, the best approach is ultimately agreeing on evaluation protocols and "robust post-hoc evaluation" which might include, among other things, an error analysis.

Data Content and Composition

Data poisoning attacks on discovery processes largely comes down to modifying training data. If one or more documents in training data can be altered to train the system so that it incorrectly identifies features associated with responsive documents, then the system has been poisoned. It has been demonstrated in a sentiment prediction model that would otherwise behave normally but would automatically flag a document as "positive" if it contained "Donald Trump" and negative if it contained "Apple iPhone." (Wallace, Zhao, Feng, & Singh, 2021) An interesting problem for this is how to get the document in the training data. Though seed sets don't necessarily need to be shared by document producers, the creation of them does fall under intense scrutiny. But in active learning systems, when a poisoned document gets processed it can have a strong misleading impact.

Adversarial document examples occur when a document tricks a machine learning system to draw the wrong conclusion about itself. These are often inadvertent, but it can also be deliberate: e.g., in image classification, it is possible to add imperceptible noise so that an image is interpreted as a “gibbon” instead of a “panda.” Adversarial examples can become poisonous if in the training set. With textual documents, it may be more difficult than adding "imperceptible noise" as features are derived from words that are present.

III. Generative AI and E-Discovery

As of this writing, AI chatbots have been integrated in publicly available search engines (e.g., Microsoft’s Bing). As Google integrates their own version, it should be assumed that people will begin to modify how they construct queries against most information systems. The process of querying for documents in the legal discovery context is heavily influenced by the use of keyword searches, a practice that many lawyers are trained to use for research. TREC established that Recall can be drastically improved by query expansion, whether automatic or through manual relevance feedback. (Grossman & Cormack, 2010)

As TAR potentially gets bogged down in negotiation and litigation, strong validation requirements may lead towards a return to the simple keyword and manual searches that lawyers are familiar with. One entry point for generative AI in e-Discovery is for suggestions of possible query expansions. The benefit of a public AI is that keyword terms that are suggested would be probabilistic, but also influenced by a massive corpus of text that exceeds any corporate e-mail collection, or the vocabulary of keyword-query constructing lawyers.

Further context-based accuracy could be gained by integrating a large language model (LLM) with the document collection subject to discovery. This brings many potential privacy, privilege, and similar concerns if the new model is both human interpretable and available to both parties of a case. The side requesting the documents may have transparency concerns in this arrangement.

Before we consider the likely roles in modifying existing TAR processes with generative AI, we should look at the impact it will have without integration. Many people are thinking about the impact of disinformation added to the internet ecosystem for the purposes of training MMLs to propagate that disinformation (or worse, create new forms). (Goldstein et al., 2023) From a discovery perspective, one concern is how a collection of ESI can be similarly polluted. A continuous learning system might help defend against this as humans review and identify misinformation in documents perceived by a system to be responsive. It could be possible to use a generative AI to flood a dataset with disinformation or, even better, use “relevant” keywords to fake documents. This behaviour is more clearly intentional obstruction, and subject to substantial sanction from the courts, if discovered. In *Decastro v. Kavadia* 309 F.R.D. 167, 169 (SDNY 2015), a party installed a program to find and delete specific files. This would be probably considered intentionality.

Even more intriguing is the possibility of using generative AI to discover the features that we would need to add to a document for deliberate poisoning, or to create adversarial examples. For adversarial examples, access to the training set or the trained model would be necessary. A local instance of a newer large language model (e.g., GPT-4) would be supplemented with the dataset. Larger firms (and law firms) would need to make sure that access to the large language model would need to be monitored and logged (e.g., which prompts were applied) to ensure that the system was not being trained in a legally questionable manner.

Transparency concerns in AI are important for litigation, especially the idea of explainability. Explainability "add-ons" designed for commercial AI applications may need to be modified and installed for TAR systems that are augmented with generative AI. (Nehme, 2023) Even with relatively simple machine learning, like that used by standard discovery systems, this would be helpful, though it may also need to be mandated by regulation. In this scenario, explainability can be a mitigating factor that can help prevent abuse in DESI.

IV. Types of Impacts

Already, there has been much discussion of incorporating generative AI, particularly ChatGPT to eliminate some of the drudgery involved in legal practices. Users have demonstrated the technology's capabilities in generating frameworks for legal briefs, identifying obvious arguments and providing an outline for a submitted document. These activities should be carefully supervised, especially if the tool starts making citations. In academic writing, bots have been shown to frequently "hallucinate" citations that don't actually exist, (Ji et al., 2023) and it does not require a stretch of the imagination to conclude that this could happen in legal writing as well.

But what of legal procedure that does not involve writing legal arguments? Concerning discovery, such bots might be involved in generating queries that would be the basis for a formal request for production of documents. Or it may make suggestions which could be a starting place for negotiations of discovery parameters. When it comes to the actual retrieval of documents, the generative AI could be used to improve queries, either through pseudo-relevance feedback, or with actual feedback from the human reviewer.

There are some concerns with how an AI-assisted TAR system would work. If machine learning is involved in the assessment of whether a document is responsive, or if it can be held pack for reasons of privilege, it will be up to a human assessor to express the basis of that decision. There is no way to determine exactly "why" the AI found the document to be responsive. Human follow-up will have to assess whether AI claims are supported by the text. To the extent that a natural language generating AI produces "reasoning," to support a decision this will also need to be validated by a human. In contrast, a search query result can be broken down to the presence of particular terms in the document, and what their weight has been in making a probabilistic estimate of relevance. Even if an AI-augmented TAR system is able to generate "reasoning" for its decision-making, it will need to be understandable by a human so that it can be validated. It is possible that the explanation may include or reflect statistical artifacts from its own training set, which could compound communications about the documents.

V. Conclusion

Like many professional sectors, the legal world is looking at newer machine learning technologies for possible improvements in productivity. For more than a decade, machine learning has already been employed to reduce costs involved in processing and reviewing document collections subject to discovery production requests. Machine learning has made great leaps forward in recent years as large-scale computing has enabled the development of large language models, deep learning, and generative pre-trained transformers (GPT). As law firms weigh the benefits, risks, costs and new opportunities of these technologies, it would be useful to examine how litigants have responded to issues such as transparency, explainability, and adversarial negotiations over the parameters limiting the space within which a machine learning system may operate. Incorporating these new technologies may not be straightforward, especially when placed in the context of the legal process frameworks that place a high value on human expertise.

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