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Job Aid or Job Slayed? The Perceived Impact of Artificial Intelligence on Medical and Legal
Work

by

Jessica L. Helsten

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

Of

Executive Doctorate in Business

In the Robinson College of Business

Of

Georgia State University

GEORGIA STATE UNIVERSITY

ROBINSON COLLEGE OF BUSINESS

2019

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ACCEPTANCE

This dissertation was prepared under the direction of the *JESSICA L. HELSTEN* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ACKNOWLEDGEMENTS

To my family, friends, colleagues, classmates, and professors who cheered me on and especially to Carrington and Greg who supported and encouraged me along this journey and who sacrificed to allow me to achieve this goal.

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ABSTRACT

Job Aid or Job Slayed? The Perceived Impact of Artificial Intelligence on Medical and Legal

Work

by

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May 2019

Chair: Nathan Bennett

Major Academic Unit: Executive Doctorate in Business

Advances in technology are traditionally seen as beneficial to society. According to the *MIT Technology Review* article “How Technology is Destroying Jobs,” this was the case until the year 2000 (Rotman, 2013). Previous research (e.g., Walter & Lopez, 2008) has shown a relationship between perceived threat to professional autonomy and intention to use technology among physicians. This study expands the scope of highly-skilled, well-educated professionals to consider the perceptions of artificial intelligence held by physicians and lawyers and the relationship these perceptions have with perceived job displacement and perceived impact to professional autonomy. The purpose of this quantitative research study was to make an empirical contribution to the body of knowledge studying job displacement and professional autonomy by presenting the findings of survey data from 75 physicians specializing in radiology and 75 lawyers specializing in contract, transactional, and mergers and acquisitions law in the United States. Survey results suggest that physicians, for the most part, perceive artificial intelligence as a job aid; whereas, the majority of lawyers perceive that artificial intelligence will have a neutral impact on their jobs. Practical implications of the survey results are to provide education for lawyers regarding the benefits of using artificial intelligence for contract review and creation, e-

discovery, fraud detection, and due diligence performance. For physicians, who are more comfortable with the idea of using artificial intelligence in their work, more applications for human plus machine partnerships should be further explored.

INDEX WORDS: Artificial intelligence, Physicians, Lawyers, Job displacement, Professional autonomy

I CHAPTER I: INTRODUCTION

Economists and others have debated how technological progress since the Industrial Revolution of the 1700s has affected workers (Mokyr, Vickers, & Ziebarth, 2015). In his article “How Technology is Destroying Jobs,” Rotman (2013) argues that technological innovations have been replacing jobs since the Industrial Revolution. In 1900, nearly half (41 percent) of American workers and 22 million animals were engaged in labor intensive agricultural work on rural farms (Dimitri, Effland, & Conklin, 2005). Due to technological innovation—the mechanization of farms and the use of tractors in place of work animals—the percentage of Americans working in agriculture dropped to only 2 percent by the year 2000 (Dimitri et al., 2005). Technological innovations during the Industrial Revolution displaced some workers such as the artisan weaver with his hand loom or the agricultural worker on the rural farm but introduced new jobs in the manufacturing sector such as the factory worker in a textile mill—that is, the growth of the manufacturing sector drove the creation of new jobs and increased employment, absorbing workers displaced by textile and farm mechanization (Ford, 2015).

Similar to what happened to the agricultural sector and partly due to increasing automation, the proportion of Americans employed in manufacturing has dropped from 30 percent in the “Golden Age of Capitalism” (1945 to the mid-1970s) to around 8 percent today (Holzer, 2017; Rotman, 2013). Fortunately, around this same postwar period, the service sector burgeoned, providing manufacturing workers, displaced by factory mechanization, opportunities for employment (Ford, 2015). According to Fuchs (1965), the US was the first country to become a “service economy” with more than fifty percent of the working populace not participating in the production of tangible goods. The service sector, as characterized by Fuchs

(1965), is comprised of “trade, finance, insurance, and real estate; personal, professional, business, and repair services; and general government” (p.344).

Four years later in 1969, Drucker invented the term “knowledge worker” to define these service economy workers as people who apply “productive work ideas, concepts and information rather than manual skill or brawn” (Reinhardt, Schmidt, Sloep, & Drachsler, 2011, p. 158).

Knowledge workers are highly educated professionals who use their intelligence and creative thinking abilities to solve problems. They must constantly stay abreast of the latest information and techniques in their respective fields (Reinhardt et al., 2011). Hagel III, Brown, and Davison (2010) describe traditional knowledge workers as “engineers, scientists, architects, educators, researchers, coders, [and] artists” (p. 1).

Since the year 2000, there has been a widening gap between job growth and productivity in the US (Rotman, 2013). Rotman (2013), using real median household income as a proxy for job growth and real gross domestic product (GDP) per capita as a proxy for productivity, defines the gap between job growth and productivity as the gap between these two measures. The graph below from the Federal Reserve Bank of St. Louis illustrates the trend of GDP per capita and median household income growth, adjusted for inflation, for the years 1993 to 2016. The trend lines show that in the year 2000, the gap between GDP and median income was 7.1. That gap had increased to 30.4 by the year 2014 and reversed course slightly to 25.7 by 2016. Median income decreased slightly between 2000 and 2014 as GDP increased, showing greater income inequality, i.e., increases in productivity were not translating to increases in income for middle-income Americas (Irwin, 2014).

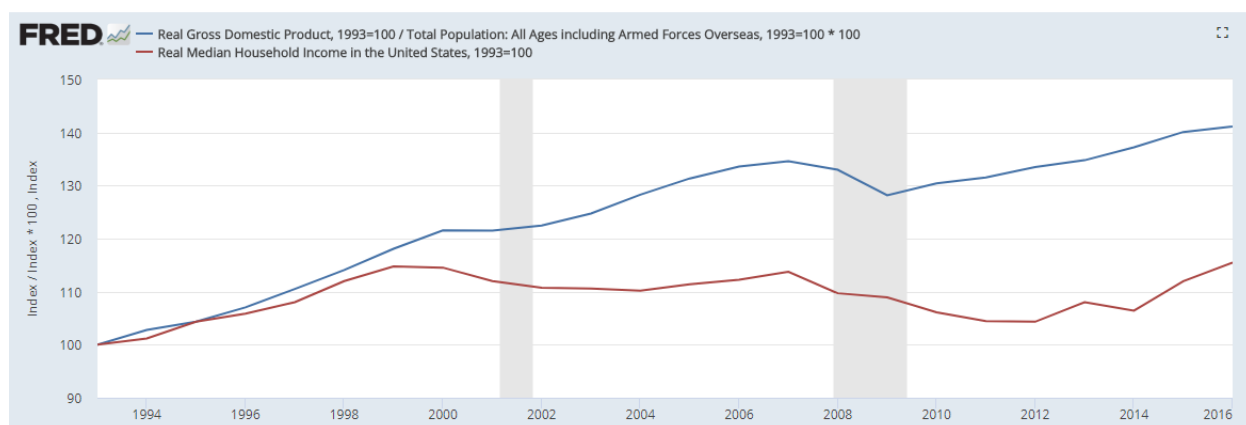


Figure 1: GDP per capita and median household income growth

Source: Federal Reserve Bank of St. Louis¹

In the US, knowledge workers with a professional degree have the lowest unemployment (1.6 percent) and the highest mean usual weekly earnings (\$1,745)². A June 2018 article in *The Atlantic* refers to physicians, lawyers, . . . and assorted other professionals as the “New American Aristocracy,” “the 9.9 Percent,” with a net worth of between \$1.2 million and \$10 million (Stewart, 2018, p. 1). Holders of professional degrees, such as physicians and lawyers, earn the most over their work-life, an average of \$4.4 million (Longley, 2017). Physicians and lawyers enjoy double-digit returns on education investment over their working lifetimes, 16-18 percent and 23 percent, respectively (Weeks & Wallace, 2002).

In 1955, Dartmouth math professor John McCarthy coined the term artificial intelligence (AI) (Brynjolfsson & McAfee, 2017). Today, an assortment of “applications and techniques fall under the broad umbrella of AI, ranging from neural networks to speech/pattern recognition to genetic algorithms to deep learning” (Jarrahi, 2018, p. 578). These applications and techniques represent a substantial opportunity in business not seen since the advent of smartphones and tablet computers (McCracken, 2017). Unlike traditional software that must be physically

¹ https://fred.stlouisfed.org/graph/?graph_id=195323#

² https://www.bls.gov/emp/ep_table_001.htm

reprogrammed to adjust to the changing requirements of the user community, artificial intelligence technology is able to learn and adapt without reprogramming (Brynjolfsson & McAfee, 2017). “AI can drink from the firehose” (Hall, 2016, p. 24) digesting and analyzing vast amounts of both structured and unstructured data to form hypotheses with accompanying confidence levels (Arruda, 2017; T. A. Patel et al., 2017; Tsang et al., 2017). As an example, IBM’s Watson Health is an AI clinical decision support system with the advertised capability of using patient information to assist physicians in diagnosing disease and recommending treatment (Rotman, 2013; Tsang et al., 2017). As an example of the application of IBM Watson Health, “oncologists at Memorial Sloan-Kettering Cancer Center in New York are using IBM’s Watson supercomputer to provide chronic care and cancer treatment diagnostics by accessing knowledge from 600,000 medical evidence reports, two million pages of text from 42 medical journals, and 1.5 million patient records and clinical trials in the field of oncology” (MGI, 2013, p. 45).

The job tasks available to human workers have changed since the Industrial Revolution and the debut of automation. Up to now, the impact has primarily affected manual laborers; however, in the 21st century, technology has developed to a level of sophistication where it increasingly mimics the cognitive capabilities of humans. In the past, education was a means for workers to acquire new skills, stemming the destructive effects of technological substitution for human labor (Frey & Osborne, 2017).

Due to their ability to use their intelligence and creative thinking abilities to solve problems, well-educated professionals have been relatively immune to the onslaught of job automation. The combination of “information inflation” (big data); low-cost, high-power computing; and recent advances in artificial intelligence show this is changing (Barry, 2013). Weissmann (2012) describes lawyer as “just another breed of knowledge worker . . . paid to

research, analyze, write, and argue—not unlike an academic, a journalist, or an accountant. So when software comes along that's smarter or more efficient at those tasks than a human with a JD, it spells trouble” (p. 1). Along the same lines, Ford (2015) predicts that more education and training will not necessarily ensure effective protection against job automation in the coming years, unlike in the past..

Nearly 40 years ago, Schrank (1981, p. 133) asked the question, “What will happen to blue-collar workers when robots take over their jobs? Will there be nothing left but some old clothes on a peg and a few mementos kept around in museums of the industrial era?” In the 21st century, with the latest advances in artificial intelligence threatening the job tasks of knowledge workers, what will happen to white-collar workers? What sector will arise to absorb those workers displaced by ubiquitous artificial intelligence? Ford (2015) warns that a significant number of college-educated, white-collar workers will find that their jobs are in the crosshairs as predictive algorithms and automation are swiftly advancing in capability. Knowledge workers, whose jobs were mostly unaffected by the first and second Industrial Revolutions, may find their jobs changing substantially, if not entirely eliminated by recent advances in automation and artificial intelligence.

With this knowledge of the changing job landscape for highly-educated knowledge workers, the purpose of this study is to conduct an examination into the attitudes of skilled professionals toward artificial intelligence with regard to job displacement and professional autonomy. To that aim, the objective of this research is to study the perceived impact of artificial intelligence on job tasks for knowledge workers such as physicians³ and lawyers. This is an

³ The term physician is used to denote medical doctor throughout the paper to distinguish from lawyers who may also be doctors, that is, Doctor of Jurisprudence. Physician is also the most commonly used term in the literature.

important question because physicians and lawyers make huge investments in their education and training and expect lucrative returns on those investments.

To control for specialization, only radiologists and lawyers specializing in contract, transactional, and mergers and acquisitions law were studied since these specializations are most impacted by current capabilities of AI technology that is available on the market. As evidence of this claim, Enlitic, a startup company committed to “revolutionizing diagnostic healthcare,” has developed an AI system that analyzes medical images such as CT scans and x-rays for malignant tumors with 50 percent more accuracy in a comparison test against three human radiologists (The Economist, 2016). Expert advice doling supercomputers are an example, thanks to AI, of how jobs that are now being performed by highly trained white-collar workers can be automated. “[A] highly trained and specialized radiologist may now be in greater danger of being replaced by a machine than his own executive assistant” (The Economist, 2016). AI began encroaching on the domain of legal professionals when in 2010, “machine learning [a subset of AI] reached a point where software could, with guidance from senior lawyers, effectively take over the time-intensive task of legal discovery, in which one party in a lawsuit combs through its documents to determine what it must show to the other side before trial. This is a job [task] that junior lawyers, paralegals, or—increasingly—less expensive contract lawyers had traditionally done . . .” (Byrnes, 2015, p. 64).

Will a medical or law degree be worth the time and financial investment if AI can perform the same job tasks more quickly and cheaply? What specializations will be worth pursuing in the medical and legal fields that will value both human and machine contribution? In the next chapter follows a review of previous literature on technological advancements and the impact to humans as well as human perceptions of the new technology applied in their jobs.

II CHAPTER II: LITERATURE REVIEW

The aim of the literature review that follows is to give context for this study by reviewing the impact of past technological innovations and exploring the convergence of modern technological capabilities with highly-skilled human professional job tasks leading to the question of how knowledge workers perceive the impact of AI on their job tasks. The review that follows is delineated into five sections: “man vs. machine,” “the knowledge worker in danger,” “enter the supercomputer,” “artificial intelligence and projected job displacement,” and “previous literature on perception of technology and knowledge workers.” The first section, man vs. machine, discusses the advent of machines and automation and the impact this has had on job tasks performed by humans over the past 300 years. The second section, the knowledge worker in danger, discusses the attributes of knowledge workers and the latest advances in technology that could potentially replace knowledge worker job tasks. The third section, enter the supercomputer, discusses artificial intelligence offerings in the medical and legal spheres. The fourth section, artificial intelligence and projected job displacement, discusses two studies that looked at the job tasks of physicians and lawyers and compared them to current technologies to calculate what percentage of job tasks could be automated. The final section, previous literature on perceptions of technology and knowledge workers, presents findings from a qualitative study that analyzed fingerprints technicians’ perceptions of the automation of their job tasks, as well as, the transformational impact of automation on pilots.

II.1 Man vs. Machine

Humans have been leveraging their physical might and complex mental capabilities for millennia to perform tasks necessary to their survival and prosperity. The Industrial Revolution of the 1700s introduced a competitor to human might, the machine. This time in human history

has been dubbed the First Machine Age by Brynjolfsson and McAfee (2014, pp. 7-8); a time when “[m]achines take away the dirty and dangerous—industrial equipment from looms to the cotton gin, relieves humans of onerous manual labor” (Davenport & Kirby, 2015, p. 64). Human brawn or muscle power was steadily replaced with machine power (Brynjolfsson & McAfee, 2014).

Davenport and Kirby (2015) delineate three automation eras—the first of which is the Industrial Revolution. The second era, the 20th century, is described as the era in which “[m]achines take away the dull—automated interfaces, from airline kiosks to call centers, relieve humans of routine service transactions and clerical chores” (Davenport & Kirby, 2015, p. 64). The third era, the 21st century, is described as the era in which “[m]achines take away decisions—intelligent systems, from airfare pricing to IBM’s Watson, make better choices than humans, reliably and fast” (Davenport & Kirby, 2015, p. 64). Brynjolfsson and McAfee (2014) call this third era the Second Machine Age, marked by the advent of computers and other advanced technologies capable of replacing human mental power.

II.2 The Knowledge Worker in Danger

Knowledge workers are professionals that “think for a living” (Megill, 2013). The bulk of knowledge worker job tasks have required skills that, up until recently, a computer could not match. These abstract tasks are characteristic of professional, managerial, and technical jobs and require highly-educated and analytical workers capable of inductive reasoning, skillful communication, and the ability to achieve mastery of a domain (Autor, 2015).

Job tasks performed by knowledge workers were protected by Polanyi’s Paradox, i.e., if a human cannot describe the steps to break down a task in such a way that can be programmed, then a computer cannot perform the task (Autor, 2015). Recent advances in artificial intelligence

overcome Polanyi's Paradox and, in turn, are replacing job tasks that heretofore could only be done by knowledge workers. The extraordinary progress in artificial intelligence over the past few decades is often attributed to Moore's Law (Bruun & Duka, 2018). Moore's Law was named for Gordon Moore who in 1965 observed that computer processing capability doubles every 18 months. "[I]f we set the starting point as the 1960s, 32 doublings each at an interval of 18 months, brings us to the start of the twenty-first century . . . after which point exponential growth yields explosive results" (Bruun & Duka, 2018, p. 2). Current artificial intelligence technology is capable of consuming vast amounts of data and making connections between data points; it can be trained to understand, form hypotheses, and learn from experience, like humans (MGI, 2013). "[H]ighly trained analysts and other so-called knowledge workers are seeing their work circumscribed by decision-support systems that turn the making of judgments into a data-processing routine" (Carr, 2014, p. 17).

II.3 Enter the Supercomputer

International Business Machines (IBM) Watson is arguably the most high-profile AI on the market today. IBM Watson is an advanced supercomputer marrying AI and complex analytical software to perform as a "question answering" machine. In 2011 on the popular game show *Jeopardy!*, IBM Watson competed against "two of the best knowledge workers" in the game show industry (Brynjolfsson & McAfee, 2014, p. 16) and won. In the years following that victorious moment, the application of IBM Watson has expanded into several industries including the medical and legal fields with Watson Health and ROSS Intelligence, respectively. IBM's vision for Watson Health, is to take the enormous amounts of personal and academic health data that is generated every single day and, using IBM Watson, uncover insights that will enable better patient care (Lorenzetti, 2016). ROSS Intelligence, powered by IBM Watson, is

being used for job tasks traditionally performed by human lawyers e.g., legal research, searching legislation and case law to answer questions (Mills, 2016; Remus & Levy, 2015; Sobowale, 2016). ROSS Intelligence uses the natural language processing and cognitive computing capabilities of IBM Watson to forecast the result of court cases, assess legal precedents, and suggest materials for case preparation (Nelson & Simek, 2016).

Interest in the application of AI in the medical field dates to the early 1970s when researchers turned to the technology to examine challenging problems in medicine and biology (V. L. Patel et al., 2009). From the early 1970s to mid-1980s, expert systems, an approach to AI that uses the knowledge of domain experts to create computer programs specific to a field or industry, were used in bank loan screening, medical, and sales applications. By the mid-1990s, however, expert systems fell out of favor as these systems came to be perceived as slow and clumsy (Foote, 2016). In 1991, the Institute of Medicine set the goal that computers would be used by all physicians in their practices by the year 2000 to improve patient care (Evans, 2016). By 2001, 18 percent of physicians were using electronic health record (EHR) systems (BHR, 2015). From the 1970s to today, considerable progress has been made as computing speed and memory has increased exponentially and as the use of EHRs has expanded (Bennett & Hauser, 2013).

An exhaustive list of all of the AI clinical decision support systems (CDSS) on the market today is beyond the scope of this study; however, some examples are as follows: Enlitic is a startup company that develops CDSS products that use deep learning, a subset of machine learning, to help diagnose cancer by processing medical data, images, patient histories and EHRs (Brynjolfsson & McAfee, 2017). MOTTE is an AI CDSS developed by researchers at Houston's Methodist Hospital. The Natural Language Processing (NLP)-capabilities of MOTTE were

employed to examine mammography and pathology reports from 543 patients with invasive breast cancer. The AI was able to detect breast cancer subtypes with 99 percent accuracy, 30 times faster than it would take a clinician to manually review the data (T. A. Patel et al., 2017).

In the legal profession, AI is being used in contract review and creation, document search for information relevant to litigation (e-discovery), fraud detection, and due diligence performance (Mangan, 2017). Lawgeex is a software platform which uses machine learning to compare an uploaded new contract to its database of similar contracts, learning as it performs the review (Mangan, 2017). The software provides a report, noting where the contract deviates from similar contracts (Abramowitz, 2016). LawGeex (2018) conducted a study comparing the performance of 20 US lawyers experienced in contract review and corporate law against that of the LawGeex AI in recognizing issues in five non-disclosure agreements (NDAs). The results of the study were that the AI had a 6 percent error rate versus a 15 percent error rate for the human lawyers. RAVN ACE sifts through documents to identify and extract items of interest in minutes—a task it would take a human days to complete (Mangan, 2017). The accuracy of RAVN ACE was tested by using it to analyze a deal that had already been completed. RAVN ACE failed to identify some of the items in the contracts that were identified by the human contract reviewers; conversely, it identified some items that had previously been missed (Mangan, 2017). UK investigators from the Serious Fraud Office used RAVN ACE to review documents pertaining to a bribery and corruption case involving Rolls-Royce. It took just 50 days for RAVN ACE to review 30 million documents (Ambrogi, 2017). The software COIN (Contract Intelligence) was used by JP Morgan for document review. COIN took seconds to perform the task which would have taken legal aides 360,000 hours to perform (Winick, 2018).

From the above examples, it is clear that AI has a foothold in both medical and legal professions. It is already changing practice and getting better every year. Who knows how far it can go? Will it replace part, or all of the work humans currently do today? The next section tells us what economists and business consultants have to say on the matter.

II.4 Artificial Intelligence and Projected Job Displacement

Much of the current literature by economists and business consultants on artificial intelligence and automation focuses on job elimination by 21st century technologies. According to the US Council of Economic Advisers' February 2016 annual report, an estimated 4 percent of jobs that pay more than \$40 an hour could be automated. Frey and Osborne (2017) studied 702 occupations from the US Department of Labor's O*NET and listed the probability of computerization of those jobs. Frey and Osborne found that, in the next decade or two, 47 percent of jobs in the US are at high-risk of being displaced by automation. Figure 2 below depicts their findings.

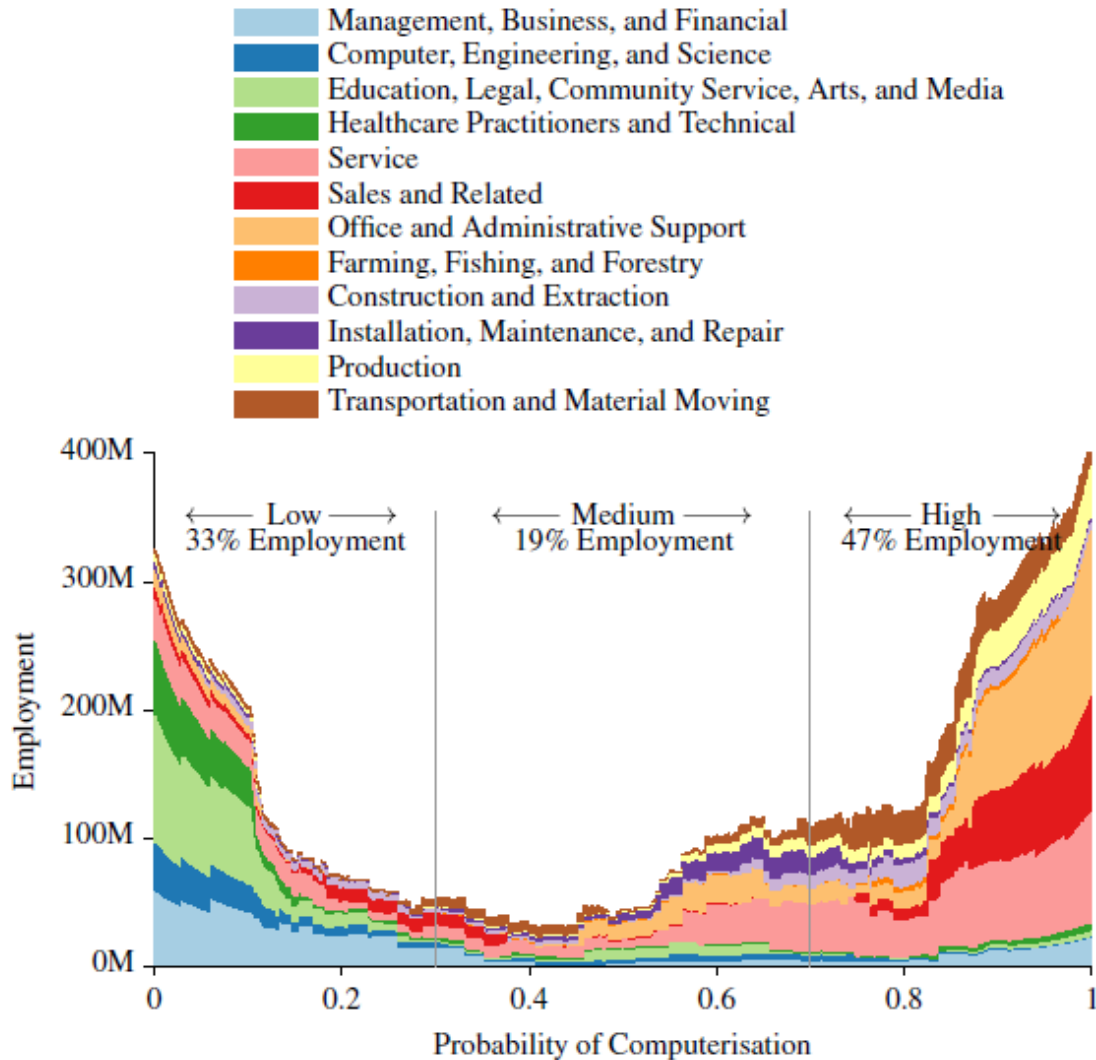


Figure 2: Employment affected by computerization

Source: Frey and Osborne (2017).

Knowledge worker jobs had a low susceptibility to computerization according to their study. The probability of physicians' and surgeons' jobs being replaced by technology was 0.42 percent and these professions ranked 15th least likely to be replaced out of 702 occupations. The probability of lawyers' jobs being replaced by technology was 3.5 percent and this profession ranked 115th least likely to be replaced out of 702 occupations. Telemarketers had the highest probability of being replaced by technology.

Remus and Levy (2015) analyzed data from Sky Analytics, a company that provides data broken down by tasks and number of hours spent on tasks from invoices for law firms. Remus and Levy categorized the tasks based on the current ability of computer technology to perform the tasks. They found that 13 percent of job tasks performed by lawyers could be automated in the next five years. An analysis by the McKinsey Global Institute of data from the O*NET database of the US Department of Labor found that almost a quarter of the work performed by physicians and lawyers could be automated using current technology (MGI, 2017).

II.5 Previous Literature on Perceptions of Technology and Knowledge Workers

If AI can potentially perform up to 25 percent of their job tasks, it is important to know how physicians and lawyers perceive this encroachment. People's perceptions of technology's usefulness correlate positively with their willingness to accept and use this technology (F. D. Davis, 1989). As an example from the literature, C. J. Davis and Hufnagel (2007) studied novice and expert occupationally certified fingerprint technicians (FPT) and their reactions to and perceptions of the automation of their work and the altering of their work processes. According to their findings, novice FPTs liked the new system since it flattened the expertise-based hierarchy and put them on an even playing field with the experts. Use of the National Automated Fingerprint Identification System (NAFIS) offered the novices new challenges. It also gave them a more significant and visible role in the process of identifying criminals. The expert FPTs, however, perceived the new system as a black box since the algorithms it employed to match crime scene fingerprints with suspected criminals were proprietary, which also made testifying in court difficult since the experts could not explain how the system came to the conclusions that it did. The expert FPTs felt the NAFIS reduced their creativity since they were bound by the rules of the system and felt that the system reduced their autonomy by dictating how their work should

be done. Additionally, the system presented challenges to enculturation since part of the apprenticeship activities that were used to train novices in the past could now be done by the system.

Other perceptions of the transformational impact of technology on knowledge workers can be found in aviation. Carr (2014, p. 52) writes:

“[T]he job of the commercial pilot has lost its aura of romance and adventure. The storied stick-and-rudder man, who flew by a sense of feel, now belongs more to legend than to life. On a typical passenger flight these days, the pilot holds the controls for a grand total of three minutes—a minute or two when taking off and another minute or two when landing. What the pilot spends a whole lot of time doing is checking screens and punching in data. ‘We’ve gone from a world where automation was a tool to help the pilot control his workload,’ observes Bill Voss, president of the Flight Safety Foundation, ‘to a point where the automation is really the primary flight control system in the aircraft.’ Writes aviation researcher and FAA advisor Hemant Bhana, ‘As automation has gained in sophistication, the role of the pilot has shifted toward becoming a monitor or supervisor of the automation.’”

II.6 Summary

Over the last 300 years, machines have steadily replaced human laborers in performing job tasks. A race to gain ever-increasing levels of education characterized the 20th century as technological advances led to the replacement of manual laborers with machines and the creation of highly skilled white-collar jobs (Frey & Osborne, 2017). These white-collar jobs are under siege by the latest advances in artificial intelligence in the 21st century; will well-educated professionals lose their privileged status as sole purveyors of esoteric knowledge and expertise

and the control, autonomy, and economic benefits that status confers (Z. Walter & Lopez, 2008)? Or, will AI, augment these professionals' specialized skills and training, benefiting client and professional, alike? Economists and business consultants have taken an empirical approach by analyzing job task characteristics and the current capabilities of AI, thereby offering predictions of what the percentage of the impact could be of the latest advances in technology on job tasks. What is missing from the literature is the perceptions of those impacted. Until we begin to understand the perceptions of the impact of artificial intelligence held by professionals, an important piece of the job displacement and professional autonomy discussion will be missing. Until we understand their perspective, we will not know if efforts will need to be made to make professionals more aware of the benefits of using AI to increase their acceptance and adoption of the technology or if new entrants into the professions will need to be steered into other specializations not displaced by AI. Will AI adoption in the medical and legal professions follow the same trajectory as that of fingerprint reading or the aviation industry, removing autonomy and relegating physicians and lawyers to "monitors or supervisors of automation?" This study attempts to address the lacuna in the current literature of perceptions of the impact of artificial intelligence technology on job tasks in the medical and legal fields. In the next chapter, the research question, hypotheses, theoretical underpinnings, and research model for this study are presented.

III CHAPTER III: MODEL DEVELOPMENT

The advent of predictive analytics produced by AI machine learning algorithms presents a real threat to the sort of specialized knowledge work that distinguishes and protects professionals such as physicians and lawyers. On the medical front, AI has a potential impact on any medical specialty that involves pattern recognition, e.g., analysis of medical images, to make medical diagnoses. “Deep learning [a subset of AI] is agnostic to the type of image data used and could be adapted to other specialties [other than dermatology], including ophthalmology, otolaryngology, radiology and pathology” (Esteva et al., 2017, p. 118). Esteva et al. (2017) compared the diagnostic performance of an AI referred to as a CNN (convolutional neural network) against 21 human experts (dermatologists). The CNN was trained with 129,450 clinical images and was found to be just as accurate as the board-certified dermatologists in classifying skin cancer. Liu et al. (2017), using a CNN to detect tumors, found that the CNN had a detection rate of 92.4 percent accuracy compared with a rate of 73.2 percent for human pathologists.

On the legal front, AI is reducing the opportunities of junior lawyers to get on-the-job training through document review (Winick, 2018); this has been the traditional means by which junior lawyers have learned the craft (Simpson, 2016). A study comparing results from an exhaustive manual review of documents by human lawyers and technology-assisted review processes, which used AI to sort relevant (responsive) from non-relevant (non-responsive) documents, found that the technology-assisted processes achieved superior results (Grossman & Cormack, 2011). According to Frey and Osborne (2017), tasks that have been the domain of contract and patent lawyers are gradually being taken on by complex algorithms. Need for reviewing attorneys may wane as predictive coding, AI machine learning software that determines the relevance of discovery documents, makes discovery more efficient and cost effective (Barry, 2013).

How will well-educated professionals fair in the 21st century, the third era of automation, in which machines take away decisions, making reliable and fast choices better than humans (Davenport & Kirby, 2015)? A 2015 Altman Weil survey⁴ of legal professionals at the level of managing partner or chair asked their opinion as to whether they could foresee a Watson-like system replacing jobs in their firm over the next five to ten years. The survey results revealed that 35 percent of respondents could foresee replacement of first year associates, 19.2 percent replacement of second- and third-year associates and 6.4 percent replacement of fourth through sixth year associates. Without these entry level positions, how will young lawyers gain the experience to become seasoned professionals? Whereas AI may be a job-killer in the legal field, it can alternatively be construed as a much-needed job aid in the medical field. Contrary to conventional wisdom, more experience is inversely related to quality of patient care due, in part, to outdated knowledge and less inclination to adhere to the latest advances in technology, standards of practice and clinical care guidelines (Choudhry, Fletcher, & Soumerai, 2005; Tsugawa, Newhouse, Zaslavsky, Blumenthal, & Jena, 2017). A 2017 study of physicians who treat hospitalized patients found that years of experience, as measured by number of years out of residency, is positively correlated with patient mortality (Tsugawa et al., 2017). AI could put the most current treatment options at physicians' fingertips, providing consistent quality of care to patients, regardless of the physicians' years of experience. Application of AI to data from EHRs of Centerstone Research Institute patients resulted in 30-35 percent more favorable patient outcomes at 50 percent of the cost compared to the traditional treatment-as-usual case-rate/fee-for-service model of healthcare (Bennett & Hauser, 2013). The following research hypotheses were tested on the basis of the findings from the above-mentioned studies:

⁴ http://www.altmanweil.com/dir_docs/resource/1c789ef2-5cff-463a-863a-2248d23882a7_document.pdf

Hypothesis 1a (H1a): Perceived performance of AI is positively correlated with perceived job displacement associated with AI.

Hypothesis 1b (H1b): Profession and specialization moderate the relationship between perceived performance of AI and perceived job displacement associated with AI such that the relationship is much stronger for lawyers.

Z. Walter and Lopez (2008), studying physicians and their perceptions of electronic medical records and clinical decision support systems, contend that professionals such as physicians and lawyers enjoy privileged status as sole purveyors of esoteric knowledge and expertise. This status grants these professionals autonomy, control of resources, and economic benefits. The results of their study found a statically significant, negative relationship between perceived threat to professional autonomy and behavioral intention to use the technology.

Far more research has been conducted on physicians and technology acceptance (see Aggelidis & Chatzoglou, 2009; Chau & Hu, 2002; Egea & Gonzalez, 2011; Holden & Karsh, 2010; Melas, Zampetakis, Dimopoulou, & Moustakis, 2011; Z. Walter & Lopez, 2008; Yi, Jackson, Park, & Probst, 2006; Zoltan & Chapanis, 2007) than on lawyers and technology acceptance. A study of attitudes towards computers of certified public accountants, pharmacists, lawyers and physicians found that, in general, lawyers had the least experience with computers. Lawyers were also “most likely to describe computers with negative terms, such as depersonalizing, formal and difficult” (Zoltan & Chapanis, 2007, p. 55). Innovation has not come swiftly to the legal profession because it is bound by tradition and holds a privileged status in society (Simpson, 2016). “[T]he working practices of lawyers ... have not changed much since the time of Charles Dickens” (Susskind & Susskind, 2015, p. 67). Z. Walter and Lopez (2008) suggest examining the relationship between perceived threat to professional autonomy and

behavioral intention to use technology among other types of professionals as an area for further research. Perhaps there is an opportunity to fill a gap in the body of knowledge. From the above-mentioned previous studies' findings, the following hypotheses were developed and tested:

Hypothesis 2a (H2a): *Perceived performance of AI is positively correlated with perceived impact to professional autonomy.*

Hypothesis 2b (H2b): *Profession and specialization moderate the relationship between perceived performance of AI and perceived impact to professional autonomy such that the relationship is much stronger for lawyers.*

The theoretical underpinnings for the current study borrow from the technology acceptance model (TAM) and the job characteristics model (JCM). TAM is the most widely used model in information systems research to explain and predict system-user acceptance, adoption, and usage (Aggelidis & Chatzoglou, 2009; Gefen, Karahanna, & Straub, 2003; Gregor, 2006; Schepers & Wetzels, 2007; Tong, Wong, & Lee, 2015). TAM was developed by Fred Davis in 1989 as an outgrowth of the theory of reasoned action (TRA) from social psychology (see Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975) to address a shortage of reliable and validated measurement scales for explaining and predicting computer technology usage behavior (F. D. Davis, 1989; F. D. Davis, Bagozzi, & Warshaw, 1989). From a practical perspective, the ability to explain and predict system usage with validated measures provides benefits to many stakeholders such as managers, vendors and end-users in deciding on the best system and system features as well as maximizing productivity gains from user acceptance and usage of said system (F. D. Davis, 1989).

Davis' original 1989 TAM model consisted of two independent variables: perceived usefulness and perceived ease of use and one dependent variable: system use/behavioral

intention to use. The validity and reliability of the questionnaire and measurement scales used by Davis have been confirmed by several replication studies (see Adams, Nelson, & Todd, 1992; Hendrickson, Massey, & Cronan, 1993; Segars & Grover, 1993; Subramanian, 1994; Szajna, 1994). A subsequent study by F. D. Davis et al. (1989) found that TAM explained 47 percent of the variance in behavioral intention to use technology.

The extended technology acceptance model (TAM2) was created by Venkatesh and Davis to gain further understanding of user technology acceptance and adoption (Venkatesh & Davis, 2000). “TAM2 incorporates additional theoretical constructs spanning social influence processes (subjective norm, voluntariness, and image) and cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use)” (Venkatesh & Davis, 2000, p. 187).

As another extension to TAM, Gefen et al. (2003) examined knowledge-based familiarity. They defined familiarity as the “experience with the what, who, how, and when of what is happening” (Gefen et al., 2003, p. 63). Research supports the idea that older workers prefer what is familiar to them and have greater difficulty adapting to change (Morris & Venkatesh, 2000). Morris and Venkatesh (2000) hypothesized that age is negatively correlated with both short-term and long-term system usage. The results of their study suggest that there is a negative correlation between age and system usage in the short and long term. Ahmad et al. (2011) found age to have a statistically significant effect on the TAM construct relationships.

Yi and Hwang (2003) extended TAM by incorporating the intrinsic motivation variable from social psychology, self-efficacy, to predict the usage of web-based information systems. The researchers identified two aspects of self-efficacy: general computer self-efficacy and application-specific self-efficacy. Prior research studies found application-specific self-efficacy

to have a more powerful effect. The findings from Yi and Hwang (2003) showed a significant, positive influence of application-specific self-efficacy on system usage. Kwon, Choi, and Kim (2007) examined how the individual characteristic, self-efficacy, affected the user acceptance of GPS-based technology. The results of their study were mixed, that is, self-efficacy had a positive effect on perceived ease-of-use but no effect on perceived usefulness.

Research studies by Schepers and Wetzels (2007) and Ahmad et al. (2011) considered the moderating effects of such factors as type of respondents, type of technology, culture, gender and age. A meta-analysis of 63 TAM research studies found that type of respondent was a significant moderator of the relationship between perceived usefulness and behavioral intention to use technology (Schepers & Wetzels, 2007).

Chau and Hu (2002) applied the technology acceptance model (TAM) and the theory of planned behavior (TPB) in studying the usage intentions of telemedicine technology of 400+ physicians. The study chose the perceived usefulness, perceived ease of use and behavioral intention constructs from TAM. The final construct from the original TAM, system adoption/usage, was excluded from the research model, the researchers citing previous studies as justification for behavioral intention as a dependent variable. The results of their study found that TAM explained 42 percent of the variance in behavioral intention, whereas, TPB explained 37 percent. Z. Walter and Lopez (2008), also studying physicians' perceptions of technology applied in the medical field, introduced a new construct from the job characteristics model to the technology acceptance model specific to the concerns of highly-skilled professionals—perceived threat to professional autonomy.

From the preceding literature it is clear that AI is a threat to certain specializations in the medical and legal fields; that is, tests of job task performance of AI technology in the medical

and legal fields show that AI performs on par or superior to humans. The perceptions held by physicians and lawyers in affected specializations of the disruptive impact of AI is unknown. TAM and JCM have been used in the past by researchers to examine the perceptions of physicians of technologies such as telemedicine and clinical decision support systems. This study extends that research by applying TAM to physicians' perceptions of AI while also adding a less researched professional in this space, the lawyer, for contrast and comparison. Building on the above-cited examples of studies that have used TAM and JCM to understand perceptions of technology, the below research model was constructed to understand the perceptions held by physicians and lawyers with regard to job displacement and impact to professional autonomy associated with AI.

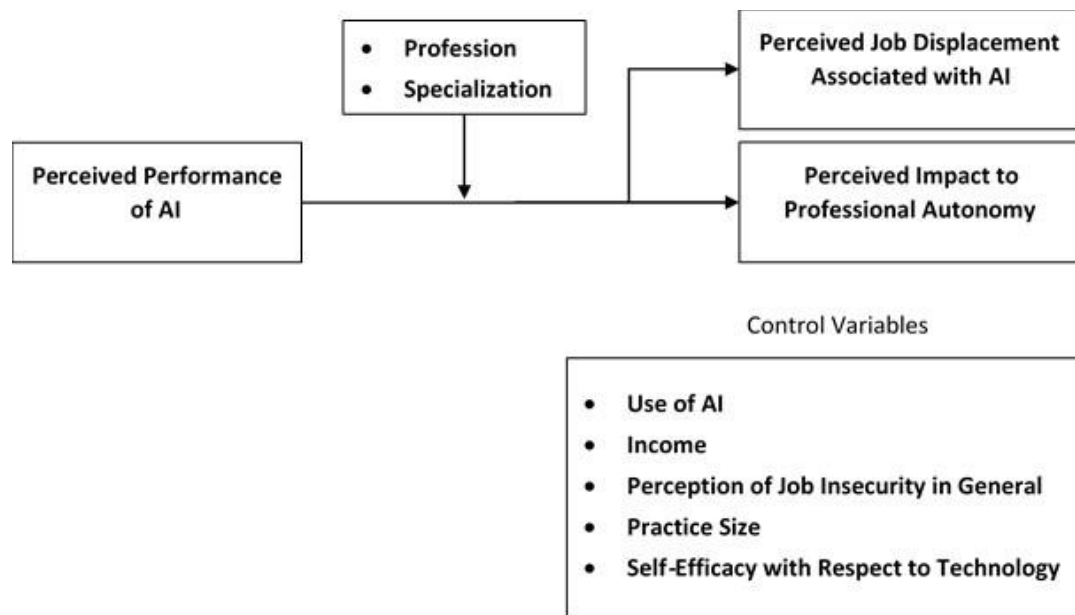


Figure 3: Research model

Source: Inspired by (Agarwal & Prasad, 1998; Chao & Kozlowski, 1986; F. D. Davis, 1989; F. D. Davis et al., 1989; Gefen et al., 2003; Venkatesh & Davis, 2000; Z. Walter & Lopez, 2008; Yi & Hwang, 2003).

Figure 3 above depicts the model for this research study, borrowing one construct from the technology acceptance model (TAM): perceived usefulness, two constructs from the extended technology acceptance model (TAM2): job relevance and output quality, and two

constructs from the job characteristics model: job displacement and autonomy. Researchers Z. Walter and Lopez (2008) added autonomy, a construct from the job characteristics model (JCM) to TAM in their study of physicians' acceptance of clinical decision support systems, renaming the construct: perceived threat to professional autonomy; this study will refer to this construct as perceived impact to professional autonomy.

The following TAM and TAM2 constructs related to hands-on experience have been excluded from the model: perceived ease of use, subjective norm, voluntariness, image, and result demonstrability, since survey participants of this study will not be given access to any AI systems. Additionally, in the Chau and Hu (2002) study of physicians, perceived ease of use did not have a statistically significant influence on behavioral intention to use technology. This finding coincides with Venkatesh and Davis (2000) who found that perceived ease of use is a less consistent predictor of behavioral intention across studies and over time. Subjective norm was also not found to have a statistically significant influence on behavioral intention. In the final analysis, Chau and Hu (2002) found perceived usefulness to be the most important factor influencing the acceptance of telemedicine technology by physicians. The salience of perceived usefulness to physician acceptance was confirmed by Yi et al. (2006).

As mentioned above, Chau and Hu (2002) did not find a statistically significant relationship between perceived ease of use and subjective norm with behavioral intention to use technology for physicians. The research findings of Chau and Hu (2002) also seem to suggest that the social influence constructs from TAM2 such as subjective norm, voluntariness, and image might not be applicable to physicians, as physicians are more likely to come to their own conclusions and thus may rely less on the opinions of others. Yi et al. (2006), in their study of

personal digital assistant (PDA) acceptance of physicians, also found the relationship between perceived ease of use and behavioral intention to be non-significant.

Familiarity, self-efficacy, age and years in practice have been studied in the literature in relation to the traditional TAM measures. Perception of job insecurity has been studied in the literature in relation to the traditional JCM constructs. To control for other explanations of the perceptions of the survey participants toward AI, these variables were measured in this study.

Perceived performance of AI is the independent variable in this study. Job relevance and output quality are antecedents to the variable perceived usage in the TAM2 model. In this study, the three variables were averaged to represent the measure perceived performance of AI. There is precedent in the literature. Chiu, Tsai, and Fan Chiang (2013) studied the relationship between job characteristics and attitudes toward web-based continuing learning (AWCL) among nurses. In their study, AWCL was an average of TAM variables perceived usefulness, perceived ease of use, affection, and behavior.

The moderating effects of profession and specialization were also examined in this study. The variables use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology were control variables. Demographic information on the survey participants, such as, age, employment status, gender, location of practice, race, and years in practice was also captured. The variables for this study are defined in Table 1. Since the current study asks questions pertaining to participants' opinions, all dependent and independent variables in the study are prefaced with the word "perceived."

Table 1: Variable summary

Variable	Definition
<i>Dependent Variables (DV)</i>	
Perceived Job Displacement	The extent to which an individual believes that his or her job security is at risk (Chao & Kozlowski, 1986).
Perceived Impact to Professional Autonomy	The extent to which an individual believes that using a specific system would reduce his or her control over the conditions, processes, procedures or content of his or her work (Z. Walter & Lopez, 2008).
<i>Independent Variable (IV)</i>	
Perceived Performance	An average of perceived job relevance, perceived output quality and perceived usefulness.
<i>Subscales of Perceived Performance</i>	
Perceived Job Relevance	The extent to which an individual believes that the AI technology applies to his or her job (Venkatesh & Davis, 2000).
Perceived Output Quality	The extent to which an individual believes that the AI technology will perform tasks well (Venkatesh & Davis, 2000).
Perceived Usefulness	The extent to which an individual believes that using AI technology would improve the performance of his or her job (F. D. Davis, 1989).
<i>Moderator(s)</i>	
Profession	The vocation of the survey participant, either physician or lawyer.
Specialization	The area of professional expertise of the survey participant, limited to radiology, contract law, transactional law or mergers & acquisitions law.
<i>Control Variables (CV)</i>	
Use of AI	How recently has the survey participant been exposed to AI in a work setting.
Income	The survey participant's income.
Perception of Job Insecurity in General	The feeling or overall concern of an employee that his or her job is at risk or that he or she is likely to experience involuntary job loss in the not too distant future (Schumacher, Schreurs, Van Emmerik, & De Witte, 2016).
Practice Size	The number of workers with the same specialization in the survey participant's practice.
Self-Efficacy with Respect to Technology	An individual's judgement of his or her ability to perform a specific task (Yi & Hwang, 2003).
<i>Demographic Variables</i>	
Age	The number of years since the survey participant was born.
Employment Status	The degree to which the survey participant participates in the workforce.

Gender	The gender, male or female, with which the survey participant identifies.
Location of Practice	The geographical region in the US in which the survey participant practices their specialization.
Race	The one or more ethnicities with which the survey participant identifies.
Years in Practice	The number of years since the survey participant received their highest degree related to their specialization (Z. Walter & Lopez, 2008).

To conclude this chapter, the technology acceptance model (TAM) is the most commonly used model in information systems research to explain and predict technology usage behavior. Modifications and extensions to the model have continued since its original debut. Several studies researching technology acceptance of physicians have been done; far fewer have studied lawyers. Chau and Hu (2002) caution against generalizing their findings of the technology acceptance of physicians to other professionals. The current study presents an opportunity to gain more insights into the perceptions held by physicians and lawyers of artificial intelligence technology in the medical and legal fields by testing hypotheses derived from the literature that examine the relationships between perceived performance of AI and perceived job displacement associated with AI and perceived performance of AI and perceived impact to professional autonomy. The next chapter presents a discussion of the method used to test these hypotheses.

IV CHAPTER IV: METHOD

A survey panel, recruited by Qualtrics, was used in this study to gather a sample of radiologists and lawyers specializing in contract, transactional, or mergers and acquisitions law in the US. Use of survey panels for online surveys has become increasingly popular in social science research (Boas, Christenson, & Glick, 2018). Opt-in online panels present an advantage over conventionally sourced samples to survey difficult to reach populations such as white-collar workers (Brandon, Long, Loraas, Mueller-Phillips, & Vansant, 2014). “When the research question requires more narrowly focused samples with specific expertise and domain knowledge, the researcher can buy the contact information for these subpopulations and solicit responses directly” (Brandon et al., 2014, p. 9). S. L. Walter, Seibert, Goering, and O'Boyle (2016) compared response patterns and relationships among variables from studies using samples from online panel sources (e.g., StudyResponse, MTurk, Qualtrics) versus conventionally sourced samples. The researchers’ results suggest that the response patterns, as well as the relationships between variables, are similar for online panels and conventionally sourced samples. According to a study conducted by Boas et al. (2018), Qualtrics provides the most demographically representative sample compared with other online recruiters such as Facebook and Amazon Mechanical Turk.

Study participants were selected from among those who had volunteered or registered to participate in Qualtrics online surveys and were recruited based on profession, specialization, gender and years in practice. Participants were compensated for their participation in the study based on their panelist agreement with Qualtrics. Due to the fact that the sample for this study was not a probability sample, but rather was based on respondents who initially opted-in to participate in the panel, calculation of the estimates of sampling error was not possible (AAPOR, 2018).

A total of 316 invitations to take part in the study were sent to physicians specializing in radiology. The target gender distribution of radiologists for recruitment was 75 percent male and 25 percent female to match the percentage of active male and female radiologists in the US (AAMC, 2015) so that a representative sample of radiologists was achieved. To solicit a range of years in practice, Qualtrics added a recruitment filter of 23 radiologists with 0-5 years in practice, 29 radiologists with 6-15 years in practice and 23 radiologists with 16+ years in practice at my request. The online survey was attempted by 166 (53 percent) physicians; 147 surveys were completed, resulting in an initial response rate of 47 percent. Of the 147 surveys that were completed, 72 were from physician respondents (49 percent) who were ultimately ineligible from participation for choosing a specialization other than radiology. After the data quality checks, the effective sample size was 75 for physician radiologists.

Panel demographic data was not available to identify contract, transactional, and mergers and acquisitions lawyers a priori. As a result, invitations to participate were extended to 1,122 lawyers in order to be certain to include the necessary number of specialists required. The target gender distribution of lawyers for recruitment was 64 percent male and 36 percent female to match the population of male and female lawyers in the US (ABA, 2018) so that a representative sample of male and female lawyers was achieved. At my request and to solicit a range of years in practice, Qualtrics added a recruitment filter of 23 lawyers with 0-5 years in practice, 29 lawyers with 6-15 years in practice and 23 lawyers with 16+ years in practice to solicit a range of years in practice to ensure variability in the data for this variable. The online survey was attempted by 771 (69 percent) lawyers; 634 surveys were completed, representing a response rate for lawyers of 57 percent. Of the 634 surveys, 559 were from lawyer respondents (88 percent) who were screened out from analysis for choosing a specialization other than contract, transactional, or

mergers and acquisitions law. After the data quality checks, the effective sample size was 75 for lawyers specializing in contract, transactional, or mergers and acquisitions law.

The age of physician survey respondents ranged between 29 and 79 years, the mean age for physicians was 47.4 years ($SD = 12.2$ years). The age range for the target sample of lawyer specializations—contract, transactional, and mergers and acquisitions law—was 24 to 78 years, the mean age was 45.5 years ($SD = 14.1$ years). Additional demographic data for the survey respondents is summarized in Table 2 below.

Table 2: Demographic characteristics for the total sample ($N = 150$)

Variable	Values	Physician Demographics		Lawyer Demographics	
		<i>N</i>	%	<i>N</i>	%
Employment Status	Employed full time	68	90.7	67	89.3
	Employed part time	6	8.0	6	8.0
	Unemployed looking for work			1	1.3
	Retired	1	1.3	1	1.3
	Total	75	100.0	75	100.0
Gender	Male	62	82.7	46	61.3
	Female	13	17.3	29	38.7
	Total	75	100.0	75	100.0
Income	Less than \$99,999	6	8.0	23	30.7
	\$100,000 to \$199,999	2	2.7	28	37.3
	\$200,000 to \$299,999	13	17.3	18	24.0
	\$300,000 to \$399,999	20	26.7	5	6.7
	\$400,000 to \$499,999	15	20.0	1	1.3
	\$500,000 or more	18	24.0		
	Missing	1	1.3		
Total	75	100.0	75	100.0	
Location of Practice	Northeast	24	32.0	18	24.0
	Midwest	16	21.3	14	18.7
	South	15	20.0	20	26.7
	West	20	26.7	21	28.0
	Other			2	2.7
	Total	75	100.0	75	100.0
Practice Size	1	1	1.3	13	17.3
	2–5	5	6.7	21	28.0
	6–10	14	18.7	16	21.3
	11–30	19	25.3	11	14.7
	31–100	31	41.3	6	8.0
	101+	5	6.7	8	10.7
	Total	75	100.0	75	100.0

Race	White/Non-Hispanic	52	69.3	65	86.7
	Black or African American	2	2.7		
	Asian	9	12	1	1.3
	Latino/Hispanic	3	4	5	6.7
	Prefer not to identify	6	8		
	More than one	3	4	4	5.3
	Total	75	100.0	75	100.0
Specialization	Contract Law			52	69.3
	Mergers and Acquisitions Law			6	8.0
	Transactional Law			17	22.7
	Radiology	75	100.0		
	Total	75	100.0	75	100.0
Years in Practice	0-5 years	16	21.3	17	22.7
	6-15 years	31	41.3	33	44.0
	16+ years	28	37.3	25	33.3
	Total	75	100.0	75	100.0

Since this research study involves human subjects, approval was sought from Georgia State University's Institutional Review Board (IRB) before participants were contacted. After IRB approval was received, emails were sent to the sample of potential participants. The emails contained a link to the online survey. Prospective participants were made aware that the purpose of the study was to analyze their views on medical and legal artificial intelligence technology and that they were being invited to participate because of their professional status as a physician or lawyer. Participants were compensated according to their panelist agreement. They were informed that participation is completely voluntarily and that their responses will be kept confidential. Participants were provided with the author's contact information should they have questions or concerns about the study and were thanked for their participation. Overall, the survey was estimated to take about 10 minutes to complete.

The survey consisted of 35 questions. Participants were asked their opinions of the job displacement, impact to professional autonomy, job relevance, output quality and usefulness of AI on a 7-point Likert scale. To control for alternative explanations for the survey respondents' perceptions, the survey included questions on use of AI, income, perception of job insecurity in

general, practice size, and self-efficacy with respect to technology. Additionally, survey participants were asked demographic questions, such as, age, employment status, gender, location of practice, race, and years in practice. The measures for this study are further described below:

IV.1 Dependent Variables

Perceived job displacement. Participants were asked five items adapted from Chao and Kozlowski (1986) for the construct: perceived job displacement. The items were measured on a seven-point Likert scale and read as follows: “AI will reduce my job security”; “I fear that someday I will lose my job to AI”; “AI will make me less useful as a worker”; “The introduction of AI will slowly displace radiologists/contract lawyers/transactional lawyers/mergers and acquisitions lawyers”; “The use of AI will mean less and less work for radiologists/contract lawyers/transactional lawyers/mergers and acquisitions lawyers.” Responses were averaged to form a total score for perceived job displacement ($\alpha = .90$).

Perceived impact to professional autonomy. Participants were asked two items for perceived impact to professional autonomy adapted from the Z. Walter and Lopez (2008) perceived threat to professional autonomy construct. The items and scales read as follows: “Using AI may decrease my control (professional discretion) over the day-to-day decisions I make on the job” (1 = Extremely Unlikely, 7 = Extremely Likely); “Using AI may decrease my professional discretion over course of action decisions.” Responses were averaged to form a total score for perceived impact to professional autonomy ($\alpha = .90$).

IV.2 Independent Variable

Perceived performance. The perceived performance construct is a composite of perceived job relevance, perceived output quality and perceived usefulness.

Perceived job relevance. Participants were asked two items adopted and adapted from Venkatesh and Davis (2000) measuring perceived job relevance. The items were measured on a seven-point Likert scale and read as follows: “I can foresee usage of AI being important in my job”; “I can foresee usage of AI being relevant in my job”.

Perceived output quality. Participants were asked two items adopted and adapted from Venkatesh and Davis (2000) measuring perceived output quality. The items and scales read as follows: “The quality of the output I would get from AI technology would be high” (1 = Extremely Unlikely, 7 = Extremely Likely); “I would have no problem with the quality of the AI technology’s output.”

Perceived usefulness. Participants were asked four items adopted and adapted from F. D. Davis (1989) measuring perceived usefulness. The items and scales read as follows: “Using AI in my job would improve my performance” (1 = Extremely Unlikely, 7 = Extremely Likely); “Using AI in my job would increase my productivity”; “AI in my job would enhance my effectiveness”; “I would find AI useful in my job.” Responses were averaged to form a total score for perceived performance ($\alpha = .96$).

IV.3 Moderators

Profession. Participants were asked about their profession. Profession is coded: 0 = physician, 1 = lawyer.

Specialization. Participants were asked about their primary professional area of specialization. Participants were provided a list of specializations from which to choose (0 = radiology, 1 = contract law, 2 = mergers and acquisitions law, 3 = transactional law).

IV.4 Control Variables

Use of AI. Participants were asked one question gauging their use of AI in their work setting to control for alternative explanations for perceived job displacement and perceived impact to professional autonomy. This question was adapted from a Reaction Data (2018) research report on machine learning in medical imaging. The question and scale read as follows: “When does your office/firm plan to adopt AI?” (1 = I don’t think we will ever use AI, 6 = We’ve been using AI for 6 or more months).

Income. Participants were given six income categories from which to choose.

Perception of Job Insecurity in General. Participants were asked one item for perception of job insecurity adapted from Schumacher et al. (2016). The item and scale read as follows: “I feel insecure about the future of my job” (1 = Strongly Disagree, 7 = Strongly Agree).

Practice Size. Participants were asked an open-ended question regarding how many other physicians or lawyers of their same specialization were in their practice. This data was then aggregated into six categories.

Self-Efficacy with Respect to Technology. Participants were asked one item for self-efficacy with respect to technology (Krause, 2017; Yi & Hwang, 2003). The item and scale read as follows: “I feel confident in my ability to use technology” (1 = Strongly Disagree, 7 = Strongly Agree).

Demographics. Participants were asked demographic questions regarding their age, employment status, gender, location of practice, race, and number of years in practice. Table 3 below describes the demographic variables for this study.

Table 3: Description of demographic variables

Variable	Type	Values
Age	Ratio	Calculated as the current year minus the survey participant's birth year.
Employment Status	Nominal	1 = Employed full time, 2 = Employed part time, 3 = Unemployed looking for work, 4 = Unemployed not looking for work, 5 = Retired, 6 = Student, 7 = Disabled
Gender	Nominal	0 = male, 1 = female
Location of Practice	Nominal	1 = Northeast, 2 = Midwest, 3 = South, 4 = West, 5 = Other
Race	Nominal	1 = White/Non-Hispanic, 2=Black or African American, 3=American Indian or Alaska Native, 4=Asian, 5=Native Hawaiian or Pacific Islander, 6=Latino/Hispanic, 7=Middle Eastern, 8=European/Mediterranean, 9=Other, 10=Prefer not to identify, 11=More than one
Years in Practice	Ratio	Calculated as the current year minus the year the survey participant received their highest degree related to their specialization.

The study data collection occurred between July and August 2018. The survey was conducted using Qualtrics' online survey software licensed by Georgia State University. The results of the analysis of the data collected will be delivered in the next chapter.

V CHAPTER V: RESULTS

The results chapter is presented in the following manner: First, the purpose of the study is revisited. Second, univariate data is examined to assess the central tendency, variability, and distribution of the survey responses. Third, correlational results are looked at to see if patterns in the data support hypothesized variable relationships, as well as other interesting relationships in the data. Fourth, additional variables are depicted that provide a richer understanding of how physicians and lawyers perceive AI. Lastly, the results of the tests of hypotheses are presented.

The purpose of this study was to investigate attitudes towards AI with respect to job displacement and professional autonomy held by physicians specializing in radiology and lawyers specializing in contract, transactional, or mergers and acquisitions law. Use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology were also examined to see whether these variables affected the survey participants' attitudes.

Table 4 below shows the descriptive statistics, including skewness and kurtosis, for the measures. Mean-item scores were calculated for the composite variables perceived job displacement, perceived impact to professional autonomy, and perceived performance by summarizing the scores for the individual items and dividing by the number of items in the respective scale.

Since parametric testing was used to test the hypotheses, skewness and kurtosis were calculated to test the normality of the data. The shape of the data distribution impacts statistical tests and estimators differently, according to DeCarlo (1997), for instance, skew appears to affect means more than kurtosis does and kurtosis affects tests of variances and covariances more than skew does. A skewness or kurtosis value of zero indicates that the data is normally distributed (Miles & Shevlin, 2010). The absolute values of skewness for perceived job displacement,

perceived impact to professional autonomy, income, perception of job insecurity in general, practice size, and profession were less than 1.0. For perceived performance, use of AI, self-efficacy with respect to technology, and specialization the skewness was greater than 1.0, but less than 2.0. The skewness statistics for the above-mentioned variables indicate that the data are not normally distributed but are within acceptable limits for parametric testing; that is, the data do not depart significantly from normality (Miles & Shevlin, 2010).

The absolute values of kurtosis for perceived job displacement, perceived impact to professional autonomy, perceived performance, use of AI, perception of job insecurity in general, years in practice, and specialization were all within acceptable limits, below 1.0 (Miles & Shevlin, 2010). The absolute values of kurtosis for income and practice size were between 1.0 and 2.0, which might have an effect on parameter estimates according to Miles and Shevlin (2010); however, Miles and Shevlin also say, “In the more complex case of regression analysis, kurtosis can affect the parameter estimates as well as the standard errors, but the effects are usually small unless the kurtosis is severe” (p. 81). The absolute values of kurtosis for self-efficacy with respect to technology and profession were 4.0 and 2.0, respectively. These variables were not transformed to compensate for the kurtosis since it was felt that the effect on the regression analysis to test the hypotheses would be small.

Table 4: Descriptive statistics for the target sample (N = 150)

Measure	Valid	Missing	Mean	Median	Mode	S.D.	Skewness		Kurtosis		Min.	Max.
							Statistic	Std. Error	Statistic	Std. Error		
1. Perceived Job Displacement	150	0	3.19	2.90	2.60	1.41	.56	.20	-.28	.39	1.00	7.00
2. Impact to Prof. Autonomy	150	0	4.11	4.00	4.00	1.51	-.38	.20	-.63	.39	1.00	7.00
3. Perceived Performance	150	0	4.96	5.29	5.00	1.40	-1.10	.20	.90	.39	1.00	7.00
4. Age	150	0	46.45	43.00	35.00	13.16	.63	.20	-.58	.39	24.00	79.00
5. Employment Status	150	0	1.15	1.00	1.00	.55	5.28	.20	32.47	.39	1.00	5.00
6. Use of AI	150	0	2.43	2.00	2.00	1.42	1.27	.20	.95	.39	1.00	6.00
7. Gender	150	0	.28	.00	.00	.45	.99	.20	-1.03	.39	.00	1.00
8. Income	149	1	3.15	3.00	3.00	1.63	.31	.20	-1.01	.39	1.00	6.00
9. Location of Practice	150	0	2.54	3.00	1.00	1.20	.01	.20	-1.39	.39	1.00	5.00
10. Job Insecurity in General	150	0	3.17	2.50	2.00	1.79	.55	.20	-.92	.39	1.00	7.00
11. Practice Size	150	0	3.59	4.00	5.00	1.48	-.15	.20	-1.02	.39	1.00	6.00
12. Race	150	0	2.31	1.00	1.00	2.86	2.18	.20	3.47	.39	1.00	11.00
13. Self-Efficacy with Tech.	150	0	5.99	6.00	6.00	1.02	-1.73	.20	4.11	.39	2.00	7.00
14. Years in Practice	150	0	17.42	14.00	10.00	13.03	.79	.20	-.41	.39	.00	52.00
15. Profession	150	0	.50	.50	.00 ^a	.50	.00	.20	-2.03	.39	.00	1.00
16. Specialization	150	0	.77	.50	.00	.97	1.24	.20	.56	.39	.00	3.00

Note: a. Multiple modes exist. The smallest value is shown

Tests of means were run to explore variance in the dependent variables by different groups. A comparison of the mean scores for the dependent variable, perceived impact to professional autonomy, showed that lawyers, $M = 3.8$, more so than physicians, $M = 4.4$, felt that it was less likely that AI would decrease their professional discretion over the day-to-day and course of action decisions made on the job. The difference in means was significant at the $p < .05$ level, the effect size, eta squared, was .04. As further evidence of the differences in perceptions of physicians and lawyers, here are some quotes taken from the free-response question. As a frame of reference, the survey ended with a free-response question to allow survey participants to provide qualitative commentary as further explanation of their perceptions of AI and the impact to their jobs. The question asked, “If AI were implemented in your office/practice, do you think your job would change? If yes, in what way(s)?” The following quotes are representative of lawyers and physicians:

“Some of the more administrative tasks (looking up contracts in a database, determining risk management positions) would be made much easier. It would certainly make me more efficient. I think that AI would eliminate some clerical positions, but not many.” (63-year-old, female transactional lawyer) *“[M]y job would require that each agreement be screened by AI. The results of such screening would likely increase the reliability and thoroughness of my review, but would not be likely to affect the substance of my advice to clients. AI would enable me to review documents more quickly, thereby reducing response time to client requests. I don't foresee any likelihood that my job would ever be eliminated by AI, because I don't think AI will be proficient enough to enable assignment of my job to a paralegal or legal secretary. For example, although I am only given agreements to review, sometimes I see the need for a patent search or other legal issues that AI might miss.”* (78-year-old, male contract lawyer) *“would be*

forced to use it, and justify disagreement with AI findings.” (70-year-old, male retired radiologist) “AI is horrible. If someone wants his or her scan read by AI instead of a radiologist, that’s a person who will have a terrible outcome. AI may be beneficial as a final check but my experience is that AI misses the important diagnoses far more often than it catches it, and it serves as a legal liability as well.” (35-year-old, male radiologist)

Turning to the other dependent variable, perceived job displacement associated with AI, an analysis by age groups, millennials vs. mid-career as defined in Gallup-Northeastern (2018), showed that the 44 millennial respondents (ages 19-36), $M = 3.7$, were more likely to think that AI would reduce their job security or that they would one day lose their job to AI than the 56 mid-career respondents (ages 37-51), $M = 3.1$. The difference in means was significant at the $p < .05$ level, the effect size, eta squared, was .04. A further analysis by generational group—Baby Boomers (ages 54-72), Generation X (ages 38-53), and Millennials (ages 21-37)—showed that the 38 Baby Boomer respondents, $M = 2.7$, were less likely to think that AI would reduce their job security or that they would one day lose their job to AI than the 47 Millennials, $M = 3.6$. The difference in means was significant at the $p < .05$ level, the effect size, eta squared, was .05. The following quotes, taken from the free-response survey question, are representative of Baby Boomers and Millennials, respectively:

“I am self-employed and I do not anticipate that having AI compare a given contract with other contracts would be a useful tool nor would it replace me.” (58-year-old, female contract lawyer) “I do not anticipate a significant change.” (67-year-old, male radiologist) “I think it would take years before artificial intelligence would be to the point of seriously affecting my job. I think when we implement it, it will be helpful in a similar way as smartphones have been helpful. Over the years though, I can see it taking more and more jobs in a lot of jobs including

those in contract law. I'm hopeful that we can find a way to keep people employed even as AI gets smarter and cheaper. That said, I could see myself and others in my field being forced to change careers in ten or so years.” (32-year-old, female contract lawyer) *“I am [an] interventional radiologist so that part of my job would not suffer. At the beginning for diagnostic radiologists, AI should help and make the job easier, however as AI gets better and makes less errors that require human correction, AI will eventually replace radiologists.”* (36-year-old, male radiologist)

Analysis of perceived job displacement associated with AI by profession revealed differences between physicians, $M = 3.3$, and lawyers, $M = 3.0$, however the differences were not statistically significant. Although this study is focused on cross-profession (physicians vs. lawyers) comparisons of perceptions of the impact of AI, since additional data was available for lawyers, a within-profession comparison was possible. As mentioned earlier in the methods section on p. 29, in addition to the 75 survey responses from the targeted group of lawyers specializing in contract, transactional, or mergers and acquisitions law, 559 surveys were completed from nontargeted lawyers specializing in other areas of law. This additional data allowed for the testing of the hypothesis that those lawyers most likely to be at risk of job displacement due to AI (the target group) would perceive more of an impact to their jobs and professional autonomy from AI versus the nontarget group. To accomplish this, a test of means was run to explore variance in the dependent variables by the target and nontarget lawyer groups.

A comparison of the mean scores for the first dependent variable, job displacement associated with AI, showed that the target group of lawyers, $M = 3.0$, did perceive more job displacement associated with AI than the nontarget group as a whole, $M = 2.9$; however, the difference was not significant. Comparing the means of the target group to individual

specializations revealed significant differences to the means of lawyers specializing in family and juvenile law, intellectual property law, and sports and entertainment law. The 50 lawyers specializing in family and juvenile law, $M = 2.6$, the 31 intellectual property lawyers, $M = 2.5$, and the nine sports and entertainment lawyers, $M = 2.3$, all felt that it was less likely that AI would displace their jobs. The differences in means were significant at the $p < .05$ level, the effect sizes, η^2 s, were .03, .04, and .04, respectively.

A comparison of the mean scores for the second dependent variable, perceived impact to professional autonomy, showed that there was not a significant difference in perceptions between the target group of lawyers, $M = 3.8$, and the nontarget group as a whole, $M = 3.9$. Comparing the means of the target group to individual specializations revealed significant differences to the means of lawyers specializing in health law. The 21 lawyers specializing in health law, $M = 4.5$, felt that it was more likely that AI would decrease their professional discretion over the day-to-day and course of action decisions made on the job. The difference in means was significant at the $p < .05$ level, the effect size, η^2 , was .03.

To assess the convergent validity of the three composite variables: perceived performance of AI, perceived job displacement associated with AI, and perceived impact to professional autonomy, a confirmatory factor analysis was run. The factor loadings from the confirmatory factor analysis are shown in Table 5 below. According to Hair, Black, Babin, and Anderson (2009) for the sample size of this study, $N = 150$, factor loadings of 0.45 and above are considered to be significant. In the research model for the current study, all factor loadings of the items were greater than 0.60, with most of the factor loadings above 0.80. Therefore, all constructs in the model had adequate convergent validity. Question 15, "I would have no problem with the quality of the AI technology's output," had a factor loading of .61 and was

removed from the calculation of the composite variable for perceived performance. The wording of the question may have been confusing to the survey respondents.

Table 5: Factor loadings of items (N = 150)

Measure	1	2	3
1. PP 1	.89		
1. PP 2	.90		
1. PP 3	.93		
1. PP 4	.91		
1. PP 5	.89		
1. PP 6	.61		
1. PP 7	.90		
1. PP 8	.86		
2. PJD 1		.75	
2. PJD 2		.85	
2. PJD 3		.81	
2. PJD 4		.90	
2. PJD 5		.82	
3. PIA 1			.89
3. PIA 2			.89

Note: PP = Perceived Performance of AI, PJD = Perceived Job Displacement Associated with AI, and PIA = Perceived Impact to Professional Autonomy.

Table 6 below shows correlations and Cronbach's α reliabilities. Preliminary analyses compared control variables (use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology) with the main variables of interest (profession, specialization, perceived performance of AI, perceived job displacement associated with AI and perceived impact to professional autonomy).

Table 6: Correlations and Cronbach's α for the target sample ($N = 150$)

Measure	1	2	3	4	5	6	7	8	9	10
1. Perceived Job Displacement	(.90)									
2. Perceived Impact to Prof. Autonomy	.51**	(.90)								
3. Perceived Performance	.17*	.16*	(.96)							
4. Use of AI	-.10	.02	.40**	-						
5. Income	.03	.21**	.19**	.21**	-					
6. Perception of Job Insecurity in General	.39**	.29**	.11	-.03	-.02	-				
7. Practice Size	-.02	.01	.26**	.27**	.31**	-.05	-			
8. Self-Efficacy with Technology	.02	.12	.30**	.17*	.07	.01	.08	-		
9. Profession	-.10	-.20**	-.31**	-.33**	-.65**	.03	-.40**	-.24**	-	
10. Specialization	-.12	-.17*	-.19*	-.24**	-.45**	.00	-.31**	-.19*	.79**	-

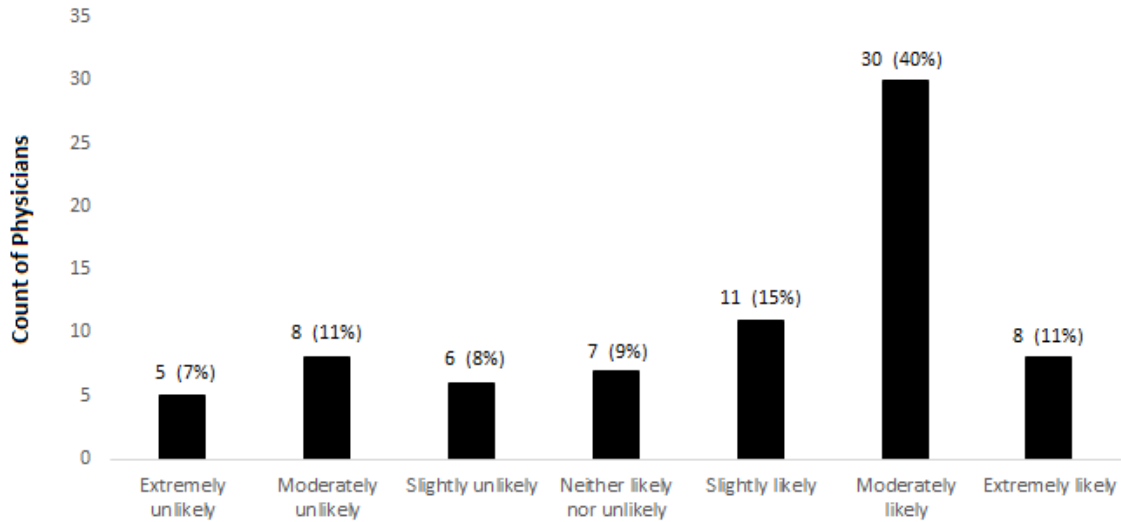
Notes: Cronbach's α reliabilities appear in the diagonals in parentheses; profession is coded (0 = physician, 1 = lawyer); specialization is coded (0 = radiology, 1 = contract law, 2 = M&A law, 3 = transactional law)

** . Correlation is significant at the 0.01 level (1-tailed).

* . Correlation is significant at the 0.05 level (1-tailed).

The data from Table 6 show that the relationships between practice size and either of the dependent variables was not statistically significant. There were also not statistically significant relationships between income, profession, specialization and the dependent variable: perceived job displacement. There were, however, statistically significant relationships between income, profession, specialization and the other dependent variable: perceived impact to professional autonomy. Income and perceived impact to professional autonomy were positively correlated ($r = .21, p < .01$). Profession and perceived impact to professional autonomy were moderately correlated such that physicians saw more of an impact ($r = -.20, p < .01$). Specialization and perceived impact to professional autonomy were moderately correlated as well ($r = -.17, p < .05$).

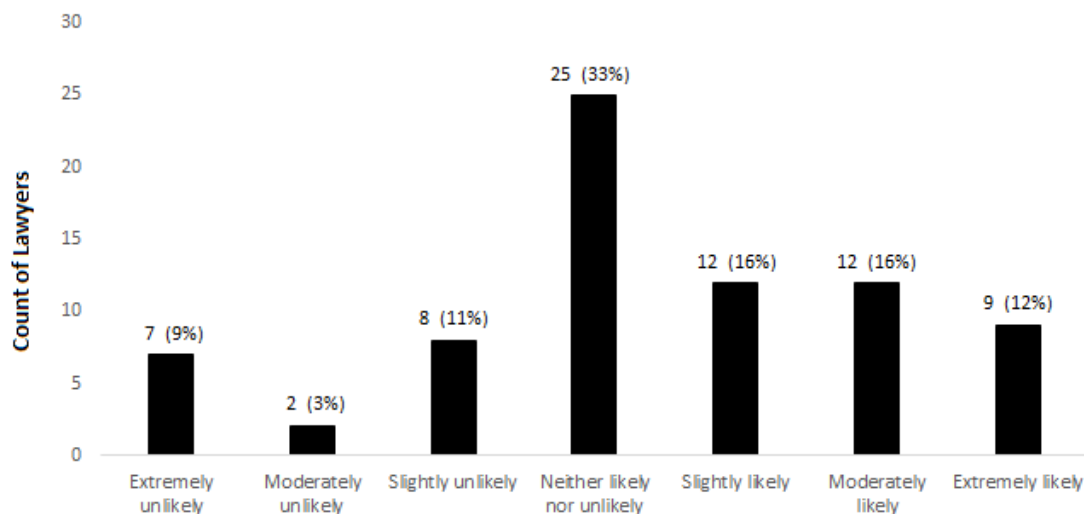
To gain further insights into the perceptions held by physicians and lawyers of the future impact of AI on their specializations, respondents were asked the question: "Given the pace of advances in AI in your field, how likely would you be to recommend your specialization as a career with a future to someone interested in pursuing this specialization?" Figure 4 shows the responses for radiologists; 40 percent responded moderately likely.



Notes: Specialization = Radiology

Figure 4: Likelihood of recommending radiology as a specialization with a future ($N = 75$)

Conversely, as figure 5 shows below, 33 percent of lawyers specializing in contract law, transactional law, or mergers and acquisitions law responded neither likely nor unlikely. This may suggest that radiologists are optimistic about the future of their specialization even with AI's impact; whereas, lawyers are less certain of the future of their specializations.

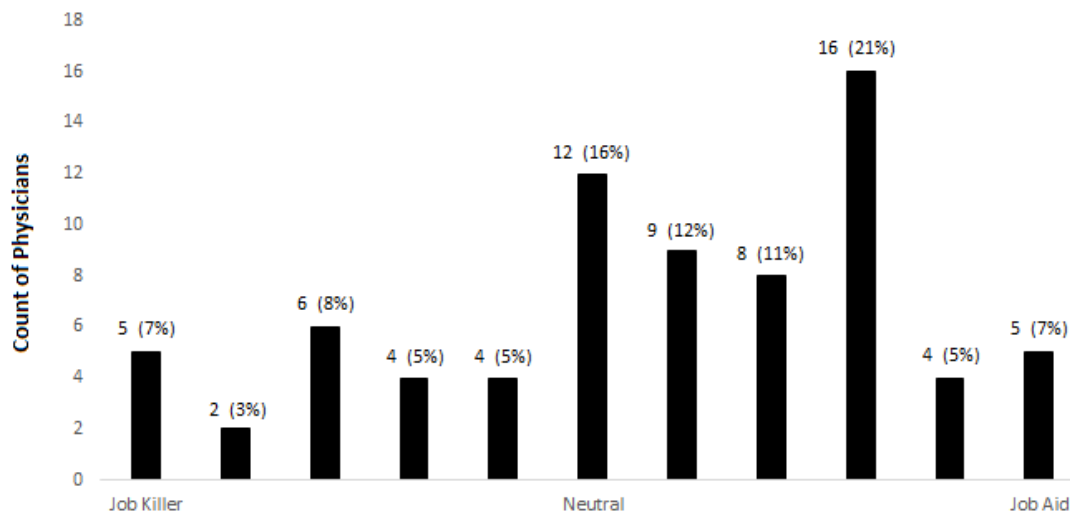


Notes: Specializations = Contract, transactional and mergers & acquisitions law

Figure 5: Likelihood of recommending contract law, transactional law, or mergers and acquisitions law as a specialization with a future (N = 75)

The differences in the perceptions of physicians and lawyers may be further explained by their responses to the question, “At the end of the day, I think AI is going to . . .” The answer option was a slider bar which contained three nodes: “be a job killer,” “have a neutral impact” or “be a job aid.” Figure 6 below shows the responses for radiologists. In general, radiologists were bullish. Comments from the free-response question from radiologists who saw AI as a job aid were as follows:

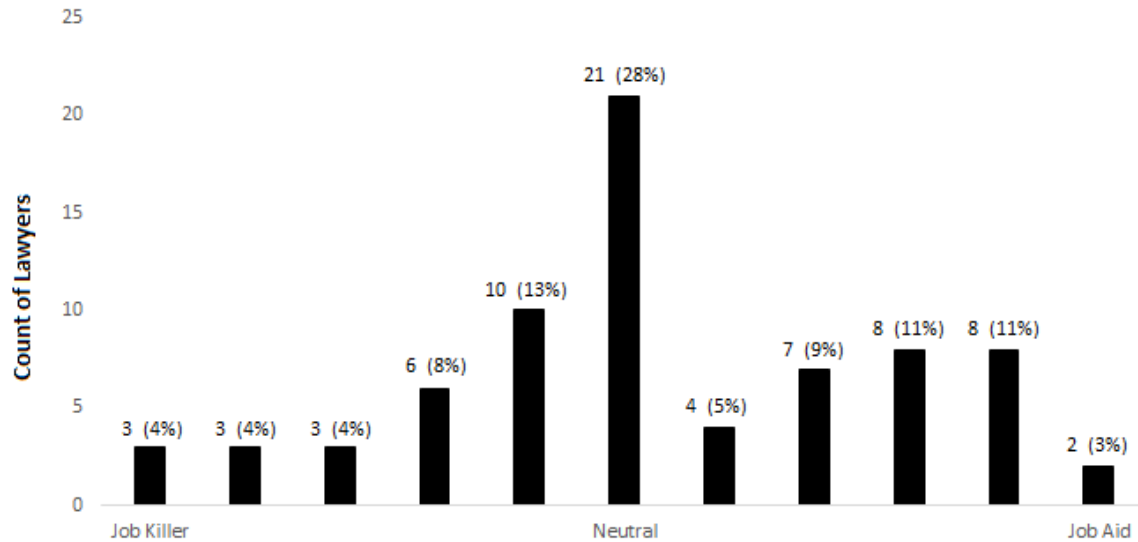
“[AI would] make me more accurate and efficient, just like [the] internet revolution in [the] past (google).” “[I]t would enhance my abilities as a Radiologist, integrating medical data with imaging data. It would improve patient care by streamlining imaging processes, and it would improve patient safety by decreasing acceptable radiation doses for imaging.” “Would be faster and more efficient. AI could interpret easy exams leaving harder cases for humans.”



Notes: Specialization = Radiology

Figure 6: Impact of AI on radiology jobs (N = 75)

Figure 7 below shows the response distribution for lawyers specializing in contract law, transactional law, or mergers and acquisitions law. Lawyers were less certain of the impact of AI, perhaps unwilling to take a stance. Twenty-eight percent of lawyers answered that AI would have a neutral impact. Moreover, looking at the responses to the free-response question for the extremes—job killer and job aid—lawyers’ comments were more neutral compared with those of physicians. For example, one radiologist who perceived AI as a job killer felt that AI “*would initially be useful until I was eventually replaced.*” Another radiologist who saw AI as a job killer commented, “*I will still be of use; but will likely earn less income.*” This was put more succinctly by yet another radiologist: “*less work, less money.*” Whereas, one contract lawyer in the job killer camp merely commented, “*It could take my job*” and a transactional lawyer in the job aid camp commented, “*Less time on routine tasks and more time to improve documents and negotiate better outcomes.*”



Notes: Specializations = Contract, transactional and mergers & acquisitions law

Figure 7: Impact of AI on contract law, transactional law, or mergers and acquisitions law jobs (N = 75)

From the preceding analyses, a picture is forming such that physicians see AI as a job aid but also as an impact to their professional autonomy. Lawyers, on the other hand, are on the fence. Additionally, hypothesized relationships between profession, specialization and perceived job displacement associated with AI may not be supported. In the following paragraphs, these findings will be further examined in the test of hypotheses.

A series of hierarchical multiple regression analyses, reported in Tables 7 through 9, were conducted to test the hypotheses. Two dependent variables were tested: perceived job displacement associated with AI (Models 1-4) and perceived impact to professional autonomy (Models 5-8). The models show the regression results for the main effect and moderator relationships, controlling for use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology. Variance Inflation Factors (VIFs) for all

control and independent variables in Models 1 through 8 were within acceptable limits, under four, suggesting that multicollinearity was not a concern (Miles & Shevlin, 2010).

Table 7 summarizes the results from the hierarchical multiple regression analysis for perceived job displacement associated with AI (Models 1-4) for the main effect and moderator relationship, controlling for use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology. Hypothesis 1a predicted that perceived performance of AI would be positively correlated with perceived job displacement associated with AI. In the first step of the hierarchical multiple regression (Model 1), five control variables were entered: use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology. This model was statistically significant ($F_{(5, 143)} = 5.46; p < .001$) and explained 16.0 percent of the variance in perceived job displacement associated with AI. Only perception of job insecurity in general made a significantly unique contribution to the model. After entering the independent variable perceived performance of AI in Model 2, the total variance explained by the model was 19.0 percent ($F_{(6, 142)} = 5.56; p < .001$). In support for hypothesis H1a, there was a medium, positive correlation between perceived performance of AI and perceived job displacement of AI. The introduction of perceived performance of AI explained an additional 3.0 percent of the variance in perceived job displacement associated with AI, after controlling for use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology ($\Delta R^2 = .03; F_{(1, 142)} = 5.24; p < .05$). In Model 2, two control variables and the independent variable were statistically significant, with perceived job insecurity in general recording a higher Beta value ($\beta = .28, p < .001$) than use of AI ($\beta = -.16, p < .05$) and perceived performance of AI ($\beta = .20, p < .05$).

Hypothesis 1b predicted that profession and specialization would moderate the relationship between perceived performance of AI and perceived job displacement associated with AI such that the relationship would be much stronger for lawyers. After entry of profession in Model 3 the total variance explained by the model was 20.9 percent ($F_{(7, 141)} = 5.31; p < .001$). The introduction of profession explained an additional 1.8 percent of the variance in perceived job displacement associated with AI, after controlling for use of AI, income, perception of job insecurity in general, practice size, self-efficacy with respect to technology and perceived performance ($\Delta R^2 = .02; F_{(1, 141)} = 3.28; p < .05$). In Model 3, four out of the seven control and independent variables were statistically significant, with profession recording a higher Beta value ($\beta = -.55, p < .05$) than perceived job insecurity in general ($\beta = .28, p < .001$), use of AI ($\beta = -.19, p < .05$), and perceived performance of AI ($\beta = .19, p < .05$). The interaction term of perceived performance of AI and profession was added in Model 4. The model was significant ($F_{(8, 140)} = 4.84; p < .001$); however, contrary to expectations, the interaction effect between profession and perceived performance of AI in relationship to perceived job displacement associated with AI was not statistically significant, $F_{(1, 140)} = 1.41, n.s.$, H1b was not supported.

Table 7: Summary of hierarchical regression analysis for perceived job displacement associated with AI (N = 150)

	Perceived Job Displacement associated with AI							
	Model 1		Model 2		Model 3		Model 4	
	β	t	β	t	β	t	β	t
<i>Controls</i>								
Use of AI	-.10	-1.26	-.16*	-1.95	-.19*	-2.23	-.17*	-1.97
Income	.04	.60	.03	.44	-.06	-.72	-.05	-.61
Job Insecurity in General	.30***	5.01	.28***	4.68	.28***	4.75	.29***	4.88
Practice Size	.01	.09	-.02	-.26	-.05	-.65	-.06	-.76
Self-Efficacy with Technology	.04	.36	-.02	-.22	-.06	-.56	-.06	-.51
<i>Independent Variables</i>								
Perceived Performance (PP)			.20*	2.29	.19*	2.13	.31*	2.30
Profession					-.55*	-1.81	.50	.53
PP \times Profession							-.20	-1.19
<i>R</i>	.40		.44		.46		.47	
<i>R</i> ²	.16		.19		.21		.22	
ΔR^2			.03		.02		.01	
<i>F</i> for ΔR^2	5.46***		5.24*		3.28*		1.41	
Model <i>F</i>			5.56***		5.31***		4.84***	

Notes: Standardized regression coefficients are presented; statistical significance: * $p < .05$; ** $p < .01$; *** $p < .001$ (1-tailed); profession is coded (0 = physician, 1 = lawyer)

Table 8 summarizes the results from the hierarchical multiple regression analysis for perceived impact to professional autonomy (Models 5-8) for the main effect and moderator relationship, controlling for use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology. Hypothesis 2a predicted that perceived performance of AI would be positively correlated with perceived impact to professional autonomy. In the first step of the hierarchical multiple regression (Model 5), five control variables were entered: use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology. This model was statistically significant $F_{(5, 143)} = 4.10$; $p < .001$ and explained 14.7 percent of the variance in perceived impact to professional autonomy. Both income and perception of job insecurity in general made a significantly unique contribution to the model. After entering the predictor variable perceived performance of AI in

Model 6, the total variance explained by the model was 15.4 percent ($F_{(6, 142)} = 4.30; p < .001$). Table 6 on p. 44 showed a small, positive correlation between perceived performance of AI and perceived impact to professional autonomy, $r = .16, p < .05$; however, after controlling for use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology, the introduction of perceived performance of AI into the model was not significant ($\Delta R^2 = .01; F_{(1, 142)} = 1.10; n.s.$). Hypothesis 2a was not supported.

Hypothesis 2b predicted that profession and specialization would moderate the relationship between perceived performance of AI and perceived impact to professional autonomy such that the relationship would be much stronger for lawyers. After entry of profession in Model 7 the total variance explained by the model was 15.9 percent ($F_{(7, 141)} = 3.82; p < .01$). The introduction of profession explained an additional .6 percent of the variance in perceived impact to professional autonomy, after controlling for use of AI, income, perception of job insecurity in general, practice size, self-efficacy with respect to technology and perceived performance, which was not significant ($\Delta R^2 = .01; F_{(1, 141)} = .92; n.s.$). The interaction term of perceived performance of AI and profession was added in Model 8. The total variance explained by the model was 17.7 percent ($F_{(8, 140)} = 3.77; p < .001$). The interaction term of perceived performance of AI and profession explained an additional 1.8 percent of the variance in perceived impact to professional autonomy, after controlling for use of AI, income, perception of job insecurity in general, practice size, self-efficacy with respect to technology and perceived performance ($\Delta R^2 = .02; F_{(1, 140)} = 3.04; p < .05$). In Model 8, two of the control variables and two of the independent variables were statistically significant, with the interaction term of perceived performance of AI and profession recording a higher Beta value ($\beta = -.33, p < .05$) than perceived performance of AI ($\beta = .29, p < .05$), perceived job insecurity in general ($\beta = .26,$

$p < .001$), and income ($\beta = .17, p < .05$). Hypothesis 2b was not supported. Although profession and specialization did moderate the relationship between perceived performance of AI and perceived impact to professional autonomy, the relationship was stronger for physicians, not lawyers.

Table 8: Summary of hierarchical regression analysis for perceived impact to professional autonomy ($N = 150$)

	Perceived Impact to Professional Autonomy							
	Model 5		Model 6		Model 7		Model 8	
	β	t	β	t	β	t	β	t
<i>Controls</i>								
Use of AI	-.02	-2.0	-.05	-.53	-.06	-.67	-.03	-.35
Income	.21***	2.82	.21***	2.73	.15	1.62	.17*	1.79
Job Insecurity in General	.25***	3.79	.24***	3.59	.24***	3.61	.26***	3.84
Practice Size	-.06	-.66	-.07	-.81	-.09	-1.00	-.10	-1.17
Self-Efficacy with Technology	.16	1.39	.13	1.08	.11	.87	.12	.96
<i>Independent Variables</i>								
Perceived Performance (PP)			.10*	1.05	.09	.95	.29*	1.95
Profession					-.32	-.96	1.37	1.33
PP \times Profession							-.33*	-1.74
R	.38		.39		.40		.42	
R^2	.15		.15		.16		.18	
ΔR^2			.01		.01		.02	
F for ΔR^2	4.94***		1.10		.92		3.04*	
Model F			4.30***		3.82***		3.77***	

Notes: Standardized regression coefficients are presented; statistical significance: * $p < .05$; ** $p < .01$; *** $p < .001$ (1-tailed); profession is coded (0 = physician, 1 = lawyer)

Table 9 summarizes the results from the hierarchical multiple regression analysis for perceived job displacement associated with AI (Models 8-9) and perceived impact to professional autonomy (Models 10-11) splitting the data by profession and controlling for use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology. Model 9 shows that, for physicians, the total variance in perceived job displacement explained by the model was 39.7 percent ($F_{(6, 67)} = 7.36; p < .001$). Perceived performance explained an additional 5.7 percent of the variance in perceived job displacement

associated with AI for physicians, after controlling for use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology ($\Delta R^2 = .06$; $F_{(1, 67)} = 6.29$; $p < .05$). Model 10 shows that, for lawyers, the relationship between perceived performance and perceived job displacement associated with AI, after controlling for use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology was not significant ($F_{(6, 68)} = 1.56$; n.s).

Model 11 shows that, for physicians, the total variance in perceived impact to professional autonomy explained by the model was 31.0 percent ($F_{(6, 67)} = 5.01$; $p < .001$). Perceived performance explained an additional 5.8 percent of the variance in perceived impact to professional autonomy for physicians, after controlling for use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology ($\Delta R^2 = .06$; $F_{(1, 67)} = 5.60$; $p < .05$). Model 12 shows that, for lawyers, the relationship between perceived performance and perceived impact to professional autonomy, after controlling for use of AI, income, perception of job insecurity in general, practice size, and self-efficacy with respect to technology was not significant.

Table 9: Summary of hierarchical regression analysis, split by profession (N = 150)

	Perceived Job Displacement				Perceived Impact to Professional Autonomy			
	Physicians (N = 75)		Lawyers (N = 75)		Physicians (N = 75)		Lawyers (N = 75)	
	Model 9		Model 10		Model 11		Model 12	
	β	<i>t</i>	β	<i>t</i>	β	<i>t</i>	β	<i>t</i>
<i>Controls</i>								
Use of AI	-.11	-1.19	-.17	-.95	.00	.00	-.02	-.09
Income	.02	.19	-.31*	-2.01	.16	1.55	.06	.32
Job Insecurity in General	.49***	5.86	.08	.88	.39***	4.56	.10	.96
Practice Size	-.19	-1.37	-.01	-.13	-.19	-1.31	-.09	-.74
Self-Efficacy with Technology	.01	.03	-.07	-.51	-.03	-.17	.21	1.28
<i>Independent Variables</i>								
Perceived Performance (PP)	.34***	2.51	.18	1.41	.33*	2.37	-.01	-.08
<i>R</i>	.63		.35		.56		.23	
<i>R</i> ²	.40		.12		.31		.05	
ΔR^2	.06		.03		.06		.00	
<i>F</i> for ΔR^2	6.29*		1.99		5.60*		.01	
Model <i>F</i>	7.36***		1.56		5.01***		.61	

Notes: Standardized regression coefficients are presented; statistical significance: * $p < .05$; ** $p < .01$; *** $p < .001$ (1-tailed)

Lastly, Table 10 summarizes the results from the within-profession hierarchical multiple regression analysis for perceived job displacement associated with AI (Models 13-14) and perceived impact to professional autonomy (Models 15-16) splitting the data by target and nontarget group lawyers and controlling for use of AI, income, perception of job insecurity in general, and self-efficacy with respect to technology. Practice size was removed from the regression analysis since this data was not available for the nontarget group. Model 13 shows that, for the target group lawyers, the relationship between perceived performance and perceived job displacement associated with AI, after controlling for use of AI, income, perception of job insecurity in general, and self-efficacy with respect to technology was not significant. The relationships were significant; however, for the nontarget group of lawyers. Model 14 shows that, for nontarget group lawyers, the total variance in perceived job displacement explained by the model was 18.2 percent ($F_{(5, 553)} = 24.68$; $p < .001$). Perceived performance explained an additional 4.3 percent of the variance in perceived job displacement associated with AI for

nontarget group lawyers, after controlling for use of AI, income, perception of job insecurity in general, and self-efficacy with respect to technology ($\Delta R^2 = .04$; $F_{(1, 553)} = 28.82$; $p < .001$). As with Model 13, model 15 shows that, for target group lawyers, the relationship between perceived performance and perceived impact to professional autonomy, after controlling for use of AI, income, perception of job insecurity in general, and self-efficacy with respect to technology was not significant. Lastly, model 16 shows that, for nontarget group lawyers, the total variance in perceived impact to professional autonomy explained by the model was 6.1 percent ($F_{(5, 553)} = 7.25$; $p < .001$). Perceived performance explained an additional 2.1 percent of the variance in perceived impact to professional autonomy for nontarget group lawyers, after controlling for use of AI, income, perception of job insecurity in general, and self-efficacy with respect to technology ($\Delta R^2 = .02$; $F_{(1, 553)} = 12.15$; $p < .001$).

Table 10: Summary of hierarchical regression analysis, split by target and nontarget group lawyers (N = 634)

	Perceived Job Displacement				Perceived Impact to Professional Autonomy			
	Target (N = 75)		Nontarget (N = 559)		Target (N = 75)		Nontarget (N = 559)	
	Model 13		Model 14		Model 15		Model 16	
	β	<i>t</i>	β	<i>t</i>	β	<i>t</i>	β	<i>t</i>
<i>Controls</i>								
Use of AI	-.18	-1.02	.10*	2.04	-.06	-.30	-.01	-.22
Income	-.31*	-2.08	-.01	-.19	.04	.20	.06	.872
Job Insecurity in General	.08	.92	.23***	8.14	.11	.108	.15***	4.21
Self-Efficacy with Technology	-.07	-.51	-.05	-1.08	.21	1.29	.03	.58
<i>Independent Variables</i>								
Perceived Performance (PP)	.18	1.43	.22***	5.37	-.01	-.03	.18***	3.49
<i>R</i>	.35		.43		.21		.25	
<i>R</i> ²	.12		.18		.04		.06	
ΔR^2	.03		.04		.00		.02	
<i>F</i> for ΔR^2	2.05		28.82***		.00		12.15***	
Model <i>F</i>	1.89		24.68***		.63		7.25***	

Notes: Standardized regression coefficients are presented; statistical significance: **p* < .05; ***p* < .01; ****p* < .001 (1-tailed). Practice size was excluded from the analysis since this data was not collected for nontarget lawyers.

Discussion of the research findings, study limitations, topics for future research, and the conclusion will be presented in the next and final chapter.

VI CHAPTER VI: DISCUSSION AND CONCLUSION

In their book *The Future of the Professions: How Technology Will Transform the Work of Human Experts*, Susskind and Susskind (2015, p. 50) ask the question: “[T]o what problem are the professions our solution?” They describe the professions as “a pragmatic fix, reflecting the fact that human beings cannot know or do everything themselves” (p. 33). Physicians and lawyers are highly-educated, highly-trained, licensed, professional service providers. They have held a privileged status in society as sole purveyors of esoteric knowledge and expertise. The aim of this study was to gain insight into the perceived impact of AI on job tasks as predictive analytics generated by AI machine learning algorithms threaten the specialized knowledge work that distinguishes and protects these professionals. To achieve this objective, 150 physicians and lawyers practicing in the US were surveyed. Models were tested to examine the relationships between perceived performance of AI held by physicians and lawyers and perceived job displacement associated with AI as well as perceived impact to professional autonomy.

Studies on the relationship between technology and job displacement have previously focused on blue-collar workers (Schrank, 1981) and the percentage of job tasks in white-collar jobs that could be impacted by recent advances in automation and artificial intelligence (Frey & Osborne, 2017; MGI, 2017; Remus & Levy, 2015). Studies on the relationship between technology and perceived impact to professional autonomy have previously focused on fingerprint technicians (C. J. Davis & Hufnagel, 2007), commercial airplane pilots (Carr, 2014), and physicians (Z. Walter & Lopez, 2008). The current study builds on these previous studies by including another group of professionals, lawyers, as well as, capturing the perceptions held by physicians and lawyers of AI in their practices given the estimates from the literature that approximately 25 percent of physicians’ and lawyers’ job tasks could be automated with current

technology (MGI, 2017). The gap in understanding the perceptions of a subset of highly-educated, highly-trained professionals, such as physicians and lawyers, is an opportunity to inform providers of artificial intelligence technology in the medical and legal fields on where physicians and lawyers are in their comfort with and acceptance of AI in their practice.

A quantitative analysis of survey results from 75 physicians specializing in radiology and 75 lawyers specializing in contract, transactional, and mergers and acquisitions law was done to analyze the relationships between the constructs. These specializations were chosen because they are most impacted by current capabilities of the AI technology that is available on the market. Survey target respondents ranged in age from 24 to 79. Physicians and lawyers ages 24 to 36 were more likely to think that AI would reduce their job security or that they would one day lose their job to AI than respondents ages 37 to 51. These findings are consistent with the larger US population of adults. A Gallup-Northeastern (2018) study of survey data collected from US adults in 2017 which found that 18- to 35-year-olds were more worried about their jobs being eliminated by AI than 36- to 50-year-olds.

Turning to the results of the hypothesis testing, in support of hypothesis 1a, the results showed a significant, positive relationship between perceived performance of AI and perceived job displacement associated with AI. These findings reflect recent studies of US adults' perceptions of AI and job displacement. A 2016 study by the Pew Research Center found that 65 percent of Americans expect AI to do much of the work that people are currently doing within the next 50 years (Smith, 2016). According to a study conducted by Gallup-Northeastern (2018), 71 percent of white-collar workers and 72 percent of US adults with a bachelor's degree or higher agree that increased use of AI will eliminate more jobs than it creates. Hypothesis 1b, which predicted that profession and specialization would moderate the relationship between perceived

performance of AI and perceived job displacement associated with AI, was not supported by the data. Diving into the data further by splitting the data by profession, the results of this study suggest that physicians, specifically radiologists, skew toward perceiving artificial intelligence as a job aid but also see a relationship between the performance of AI and increased job displacement. Perhaps this appreciation for the capabilities of AI stems from their familiarity with technology. Over the past decade, more than ninety of hospitals in the US have been computerized, making physicians some of the most technologically avid people in American society (Gawande, 2018). Another possible explanation for the greater perceived impact of AI on jobs among physicians versus lawyers can be found in Gallup-Northeastern (2018) in which research findings revealed that 22 percent of Americans thought that healthcare jobs would be among those first eliminated by AI versus only nine percent choosing law and policy as the first to be displaced.

Hypothesis 2a, which predicted that perceived performance of AI would be positively correlated with perceived impact to professional autonomy, was also not supported by the data. Although hypothesis 2b was not supported, consistent with Z. Walter and Lopez (2008) profession did moderate the positive relationship between perceived performance of AI and perceived impact to professional autonomy, the relationship being stronger for physicians.

Notably, the results from lawyers specializing in contract, transactional, and mergers and acquisitions law in this study were somewhat mixed. Lawyers, practitioners of a profession steeped in tradition, were almost evenly divided in their perceptions of AI as a job killer or job aid, with the majority having the perception that AI will have a neutral impact on their jobs. I think this explains why there was not a significant relationship between perceived performance of AI and perceived job displacement nor perceived impact to professional autonomy. Although

self-efficacy with respect to technology was controlled for, it could be that lawyers are less aware of the capabilities of AI and; therefore, do not know what to make of its potential impact on their jobs. A survey of Quartz readers—Quartz is an online magazine geared toward business professionals interested in technological and other disruptive changes—found that although 90 percent of survey respondents thought that within the next five years up to 50 percent of jobs would be lost to AI, only nine percent thought that they were at risk of losing their own job to AI, regardless of how familiar they were with AI (Edwards & Edwards, 2017).

Although physicians saw a relationship between perceived performance of AI and job displacement, only 25 percent feared that someday they would lose their jobs to AI. Likewise, only 15 percent of lawyers felt the same way. The average for the two combined was 20 percent which is in line with similar study findings for white-collar workers. The Gallup-Northeastern (2018) study, for example, found that whereas 71 percent of American white-collar workers think that adopting AI technology will destroy more jobs than it creates, only 19 percent are worried about their own jobs being eliminated due to AI. The authors claim that white-collar workers and adults with education levels at or above a bachelor's degree are generally more optimistic about AI's potential impact on their lives and work. This optimism contrasts sharply with reports that the introduction of AI could eliminate up to 70 percent of white-collar jobs over the next 20 years, which means these individuals, in particular, may be poorly prepared and overly confident in their ability to respond to the impending economic shift (Gallup-Northeastern, 2018). Professionals may be in for a rude awakening. As a quote from *The New Yorker* puts it, “I think that if you work as a radiologist you are like Wile E. Coyote in the cartoon, . . . [y]ou’re already over the edge of the cliff, but you haven’t yet looked down. There’s no ground underneath” (Mukherjee, 2017, p. 12). Evidence for this “not my job”

mentality can be seen in answers to the free-response question at the end of the survey from a handful of lawyers, for instance, who felt that their secretaries' jobs might be in danger of being displaced by AI:

“I think it would change the work I’m expe[c]ted to do, and also would probably replace a lot of secretaries’ jobs across the field.” (27-year-old, male lawyer) *“I would get work done a lot faster. My secretary would probably become obsolete. I do not think AI could displace attorneys and paralegals because these jobs require creativity and critical, strategic analysis to suit the needs of particular clients. I think AI would make it easier and faster for me to do work I actually don’t enjoy doing, the more robotic aspects of my job. I’m open to it, but I think it’s important for people to realize that some people will be replaced and some people won’t.”* (30-year-old, male contract lawyer) *“less need for secretaries”* (44-year-old, male lawyer)

Looking at the data from all lawyers who responded to the survey, the within-profession analysis of lawyers’ perceptions showed that sports and entertainment lawyers, intellectual property lawyers, and family and juvenile lawyers were the least worried about job displacement associated with AI, respectively. The following quotes from the free-response question are representative of these lawyers:

“I don’t think much would change. Contracts will always need human review and evaluation. It may help in the initial creation, but a human touch will be necessary to finalize them.” (53-year-old, male sports and entertainment lawyer) *“[I]t would be a tool I use and that is all it would be”* (39-year-old, male sports and entertainment lawyer) *“There would be change, but not much. Only the most mundane jobs will be replaced initially. It is hard to tell what would happen later.”* (57-year-old, male intellectual property lawyer) *“This type of work is not likely to benefit from AI at its current levels.”* (37-year-old, female intellectual property lawyer) *“I think*

[I] would waste a bunch of time learning how to use it so that I could tell others that I use it, but that it wouldn't really help me much." (46-year-old, male intellectual property lawyer) *"In the representation of children, I can't fathom how a child would interact with a robot and the robot being able to determine the merits of different demeanor cues."* (39-year-old, male family and juvenile lawyer) *"I can't fathom how AI would play a role in my job, so it's hard to come up with a good response. My practice is so focused on me knowing the clients and their issues that I don't see how AI would assist with that in any way."* (36-year-old, female family and juvenile lawyer)

Another finding from the within-profession analysis of lawyers was that lawyers specializing in health law felt that it was more likely, compared with the target lawyer group, that AI would decrease their professional discretion over the day-to-day and course of action decisions made on the job. A 33-year-old, female health lawyer directly addressed this concern in her answer to the free-response question: *"I worry that I would have less autonomy. I also worry that it would have unforeseeable impacts on people's due process rights, since I work in government."*

Returning to the issue of perceived job displacement, an alternative possible explanation for the low concern of lawyers about AI and job displacement might be that there may be less unbiased evidence of the accuracy of the results from law-focused AI technology from independently commissioned studies. The studies referenced in this paper were sponsored by companies that developed or sold legal-focused AI products. Here are quotes from the free-response question speaking to the issue of the accuracy of AI:

"AI couldn't do my current job. I have used AI in the discovery process of litigation and it was highly inaccurate and cost more money to recode miscoded documents than just hiring

actual attorneys to process documents.” (33-year-old, female intellectual property lawyer) “It would increase work load as it would require review to [e]nsure that the product was accurate” (68-year-old, male employment and labor lawyer) “I would spend more time correcting what some AI program thinks belongs in an agreement” (47-year-old, male criminal lawyer) “I would spend a lot of time correcting the incorrect results given by AI. This is because AI would be developed by individuals with no common sense and no understanding of the real world and the way jobs are performed” (68-year-old, male real estate lawyer) “I work for state government as an attorney not in private practice. I do not foresee any possible application for AI in my job because all of our outgoing documents must be carefully reviewed and checked for content and decisions by actual persons. There is absolutely no room for machine error” (48-year-old, female lawyer)

Lastly, it is also worth mentioning that another key finding of this study was that the control variable, perception of job insecurity in general, was a strong predictor of the perceived job displacement associated with AI for physicians and lawyers surveyed for this study.

This study adds to and extends the literature by contributing several relevant findings on medical and legal knowledge workers' perceptions of the impact of artificial intelligence on job displacement and professional autonomy. Physicians' and lawyers' perceptions were analyzed through the lens of constructs adapted from the technology acceptance model (TAM) and job characteristics model (JCM). Similar to previous studies (C. J. Davis & Hufnagel, 2007; Z. Walter & Lopez, 2008), the findings show a relationship between perceived performance of AI and perceived job displacement and perceived impact to professional autonomy for physicians specializing in radiology. This study also contributes by adding a human perspective to the empirical numbers on job task automation provided in studies by (Frey & Osborne, 2017; MGI,

2017; Remus & Levy, 2015). Practical implications of the survey results for physicians, who are more comfortable with the idea of using artificial intelligence in their work, are to further explore more applications for human plus machine partnerships with an emphasis on job augmentation, not replacement. An example of the potential advantages of human plus machine partnerships comes from a study on diagnosing metastatic breast cancers which compared the accuracy of an AI versus a human pathologist. The AI achieved 92.5 percent accuracy in detecting the difference between slides containing metastasis and normal slides, the human pathologist achieved 96.6 percent accuracy and the two combined (pathologist + AI) achieved 99.5 percent accuracy (Wang, Khosla, Gargeya, Irshad, & Beck, 2016).

For lawyers, who may be less aware or convinced of the advantages of applying AI in their field, practical implications would be to provide education for lawyers regarding the benefits of using artificial intelligence for contract review and creation, e-discovery, fraud detection, and due diligence performance which could free up time for more value-added activities.

It is recognized that this study is bound by several limitations (scope, generalizability, sample recruitment, sampling size, method). Although there are AI offerings in several industries, the scope of this study centered on the impact of AI on knowledge workers, specifically on well-educated professionals, such as, physicians and lawyers. To control for specialization, only radiologists and lawyers specializing in contract, transactional, and mergers and acquisitions law were studied since these specializations are most impacted by current capabilities of the AI technology that is available on the market. Generalizability of the findings is another limitation of this study. Although two groups of professionals were studied, their responses may not be representative of all well-educated professionals. Future studies might

wish to incorporate other white-collar professionals whose job tasks are squarely in the sights of AI technology based on the research studies of Frey and Osborne (2017) and MGI (2017).

A small sample from Qualtrics' opt-in online panels was used to recruit participants for the study. Future research might consider polling a large, random sample of physicians at a large medical institution and lawyers at a large law firm or multiple medical institutions and law firms. Additionally, the study geography is limited to the United States. Future studies may consider replicating the study in other countries. For instance, would perceptions be different in China due to the Chinese government support for AI research? From a medical perspective, with the aging population, decreased birth rate, and acceptance of nurse robots in Japan, would perceptions of AI be different there?

The data for this study were captured at a single point in time, using a survey, and all data were self-reported. A Harman's single factor test was performed on the data, and the maximum variance explained by a single factor in the dataset was 44.28 percent, which is less than 50 percent; however, I acknowledge the limitations of the method used and the potential for common method bias. Future research may consider conducting before and after surveys, incorporating exposure to AI applications in the medical and legal fields and capturing respondents' perceptions before and after exposure. Additionally, the current study's findings could be extended with a qualitative case study or multiple case study, providing more depth regarding the perceptions of professionals. Another area for future research would be to examine optimism bias as it relates to perceptions of job displacement associated with AI. Future research could also take a deeper look into the strong relationship between perception of job insecurity in general and perceived job displacement associated with AI for physicians and lawyers.

Some additional ideas for future research could be to examine the impact of AI technology adoption on job availability for physicians and lawyers. In the case of physicians, could nurses and nurse practitioners use AI technology to diagnose and treat disease, eliminating the need for physicians to perform these tasks? In the case of young lawyers, how will they gain practical experience if legal research is now automated? Conversely, will more rewarding opportunities become available to young lawyers once the tedious task of legal research is automated?

On April 11, 2018, the US Food and Drug Administration (FDA) released a statement approving the marketing of an AI-based device capable of screening patients for diabetic retinopathy. IDx-DR is the first device approved for marketing that is capable of making a screening decision without the need of a clinician to interpret the image or results, enabling health care providers who are not normally involved in eye care to use it for diagnosis (FDA, 2018). The FDA has also given clearance to Arterys Inc. for its AI oncology imaging suite which will aid radiologists in evaluating MRI and CT scans for the presence of liver lesions and lung nodules (Arterys, 2018). The US House Oversight Committee published a white paper on findings and recommendations on AI and four areas: the workforce, data privacy, biases, and malicious use of AI (HCOR, 2018). As regulatory agencies and government bodies approve the use of AI, how will professionals be impacted and will their perceptions of job displacement associated with AI and impact to professional autonomy change?

In conclusion, models were tested to examine the relationships between perceived performance of AI and perceived job displacement associated with AI and perceived impact to professional autonomy for physicians specializing in radiology and lawyers specializing in contract, transactional, and mergers and acquisitions law in the United States. The findings of

this study suggest that the physicians surveyed in this study perceive AI as a job aid but also acknowledge its potential for job displacement and impact to professional autonomy. The lawyers surveyed in this study, however, perceived a neutral impact to their job tasks as a result of adopting AI technologies.

AI is being positioned in the market as an intelligent assistant, designed to help humans make better decisions. In the short term, physicians and lawyers will be needed to “teach” AI what is relevant in the sea of data it is consuming. In the long term, will the time saved by adopting AI technology be re-allocated to other job tasks or will it lead to the elimination of jobs in the medical and legal fields? The current study is an important one in furthering research regarding the perceived impact of AI technology on medical and legal work.

APPENDIX

Appendix A: Survey Instrument

Dear Participant:

My name is Jessica Helsten and I am a graduate student at Georgia State University. For my dissertation, I am examining perceptions towards the use of artificial intelligence in the medical and legal fields. Because you are a physician or lawyer, I am inviting you to participate in this research study.

In 1955, Dartmouth math professor John McCarthy coined the term artificial intelligence (AI). AI is a powerful tool capable of simulating human intelligence. Today, AI is garnering enormous attention in many industries such as healthcare and the law. Tech giants like Apple, Amazon, Google, IBM, and Salesforce are spending tens of billions on AI. AI technologies are reshaping how people integrate information, analyze data, and use the resulting output to improve decision-making.

Participation in this survey will require approximately 10 minutes of your time. You will be compensated for your participation according to the terms of your panelist agreement. There is no known risk for participating in this survey. Your participation is completely voluntary, and you may refuse to participate at any time. Your responses will be kept private to the extent allowed by law. I will have access to the information you provide. No personally identifiable information will be collected from you. The results of this study will be summarized and reported in group form.

Please contact me at jhelsten1@student.gsu.edu if you have questions, concerns, or complaints about this study or your part in it. Contact the GSU Office of Human Research Protections at 404-413-3500 or irb@gsu.edu if you want to talk to someone who is not part of the study or if you have questions about your rights as a research participant. You can talk about questions, concerns, offer input, obtain information, or suggestions about the study. If you are willing to volunteer for this research, please acknowledge by clicking the arrow button below to begin the survey. Thank you.

1. What is your profession?

0 1
Physician Lawyer

2. What is your primary professional area of specialization? (radiologist, contract lawyer, transactional lawyer, or mergers and acquisitions lawyer)

3. Approximately how many years have you been in practice?

- 1 0-5 years
- 2 6-15 years
- 3 16+ years

4. What year did you receive your highest degree related to your specialization?

Please indicate your level of agreement with the following statements:

5. I feel insecure about the future of my job.

1	2	3	4	5	6	7
Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

6. I feel confident in my ability to use technology.

1	2	3	4	5	6	7
Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

7. I like to experiment with new technology.

1	2	3	4	5	6	7
Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

8. I am usually one of the first among my colleagues/peers to explore new technology.

1	2	3	4	5	6	7
Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

For Physicians:

An example of the use of artificial intelligence in the medical field is analysis of medical images to look for disease patterns. Apps developed by companies like Zebra Medical

Vision and Arterys allow physicians to feed images in and receive health predictions or diagnosis suggestions.

The following questions will ask your opinions of medical-focused artificial intelligence (AI) technology in your job:

For Lawyers:

Examples of the use of artificial intelligence in the legal field are contract review and creation, fraud detection and due diligence performance. Lawgeex is a software platform which uses AI to compare an uploaded new contract to its database of similar contracts, learning as it performs the review. The software provides a report, noting where the contract deviates from similar contracts.

The following questions will ask your opinions of law-focused artificial intelligence (AI) technology in your job:

9. Prior to taking this survey, how familiar were you with AI?

- 1 Not familiar at all
- 2 Slightly familiar
- 3 Moderately familiar
- 4 Very familiar
- 5 Extremely familiar

10. Using AI in my job would improve my performance.

1	2	3	4	5	6	7
Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

11. Using AI in my job would increase my productivity.

1	2	3	4	5	6	7
Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

12. Using AI in my job would enhance my effectiveness.

1	2	3	4	5	6	7
Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

13. I would find AI useful in my job.

1	2	3	4	5	6	7
Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

14. The quality of the output I would get from AI technology would be high.

1	2	3	4	5	6	7
Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

15. I would have no problem with the quality of the AI technology's output.

1	2	3	4	5	6	7
Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

16. I can foresee usage of AI being important in my job.

1	2	3	4	5	6	7
Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

17. I can foresee usage of AI being relevant in my job.

1	2	3	4	5	6	7
Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

18. Using AI may decrease my control (professional discretion) over the day-to-day decisions I make on the job.

1	2	3	4	5	6	7
Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

19. Using AI may decrease my professional discretion over course of action decisions.

1	2	3	4	5	6	7
Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

20. AI will reduce my job security.

1	2	3	4	5	6	7
Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

21. I fear that someday I will lose my job to AI.

1	2	3	4	5	6	7
Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

22. AI will make me less useful as a worker.

1	2	3	4	5	6	7
Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

23. The introduction of AI will slowly displace radiologists/contract lawyers/transactional lawyers/mergers and acquisitions lawyers.

1	2	3	4	5	6	7
Extremely improbable	Moderately improbable	Slightly improbable	Neither probable nor improbable	Slightly probable	Moderately probable	Extremely probable

24. The use of AI will mean less and less work for radiologists/contract lawyers/transactional lawyers/mergers and acquisitions lawyers.

1	2	3	4	5	6	7
Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree

25. Given the pace of advances in AI in the medical/legal field, how likely would you be to recommend radiology/contract law/transactional law/mergers and acquisitions law as a career with a future to someone interested in pursuing this specialization?

1	2	3	4	5	6	7
Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely

The following question will ask you to use a “slider” to indicate the impact you think AI will have.

26. At the end of the day, I think AI is going to . . .

be a job killer.

have a neutral impact.

be a job aid.

27. In what state do you primarily practice?

28. How many other radiologists are in your department/practice/center?

28. How many other contract/transactional/M&A lawyers are in your practice area/firm?

29. When does your department/practice/center plan to adopt AI?

29. When does your practice area/firm plan to adopt AI?

- 1 I don't think we will ever use AI
- 2 We're 3+ years away from adopting AI
- 3 We're 1-2 years away from adopting AI
- 4 We're planning on adopting AI in the next 12 months
- 5 We just adopted some AI
- 6 We've been using AI for 6 or more months

30. What is your gender?

- 0 1
Male Female

31. What year were you born?

32. What is your current employment status?

- | | | | | | | |
|-----------------------|-----------------------|-----------------------------------|---------------------------------------|---------|---------|----------|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| Employed
full time | Employed
part time | Unemployed
looking for
work | Unemployed
not looking
for work | Retired | Student | Disabled |

33. Please select one or more of the following races that best describes you: (Mark all that apply.)

- White/Non-Hispanic (1)
- Black or African American (2)
- American Indian or Alaska Native (3)
- Asian (4)
- Native Hawaiian or Pacific Islander (5)
- Latino/Hispanic (6)
- Middle Eastern (7)
- European/Mediterranean (8)
- Other (9)
- Prefer not to identify (10)

34. What is your income?

- 1 Less than \$99,999
- 2 \$100,000 to \$199,999
- 3 \$200,000 to \$299,999
- 4 \$300,000 to \$399,999
- 5 \$400,000 to \$499,999
- 6 \$500,000 or more

35. If AI were implemented in your office/practice, do you think your job would change? If yes, in what way(s)? Consider your job tasks, responsibilities, and relationships with others in your answer.

Thank you!

Appendix B: Full Correlations Table

Table 11: Full correlations and Cronbach's α for the target sample ($N = 150$)

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Perceived Job Displacement	(.90)															
2. Perceived Impact to Professional Autonomy	.51**	(.90)														
3. Perceived Performance	.17*	.16*	(.96)													
4. Age	-.13	-.11	-.08	-												
5. Employment Status	-.04	-.02	-.04	.32**	-											
6. Familiarity	-.10	.02	.40**	.07	.00	-										
7. Gender	-.05	-.02	-.11	-.23**	-.03	-.14*	-									
8. Income	.03	.21**	.19**	.17*	.04	.21**	-.20**	-								
9. Location of Practice	.03	.00	-.10	-.02	-.01	-.18*	.04	-.07	-							
10. Perception of Job Insecurity in General	.39**	.29**	.11	-.07	.04	-.03	-.03	-.02	-.04	-						
11. Practice Size	-.02	.01	.26**	-.16*	-.13	.27**	-.01	.31**	-.14*	-.05	-					
12. Race	.01	.15*	.06	-.06	.10	.01	-.09	.16*	.01	.00	-.04	-				
13. Self-Efficacy with Technology	.02	.12	.30**	-.23**	-.30**	.17*	-.05	.07	-.19*	.01	.08	.20**	-			
14. Years in Practice	-.17*	-.14*	-.15*	.88**	.31**	.02	-.30**	.10	.01	-.07	-.20**	-.09	-.24**	-		
15. Profession	-.10	-.20**	-.31**	-.07	.02	-.33**	.24**	-.65**	.11	.03	-.40**	-.14*	-.24**	.07	-	
16. Specialization	-.12	-.17*	-.19*	-.04	.06	-.24**	.24**	-.45**	.08	.00	-.31**	-.10	-.19*	.07	.79**	-

Notes: Cronbach's α reliabilities appear in the diagonals in parentheses; profession is coded (0 = physician, 1 = lawyer); specialization is coded (0 = radiology, 1 = contract law, 2 = M&A law, 3 = transactional law)

** . Correlation is significant at the 0.01 level (1-tailed).

* . Correlation is significant at the 0.05 level (1-tailed).

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