

# AUGMENTED LAWYERING

*John Armour,<sup>\*</sup> Richard Parnham<sup>\*\*</sup> and Mari Sako<sup>\*\*\*</sup>*

## ABSTRACT

*How will artificial intelligence (AI) and associated digital technologies reshape the work of lawyers and structure of law firms? Legal services are traditionally provided by highly-skilled humans—that is, lawyers. Dramatic recent progress in AI has triggered speculation about the extent to which automated systems may come to replace humans in legal services. A related debate is whether the legal profession’s adherence to the partnership form inhibits capital-raising necessary to invest in new technology. This Article presents what is to our knowledge the most comprehensive empirical study yet conducted into the implementation of AI in legal services, encompassing interview-based case studies and survey data. We focus on two inter-related issues: how the nature of legal services work will change, and how the firms that co-ordinate this work will be organized. A central theme is that prior debate focusing on the “human vs technology” aspect of change overlooks the way in which technology is transforming the human dimensions of legal services.*

*Our analysis of the impact of AI on legal services work suggests that while it will replace humans in some tasks, it will also change the work of those who are not replaced. It will augment the capabilities of human lawyers who use AI-enabled services as inputs to their work and generate new roles for*

---

<sup>\*</sup> Professor of Law and Finance, Faculty of Law, University of Oxford. Fellow of the British Academy and the European Corporate Governance Institute.

<sup>\*\*</sup> Research Fellow, Saïd Business School, University of Oxford.

<sup>\*\*\*</sup> Professor of Management Studies, Saïd Business School, University of Oxford.

This research is funded by UKRI pursuant to the *Next Generation Services* Industrial Strategy Challenge Fund. It forms part of the program *Unlocking the Potential of AI in English Law*: <https://www.law.ox.ac.uk/unlocking-potential-artificial-intelligence-english-law>. We are grateful for comments on earlier drafts from David Brock, Edward Greene, James Faulconbridge, Jens Frankenreiter, Talia Gillis, Simon Gleeson, Victor Goldberg, Jeff Gordon, Bruce Kogut, Martin Korman, Matthew Jennejohn, Frank Levy, Amir Licht, Josh Mitts, John Morley, Alex Raskolnikov, Richard Susskind, and Eric Talley. This paper has also benefited from feedback received at a Columbia Law School Blue Sky Workshop, a Business Law Workshop at Oxford University, Linklaters LLP, Northwestern University Kellogg Business School, the Oxford Saïd Business School Annual Conference on Professional Services Firms 2020, the Annual Conference of the Society for the Advancement of Socio-Economics (SASE) 2020, Slaughter and May, an ECGI Spotlight Seminar and a Yale Law School Center for the Study of Corporate Law Roundtable.

*legal experts in producing these AI-enabled services. We document these new roles being clustered in multidisciplinary teams (“MDTs”) that mix legal with a range of other disciplinary inputs to augment the operation of technical systems. We identify challenges for traditional law firm partnerships in implementing AI. Contrary to prior debate, these do not flow from constraints on finance to invest in technical assets. Rather, the central problems have to do with human capital: making necessary strategic decisions; recruiting, coordination and motivation the necessary MDTs; and adjusting professional boundaries. These findings have important implications for lawyers, law firms and the legal profession.*

## CONTENTS

I.	AI and Lawyers .....	11
A.	The Impact of Automation.....	11
B.	Today’s AI and its Limits .....	15
C.	Using AI to Scale Legal Services: Use-Cases for Deployment.....	18
1.	Discovery: technology-assisted review.....	20
2.	Due diligence and contract analytics.....	21
3.	Legal research .....	23
4.	Billing and utilization.....	24
D.	The AI Pipeline and Multidisciplinary Teams.....	25
1.	Requirements.....	26
2.	Design/procurement .....	26
3.	Data ingestion.....	26
4.	Data labelling .....	27
5.	Application of results .....	28
6.	The human capital mix in the AI pipeline.....	29
II.	AI and Legal Services Firms .....	30
A.	Do Law Firms Struggle with Using AI Technology?.....	30
B.	Big Law’s Deployment of AI .....	36
1.	Strategic decision-making.....	36
2.	Teams for implementation .....	38
3.	Summary .....	41
C.	Corporate Legal Departments.....	42
1.	Strategic decision-making.....	42
2.	Teams for implementation .....	44
D.	Alternative Legal Service Providers .....	45
1.	Strategic decision-making.....	46
2.	Teams for implementation .....	47
E.	Emerging Patterns: AI and Organizational Form .....	48

III. Quantitative Results .....	50
A. Survey Data.....	50
B. Univariate Results.....	51
C. Multivariate Results.....	53
IV. Implications .....	55
A. Lawyers.....	56
1. Classical advisory roles: augmented by technology .....	56
2. New multidisciplinary roles: augmenting technology .....	58
B. Law Firms .....	59
C. The Legal Profession .....	64

## INTRODUCTION

Legal services are traditionally provided by highly-skilled humans—that is, lawyers. During the past two decades, the costs of legal services have risen significantly.<sup>1</sup> At the same time, technological progress with artificial intelligence (AI) has been dramatic.<sup>2</sup> There is enormous optimism about the potential of AI as a general-purpose technology to deliver widespread productivity enhancements across the economy.<sup>3</sup> What will be the impact of AI on the way in which legal services work is delivered, and can it provide a way to augment productivity? Much of the debate to date has focused on the capabilities of technical systems, asking “can machines replace lawyers?” Some argue that the entire way in which legal services are delivered will be radically transformed,<sup>4</sup> while others maintain that only a small fraction of the

---

<sup>1</sup> See, e.g., 2019 Report on the State of the Legal Market. (2019). (Defining productivity as hours billed per month and showing constant, or slightly declining, average billable hours per lawyer across the US over the period 2007-2018); Legal Sector Services Forecasts 2017-2025. (2017).

<sup>2</sup> See generally, MICHAEL WOOLDRIDGE, *THE ROAD TO CONSCIOUS MACHINES: THE STORY OF AI* (Pelican. 2020). Progress in AI is reviewed in Section I.B, *infra*.

<sup>3</sup> See, e.g., AI as the next general-purpose technology: a Political-Economy Perspective. No. 0898-2937(2018); ANDREW MCAFEE & ERIK BRYNJOLFSSON, *MACHINE, PLATFORM, CROWD: HARNESSING OUR DIGITAL FUTURE* (WW Norton & Company. 2017).

<sup>4</sup> The best-known advocate for this position is Richard Susskind, who has pointed the way to technological transformation of the legal profession for nearly three decades:

tasks performed by lawyers are capable of being automated.<sup>5</sup> Yet while AI will surely render some roles redundant, humans will still be crucial for legal services for the foreseeable future. And just because humans continue to be involved does not mean they will necessarily be “lawyers” in the sense we understand the term today.<sup>6</sup> We argue that understanding how AI will augment lawyering requires a focus on two inter-related aspects of these human dimensions: how the nature of legal services work will change, and how the firms that co-ordinate this work will be organized. We develop and substantiate our analysis with what is to our knowledge the most comprehensive empirical study yet conducted into the implementation of AI in legal services.

This Article begins with the impact of AI on legal services work.<sup>7</sup> Understanding this requires an appreciation not only of what is technically possible, but also the economics and logistics of deployment. Today’s AI is based on machine learning (ML), the core of which is the prediction of outcomes by identifying complex statistical relationships within a dataset.<sup>8</sup> Through the application of natural language processing (NLP), these methods can be applied to the unstructured textual data that form the bedrock of legal materials. These models require training on multiple prior examples and assembling and reviewing large quantities of data involve high fixed costs. This helps to unify the contexts or “use-cases” in which AI is currently being deployed. These are tasks for which relevant data are readily available and in

---

RICHARD E. SUSSKIND, *THE FUTURE OF LAW : FACING THE CHALLENGES OF INFORMATION TECHNOLOGY* (Clarendon Press; Oxford University Press. 1996); RICHARD E. SUSSKIND, *THE END OF LAWYERS? : RETHINKING THE NATURE OF LEGAL SERVICES* (Oxford University Press. 2008); RICHARD E. SUSSKIND & DANIEL SUSSKIND, *THE FUTURE OF THE PROFESSIONS : HOW TECHNOLOGY WILL TRANSFORM THE WORK OF HUMAN EXPERTS* (Oxford University Press First edition. ed. 2015). See also Daniel Martin Katz, *Quantitative legal prediction-or-how I learned to stop worrying and start preparing for the data-driven future of the legal services industry*, 62 EMORY LJ (2012); Daniel Martin Katz, *The MIT School of Law-A perspective on legal education in the 21st century*, U. ILL. L. REV. (2014); Benjamin Alarie, et al., *Using Machine Learning to Predict Outcomes in Tax Law*, 58 CAN. BUS. LJ (2016).

<sup>5</sup> See e.g., Dana Remus & Frank Levy, *Can robots be lawyers: Computers, lawyers, and the practice of law*, 30 GEO. J. LEGAL ETHICS (2017). See also Eric L Talley, *Is the future of law a driverless car? assessing how the data analytics revolution will transform legal practice*, 174 JOURNAL OF INSTITUTIONAL & THEORETICAL ECONOMICS (2017).

<sup>6</sup> See, e.g., SUSSKIND & SUSSKIND, 263-67. 2015. (sketching a range of possible future professional roles).

<sup>7</sup> *Infra*, Part I.

<sup>8</sup> See *infra*, Section I.B and sources cited therein.

which results can be scaled, such as discovery review, contract analytics, and legal research.<sup>9</sup>

To the extent that AI is deployed for such legal tasks, the technology *substitutes* for humans. However, the technical and economic constraints on AI's deployment mean that more specialized and unique tasks will for the foreseeable future exclusively be performed by human lawyers.<sup>10</sup> So too will client-facing activities, which require an understanding of social context on which consistent data are hard to gather. AI will nevertheless profoundly impact lawyers performing such tasks. It will *augment* their productivity, serving to increase the value of their human capital.

Less obviously, the deployment of AI will also create demand for new types of human role. We present the first empirically-grounded account of what these *new* roles will look like in legal services.<sup>11</sup> We draw on rich qualitative data from over fifty interviews with relevant professionals to detail the way in which AI is actually implemented.<sup>12</sup> Implementation requires a “pipeline” in which the tasks to be performed must first be specified and the relevant data gathered and checked, before the system then performs its analytics; subsequently the output must be regularly reviewed by subject-matter experts. Most of these steps require human input from a range of different disciplines—including legal—working together in *multi-disciplinary teams* (MDTs). Delivering legal services through such technology pipelines therefore requires the assembly and management of MDTs in which some members have legal expertise. These “lawyers” in turn serve to *augment* the AI system's efficacy, as part of an MDT whose overall capability includes a range of other types of human capital, such as data science, project management, and design thinking. The work of these legal experts in MDTs is very different from traditional “lawyering”.

The emerging picture is of three margins along which the deployment of AI technologies affect the work of lawyers. First, technology *substitutes* for humans in traditional legal tasks for which automated systems are capable and cost-effective. This in turn drives the second margin: automation of tasks augments the capacity of human lawyers performing traditional legal tasks. These lawyers rely on the automated systems as an input to their work, enabling them to focus on those aspects on which they have comparative advantage. Their work is augmented by *consumption* of AI-enabled services.

---

<sup>9</sup> See *infra*, Section I.C.

<sup>10</sup> See *infra*, Section I.A.

<sup>11</sup> See *infra*, Section I.D.

<sup>12</sup> For details of our interviewees and methodology, see *infra*, Section II.A.

The third margin concerns the actual *production* of these AI-enabled legal services. Setting up and running the relevant systems generates new roles for humans working in MDTs. Part of this involves the application of legal expertise, which in this case augments the technology.

Having established these different ways in which human “lawyers” will relate to AI systems, this Article then turns to the impact of these changes in legal work on the organizational structure of legal services firms.<sup>13</sup> Law firms are organized as partnerships,<sup>14</sup> an organizational form that is rare in business generally. In the United States, as in many other countries, this is mandated by professional ethics rules, which prohibit lawyers from sharing profits with non-lawyers.<sup>15</sup> However, the partnership form also has a strong economic rationale for firms whose key assets are human capital.<sup>16</sup> Because these assets cannot be “owned” by the firm, raising outside capital—a core function of the corporate form adopted by most businesses—is unnecessary. What matters instead is the retention and motivation of key personnel, for which sharing profits and control amongst partners are powerful mechanisms.

The re-shaping of legal services by technology has potential to disrupt these economic advantages of the partnership. In theory, as technology drives a growing share of legal services firms’ productivity, these firms will in turn face growing need for outside capital for investment in technical systems.<sup>17</sup> The corporate form facilitates capital-raising from diversified shareholders,<sup>18</sup> not only providing funds to acquire non-human assets, but also increasing the

---

<sup>13</sup> *Infra*, Part II.

<sup>14</sup> Law firm partnerships are now commonly of the limited liability (“LLP”) form: see Scott Baker & Kimberly D Krawiec, *The Economics of Limited Liability: An Empirical Study of New York Law Firms*, U. ILL. L. REV. (2005). (documenting shift from unlimited to limited liability partnership form).

<sup>15</sup> The ABA’s Model Rules of Professional Conduct, adopted by most state Bar Associations, restrict the sharing of fees by lawyers with nonlawyers and prohibit partnerships with nonlawyers or corporations with nonlawyer shareholders (the “fee-sharing prohibition”): ABA Model Rules of Professional Conduct, Rule 5.4.

<sup>16</sup> Henry Hansmann, *When does worker ownership work? ESOPs, law firms, codetermination, and economic democracy*, 99 THE YALE LAW JOURNAL (1990); HENRY HANSMANN, *THE OWNERSHIP OF ENTERPRISE* (Belknap Press. 1996).

<sup>17</sup> Gillian K Hadfield, *The cost of law: Promoting access to justice through the (un) corporate practice of law*, 38 INTERNATIONAL REVIEW OF LAW AND ECONOMICS (2014).

<sup>18</sup> REINIER KRAAKMAN, et al., *THE ANATOMY OF CORPORATE LAW: A COMPARATIVE AND FUNCTIONAL APPROACH* (Oxford University Press. 2017).

organization's risk tolerance, crucial for innovation.<sup>19</sup> Critics argue that the rules mandating lawyer-only partnerships are now displacing innovation from US law firms into other organizations not subject to these restrictions:<sup>20</sup> in-house legal teams in corporations, and latterly, so-called "alternative legal service providers" (ALSPs), which provide auxiliary legal services but do not engage in the practice of law.<sup>21</sup> This concern underpins recent moves by the state Bar Associations in Arizona, California, and Utah to relax the partnership rule and permit lawyers to organize in corporations.<sup>22</sup>

However, the extent to which professional ethics rules have come to impede efficient organization of legal services firms depends in turn on how much the implementation of technology has disrupted traditional patterns of working. Of particular importance is the extent to which the optimal mix of human and non-human capital has shifted for these firms. Yet this is hard to assess simply by looking at US practices, because the professional ethics rules themselves constrain outcomes. Rather, what is needed is evidence from a counterfactual in which the regulatory constraint is not binding. To shed light on these issues we present findings from a systematic empirical study of the deployment of AI in legal services in the United Kingdom.<sup>23</sup> A regulatory change in 2007 made it possible for UK lawyers to organize as public corporations.<sup>24</sup> By studying practice in the UK, we can observe the

---

<sup>19</sup> Gillian K Hadfield, *Legal barriers to innovation: The growing economic cost of professional control over corporate legal markets*, 60 STAN. L. REV., 1727 (2007); Capturing Technological Innovation in Legal Services. pt. 116 (2017). N. Malhotra, et al., *Career pathing and innovation in professional service firms*, 30 ACADEMY OF MANAGEMENT PERSPECTIVE (2016).

<sup>20</sup> Legal Market Landscape Report. pt. 32 (2018).

<sup>21</sup> ALSPs are a heterogenous range of firms that do not fit into the traditional dualism of law firms and client in-house teams. See Alternative Legal Service Providers 2019. (2019).(describing scope of sector).

<sup>22</sup> See ARIZONA 2019. Task Force on the Delivery of Legal Services: Report and Recommendations. Supreme Court, State of Arizona; CALIFORNIA 2020. State Bar of California Task Force on Access through Innovation of Legal Services: Final Report and Recommendations. State Bar of California; UTAH 2019. Narrowing the Access-to-Justice Gap by Reimagining Regulation: Report and Recommendations. Utah State Bar Working Group on Regulatory Reform.

<sup>23</sup> Our empirical study consists of interviews and survey data analysis. Mixed methods (interviews and quantitative data analysis) are rarely used. For systematic data analysis, see Remus & Levy, GEO. J. LEGAL ETHICS, (2017). (using Sky Analytics data to gauge which tasks in the Uniform Task-based Management System (UTBMS) taxonomy are likely to be automated).

<sup>24</sup> Legal Services Act (UK) 2007, Part 5. This also permits the sharing of ownership of partnerships with non-lawyers.

ways in which AI is being deployed, and the organizational forms used, in a common law system in which the partnership form is no longer imposed on lawyers. We combine interviews with over fifty professionals, giving a descriptively rich set of insights into processes and motivations from which hypotheses can be developed, with quantitative data from a survey of lawyers against which hypotheses can be tested.<sup>25</sup>

We present case studies of the implementation of AI in three different types of organization: law firms, corporate in-house teams, and ALSPs.<sup>26</sup> Consistently with the critique of the partnership rule, we find that law firms face unique challenges with the implementation of technology, not shared by the other organizational types. However, the contours of the problem on the ground are quite different from those emphasized in the literature. While the literature focuses on the difficulties faced by partnerships in raising outside capital,<sup>27</sup> this turns out not to be a significant challenge in practice. The scale of large law firms mean that they have sufficient financial capability to invest in technological capital. Rather, the problem is with recruiting, motivating and managing the *non-legal* human capital needed to make the technology work. Non-legal human capital is hard for a law firm partnership to recruit, as there is no way for such persons to progress to partnership. And a management structure composed solely of lawyers is poorly suited to coordinating an MDT. Our cases studies of in-house teams and ALSPs suggest these problems are more readily solved in businesses organized as corporations.

Our interview findings emphasize the importance of multidisciplinary human capital for the successful deployment of AI in legal services. This leads us to formulate two hypotheses: (1) AI deployment in legal services is associated with MDTs; (2) MDTs in legal services are less associated with law firm partnerships than corporations. We test these hypotheses with quantitative data collected through a survey of lawyers.<sup>28</sup> Consistently with our first hypothesis about the association between MDTs and AI, we show that in a multivariate framework, respondent lawyers who work closely with non-lawyer professionals are significantly more likely to use AI applications than those who work exclusively with other lawyers. Moreover, consistently with our second hypothesis about the fit between organizational governance type and MDTs, we report that respondent lawyers who work in law firm

---

<sup>25</sup> For details of our survey methodology, see *infra* Section III.A.

<sup>26</sup> *Infra*, Sections II.B-II.D.

<sup>27</sup> Hadfield, INTERNATIONAL REVIEW OF LAW AND ECONOMICS, (2014).

<sup>28</sup> *Infra*, Part III.



partnerships are significantly less likely to work with non-lawyers, and to deploy AI applications, than respondent lawyers who work in corporations.

This Article's contributions are fourfold. First, we offer an integrated analysis of the different margins along which AI will impact legal services work: substitution for some tasks; augmentation of human lawyers who consume AI-enabled services; and augmentation by humans with legal expertise of the production of these AI-enabled services. Second, we present what is to our knowledge the first empirically-grounded account of the new roles that the deployment of AI will generate in legal services—working in MDTs that mix legal expertise with a range of other disciplinary inputs. Third, our empirical findings contrasting the deployment of AI-enabled legal services in different types of organization show that the challenges for lawyer-only partnerships in implementing AI lie not in capital constraints, but in the difficulties in coordinating the human side of the process—recruiting and motivating MDTs. Fourth, our case studies of UK law firms suggest that there will remain a strong economic rationale for traditional legal advisory firms—whose interaction with AI-enabled legal services will primarily be via consumption, rather than production—to remain organized as partnerships even in the absence of any regulatory requirement to do so.

Our findings have important implications for lawyers, law firms and the legal profession.<sup>29</sup> Our analysis shows that the way in which legally-trained staff will be able to interact with AI-based technology manifests itself in two distinct modes: as consumers or as producers. For the foreseeable future there will continue to be a need for human lawyers working in classical advisory roles.<sup>30</sup> While AI systems will substitute for lawyers in some tasks, this may be offset by increased demand for the lawyers whose service offerings are augmented by the AI. Lawyers working in these augmented roles will primarily be *consumers* of legal technology. At the same time, there will be new roles for persons with legal training as part of multidisciplinary teams.<sup>31</sup> Persons with legal human capital working in these roles will likely be *producers*, rather than simply consumers, of AI-enabled legal services. The necessary training and career structure of persons in the two types of role will be quite different.

For law firms, our UK data suggest a surprising finding:<sup>32</sup> relaxing professional ethics rules about profit-sharing has not resulted in the

---

<sup>29</sup> *Infra*, Part IV.

<sup>30</sup> See *infra*, Section IV.A.1.

<sup>31</sup> See *infra*, Section IV.A.2.

<sup>32</sup> See *infra*, Section IV.B.

transformation of law firms into corporations in order to embrace technology. This is despite the real hindrances we have documented for the deployment of legal technology in partnerships. While reluctance to change might initially be explained by inertia,<sup>33</sup> we are now thirteen years into the new regime. Our analysis suggests an economic explanation: making the business form conducive to MDTs (in which lawyers serve as producers of AI) makes it *less* attractive to the key human capital needed for the classical legal tasks that AI cannot yet do. Law firms seeking to focus on these tasks still need to attract and retain the best talent. Legal services firms may therefore need to choose which aspect of legal work—classical lawyering or the production of legal technology services—is at the core of their business model.<sup>34</sup>

Finally, a remaining open question, in our minds, is whether the rise of augmented lawyering will be capable of being accommodated within the existing institutional structures of the legal profession.<sup>35</sup> The existing structure is that of occupational licensing, so that only licensed lawyers are authorized to practice law, just as only licensed doctors can practice medicine. If law firms do not engage in the production of AI-related legal services, but satisfy themselves with being mere consumers, we suggest that the work of lawyers-as-producers is increasingly likely to be seen as part of a distinct or hybrid profession.<sup>36</sup> Depending on professional regulation, the scope of “augmented lawyering” may become narrowly defined, admitting lawyers-as-consumers only, or broader, admitting both lawyers-as-consumers and lawyers-as-producers, into the legal profession.

This Article proceeds in four Parts. Part I considers the impact of AI on the work of human lawyers. Part II turns to the relationship between AI deployment and the organizational structure of legal services firms. Part III introduces our survey dataset and presents quantitative findings consistent with the hypotheses developed in Parts I and II. In Part IV considers the implications of our findings for lawyers, legal services firms, and the legal profession.

---

<sup>33</sup> Sundeep Aulakh & Ian Kirkpatrick, *Changing regulation and the future of the professional partnership: the case of the Legal Services Act, 2007 in England and Wales*, 23 INTERNATIONAL JOURNAL OF THE LEGAL PROFESSION (2016).

<sup>34</sup> On the emerging range of business models facilitated by technology in legal services, see John Armour & Mari Sako, *AI-enabled business models in legal services: from traditional law firms to next-generation law companies?*, 7 JOURNAL OF PROFESSIONS AND ORGANIZATION (2020).

<sup>35</sup> See *infra*, Section IV.C.

<sup>36</sup> See Noordegraaf, M., *Hybrid professionalism and beyond:(New) Forms of public professionalism in changing organizational and societal contexts*. JOURNAL OF PROFESSIONS AND ORGANIZATION (2015).

## I. AI AND LAWYERS

### A. *The Impact of Automation*

Various recent survey-based studies indicate that AI usage in legal services is modest,<sup>37</sup> but increasing.<sup>38</sup> How will this extrapolate, and with what impact on the profession? Wholesale transformation of the professions by technology has long been predicted by some commentators.<sup>39</sup> Richard Susskind, an early exponent of the benefits of the application of AI to legal services, has long argued that the work done by many human lawyers will come to be undertaken by machines. As he puts it:<sup>40</sup>

“[T]here is no obvious reason that many of today’s professionals won’t be displaced by increasingly capable systems and then fade from prominence, much as blacksmiths, tallow chandlers, mercers, and many trades became redundant in their day.”

Clearly, if machines become universally cheaper and more effective than humans, then the latter face “technological unemployment.”<sup>41</sup> Whether this comes to pass, however, depends on the capabilities of automated systems, and their costs.

Sceptics respond that much of lawyers’ work cannot be performed by automated systems, nor are machines likely to develop such capabilities any

---

<sup>37</sup> Sako et al., *Lawtech Adoption and Training: Findings from a Survey of Solicitors in England and Wales*. (2020).(Figure 4) 2019 Global Legal Department Benchmarking Report. (2019).(Figure 3)ABA TECHREPORT 2019. (2019).

<sup>38</sup> Sako, et al., 10. 2020.(Figure 11); 2018 Law Firms in Transition: An Altman Weil Flash Survey. (2018). (Chart 3: US law firm increased AI adoption trends over a 2-year period); see also Wouters Kluwer, *The 2020 Wouters Kluwer Future Ready Lawyer – Performance Drivers* (2020) at 14; *Innovate to Accumulate*, *The Lawyer*. Nov 2018 at 40 – 41 (lists the priority investments of 52 top UK surveyed firms – around 70% said AI).

<sup>39</sup> See, e.g., RICHARD SUSSKIND, *TRANSFORMING THE LAW: ESSAYS ON TECHNOLOGY, JUSTICE AND THE LEGAL MARKETPLACE* (Oxford University Press. 2000);SUSSKIND, *The end of lawyers? : rethinking the nature of legal services*. 2008;RICHARD E. SUSSKIND, *TOMORROW’S LAWYERS : AN INTRODUCTION TO YOUR FUTURE* (Oxford University Press. 2013);SUSSKIND & SUSSKIND. 2015;Katz, EMORY LJ, (2012);Katz, U. ILL. L. REV., (2014).

<sup>40</sup> Richard Susskind, *AI, work and ‘outcome-thinking’*, 34 *BRITISH ACADEMY REVIEW* 30, 31 (2018).

<sup>41</sup> Daniel Susskind, *A model of technological unemployment*, (2018);Jeffrey D Sachs, et al., *A One-Sector Model of Robotic Immiseration*, in *DIGITIZED LABOR* (2018).

time soon.<sup>42</sup> Of course, it is not necessary for machines actually to emulate *what lawyers do* if the outcomes that lawyers deliver for their clients can be delivered more cheaply without humans.<sup>43</sup> And a significant *increase* in technical capabilities, even if it stops well short of complete automation, may be enough to trigger a restructuring of working practices. It is worth situating this debate in the context of the general literature on the “future of work”, which considers how technological change will impact human working practices from an economy-wide perspective.<sup>44</sup> The effects are more complex than just the idea of machines substituting for humans.

To understand the impact of technology on work, we need to break job descriptions down into their component tasks. This is because technical systems are not designed to perform particular human “jobs”, rather, they are designed to perform component *tasks* that workers undertake.<sup>45</sup> A typical job role involves a range of different tasks. Some are capable of automation, and some are not. It follows that the scope of what computers can do better than humans does not map neatly onto existing human roles within organizations. There are three distinct margins for change. The first is where technical systems *substitute* for humans.<sup>46</sup> This affects human roles consisting

---

<sup>42</sup> See, e.g., Remus & Levy, GEO. J. LEGAL ETHICS, (2017). (“Even where automation has made significant progress, its impact has been less than the headlines would have us believe.”)

<sup>43</sup> Susskind, BRITISH ACADEMY REVIEW, (2018), *supra* note 40.

<sup>44</sup> See generally, David H Autor, *Why are there still so many jobs? The history and future of workplace automation*, 29 JOURNAL OF ECONOMIC PERSPECTIVES (2015); DAVID AUTOR, WORK OF THE PAST, WORK OF THE FUTURE (National Bureau of Economic Research, 2019); Daron Acemoglu & Pascual Restrepo, *Automation and new tasks: how technology displaces and reinstates labor*, 33 JOURNAL OF ECONOMIC PERSPECTIVES (2019); Artificial intelligence, automation and work. No. 0898-2937(2018); Carl Benedikt Frey & Michael A Osborne, *The future of employment: How susceptible are jobs to computerisation?*, 114 TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE (2017); ERIK BRYNJOLFSSON & ANDREW MCAFEE, THE SECOND MACHINE AGE : WORK, PROGRESS, AND PROSPERITY IN A TIME OF BRILLIANT TECHNOLOGIES (W. W. Norton & Company First Edition. ed. 2014).

<sup>45</sup> See, e.g., David H Autor, et al., *The skill content of recent technological change: An empirical exploration*, 118 THE QUARTERLY JOURNAL OF ECONOMICS, 1282-83 (2003). (describing tasks as a “machine’s eye view” of work activities); Acemoglu & Restrepo, JOURNAL OF ECONOMIC PERSPECTIVES, 6 (2019). (“Tasks are ... the fundamental unit of production.”)

<sup>46</sup> See, e.g., Acemoglu & Restrepo, Artificial intelligence, automation and work 5-6. 2018. (describing “displacement effect” where automation substitutes for humans in the performance of tasks). Autor, JOURNAL OF ECONOMIC PERSPECTIVES, 7 (2015).

primarily of tasks that are capable of automation.<sup>47</sup> For roles that consist largely of tasks that can be automated, it follows that fewer human workers will be required.<sup>48</sup> Technological advances mean that the set of tasks capable of automation is increasing over time.<sup>49</sup>

Yet the effects are quite different for roles that encompass a significant portion of tasks that cannot be automated. The productivity of humans in such roles is *augmented* by automation of those tasks machines can now do.<sup>50</sup> Humans whose work consists primarily of tasks that cannot be automated benefit from the automation of tasks that form inputs to their work.<sup>51</sup> And humans whose work consists of a mix of tasks only some of which become automated are able to focus their energies on those tasks they are uniquely capable of performing.<sup>52</sup> In each case, more of the tasks that cannot be automated can now be completed in a given time, and the human worker's productivity increases. Along this second margin, automation of some tasks

---

<sup>47</sup> As one of our interviewees put it:

“One of the things we’re looking to further develop is what we’re terming digital legal solutions. What I mean by that is solutions that effectively enable [the] giving of legal advice or execution of legal work where it’s not just making lawyers more efficient but it’s actually the solution itself. ...” (Interview 38).

<sup>48</sup> Autor, JOURNAL OF ECONOMIC PERSPECTIVES, 9-14 (2015).(summarizing impact of automation on occupations). Daron Acemoglu & Pascual Restrepo, *Robots and jobs: Evidence from US labor markets*, 128 JOURNAL OF POLITICAL ECONOMY, 2233 (2020).(reporting negative employment effects of robots concentrated in routine manual occupations such as machinists, assemblers, material handlers, where workers engage in tasks that are being automated).

<sup>49</sup> See, e.g., Acemoglu & Restrepo, Artificial intelligence, automation and work 5. 2018. (characterizing “automation” as “an expansion of the set of tasks that can be performed with [technological] capital”). BRYNJOLFSSON & MCAFEE, 11. 2014. (“computers, robots, and other digital technologies are acquiring ... skills and abilities at an extraordinary rate”). On the capabilities of today’s AI technology, see *infra*, Section I.B.

<sup>50</sup> Autor, JOURNAL OF ECONOMIC PERSPECTIVES, (2015).

<sup>51</sup> Autor, et al., THE QUARTERLY JOURNAL OF ECONOMICS, 1285 (2003). (“[increases] in the supply of routine informational inputs, both in quantity and quality, increase the marginal productivity of workers performing nonroutine tasks that demand these inputs.”)

<sup>52</sup> Acemoglu & Restrepo, JOURNAL OF ECONOMIC PERSPECTIVES, 4 (2019).(describing “productivity effect” whereby automation increases demand for labor in non-automated tasks).

*augments* the value of the human capital associated with complementary tasks that cannot (yet) be automated.<sup>53</sup>

There is a third, less obvious, margin. The implementation of automated systems to perform substitutable tasks itself creates *new* tasks, many of which require human capital.<sup>54</sup> Perhaps the most obvious example is the rise of data scientist tasks with an increase in the demand for AI automation.<sup>55</sup> Automated systems must be designed, customized, set up, maintained, and overseen. These tasks complement, or *augment*, the functioning of the system. To the extent that these system-augmenting tasks are not themselves capable of being automated, implementing automated systems actually creates demand for the human capital necessary to perform these tasks.<sup>56</sup> These tasks likely bundle together into new jobs.<sup>57</sup>

So, in summary, automation results in reduced demand for some types of existing role, increased demand for others, and at the same time creates

---

<sup>53</sup> See Autor, JOURNAL OF ECONOMIC PERSPECTIVES, (2015).; see also Jill Grennan & Roni Michaely, Artificial Intelligence and the Future of Work: Evidence from Analysts (2019).(documenting both substitution and augmentation effects in case study of financial analysts). As one of our interviewees explained:

“[F]or high-end legal work, [we are] giving our lawyers the right tools to be able to do their work ... as effectively as possible; and then, all the way through down to the more managed service, higher volume, less complex work, helping them with technology too. So, effectively, tech enablement of our legal delivery, irrespective of the complexity or the volume of it.” (Interview 38).

<sup>54</sup> Acemoglu & Restrepo, JOURNAL OF ECONOMIC PERSPECTIVES, 4 (2019). (characterizing “reinstatement effect” whereby technological change creates demand for new roles that complement its deployment).

<sup>55</sup> Davenport, T. H & Patil, D., *Data scientist: the sexiest job of the 21<sup>st</sup> century*. HARVARD BUSINESS REVIEW (2012).

<sup>56</sup> Autor, JOURNAL OF ECONOMIC PERSPECTIVES, (2015). For example, in the design of chatbot systems, it has become common to deploy human-chatbot or ‘humbot’ teams, with humans being ready to answer queries the automated system finds difficult: see Jonathan Grudin & Richard Jacques, Chatbots, humbots, and the quest for artificial general intelligence (2019).

<sup>57</sup> David H. Autor, et al., *Upstairs, Downstairs: Computers and Skills on Two Floors of a Large Bank*, 55 ILR REVIEW (2002).Sako, M.. *Artificial intelligence and the future of professional work*. COMMUNICATIONS OF THE ACM (2020); Wilson, H. J., Daugherty, P. & Bianzino, N., *The jobs that artificial intelligence will create*. MIT SLOAN MANAGEMENT REVIEW (2017).

demand for new roles that augment the automated systems.<sup>58</sup> To apply this to the context of legal services, however, we need to understand the limits of technological capability for task automation, and map this onto legal services. Which tasks that lawyers do can be automated, which cannot, and which new tasks does automation itself engender? We now address these questions in turn. In Section I.B, we sketch the limits of the capabilities of recent advances in AI. In Section I.C, we draw on our interview research to consider the contexts in which this is being deployed in the legal sector, and the ways in which it is substituting for some existing tasks and enhancing the productivity of others. Finally, in Section I.D, we present findings about the processes by which our case study firms deploy AI in legal services, allowing us to describe the way in which it stimulates demand for new roles.

### B. *Today's AI and its Limits*

The last decade or so has seen a dramatic increase in the capability of AI-based systems,<sup>59</sup> and their application has the potential to bring about significant change in the legal sector.<sup>60</sup> However, we are still far from any kind of “artificial general intelligence” that would equal humans in the round.<sup>61</sup> We here describe these technical advances of AI and outline the types of task for which today’s AI systems are capable of substituting for humans. In so doing, we focus on “today’s” AI—that is, the state of technical possibility within the next few years; this enables us to ground the discussion in technical literature rather than speculation.<sup>62</sup>

---

<sup>58</sup> The aggregate impact so far appears to have reduced demand for human workers across the economy as a whole. That is, the number of human workers displaced by substitution effects is larger than the number benefiting from stimulation of demand for roles augmented by, or augmenting, the technical systems: see Acemoglu & Restrepo, *JOURNAL OF POLITICAL ECONOMY*, (2020). (estimating an additional robot per thousand workers reduces employment-to-population ratio by 0.2 percentage points).

<sup>59</sup> WOOLDRIDGE. 2020.

<sup>60</sup> See sources cited *supra*, notes 39-40.

<sup>61</sup> See generally Ben Goertzel, *Artificial general intelligence: concept, state of the art, and future prospects*, 5 *JOURNAL OF ARTIFICIAL GENERAL INTELLIGENCE* (2014); Lyle N Long & Carl F Cotner, *A Review and Proposed Framework for Artificial General Intelligence* (IEEE 2019).

<sup>62</sup> On the distinction between “today’s” and “tomorrow’s” AI, see John Armour & Horst Eidenmuller, *Self-Driving Corporations*, 10 *HARV. BUS. L. REV.* (2020).

We take “artificial intelligence” to involve the use of automated systems to perform tasks normally requiring human intelligence.<sup>63</sup> The origin of research into AI may be traced back to the 1950s,<sup>64</sup> since when there have been several distinct technical approaches.<sup>65</sup> For most of the field’s history, research efforts focused on so-called “top down” approaches to intelligence, involving logical reasoning and hard-coding of knowledge.<sup>66</sup> However, this approach came up against a fundamental limitation: many tasks turn out to be far too complex to be encoded in explicit rules. Premised on this technical limitation, it was until recently thought that only “routine” tasks—that is, those that can be specified by reference to a set of pre-specified rules—were susceptible to automation.<sup>67</sup>

In the last decade, however, explosions in computer power and data availability have enabled enormous progress to be made in “bottom up” inductive approaches known as “machine learning” (ML).<sup>68</sup> In ML, instead of seeking to derive answers from rules laboriously coded into expert systems, classifiers for recognizing patterns are developed by the system

---

<sup>63</sup> The definition of AI is of course itself highly contested. See, e.g., Pei Wang, *On Defining Artificial Intelligence*, 10 JOURNAL OF ARTIFICIAL GENERAL INTELLIGENCE, 8-13 (2019). (considering four different approaches to defining AI). Because we focus on the application of automated systems to particular tasks in the legal sector, the definition we use is capability-based: that is, it focused on the capability of the system to perform tasks otherwise done by human intelligence. This approach, espoused by AI pioneer Marvin Minsky (Marvin L Minsky, *Introduction to the Comtex microfiche edition of the early MIT Artificial Intelligence Memos*, 4 AI MAGAZINE, 21 (1983).), is commonly deployed by applied researchers as it provides a ready-made benchmark against which to assess progress (François Chollet, *On the measure of intelligence*, ARXIV PREPRINT ARXIV:1911.01547 (2019).) This definition is inherently dynamic, in that as the capability of AI advances, the set of tasks “ordinarily” done by humans correspondingly recedes. It consequently focuses attention on the technological frontier.

<sup>64</sup> John McCarthy, et al., *A proposal for the Dartmouth summer research project on artificial intelligence, august 31, 1955*, 27 AI MAGAZINE (2006).

<sup>65</sup> S. RUSSELL & P. NORVIG, *ARTIFICIAL INTELLIGENCE: A MODERN APPROACH* (Pearson 3rd International Edition ed. 2010); WOOLDRIDGE. 2020.

<sup>66</sup> P. HARMON & D. KING, *EXPERT SYSTEMS: ARTIFICIAL INTELLIGENCE IN BUSINESS* (Wiley & Co. 1985). On the application of expert systems to legal services, see e.g., Nancy Blodgett, *Artificial Intelligence Comes of Age*, 73 ABA JOURNAL 68(1987); RICHARD E. SUSSKIND, *EXPERT SYSTEMS IN LAW : A JURISPRUDENTIAL INQUIRY* (Clarendon; Oxford University Press. 1987).

<sup>67</sup> Autor, et al., *THE QUARTERLY JOURNAL OF ECONOMICS*, 1284-85 (2003); Daniel Susskind, *Re-Thinking the Capabilities of Machines in Economics*, DEPARTMENT OF ECONOMICS DISCUSSION PAPER SERIES, UNIVERSITY OF OXFORD (2017).

<sup>68</sup> RUSSELL & NORVIG. 2010.



from the data itself.<sup>69</sup> Progress since 2012 has largely been in a particular type of ML known as “deep learning”, which involves running multiple layers of representation of the data in series.<sup>70</sup> A typical deep learning setup consists of an input and an output layer, with multiple hidden layers in between that lie at different levels of abstraction and are linked to each other.<sup>71</sup> The learning process of the algorithm takes place via so-called back-propagation: In the course of training the algorithm, new information is fed back from the output layer over the various hidden levels and recalibrates the settings or weights of the individual neurons with the aim of improving the accuracy of results.<sup>72</sup> While most of the recent progress in ML has been through the use of deep learning methods, we refer for simplicity throughout the text to “ML” where it is necessary to emphasize contradistinction to rule-based approaches to AI.

The most widely-used approach to ML is *supervised* learning, which uses a set of training data labelled according to the dimension of interest.<sup>73</sup> The system analyses these data and determines the best way to predict the relevant outcome variable by reference to other features of the data. The trained model—that is, the algorithm with the set of parameters that optimized performance on the training dataset—is then put to work on new data to predict outcomes of interest.

---

<sup>69</sup> Brian Sheppard, *Incomplete innovation and the premature disruption of legal services*, MICH. ST. L. REV., 1851ff (2015).

<sup>70</sup> See e.g. WOOLDRIDGE. 2020; Jürgen Schmidhuber, *Deep learning in neural networks: An overview*, 61 NEURAL NETWORKS (2015); Terrence J. Sejnowski, *The unreasonable effectiveness of deep learning in artificial intelligence*, PROCEEDINGS OF THE NATIONAL ACADEMY OF SCIENCES (2020).

<sup>71</sup> These processes are often called “neural networks”, a term drawn from neurobiology, reflecting the fact that some draw inspiration from contemporary understanding of the functioning of the brain. However, their actual operation is quite different from the human brain: FRANÇOIS CHOLLET, *DEEP LEARNING WITH PYTHON* (Manning Publications Co. 2018).

<sup>72</sup> Yann LeCun, et al., *Deep learning*, 521 NATURE (2015).

<sup>73</sup> Approximately 95% of ML applications in use today are based on this method (MARTIN FORD, *ARCHITECTS OF INTELLIGENCE : THE TRUTH ABOUT AI FROM THE PEOPLE BUILDING IT* 186 (2018)). In the future, unsupervised learning, which simply looks for patterns in the data, and reinforcement learning which allows the machine to self-learn using only a reward signal, are expected to spread in use. Other promising techniques include semantic learning, which seeks to combine the benefits of “top down” and “bottom up” approaches (WOOLDRIDGE. 2020.).

ML has exhibited greatest successes in image recognition, exceeding human capabilities in many contexts.<sup>74</sup> This has made it possible to automate tasks previously characterized as “non-routine”, such as driving a car or recognizing human handwriting.<sup>75</sup> In relation to language, ML is combined with *natural language processing* (NLP) which converts unstructured textual data to numeric vectors that can be analyzed using ML techniques.<sup>76</sup> These essentially rely on statistical relationships between words, or patterns of words, within a corpus of text. NLP methods work well for information retrieval tasks, but struggle with semantic context, meaning that tasks requiring “social intelligence”, i.e. an appreciation of the way in which potentially ambiguous communications will be understood by humans, continue to elude ML systems.<sup>77</sup>

The need for large labelled datasets points to another important limitation: ML works well for tasks that scale, but in the absence of prior examples from which to learn, it is ineffective.<sup>78</sup> So-called “transfer learning”—that is, taking concepts learned in one context and generalizing to apply them in another—while natural for humans, is still limited to modest sideways steps in ML. Consequently, tasks requiring “creative intelligence”, to solve problems for which there are no obvious prior examples of answers, also remain beyond current ML systems.<sup>79</sup>

### C. Using AI to Scale Legal Services: Use-Cases for Deployment

This account of the limits of AI implies that some aspects of legal services work will remain beyond the scope of automation for the foreseeable future.

---

<sup>74</sup> Yanming Guo, et al., *Deep learning for visual understanding: A review*, 187 NEUROCOMPUTING, 43 (2016); Athanasios Voulodimos, et al., *Deep learning for computer vision: A brief review*, 2018 COMPUTATIONAL INTELLIGENCE AND NEUROSCIENCE (2018); Zhong-Qiu Zhao, et al., *Object detection with deep learning: A review*, 30 IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS (2019).

<sup>75</sup> Susskind, DEPARTMENT OF ECONOMICS DISCUSSION PAPER SERIES, UNIVERSITY OF OXFORD, (2017).

<sup>76</sup> DAN JURAFSKY & JAMES H. MARTIN, SPEECH AND LANGUAGE PROCESSING : AN INTRODUCTION TO NATURAL LANGUAGE PROCESSING, COMPUTATIONAL LINGUISTICS, AND SPEECH RECOGNITION (3rd (in draft) ed. 2019).

<sup>77</sup> Frey & Osborne, TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE, (2017); Lene Pettersen, *Why artificial intelligence will not outsmart complex knowledge work*, 33 WORK, EMPLOYMENT AND SOCIETY (2019); WOOLDRIDGE. 2020.

<sup>78</sup> A. Halevy, et al., *The unreasonable effectiveness of data*, 24 IEEE INTELLIGENT SYSTEMS (2009); C. Sun, et al., *Revisiting Unreasonable Effectiveness of Data in Deep Learning Era*. (2017).

<sup>79</sup> See sources cited *supra* note 77.

Interaction with clients—specifying requirements and explaining advice—commonly involves high levels of social intelligence, which professionals refer to as “client skills”.<sup>80</sup> Similarly, the first time a particular problem is solved, design work must be done anew, which necessitates creative intelligence. So, for work that is exclusively “bespoke”—that is, novel in character and unlikely to be repeated—AI is unlikely to substitute for humans any time soon. However, if multiple outputs can be based on a single design, then the tasks involved in that production can in principle be automated using ML.

We can see that there are significant economies of scale associated with the application of supervised learning to legal processes.<sup>81</sup> Labelling data will generally require human professional expertise, which is costly. However, once the system is up and running, it can make automated predictions at lower cost and greater accuracy than would be the case for a human professional decision-maker.<sup>82</sup> Consequently, economically viable use-cases will depend on there being a sufficiently large number of potential applications of a trained model, for which the training data are representative, and across which the start-up costs of labelling can be amortized.<sup>83</sup> These necessary conditions help us to understand the types of work for which AI is being used. For most legal applications, these conditions are quite restrictive. Established use-cases in legal practice, which we now consider,

---

<sup>80</sup> John Flood, *Legal professionals of the future: Their ethos, role and skills*, ROLE AND SKILLS (JANUARY 15, 2019) (2019).

<sup>81</sup> Our interviewees emphasized the importance of economies of scale. As one put it when discussing their criteria for adoption of a technology-enabled solution: “one thing that we do always discuss is: can we scale this?” (Interview 39).

<sup>82</sup> As one interviewee put it:

“Technology is more consistent – it doesn’t mean that it’s finding all the relevant documents, it’s just, when it makes one decision right, it does it all the time, and when it makes it wrong, it does it all the time. Whereas, with a human, it varies from each day, week, and person. I’ve managed reviews in other jobs that I’ve had where I supervised a team of lawyers and they go on debates – people debate about one document, about the privilege reason or whatever, and I think, with AI, it’s just ... more black and white with how it makes that decision.” (Interview 15).

<sup>83</sup> Moreover, it is possible that scale effects may be even more pronounced. In many commercial applications, feedback from the checking of results can be used to generate additional examples of labelled data for ongoing training. This opens the possibility of increasing returns, whereby there is positive feedback between increased predictive accuracy and increased user acquisition (cf. Hal Varian, *Artificial intelligence, economics, and industrial organization*, in *THE ECONOMICS OF ARTIFICIAL INTELLIGENCE* (Ajay Agrawal, et al. eds., 2019)).

consequently focus on finding specified material in a large mass of documentation.<sup>84</sup>

1. Discovery: technology-assisted review.

The earliest adoption of ML was in the context of the review of electronic documents for their relevance for a discovery exercise.<sup>85</sup> Discovery is a major component of litigation costs. According to a 2010 survey, the average amount spent on discovery by large public companies was over \$600,000 per lawsuit, more than a quarter of the total costs of litigation for these firms.<sup>86</sup> On average, just under five million documents were produced in major cases that went to trial in 2008.<sup>87</sup> The volume of information that is potentially relevant to a typical large lawsuit has grown exponentially with the universal adoption of digital communications and record-keeping since the turn of the century.<sup>88</sup> This setting creates powerful demand for tools that can help to identify potentially relevant documents more quickly and cheaply.<sup>89</sup>

So-called “eDiscovery” started out with the use of simple keyword searches,<sup>90</sup> but during the past decade this has transformed into what has become variously known as “technology-assisted review” (TAR) or “predictive coding”.<sup>91</sup> Leading platforms for this use-case are Relativity,<sup>92</sup>

---

<sup>84</sup> As one ALSP interviewee put it:

“[We look for] use-cases that can scale and that can serve the industry by partnering with law firms and law departments to be their technology enablement arm, help them get it right, help them to establish [cognitive] centers of competency, governance models, internal governance models that can scale.” (Interview 18).

<sup>85</sup> Kevin D Ashley & Will Bridewell, *Emerging AI & Law approaches to automating analysis and retrieval of electronically stored information in discovery proceedings*, 18 ARTIFICIAL INTELLIGENCE AND LAW (2010). Maura R. Grossman & Gordon V. Cormack, *Technology-assisted review in e-discovery can be more effective and more efficient than exhaustive manual review*, 17 RICHMOND JOURNAL OF LAW AND TECHNOLOGY (2011).

<sup>86</sup> Litigation Cost Survey of Major Companies. (2010).

<sup>87</sup> *Id.* at, 16.

<sup>88</sup> John H Beisner, *Discovering a Better Way: The Need for Effective Civil Litigation Reform*, DUKE LAW JOURNAL, 550-551 (2010); George L Paul & Jason R Baron, *Information inflation: Can the legal system adapt*, 13 RICH. JL & TECH., 4-15 (2006). E Donald Elliott, *How We Got Here: A Brief History of Requester-Pays and Other Incentive Systems to Supplement Judicial Management of Discovery*, 71 VAND. L. REV., 1786 (2018).

<sup>89</sup> Paul & Baron, RICH. JL & TECH., 21-25 (2006).

<sup>90</sup> *Id.* at, 21-23.

<sup>91</sup> Grossman & Cormack, RICHMOND JOURNAL OF LAW AND TECHNOLOGY, (2011); David Freeman Engstrom & Jonah B Gelbach, *Legal Tech, Civil Procedure, and the Future of Adversarialism*, UNIVERSITY OF PENNSYLVANIA LAW REVIEW, FORTHCOMING, [28-29] (2020).

<sup>92</sup> [www.relativity.com](http://www.relativity.com).

Exterro,<sup>93</sup> and Everlaw.<sup>94</sup> In a classical TAR process, a team of humans begin by identifying a “seed” set of relevant documents, based on the team’s assessment of what factors are likely to be pertinent to the case.<sup>95</sup> These are used for the initial training of an ML model.<sup>96</sup> The model is then applied to other potentially relevant information, and flags up a series of results. These are examined by the human team who annotate them according to their relevance. The “corrected” results are fed back into the model so that its training is continuous.<sup>97</sup>

Where AI is used in TAR, there are no problems with data availability—indeed, it is the very abundance of data that motivates the application. However, as the circumstances relevant to each dispute are highly specific, this necessitates the training of a new ML model for every dispute to which the technique is applied.<sup>98</sup> This means that only limited economies of scale cannot be achieved *across* different lawsuits.<sup>99</sup> However, the very size of the typical discovery endeavor means there are still clear economies of scale to deploying an AI-based system.<sup>100</sup>

## 2. Due diligence and contract analytics.

ML models are increasingly also coming to be used in due diligence for large transactions, to review large volumes of contracts for potentially

---

<sup>93</sup> [www.exterro.com](http://www.exterro.com).

<sup>94</sup> [www.everlaw.com](http://www.everlaw.com).

<sup>95</sup> Active Learning in Technology-assisted Review: Relativity’s Approach to SVM and the Tech Behind It. (2018).

<sup>96</sup> The most recent iterations of some platforms seek to cut out this first step by flagging an initial set of relevant documents based on training from other matters; these are then fed into the iterative review process that follows. See, e.g., *id.* at. (“Manually-selected documents are not required, but when available, they help ‘warm up’ the model’s definition of relevance and jump-start the project, allowing the prioritized review queue to serve up highly relevant documents even faster.”)

<sup>97</sup> Gordon V Cormack & Maura R Grossman, Evaluation of machine-learning protocols for technology-assisted review in electronic discovery 160-161 (2014).

<sup>98</sup> [Interview x].

<sup>99</sup> See *supra*, note 96.

<sup>100</sup> See sources cited *supra*, notes 88-90.

problematic terms.<sup>101</sup> Key platforms in this context are Kira,<sup>102</sup> iManage RAVN,<sup>103</sup> Seal Software,<sup>104</sup> and Luminance.<sup>105</sup> The most successful applications were initially to contexts where transaction documentation was highly standardized, such as real estate,<sup>106</sup> but deployment is now increasingly common in corporate M&A as well.

Relatedly, ML models can also be used to review incoming day-to-day contracts for a user.<sup>107</sup> In these contexts, the sorts of terms that are deemed potentially problematic are more likely to be similar across matters, permitting greater economies of scale in the use of ML models. However, capturing these economies of scale requires either a user with large quantities of relevant proprietary data (e.g. a large corporation) or for clients of the user to permit the training benefits accruing from analysis of their data to be pooled with others'.<sup>108</sup> Leading platforms for this use-case, which include

---

<sup>101</sup> One interviewee explained:

“In the transactional space, i.e. doing deals, like M&A work for example, [deployment of AI is] a relatively recent development. So, in about 2013, I would say, some new providers came on the market who all [wanted] to do similar things, and they developed their algorithms specifically to be tailored for corporate M&A due diligence purposes, so the algorithms have been trained with a document set that would enable them to pick up commonly searched terms in a due diligence context, you know, standard terms like ‘change of control’ or ‘assignment’, those kind of things. So, that was specifically tailored to that use-case.” (Interview 13).

<sup>102</sup> [www.kira.com](http://www.kira.com) (based in Toronto, founded in 2011) see Artificial Lawyer, The Kira Systems Story, Aug. 16, 2016 (<https://www.artificiallawyer.com/2016/08/16/the-kira-systems-story/>).

<sup>103</sup> [www.imanage.com/product/artificial-intelligence/](http://www.imanage.com/product/artificial-intelligence/) (RAVN was a UK-based AI startup acquired by Chicago-based legal work product management solution provider iManage in 2017).

<sup>104</sup> [www.seal-software.com/solutions/ma/](http://www.seal-software.com/solutions/ma/) (UK-based startup founded in 2010, acquired by US-based contract technology provider DocuSign in May 2020).

<sup>105</sup> [www.luminance.co.uk](http://www.luminance.co.uk) (UK-based startup founded in 2015).

<sup>106</sup> See e.g., Philipp Maximilian Müller, et al., *Fundamentals for automating due diligence processes in property transactions*, JOURNAL OF PROPERTY INVESTMENT & FINANCE (2020).

<sup>107</sup> As one interviewee explained:

“[A]n AI solution ... can compare third party [draft contracts] ... to your contracting standards ... so that you narrowly focus on what needs to be changed. Even better, [think about] building a scoring system around that, right, that goes to your conformance to your standard...” (Interview 39).

<sup>108</sup> As one interviewee explained:

“[O]n the contract automation side, where most in-house functions have started is, well, let’s make our NDA self-service, and you put in a few parameters, generate the NDA, and as long as it’s within certain parameters, it lets you, you know, execute it yourself, or if it’s outside of parameters, it routes it to the right lawyer.” (Interview 38).

Kira,<sup>109</sup> LawGeex,<sup>110</sup> Seal Software,<sup>111</sup> and ThoughtRiver,<sup>112</sup> permit users to establish a “playbook” of contract terms for their organization, which is then used to deliver a risk-assessment of incoming contracts.<sup>113</sup> They also facilitate the more effective management of contract portfolios by extracting and analyzing data such as key dates and metrics from contract text.<sup>114</sup>

### 3. Legal research

In a wide range of settings, lawyers may also make use of AI in supporting legal research. Support tools used in this context, such as LexisNexis’ LexisAdvance,<sup>115</sup> include a range of AI tools in different parts of the research process. These include expert systems to deliver checklists for lawyers researching a topic, coupled with ML search tools that learn from the user’s search strategies to suggest more effective solutions. ML is also harnessed to analyze search results and highlight words according to relevance, and to identify citation links between cases.<sup>116</sup> Looking forwards, emerging applications include, for contentions matters, ML analysis of past litigation data—not only facts and precedents, but also the records of judges and litigants—with a view to predicting outcomes in future disputes.<sup>117</sup>

---

<sup>109</sup> See *supra*, note 102.

<sup>110</sup> [www.lawgeex.com](http://www.lawgeex.com) (Tel Aviv and New York-based startup founded in 2014).

<sup>111</sup> See *supra*, note 104.

<sup>112</sup> [www.thoughtriver.com](http://www.thoughtriver.com) (Cambridge, UK based startup founded in 2015).

<sup>113</sup> See, e.g., [www.lawgeex.com/platform/](http://www.lawgeex.com/platform/) (“Step 1: Set up your playbook”); [www.thoughtriver.com/automated-contract-review](http://www.thoughtriver.com/automated-contract-review).

<sup>114</sup> See, e.g., Kira, What Contract Review Software Systems Do And Why They Exist, 2-3 (2019) (“Most companies would benefit from contract management databases that break out details of all their contracts in a searchable way. And relatively few companies have them. These databases enable greater access to information across a business. And can help mitigate risks.”).

<sup>115</sup> See LexisNexis, LexisAdvance: Advancing What’s Possible <https://www.lexisnexis.com/pdf/lexis-advance/la-overview-brochure.pdf>.

<sup>116</sup> *Id* at 4.

<sup>117</sup> Nikolaos Aletras, et al., *Predicting judicial decisions of the European Court of Human Rights: a Natural Language Processing perspective*, 2:e93 PEERJ COMPUTER SCIENCE (2016); Daniel Martin Katz, et al., *A general approach for predicting the behavior of the Supreme Court of the United States*, 12 PLOS ONE <https://doi.org/10.1371/journal.pone.0174698>(2017). Alina Petrova, et al., Predicting Outcomes in the Federal Appeals Court (2020). Leading commercial applications of this in the US are currently Lex Machina (<https://lexmachina.com/>), available through LexisNexis,

#### 4. Billing and utilization

The application of AI to the “business of law” entails leveraging proprietary data about work patterns within an organization to enable more accurate timetabling of work, thus facilitating output-based pricing models.<sup>118</sup> This type of application sits alongside more general AI-enabled human resource and client relationship management applications that have become ubiquitous in many organizations generally.<sup>119</sup> Such applications are also deployed by in-house corporate legal departments not only to manage their own personnel, but also to manage the billing of outside counsel.<sup>120</sup>

To be sure, the deployment of AI in these contexts is not a new idea, and examples can be found of attempts to leverage earlier expert systems approaches to AI in similar use-cases in the 1980s and 90s.<sup>121</sup> What has changed in recent years with the advent of machine learning is the power of the technical systems, meaning the scope of potential deployment in each context has increased.

---

and LexPredict (<https://www.lexpredict.com/>), acquired by Elevate. In the UK, Solomonic is the leading sources of litigation analytics (<https://www.solomonic.co.uk/>). One interviewee spoke about the deployment of AI in this context: “We’re using a lot of machine learning ... within our insurance claims data ... to give good guidance to our fee-earners on things like how much should you settle this case for, based on previous cases.” (Interview 9).

<sup>118</sup> See for example, Seedrs, Six Ways the legal sector is using AI right now, Dec 13, 2018 (<https://www.lawsociety.org.uk/news/stories/six-ways-the-legal-sector-is-using-ai/>). As one of our interviewees put it:

“[L]awyers are recording units of time and then writing a narrative about what they’re doing. So, millions and millions of records of unstructured data – a great opportunity for AI to be plugged in .. and to create intelligent things like ... how much this matter is going to cost or what parties are involved, or what the subject matter is, or any number of other things...” (Interview 9)

<sup>119</sup> See e.g. THOMAS H. DAVENPORT, *THE AI ADVANTAGE : HOW TO PUT THE ARTIFICIAL INTELLIGENCE REVOLUTION TO WORK* (The MIT Press. 2018).; From Fear to Enthusiasm: Artificial Intelligence is Winning More Hearts and Minds in the Workplace (2019); S. Ransbotham, et al., *Reshaping Business With Artificial Intelligence*, MIT SLOAN MANAGEMENT REVIEW (2017).

<sup>120</sup> Interview 46 (“[our billing analysis] uses AI to read legal [invoices] and to understand the domain-specific ontology of the matter type that the external lawyer is billing for, no matter what codes they use, and it understands that [terms have] a different meaning and a different weight and a different context depending upon the matter type ... We were able to reduce one insurer’s outside counsel spend by ... [one third] of their [annual total]”).

<sup>121</sup> See e.g., G. Wynn Smith, Jr., *Toward Value Billing: An Artificial Intelligence Approach*, 15 *LEGAL ECONOMICS* 23(1989).(billing); Daniel B. Evans, *Document Assembly: An Artificial Intelligence Perspective*, 16 *LAW PRACTICE MANAGEMENT* 18(1990).(document management); Richard E Susskind, *Artificial intelligence, expert systems and law*, 5 *DENNING LJ* 105, 105-107 (1990).(listing contemporary use-cases).



Our survey data give a sense of the relative levels of uptake across these different use-cases in the UK legal community.<sup>122</sup> We asked respondents, who were lawyers in private practice in England and Wales, “In which context(s) do you currently use AI-assisted legal technology?”<sup>123</sup> Just under half (48%) of respondents indicated that they used AI-assisted technology in one or more context. More specifically, 27% used it for legal research, 16% for due diligence, 13% for discovery-related work, 12% for regulatory compliance, 10% for contract analytics, 8% for predictive billing and/or utilization analytics, 2% for predictive analytics for litigation, and 7% in any other context.

In each of these use-cases, the AI system automates some tasks that would previously have been done by humans. Some paralegals and junior lawyers, whose work would have consisted largely of such tasks, are displaced. But for many lawyers, the impact is to augment their productivity. These lawyers continue to perform their traditional tasks—providing advice and interacting with clients—but in so doing benefit from the output of these AI-enabled legal services. In other words, they are *consumers* of the AI-enabled legal services, which has the effect of enhancing their own productivity.

#### D. *The AI Pipeline and Multidisciplinary Teams*

In the previous Section, we considered the contexts in which AI is deployed in legal services. These use-cases are tasks traditionally performed by humans. We have seen how these substitute for some humans and augments the work of others. What we have not yet discussed, however, are the new roles generated by the implementation of the systems. Put differently: we have seen how the outputs of these systems are *consumed*, but we have not yet considered how they are *produced*. In this Section, we present an account of how AI-based legal technology is made to work. This is best understood as a series of steps, a perspective common to engineers, which we characterize as the “AI pipeline”. Each step requires human tasks to be performed by persons with a range of different disciplinary expertise. This account is informed by our case interviews but is presented in a way that is largely independent of the organizational context.

---

<sup>122</sup> Sako, et al. 2020.

<sup>123</sup> We told respondents that by “AI-assisted” we meant “technology that uses an expert system, machine learning, and/or deep learning.”

### 1. Requirements

First, the user must articulate the relevant *requirements* for the solution. What functions is it required to perform? What data inputs can be provided by the user, and in what form? How much technical expertise will employees who work with the system have? How much tolerance for error will there be, and what mitigating measures can be deployed? At what cost must the system deliver results in order to be commercially viable? Properly analyzing requirements for legal technology entails an interdisciplinary mixture of skills—legal knowledge about the relevant tasks to be performed and the significance of the outputs; commercial understanding of costings and potential for economies of scale; data science appreciation of the nature of relevant data, its integrity, and the likely potential for error and how this should be handled in interpretation; a systems engineering perspective on how the solution will need to integrate with other software solutions already deployed by the user, in particular for employee interfaces and for data handling; a process mapping perspective to ensure that work (i.e. tasks in the AI pipeline) flows smoothly without waste; and a project management appreciation of the need to corral the various human personnel to meet milestones and deadlines. This synthesis in turn generates a set of *specifications* for the technical system, which it must deliver in order to be able to meet the requirements.

### 2. Design/procurement

Upon completion of the requirements stage, the specifications can be mapped onto legal technology vendor offerings through the procurement process. Obviously, if the requirements analysis is incomplete, this will undermine the procurement process' ability to deliver a useful solution.<sup>124</sup> Where a solution does not already exist in the marketplace, then it may be necessary to commission a new system. Again, the design process requires as an input a clear set of specifications for the desired system; delivering on this entails a mixture of computer science and design skills.

### 3. Data ingestion

Once a system is in place, the user can begin operation. For an AI system, the first step is to ingest relevant data for training the model. These data must be *relevant* to the problem sought to be solved: AI models are highly sensitive

---

<sup>124</sup> Several interviewees mentioned discovering only after paying to license a particular platform that it was not as useful as they had hoped. This had led their organizations to devote more effort to the requirements and specification stage going forward, which ideally should flag these issues as part of the procurement process.

to the specific data used to train them, and consequently the greater the difference between the characteristics of the data used for training and those used for application, the greater the likely errors.<sup>125</sup> Moreover, the data must be checked for *integrity*. This entails both legal permissions to use the data (encompassing issues of privacy, copyright and confidentiality, where relevant);<sup>126</sup> its formatting and freedom from corruption; and the security of the storage and transmission of data. Given that AI systems need large quantities of data, ingestion will likely itself need to be automated, with related mechanisms for spot-checking some fraction for relevance and integrity.

#### 4. Data labelling

For supervised learning approaches—which constitute the vast majority of applications currently in the marketplace—data ingested into the system must be *labelled* according to the dimension of interest for the purposes of training. In most commercial applications, model training is performed in a continuous fashion, sometimes referred to as “continuous active learning”,<sup>127</sup> or “online learning”,<sup>128</sup> appropriate for datasets that are evolving in real time. Performance feedback is captured by asking users to assess the accuracy of the model’s outputs in real time—are these, or are they not, examples of the desired category? For legal applications, this necessitates appropriate legal expertise.<sup>129</sup> At the same time, data science expertise is needed to ensure the effective cross-validation in this continuous learning context.<sup>130</sup>

---

<sup>125</sup> [Footnote here discussing the bias/variance trade-off. Main point being that some level of variance (overfitting) is unavoidable, and consequently differences between training and target data will lead to errors]

<sup>126</sup> Cites on these issues.

<sup>127</sup> “So previously, we were using something like a sample-based approach, but now it’s something called continuous active learning, where ...the AI really kind of learns with the human review, instead of being just trained upfront and done.” (Interview 40).

<sup>128</sup> See e.g. <https://medium.com/analytics-vidhya/data-streams-and-online-machine-learning-in-python-a382e9e8d06a>.

<sup>129</sup> “Who trains my model? [This is] probably one of the key risk factors going forward with AI. Is it someone with [legal] expertise? Is it a data scientist who’s interpreting second-hand legal theory?” (Interview 46).

<sup>130</sup> In such contexts, the model is continuously trained (and cross-validated) across the dynamic dataset. This has two benefits. First, the size of the training dataset is continuously increasing, enabling the model’s performance to improve. Second, the characteristics of the dataset may evolve or drift in some dimensions; continuous training and testing ensures that the model is always fitted in a way that incorporates all characteristics of the data as they evolve.

## 5. Application of results

The successful application of the trained model to a particular use-case again presupposes a mix of professional skills: data science knowledge in understanding the significance of the results, legal expertise to assess the implications of this for the matter in question, and client skills to explain the combined analysis to the party who will rely on the results.

For example, consider the selection of an appropriate benchmark to assess the success of a ML. A standard measure is its *accuracy* in relation to a test dataset: the proportion of observations that the model categorizes successfully.<sup>131</sup> If the dataset is imbalanced—that is, it has fewer relevant than irrelevant observations—then overall accuracy can be misleading. Consider for example a TAR exercise, searching for potentially relevant emails in a client firm’s data repository. Assume there are a million emails to be classified, of which only 10,000 (one per cent) are in fact plausibly relevant. A ML model might deliver an accuracy of 99 per cent simply by classifying all the emails reviewed as irrelevant.<sup>132</sup> Of course, this would be useless for the purpose of TAR, because it would miss all the relevant results. With a dataset comprised principally of irrelevant items, what matters is the proportion of relevant observations in the dataset that are flagged by the model, a metric known as *recall*.<sup>133</sup>

---

<sup>131</sup> See generally, Shruti Saxena, *Precision vs Recall*, Towards Data Science, May 11, 2018 (<https://towardsdatascience.com/precision-vs-recall-386cf9f89488>); Classification: Precision and Recall, Google Machine Learning Crash Course (<https://developers.google.com/machine-learning/crash-course/classification/precision-and-recall>). This is an aggregate measure, comprised of two distinct components relating to the two directions in which classification errors may be made. A model’s *precision* captures the proportion of the observations it flags as relevant (“positives”) that actually are relevant (“true positives”), i.e. This gives an indication of the level of Type I error (“false positives”), in the results. On the other hand, a model’s *recall* is the proportion of the entire population of relevant observations in the dataset that are flagged by the model as relevant, i.e.  $\text{recall} = \text{true positives} / [\text{true positives} + \text{false negatives}]$ . In these terms, overall accuracy is then understood as the sum of both true positives and true negatives (that is, the total number of observations correctly classified by the model) divided by the total number of observations in the dataset, i.e.  $\text{accuracy} = [\text{true positives} + \text{true negatives}] / [\text{true positives} + \text{true negatives} + \text{false positives} + \text{false negatives}]$ .

<sup>132</sup> This is because in the dataset as a whole, 990,000 (99%) of the emails are in fact irrelevant. Classifying the whole dataset as irrelevant will mean errors only for the 10,000 false negatives, 1% of the total.

<sup>133</sup> See *supra* note 131.

Hence assessing the appropriate degree of tolerance in performance measures will be a matter of considerable judgment.<sup>134</sup> These data science insights must be combined with contextual assessment of the legal services application. Thus, for TAR, there needs to be relevant legal expertise on call to identify the potential significance of the results for the legal merits of the matter in question. In a contract review exercise, the relevant expertise inputs may encompass not only legal, but also the commercial context.<sup>135</sup>

## 6. The human capital mix in the AI pipeline

A key insight that emerges from the foregoing discussion is that the successful deployment of AI solutions in legal services necessitates a wide range of different types of expertise at multiple stages of the process: requirements analysis, design and/or procurement, data ingestion and labelling, and application of results. This implies a multidisciplinary team (or teams) of workers providing the necessary human capital to complement the application of the technology. Moreover, understanding the pipeline nature of the exercise reveals the importance of planning and managing the process in itself. As one of our interviewees put this point succinctly:

“[Y]ou need, effectively, a solution to manage the matters, keep track of all of them, and manage who’s working on them, the delegation, the

---

<sup>134</sup> In a real-world use-case, things are often much more complex. As we have noted, the training and application of models is typically done in a continuous loop, in which the balance of the dataset may be evolving over time. This necessitates ongoing recalibration of performance measures. More challenging still, there is generally no “objective” measure of the correct classification for the entire dataset. Labelling requires human classification of the individual observations, which if done for the entire dataset defeats the purpose of the ML exercise. Hence quality control will necessarily only be for subsamples of the data. Moreover, human classification is itself error-prone. Together, this means that the benchmark against which the model’s results are assessed will be itself inaccurate, incomplete, and varying over time. Worse still, in some settings, a model’s results may be fragile to the presence of so-called “adversarial examples”—that is, items introduced into the dataset specifically to ‘spoo’ the trained classification. This is highly pertinent for AI applications to contractual review. For example, a model trained to identify “change of control” clauses in an M&A context may struggle with wording that deliberately avoids using terms used in standard documentation. Assessing the degree to which a model’s results may be brittle to adversarial examples is a complex exercise. See e.g. Arno Blaas, et al., *Adversarial Robustness Guarantees for Classification with Gaussian Processes* § 108 (2020).

<sup>135</sup> As one of our interviewees explained: “There’s what you call CLM—‘contract lifecycle management’—tools ... I think sometimes people [when thinking about CLM] think about only the lawyer’s role, when, actually, there are other participants in that – there’s procurement, and there’s also the business, who have a big role in actually drafting a contract.” (Interview 43).

workflow, etcetera, ... it's more like a production line kind of technology."<sup>136</sup>

The personnel working in these MDTs are involved in the production of AI-enabled legal services. They augment the efficacy of the system, and the deployment of AI stimulates the creation of roles involving the tasks we have described. Some of these tasks require legal expertise. However, their execution is very different from the work of traditional lawyers.

This Part has considered impact of AI on legal services work. Overall, there are three margins along which the introduction of advanced technologies affect the work of lawyers. First, technology *substitutes* for humans in traditional legal tasks for which automated systems are capable and cost-effective. For today's AI, economies of scale mean that these will need to be tasks that are repeated. Second, automation of tasks *augments* the capacity of human lawyers doing work that remains beyond the reach of automated systems: one-off or highly customized matters, and social interactions of the sort that characterize client-facing activity. These lawyers will increasingly rely on the automated systems as an input to their work, enabling them to focus on those tasks for which they have comparative advantage. Their work is augmented by *consumption* of AI-enabled services. Third, the actual *production* of these AI-enabled legal services generates new roles for humans working in MDTs who set up and manage the technology pipelines. Part of this involves the application of legal expertise, which in this case is augmenting the technology.

We now turn to the relationship between these changes in legal services *work* and the organizational structure of legal services *firms*.

## II. AI AND LEGAL SERVICES FIRMS

### A. *Do Law Firms Struggle with Using AI Technology?*

How will the changes AI is bringing to the work of lawyers impact the way in which legal services firms are organized? Law firms are traditionally structured as partnerships, an organizational form that is now rare in business generally.<sup>137</sup> The ABA's Model Rules of Professional Conduct, adopted by most state Bar Associations, restrict the sharing of fees by lawyers with

---

<sup>136</sup> Interview 38.

<sup>137</sup> R. Greenwood, et al., P2-form strategic management: corporate practices in professional partnerships, 33 *Academy of Management Journal* (1990); Michael Smets, et al., 25 years since 'P2': Taking stock and charting the future of professional firms, 4 *Journal of Professions and Organization* (2017).

nonlawyers and prohibit partnerships with nonlawyers or corporations with nonlawyer shareholders (the “fee-sharing prohibition”).<sup>138</sup> The motivating concern is that sharing profits with persons who are not subject to lawyers’ professional ethical obligations to clients would create a conflict of interest that might undermine adherence to these obligations.<sup>139</sup> As it excludes any role for outside shareholders, the fee-sharing prohibition has the effect of pushing lawyers to organize as partnerships.<sup>140</sup>

On one view, the fee-sharing prohibition is part of a range of restrictive measures that serve to insulate the legal profession from competition and preserve practitioners’ rents.<sup>141</sup> Yet even absent regulatory restrictions, there is a strong economic rationale for organizing traditional law firms as partnerships.<sup>142</sup> Legal services have historically been a human capital intensive business, reliant on specialist expertise that takes multiple years of training to acquire. In other words, law firms are “people businesses”. Their core asset is employees’ human capital. Because human capital is inalienable,<sup>143</sup> these firms have little need for outside capital to acquire assets. Rather, their challenge is to attract and retain good lawyers.<sup>144</sup> Partnership motivates senior lawyers not only through the financial incentives of profit sharing, but also through the autonomy—emphasized in psychological studies as important for employee well-being and

---

<sup>138</sup> ABA Model Rules of Professional Conduct, Rule 5.4.

<sup>139</sup> Of course, lawyers themselves face conflicts between client interests and the pursuit of profit; the ABA rule is premised on the assumption that legal professional training and ethical rules provide comparative advantage at managing this tension.

<sup>140</sup> Law firm partnerships are now commonly of the limited liability (“LLP”) form: see Baker & Krawiec, U. ILL. L. REV., (2005). (documenting shift from unlimited to limited liability partnership form).

<sup>141</sup> See, e.g., DEBORAH L RHODE, ACCESS TO JUSTICE 87-88 (Oxford University Press, 2004). (reporting comments from bar leaders that ABA regulation serves to protect the interests of lawyers); Hadfield, STAN. L. REV., 1694 (2007). (arguing there is compelling evidence that the organized bar’s regulatory agenda is motivated by protection of lawyers’ “legal service-monopoly”).

<sup>142</sup> HANSMANN, 1996; Hansmann, THE YALE LAW JOURNAL, (1990).

<sup>143</sup> Guido Calabresi & A Douglas Melamed, *Property rules, liability rules, and inalienability: one view of the cathedral*, (1972).

<sup>144</sup> OLIVER HART, FIRMS, CONTRACTS, AND FINANCIAL STRUCTURE (Clarendon press, 1995). (emphasizing importance of retaining and incentivizing employees where human capital is an important component of business assets).

retention<sup>145</sup>—that comes from participation in strategic decision-making.<sup>146</sup> Having senior employees as owners also facilitates monitoring of the highly specialized work done by junior employees,<sup>147</sup> and the “tournament” by which partners are selected creates a powerful incentive and retention mechanism for junior lawyers.<sup>148</sup> Conversely, key features of the corporate form, hierarchical management and facilitating the raising of outside capital,<sup>149</sup> are unnecessary for traditional law firms.

The very compatibility of the partnership form for a human capital business may lead to problems when the mix of assets changes. Some have argued that, as technology becomes increasingly important to the delivery of legal services, the ability to raise outside capital becomes increasingly important to permit firms to make investments in technical assets. On this view, the corporate form is better-placed to facilitate the capture of economies of scale.<sup>150</sup> Moreover, critics argue that partnership governance is likely antithetical to the adoption of new technologies.<sup>151</sup> Plenary, as opposed to delegated, decision-making creates coordination costs where there is any

---

<sup>145</sup> See, e.g., Dong Liu, et al., *The effects of autonomy and empowerment on employee turnover: Test of a multilevel model in teams*, 96 JOURNAL OF APPLIED PSYCHOLOGY (2011). (reporting negative association between employee autonomy and voluntary turnover); Edward L. Deci & Richard M. Ryan, *The importance of universal psychological needs for understanding motivation in the workplace*, in THE OXFORD HANDBOOK OF WORK ENGAGEMENT, MOTIVATION, AND SELF-DETERMINATION THEORY. (2014). (reviewing literature).

<sup>146</sup> The default position under partnership law is that all partners are entitled to participate in management decisions. While most large partnerships modify this to delegate day-to-day decisions to a subset of their number, major decisions often still require a referendum of the partners (see e.g. Uniform Partnership Act (1997), § 401(h) (“Each partner has equal rights in the management and conduct of the partnership’s business.”); § 401(k) (“A difference arising as to a matter in the ordinary course of business of a partnership may be decided by a majority of the partners. An act outside the ordinary course of business of a partnership and an amendment to the partnership agreement may be undertaken only with the affirmative vote or consent of all the partners.”)).

<sup>147</sup> Hansmann, THE YALE LAW JOURNAL, (1990).

<sup>148</sup> MARC GALANTER & T. PALAY, TOURNAMENT OF LAWYERS: THE TRANSFORMATION OF THE BIG LAW FIRMS (University of Chicago Press. 1991); Marc Galanter & William D Henderson, *The elastic tournament: A second transformation of the big law firm*, 60 STAN. L. REV. (2007).

<sup>149</sup> KRAAKMAN, et al. 2017.

<sup>150</sup> Hadfield, INTERNATIONAL REVIEW OF LAW AND ECONOMICS, (2014).

<sup>151</sup> Malhotra, et al., ACADEMY OF MANAGEMENT PERSPECTIVE, (2016).



divergence of views.<sup>152</sup> Because the partners are necessarily lawyers, they lack expertise in assessing the utility of new technologies.<sup>153</sup> And with their wealth tied up in a single firm, the partners are undiversified and so likely averse to taking risks.<sup>154</sup> Moreover, because their returns vary with partnership profits, a backward-looking measure, they likely exhibit short-termism as regards investment.<sup>155</sup> This has led to calls for the fee-sharing prohibition to be relaxed, to permit law firms to invest more effectively in non-human technical capital.<sup>156</sup>

This claim about the *economic* rationale for law firm partnership cannot be tested using data from the US, because of the fee-sharing prohibition. If the impact of technology means there are economic benefits to law firms being structured otherwise than as partnerships, then because US firms are prohibited from doing so, their practices can tell us little about the potential gains. Consequently, our empirical research focuses on the United Kingdom (“UK”), which in 2010 abolished its equivalent restrictions on fee-sharing between lawyers and non-lawyers.<sup>157</sup> The UK’s regulatory framework has consequently provided a model for the advocates of reform of the fee-sharing

---

<sup>152</sup> Eugene F Fama & Michael C Jensen, *Agency problems and residual claims*, 26 THE JOURNAL OF LAW AND ECONOMICS (1983); Frank H Easterbrook & Daniel R Fischel, *The Economic Structure of Corporate Law* (Cambridge, MA: Harvard University Press 1991); KRAAKMAN, et al. 2017. *Society*, 77. 2017. (“big partnerships often have flat senior structures so it can be easy to kill off an idea.”)

<sup>153</sup> Hadfield, *STAN. L. REV.*, 1727 (2007); *Society*, 80. 2017. (“the thought of loading up on more technology creates more stress for a group who do not like being involved with anything they do not understand.”)

<sup>154</sup> Hadfield, *STAN. L. REV.*, 1727 (2007).

<sup>155</sup> An investment outlay today will reduce current profits. Partners have no incentive to do this, even if the investment has a positive net present value, if the future returns will be earned in years after they have retired. Because profits per partner is the only benchmark of firm performance, investments that reduce it may result in retention problems for key employees. Bruce MacEwen, et al., *Law Firms, Ethics, and Equity Capital*, 21 *GEO. J. LEGAL ETHICS* (2008); Jonathan T Molot, *What’s Wrong with Law Firms: A Corporate Finance Solution to Law Firm Short-Termism*, 88 *S. CAL. L. REV.* (2014). In contrast, for public corporations, the stock price reflects the market’s assessment of the present value of current investment strategies.

<sup>156</sup> Hadfield, *INTERNATIONAL REVIEW OF LAW AND ECONOMICS*, (2014); Henderson. 2018.

<sup>157</sup> Legal Services Act 2007 (UK), Part 5. See generally, Review of the Regulatory Framework for Legal Services in England and Wales: Final Report. pt. 139 (2004). (white paper outlining background to, and rationale for, reforms).

prohibition in the US.<sup>158</sup> In other words, the UK provides a setting in which the organizational implications of technology adoption are now determined by economic forces alone, rather than regulation.

In this setting, we explore the relationship between organizational form and the two types of augmented lawyering we set out in Part I—lawyers as consumers of AI-enabled legal services (augmented by the technology) and lawyers as producers of AI-enabled legal services (augmenting the technology). We conducted 52 interviews with professionals working in three different types of organization making use of AI-enabled legal technologies: traditional law firms, corporate in-house teams, and so-called “alternative legal services providers” (ALSPs).<sup>159</sup> Interviews took place during January 2019 and July 2020 and lasted one hour on average. In each case, we undertook multiple interviews within the same organization to ensure we triangulated the account of the way in which the technology was deployed. To ensure confidentiality, we present the case study results as “ideal types”, aggregating findings from each of the three organization types.<sup>160</sup> The case study selection was designed to uncover whether there were any differences by organization type in the way in which AI deployed,<sup>161</sup> and the rich qualitative insights the interviews provide allow us to compare the organizational complementarities and frictions involved in the utilization of AI-enabled legal services.

---

<sup>158</sup> See, e.g., Hadfield, *INTERNATIONAL REVIEW OF LAW AND ECONOMICS*, 58-59 (2014). (referring to examples of innovative UK legal services firms organized in ways prohibited in the US); Henderson, 25-26. 2018.

<sup>159</sup> More specifically, our case study organizations consisted of [8] law firms, [4] ALSPs (including [2] legal technology firms) and [2] corporate legal departments.

<sup>160</sup> We undertook to maintain anonymity of all our interviewees. Owing to the ongoing refinement of AI deployment, many organizations were very sensitive about the details, and so in most cases we also entered into confidentiality agreements with the organizations. Because the number of firms operating in the sector is relatively small, if we presented case study results simply omitting the names of organizations, it would be relatively straightforward to identify which organizations were being described. Some organizations did however give permission for us to identify them, and we make express references accordingly where appropriate.

<sup>161</sup> Potentially relevant organizations were identified through a range of sources, including industry news, listings on legal technology websites, conference attendance, and referrals. We found that organizations were in general only willing to discuss their experience of implementing AI with us if key decision-makers felt that this had so far been effective. As a result, the case studies are biased towards “success cases”—that is, organizations in which AI has usefully been deployed. They are therefore useful sources of evidence as to what deployment looks like, although less informative about obstacles to success.

We negotiated with each organization to identify interviewees with a variety of roles. We typically sought to speak with a range of personnel, including “consumers”—those actually using the technology to augment traditional lawyering functions; “producers”—those whose work augmented the setting up and running of automated systems; and those involved in making strategic decisions about the procurement and deployment of the systems. Table 1 details our interviewees by organization type, organization ID and job title.<sup>162</sup> As can be seen, the job titles associated with these types varied across organizations.<sup>163</sup>

[Table 1 about here]

In the presentation of our interview findings, we focus on two dimensions across which clear differences emerged by organization type. First, we consider the overall strategy for implementation of AI. This process has come to be known in the general business context as “digital transformation”,<sup>164</sup> and entails an organization being willing to make a large-scale investment in restructuring its data capture so as to make the best use of AI, and to ensure that all its technology platform investments are interoperable in a way to avoid needless friction being generated in getting different parts of the systems to talk to one another. Our second dimension of focus is the way in which organizations assemble, co-ordinate and motivate MDTs for the operational deployment of AI.

---

<sup>162</sup> In some cases, idiosyncratic job titles were redacted to ensure the anonymity of interviewees.

<sup>163</sup> Individual interviewees were sent in advance an aide memoire of questions we intended to cover, along with an informed consent form. The questioning was open-ended: the aide memoire was used simply as a guide and more specific questions were posed in response to lines of discussion opened up by interviewees. Interviews were scheduled for an hour at a time and recorded with interviewees’ permission. The recordings were transcribed, analyzed using the NVivo package, and anonymized.

<sup>164</sup> See e.g. Saul J Berman, *Digital transformation: opportunities to create new business models*, STRATEGY & LEADERSHIP (2012); Christian Matt, et al., *Digital transformation strategies*, 57 BUSINESS & INFORMATION SYSTEMS ENGINEERING (2015); Thomas Hess, et al., *Options for formulating a digital transformation strategy*, 15 MIS QUARTERLY EXECUTIVE (2016); Gerald C Kane, et al., *Strategy, not technology, drives digital transformation*, (2015).

### B. *Big Law's Deployment of AI*

All our law firm case studies were “Big Law” firms—with hundreds of partners and an international footprint in corporate legal services. We did not set out specifically to focus on law firms of this type; rather, these were the types of firm that responded to our requests for examples of AI deployment. This suggests deployment is concentrated in larger firms, which is consistent with the fixed costs associated with setting up AI-based legal technology.<sup>165</sup> Larger law firms are more likely to have access to more client data, and to be willing to bear the infrastructure costs of capturing this. This appears to be a general pattern: survey data from both the UK and US suggest AI deployment is strongly concentrated in larger law firms.<sup>166</sup> This means that deployment is currently focused on what has been termed the “corporate hemisphere” of legal practice—serving large business organizations, as opposed to private citizens.<sup>167</sup>

#### 1. Strategic decision-making.

Our law firm interviewees saw their firms as being in an early phase of experimentation with AI and related technologies, encompassing most of the use-cases outlined in Section I.C. This had all occurred quite rapidly. As one put it:

“[A]round about three years ago, we didn’t really have any kind of resource going into innovation – and I’m not exaggerating, it really wasn’t until about then that we got this off the ground. ... We’re going through a process at the moment where we’re looking at a handful of use-cases in different practice groups, and testing different tools with each of the practices to really validate which we think is the best, or which might be the best-suited for particular circumstances, because we’re not convinced that there’s one right answer for the entire firm. So, I would describe that as a real early stage of development.”<sup>168</sup>

This will typically have been initiated following requests from clients, or by observing the actions of competitors.<sup>169</sup> Many interviewees saw considerable

---

<sup>165</sup> See *supra*, Section I.C.

<sup>166</sup> Technology and Innovation in Legal Services – Main Report: An analysis of a survey of legal service providers. pt. 75 (2018); ABA. 2019.

<sup>167</sup> JOHN P. HEINZ & EDWARD O. LAUMANN, CHICAGO LAWYERS : THE SOCIAL STRUCTURE OF THE BAR (Russell Sage Foundation ; American Bar Foundation. 1982); Henderson, 13. 2018.(distinguishing between “Organizational Client sector” and “PeopleLaw sector” of legal services).

<sup>168</sup> Interview 21.

<sup>169</sup> See Lawtech Adoption Report. (2019).

upside potential for further deployment.<sup>170</sup> Adoption is being done in a “bottom up” way, where a particular practice group or team identify a potential solution, and deploy it. There is clearly room for further development of overall firm strategy on adoption.

“In terms of things like, ‘Should we...should we invest in another AI tool, [or] should[n’t] we...?’, I mean, there’s no ... set path for getting that decision through. ... We probably would take it to the board, but that would be a kind of ‘finger in the air’ kind of a feeling.”<sup>171</sup>

This bottom-up approach leads to adoption of “point solutions”—that is, platforms that assist in a particular context within a specific practice area, but do not integrate effectively across the firm’s other technologies. This constrains the extent of economies of scale that can be achieved, because ongoing costs have to be incurred with data ingestion into the point solution if the formatting is different from the rest of the firm’s tech infrastructure. Moreover, complementary systems and protocols must be put in place to ensure the effective capture and formatting of relevant data:

“No matter how good the technology is, the underpinning data is everything, and [to harness] that underpinning data ... [o]ne needs a strategy. What data will fuel the insights that the end-user [wants]? And a law firm, or a law department, needs a governance model for determining the ... how do I put this ... the characteristics of appropriate data that will fuel AI.”<sup>172</sup>

As a consequence, several interviewees spoke of a challenge of limited up-take of platforms acquired by the firm. This seems in turn to stem from relatively little attention having been paid to the articulation of requirements, and to the organizational changes necessary to ensure successful

---

<sup>170</sup> “So ... I think there’s a huge opportunity for data mining and data usage, and I think we’re at fairly early stages of that, but ... I think firms understand [the opportunity].” (Interview 5); “I’ve got to be honest; we want to buy a lot more and we want to get to a point where we’re using our resources better.” (Interview 25).

<sup>171</sup> Interview 35.

<sup>172</sup> Interview 46. Similarly, “So, I believe that, if we are going to see ubiquity in AI in large law, as opposed to the other stuff that I’ve talked about, you’re going to see it by AI getting plugged in behind big current genres of technology, document management being one of them. You may see the same in time-recording systems” (Interview 11).

implementation of the pipeline.<sup>173</sup> Consistently with the criticisms discussed in Section II.A, some spoke of the consensus-oriented decision-making within law firm partnerships leading to conservatism about innovation, and of partners' focus on in-year profits restricting willingness to make strategic investments. As one in-house lawyer, who is involved in selecting outside counsel to perform work for their organization put it:

“[T]he eternal frustration for in-house [legal teams], is that ... it's not [law firms'] business to become more efficient or to show those efficiencies to us ... they're still going to bill the same hourly rates because that's what they need to charge to be ... to keep their partners happy, you know ... that's an age-old issue. I sat on a panel last year discussing it, and the partners were saying, 'Why should we innovate?' I was like, well, yeah [laughing]...”<sup>174</sup>

## 2. Teams for implementation

Very few of the law firms we studied actually engage in any software development of their own.<sup>175</sup> Rather, they tend to work with external legal technology (“lawtech”) firms, who design and supply a platform.<sup>176</sup> Although lawtech firms aim to develop products that users can deploy with as little support as possible,<sup>177</sup> these tools are often quite significantly

<sup>173</sup> “[F]rankly, a lot of our [law firm] clients [just] went ahead and acquired technology – they bought it and they licensed [it], and then didn't know what to do with it. It was a new, shiny toy but ... the hard work is not buying it; the hard work is trying to configure it, creating the use-case, having the patience to build that out, to have the training, to change the processes.” (Interview 51); “[O]ne ... thing that comes up a lot is people want to buy the AI software, but they don't really understand what it takes to get the AI to work. So, there's a lot of education we have in teaching them the process.” (Interview 45).

<sup>174</sup> Interview 4.

<sup>175</sup> As one interviewee put it, “We don't develop our own stuff because we're not developers”. Interview 5. Another explained: “We realized that ... proprietary development is pretty expensive and ... where we can have the most impact is actually picking very compelling but early stage legal start-ups and helping them grow.” (Interview 7, law firm).

<sup>176</sup> There was one exception amongst the firms we studied, which had engaged in development in-house: “[T]he technology [offered by lawtech vendors] was fine, but because they were trying to productize it, they couldn't tailor it enough to work for us. It wasn't a tech problem, it was [that] ... their business model wasn't what we wanted to do, and at that point [we decided], 'We could do all of this – we could build something that does all of this,' and built a really skinny system, to begin with, just really, really basic, and then we tried that and it worked and so we've built out from that.” (Interview 22).

<sup>177</sup> “[A] lot of the newer [contract automation tools] are much more focused on usability, so anyone can do it – you don't need specialist engineering teams, you don't have to use coding or variables or anything. It's much more...much easier to use, which, if you're small in-house legal team and you want to do some of it yourself, it's much easier.” Interview [X].

customized, especially for larger law firms.<sup>178</sup> In the context of AI, this customization occurs at the training stage. Commercially-available AI platforms usually come pre-trained on data available to the vendor. Law firms typically have access to proprietary data, which they use to enhance the training of the model. This training benefit is provided only to the specific “instance” of the model which the firm has licensed.

“So, we work with a third party vendor that provides the basic algorithms for some of the normal things that you would search for in a contract due diligence exercise, but we’ve invested quite a lot of time in training our specific instances of those algorithms to check for things that we look for on the transactions that we do. We’ve also dramatically expanded the scope of those algorithms, in the sense that we’ve [applied them in] different contexts and in different languages, which is, you know, very, very different from [the base product].”<sup>179</sup>

Although most of the software design is being done by external lawtech firms, law firm users have still needed to establish two new types of multidisciplinary team for their side of the implementation process. The first, typically called the “Innovation” team, is responsible for developing a coordinated approach to requirements and procurement stage of new solutions.<sup>180</sup> Innovation teams seek to collate information across the firm about which of the experiments did and did not work, alongside insights and suggestions from personnel regarding ways of improving processes through deployment, with a view to building consensus and feeding forward into more senior management deliberations.<sup>181</sup> In parallel with the Innovation team, firms are also establishing what are sometimes termed “Delivery” or “Operations” teams, involved in the actual implementation of platforms.

---

<sup>178</sup> In one case, this went even further, with the law firm partnering with external developers to deliver wholly bespoke packages: “[W]e’ve been working with ... an [external] team of data scientists who’ve helped us to build a bespoke tool for both cleaning up our historical billing data and then also for using that to try to make predictions about a future case, as and when it comes in.” (Interview 20).

<sup>179</sup> Interview 13.

<sup>180</sup> Donald J Polden, *Lawyers, leadership, and innovation*, 58 SANTA CLARA LAW REVIEW (2019); Michele DeStefano, *The law firm chief innovation officer: goals, roles and holes (Part 1 of 2)*, 2 MODERN LEGAL PRACTICE (2018).

<sup>181</sup> “[M]y team, we [are] ... trying to meld th[e] ‘ideation’ concept from the world of innovation with practicality in law firms. ... I think where we’re ending up, [is as a] sort of pragmatic honest broker ... So, we’ll have a range of things that we’re either testing or using on the stacks ... and it’s part of my team’s function to say, for this particular use-case, we recommend X, Y or Z.” (Interview 5).

They cut across the practice area groupings which organize the majority of a law firm's personnel and seek to provide access to relevant expertise for labelling and reviewing in the AI training process. Both the Innovation and Operations teams seek to bring together necessary multi-disciplinary expertise.<sup>182</sup>

However, interviewees spoke of frictions for these MDTs generated by law firms' organizational structure. In particular, in lawyer-only partnership, employees who are not lawyers cannot participate in the standard career progression structure.<sup>183</sup> Interviewees suggested that this created challenges for recruitment and retention of employees with other relevant human capital, necessary to form MDTs for deploying AI:

“What [law firms] don't have is, a lot of times, the technical know-how. I know a lot of wonderful, brilliant, talented data scientists that decidedly do not want to go work for law firms. You know, so there's a lot of churn there.”<sup>184</sup>

Others suggested that lawyers tended to under-estimate the value of the contributions of personnel from other disciplines:

“Lots of lawyers don't have that self-awareness to realize that [their] brightness, in the absence of [relevant] experience, doesn't ... help them.”<sup>185</sup>

These issues created obstacles to recruiting staff with relevant (non-legal) expertise for MDTs. As a consequence, legally-qualified personnel are deployed into roles for which other relevant skills would be better suited:

“[Y]ou look at your average business unit in a law firm and you've got law firm partners whose skills, frankly, are in the law, trying to do account

<sup>182</sup> “There is a big governance piece that my team is coordinating, with our professional support law community, to make sure that ... we've got a naming convention, we're testing and we're validating, actually, the tags that have been applied by often quite junior trainees ... to ensure that actually what we're tagging makes sense.” (Interview 36).

<sup>183</sup> This point was well-made by Larry Ribstein: Larry E Ribstein, *The death of big law*, WIS. L. REV. (2010).

<sup>184</sup> Interview 46. Similarly:

“[W]e're obviously a very good firm, with a good brand name associated, but in terms of access to young talent, in the software space, they normally don't want to join a [storied] law firm – they want to go and work for a cool software company.” (Interview 14).

<sup>185</sup> Interview 26. Similarly:

“[T]here's still a ‘God Complex’ about lawyers, that, you know, if you're a lawyer, you can do anything, just because you've got that little piece of paper that says you've passed the Bar, nothing you can't do.” (Interview 8).



management, supervision, team management, resource allocation, QA [quality assurance], things that they're ... not qualified to do."<sup>186</sup>

Of course, firms might invest in training lawyers to become skilled at the relevant other disciplinary inputs to AI pipeline teams. Interviewees thought that this would on the whole be an inefficient solution:

"I think it's about having multidisciplinary teams – data scientists, programmers, and lawyers, working together to create solutions. ... [L]awyers shouldn't be doing proper coding. There's professionals who are professional coders or professional data scientists who should be focusing on that. But it's about working with the lawyers. It's about bringing together experts in each of the domains to co-create together."<sup>187</sup>

Moreover, lawyers who invest in acquiring "non-legal" skills find themselves no longer as effective at *practicing* law as others who have not; consequently, this can adversely affect their prospects of making partner. In many law firms, partnership prospects are assessed by the "business case", which typically centers on client revenue metrics. It is hard to quantify the contribution of technology-based services to these metrics.

"I think it's going to have to change ... and that will blur, over time, the distinction between the fee-earners and non-fee-earners because I think people in pure technology roles, who have never, you know, qualified as a lawyer, who are working on a solution that helps deliver a matter, are contributing to the revenue of the firm, directly."<sup>188</sup>

### 3. Summary

What emerges from our law firm case studies is that deployment of AI is generally still at an early stage. However, law firms face challenges in recruiting, retaining and motivating talented human capital from a "non-legal" background. To date, the AI pipelines being deployed by law firms tend to bridge their organization to at least one other, such as a legal

---

<sup>186</sup> Interview 11.

<sup>187</sup> Interview 38. Similarly:

"I always say, somewhat glibly, 'Why would you turn a brilliant lawyer into a mediocre coder?'" (Interview 26).

"[W]hen you go to your [doctor], you don't expect your [doctor] to have coded their laptop – you just want them to know enough about the technology to be able to use it to help with the diagnosis. I think that's the same with lawyers: they need to know enough about how technology works, what kinds of technologies are out there, and they need to be flexible enough to be able to work in different ... work with different delivery models, and they need to be good at the law." (Interview 11).

<sup>188</sup> Interview 14.

technology provider, with many of the non-legal human capital being supplied by the latter. There remains considerable further potential for digital transformation, but partnership decision-making appears to struggle with the necessary strategic issues, and law firm partnerships struggle with the recruitment and motivation of MDTs. However, despite the emphasis in the literature on access to finance as a constraint of the partnership, we found little evidence of capital constraints posing problems for law firms' investment in technology. This likely reflects the pattern of adoption being skewed towards large firms, which can raise capital relatively easily by borrowing.<sup>189</sup>

To assess the extent to which these issues stem from the partnership structure, as opposed to the nature of the technology, or of legal services work in general, we now consider the deployment of AI in other types of legal services organization.

### C. *Corporate Legal Departments*

Traditionally, corporate legal services revolve around the relationship between outside law firms and in-house teams employed by client business corporations themselves.<sup>190</sup> In the past two decades, these in-house teams have grown much more rapidly than have law firms,<sup>191</sup> such that there is now approximately one lawyer employed in-house for every four in law firms (excluding partners).<sup>192</sup> In theory, being part of a large corporation means that there is hierarchical management and ready access to outside capital.

#### 1. Strategic decision-making.

Our corporate legal department interviews revealed a striking contrast with law firms over the level of structural change they had gone through. This was driven by strategic decisions about digital transformation of the organization as a whole, which percolated through to the legal department

---

<sup>189</sup> See, e.g., Tony Williams, *Law firm IPOs—access to a money tree?*, 2 MODERN LEGAL PRACTICE, 10 (2018). (noting traditional capital-raising by law firm partnerships involves bank borrowing).

<sup>190</sup> Henderson, 4-5. 2018. (noting divide between law firms and in-house lawyering).

<sup>191</sup> *Id.* at, 5. (over period 1997-2017 in the United States, number of lawyers employed in law firms grew by 29.5 per cent; number employed in-house grew by 203.1 per cent). Similarly in England and Wales, the number of solicitors working in-house more than doubled during 2002-2017 to 28,000, constituting 22 per cent of all solicitors (Law Society of England and Wales statistics).

<sup>192</sup> *Id.* at, 4. (as of 2017, 388,670 lawyers employed in legal services firms and 105,310 employed in industries other than legal services or government).

alongside the rest of the corporation. Key decisions had been taken to make a strategic assessment of the way in which technology was deployed, what efficiencies could be generated, what data were available to drive these, and how this related to the technology strategy for the business as a whole. This was done in some cases through the appointment of specific personnel with roles to manage technological transformation within the legal team across the whole organization. This helped to facilitate a common approach to data capture and management, allowing organizations to think beyond a series of “point solutions”:

“[O]ne of the things that [our Head of Legal Technology] did when he came in here [was to design] a five-year strategy to effectively come up with all of the building blocks, and the key part of that really, the starting point of that has been what’s the foundation data layer ... [a]nd we build it up from that. Up to that point, we had done various point solution, but we didn’t have a consistent approach to data capture or data management.”<sup>193</sup>

A key change that emerged from this high-level backing of digital transformation was investment in the requirements stage of the pipeline process. Business Analysts are employed across the organizations to assess requirements in a particular process, which then feed into the procurement of technology support and the coordination and management of human capital.

“[W]e go through a fairly methodical piece, whereby, if we need to [do] something, we’ve now got business analyst resource who will go and sit down with the users and say, ‘Tell me about your problems – what are you trying to solve?’ really get an understanding of what their requirements are, list those out, translate that into a technology solution, and then go out to market and ... find people who can provide it, bring it back, sand-box, you know, test those out with, you know, users from across the business before rolling out.”<sup>194</sup>

Interviewees felt that greater investment in data strategy and assessing requirements yielded payoffs in terms of greater returns to scale and better user adoption rates of technology.

---

<sup>193</sup> Interview 1.

<sup>194</sup> Interview 2. Or as the point was put by another interviewee:

“[W]e run a process which I would say is akin to what’s run in our bigger business, but one that works with lawyers, and has been tried and tested, and so it’s all about user adoption, because, if we don’t get the user adoption, what’s the point?” (Interview 1).

## 2. Teams for implementation

A second key difference was the multidisciplinary nature of the workforce in and around a corporate legal department. In an organization in which lawyers play a supporting role to the firm as a whole, it is relatively straightforward to deploy relevant technical and business process expertise to support and enhance the legal function. As one Director of Legal Technology explained by reference to the disciplinary mix of his team:

“So, I’ve got a [seasoned] BA [Business Analyst] ... [who] knows legal technology, document management, [etc] ... I’ve got an ex-legal engineer from [a large law firm] ... I’ve got a very seasoned program manager ... she’s worked in pharma and the food industry, never touched legal, [but] she’s got project management skills ... Another guy is ... a big-data analyst ... and is now going to be our legal data analyst, so that data science type element there. ... Another guy who was in a sort of small consultancy doing law firm tech, ... had training, did consultancy, knows people, has worked with lawyers ... and then another guy who’d worked for [a legal data provider] doing their legal tracker implementations and support...”

<sup>195</sup>However, corporate legal departments also face challenges owing to their status as a service team for the business as a whole. In the company’s overall strategic decisions about technology and digital transformation, the needs of the legal team are not foremost in executives’ minds.<sup>196</sup> Another pervasive problem for in-house teams is that, to the firm’s management, their function is simply a cost center. Management are concerned with increasing revenues and keeping costs down. Investments in legal technology have faced funding constraints because of this dynamic.

“It’s more of a challenge than incentive, which is us trying to sell a business case internally to say, ‘Can we have this much money for legal tech?’ which is a really hard sell, right?”<sup>197</sup>

The constraints on capital investment in technical solutions mean that solutions that involve outsourcing – whereby the recurring costs are lower –

---

<sup>195</sup> Interview 1.

<sup>196</sup> “[In] a mature, large operation like this ... you’re not masters of your own destiny sometimes, as an in-house legal function.” (Interview 2). In particular, decisions about technology policy taken with the interests of the company as a whole in mind shape the space in which the legal team are free to make deployment decisions: “One of the things that I hadn’t appreciated here was how little legal functions appreciate or understand their corporation’s IT architecture and IT roadmap, yeah? So, if I want to buy a piece of software that’s dependent on Chrome, forget it, right, because we’re a Microsoft house, right, and we’re going to go Microsoft for some time.” (Interview 1).

<sup>197</sup> Interview 2.

are attractive to corporate legal departments.<sup>198</sup> This leads naturally to our third case study type, alternative legal service providers.

#### *D. Alternative Legal Service Providers*

In recent years, there has been a growth in a third kind of legal service provider—so-called “alternative legal service providers” (ALSPs). ALSPs are a heterogenous range of firms that do not fit into the traditional dualism of law firms and client in-house teams.<sup>199</sup> The development and implementation of legal technology has fostered new business models in legal services,<sup>200</sup> and ALSPs are experimenting with these, focusing on providing technology-enabled legal services. Although by no means universal, many ALSPs are organized as corporations.<sup>201</sup> The fee-sharing prohibition means that these firms are not permitted, in the United States at least, to engage in the practice of law. Instead, they offer their services to practicing lawyers, who are then responsible for the supervision of their activities.<sup>202</sup> Under this framework, ALSPs sell their services to in-house teams and outside law firms<sup>203</sup>—that is, both sides of the traditional divide.

---

<sup>198</sup> “[T]here’s two options on the in-house side. One is that they buy software and they manage the software themselves and they try and figure out how to implement it, you know, how to maintain it, how to improve it, and they’ve tried to do that over the last 15 years, right, when they bought matter management, e-billing, [and so on] ... Now, what we’re finding is that, for a number of reasons – attrition, hard to find resources that actually know that, you know, their interactions with legal IT and the friction that they have, maybe even with procurement – what they’re saying is, ‘Is there a model where we can just buy this as a managed service and can I just buy a service and that comes with software and you take care of maintaining the software, improving it, learning what we need every year, configuring it to do what we need to do?’ So, we think there is a big business now in kind of managed technology solutions in corporate law departments.” (Interview 25).

<sup>199</sup> See ThomsonReuters, 3. 2019. (describing scope of ALSP sector).

<sup>200</sup> Armour & Sako, JOURNAL OF PROFESSIONS AND ORGANIZATION, 6-8 (2020). (outlining taxonomy of AI-enabled business models in legal services).

<sup>201</sup> This is not universal. The ALSP sector is quite heterogeneous and includes the so-called “Big Four” professional services firms (PriceWaterhouseCoopers, Ernst & Young, Deloitte, and KPMG), which are organized as multidisciplinary partnerships (ThomsonReuters, 4. 2019.)

<sup>202</sup> Henderson, 10-12. 2018. (outlining relationship between ALSPs and practicing lawyers).

<sup>203</sup> See ThomsonReuters, 4-6. 2019. (presenting statistics on use of ALSPs by US corporations and law firms).

## 1. Strategic decision-making

The ALSPs we spoke with have a clear vision of their business model. They offer technology-enabled services to a wide range of end users. To do this, they utilize a base platform, which they can customize for users, and also supply a team of personnel to manage the process for the user.

“[W]e never sell the product separately. So, I’m not looking to be some kind of software seller or integrator or whatever. It’s part of the service. ... we’re always trying to sell service plus technology ... the technology is only an enabler. So, when we speak to clients, we talk about human plus technology – ‘don’t think the technology is going to do everything’.”<sup>204</sup>

“[W]hen we sell our software ... and we’re doing AI, we actually hope that the customer will say, ‘Well, okay, but who’s doing the first pass review on the machine, who is QC [quality controll]-ing the machine?’ and that naturally leads into our services – ‘Oh yeah, well, you don’t want your lawyers doing that, we can provide our cost-effective lawyers to do that ... it’s not a function that you need your lawyers to be doing.’”<sup>205</sup>

The ALSPs focus on the deployment, rather than the development, of the platforms they use. The products that underpin their service offerings are bought from technology companies.<sup>206</sup>

From an organizational standpoint, most of the ALSPs we spoke with are privately held companies, although some are multi-disciplinary partnerships.<sup>207</sup> Interviewees at these companies perceived strategic benefits

---

<sup>204</sup> Interview 43.

<sup>205</sup> Interview 45. At the same time, the ALSP seeks to engage the user’s legal expertise in training the system for their particular deployment: “[O]ne thing that I’m very passionate about is not training on client data, not crowdsourcing machine learning models, but building machine learning models that the client trains, the business subject matter expert, the lawyers, train, and in a very fast way. They don’t need to know Python or [R]. ... It looks like [briefing a case], so they can train these models, and these models will reflect the way that they reason. Better that, so that law firms [and] law departments ... surface and operationalize their own best practices, rather than anonymize crowdsourced ‘best practices’ that cannot be validated forensically.” (Interview 46).

<sup>206</sup> “[W]e want to be [an elite] services company, obviously with technology at our core, but we understand that our value proposition, what we know how to do, how we train people – everything we do is around we’re a services company. And I think sometimes services companies have to be careful not to confuse themselves with being a technology company and building a lot of [different] applications. They’re entirely different business models. They’re entirely different sets of expertise, entirely different funding. And so, we are cautious of when we undertake a proprietary development ourselves, right, for that reason.” (Interview 52).

<sup>207</sup> See *supra*, note 201.

to the use of the corporate form. They spoke of avoiding the short-termism of the investment horizon for law firm partnerships engendered by the focus partnership profits:<sup>208</sup>

“We’re not a partnership that has to distribute its profits to the partners every year ... they don’t make the investment needed to think about the problems holistically, not just the technology but the training and the mindset that has to [go with it].”<sup>209</sup>

They also suggested that access to external capital – often in the form of private equity investment – helped their firms to take significant financial risks in delivering novel forms of AI-enabled legal services delivery.

## 2. Teams for implementation

A key feature of ALSPs’ business models is the recruitment and deployment of multidisciplinary teams to facilitate the adoption of technology. As one explained:

“[W]e have people that have been practicing lawyers, that really know the legal work. We have people that were general counsel, that understand the leadership and executive communication. We have people that are experienced in other large business process outsourcing, that maybe came from finance or IT or HR, to learn from their experience. We have people that are process specialists and black-belts. We have change management. We have financial analysts. Because ... it is multiple disciplines to really bring this forth in a way that is that combination of vision and a compelling new solution, with the pragmatic ... how do you implement, grounded in reality, to create success? Because, frankly, one without the other will never get you very far.”<sup>210</sup>

---

<sup>208</sup> See *supra*, note 155 and text thereto.

<sup>209</sup> Interview 50.

<sup>210</sup> Interview 51. Similarly:

“[T]he majority of the team have a more technical background. ... [Y]ou can view ‘technical skills’ in two different ways: you can be analytical, but you can’t program, and then you can have people that program, like sort of more traditional technical. [O]ur team are a mix of the[se] two, and we [also] have ... people who have less technical skills, they’re more ... client-facing: project managers, engagement managers, and consultants. Basically, they’re the bridge between the very technical people that can do the work to the client who is a layperson or ... needs that all translated” (Interview 41).

These teams are structured and coordinated using project management expertise to ensure the processes are completed as efficiently as possible.<sup>211</sup> Interviewees saw advantages to the use of the corporate form in recruiting and managing the multidisciplinary teams that augment their technology. It enables compensation and career progression to be independent of disciplinary background: the senior leadership teams of the ALSPs we interviewed encompassed individuals from a wide range of backgrounds, both legal and non-legal. More generally, the ALSPs' culture espoused a commitment to legal services innovation as one of their key selling points.

“Career progression is important and being able to grow professionally and being in an environment where you feel respected and where it’s ... one that ... cares about [your] development is important, and it does encourage—encourages incredibly, you know—Innovation.”<sup>212</sup>

In the final Section of this Part, we draw together and contrast the key findings from these three sets of case studies.

#### *E. Emerging Patterns: AI and Organizational Form*

Our qualitative data yield important insights into the relationship between organizational form and the capacity to produce AI pipeline outputs in legal services. In keeping with a criticism espoused in the literature, law firm partnerships, with their decentralized governance and lawyer-centric ownership structure, appear to face structural disadvantages in making the necessary strategic decisions about “digital transformation”—investments in data architecture, technical capital, and the appropriate human resources mix—necessary for the effective production of AI pipeline outputs. In contrast, these challenges are less pronounced in organizations structured as companies. As anticipated, delegation of decision-making power to a central authority—the board of directors—appears to facilitate making strategic decisions, and the recruitment of relevant executive expertise for making them. Moreover, issuing shares to outside investors facilitates raising capital for investment in technical systems.

---

<sup>211</sup> For example, one interviewee spoke about how the classification system used in training a model is set up:

“[W]e have very tight controls [over who has access], even with some of those technologies ... there is a workflow, but also, it means that once, for example, a paralegal has reviewed the document, and you need it to go through QA, the paralegal cannot go back and change it. It goes to the QA lane. Once the QA lane is finished, it goes into a completed column and nobody else can go back and change it.” (Interview 43).

<sup>212</sup> Interview 50.



Our data also reveal another important way that organizational form makes a difference, which has not been previously emphasized in the literature. As we saw in Part I, the deployment of AI in legal services must be augmented by multidisciplinary teams of humans. Our case studies suggest that mono-disciplinary partnerships—as law firms are structured—suffer from a disadvantage in recruitment and retention of the necessary *human* capital for these MDTs. This is not to say that law firms cannot run such teams—indeed, some have already done so successfully—rather that, at the margin, they face a set of additional costs not shared by firms organized as companies. This implies that law firms will find it easier to relate to AI pipelines as consumers—buying the AI-enabled services from another firm, perhaps an ALSP, than as producers.

Third, our case studies reveal material differences in the capacity of different types of corporate enterprise to deploy AI pipelines effectively in legal services. In-house teams working in large corporations have potential access to very large volumes of relevant data, and the corporate form facilitates the recruitment and deployment of necessary MDTs. Moreover, senior corporate executives are taking very seriously the potential gains from digital transformation, meaning that organization-wide strategic thinking about data architecture and technology deployment is occurring. To the extent that the legal team can piggy-back on this firm-wide activity, AI deployment is greatly facilitated. But where the context of legal services diverges from the wider corporate activities, it is more challenging to secure the support of senior management, because legal is characterized as a cost center rather than a revenue center. In these contexts, deployment may be easier for specialized “law companies” (one type of alternative legal service providers) that harness the beneficial organizational attributes of the corporate form in the specific context of legal services.

Our case studies, as we have noted,<sup>213</sup> potentially suffer from selection bias toward self-perceived “success cases”: firms who perceived themselves as having had no experience, or a negative experience, with the use of AI in legal services were unwilling to participate in our study. Some of the insights we have derived—such as the association between MDTs and AI deployment—are universal to these success cases. This is strongly suggestive that MDTs are a key enabler for the deployment of AI. However, without consideration of “non-success” cases, we cannot rule out the possibility that MDTs are also deployed in cases where AI is not successfully deployed, and

---

<sup>213</sup> *Supra*, text to note xx.

other factors account for the failure. Moreover, there is no reason to think that the selection bias would apply differently across different organization types, meaning that we can still derive useful insights about inter-organizational differences. Again, though, without considering “non-success” cases, we cannot be sure of the strength of this assumption. In order to test whether our findings generalize to a wider range of firms, we now turn to our quantitative data.

### III. QUANTITATIVE RESULTS

The insights from our interview research, discussed above in Parts I and II, may be formalized into two specific hypotheses that link the deployment of AI, the existence of MDTs, and organization structure, as follows. In Part I, we saw that the deployment of AI in legal services is augmented by new types of human role, involving persons with legal expertise working together with a range of other disciplines in an MDT.<sup>214</sup> We formalize this core insight as Hypothesis 1:

*Hypothesis 1:* deployment of (AI-based) lawtech is facilitated by assembly of multi-disciplinary teams (MDTs).

In Part II, we saw that law firm partnerships appear to be at a disadvantage regarding the recruitment, retention and management of non-legal human capital necessary for the successful assembly of these MDTs. We formalize this as Hypothesis 2:

*Hypothesis 2:* successful deployment of MDTs is facilitated by organizations structured as corporations rather than traditional professional partnerships such as law firms.

We now proceed to take these hypotheses to the data gathered from our survey, in order to assess the generalizability of case evidence. We first describe the survey data before presenting results from univariate and multivariate analyses.

#### A. Survey Data

The survey was conducted in conjunction with the Law Society of England and Wales (the “Law Society”) over the period November 2019 to January 2020. The Law Society maintains a register of all practicing solicitors

---

<sup>214</sup> *Supra*, Part I.

in England and Wales.<sup>215</sup> The survey questions are reproduced in the Appendix. Respondents were asked about the organization they work for, and their role within it; their professional qualifications and career aspirations; their use of technology generally and AI-assisted legal technology specifically; the expertise of colleagues with whom they work on a daily basis to complete legal work; types training they had received—and would like to receive—in relation to legal technology, and questions about their attitude to the deployment of legal technology.

We received a total of 353 valid responses,<sup>216</sup> a response rate of less than 3.5 per cent.<sup>217</sup> By organization type, 236 respondents (67 per cent) worked for law firms, 99 (28 per cent) worked for the in-house department of a business corporation, and 18 (5 per cent) worked for other types of organization, including those trading as “alternative business structures” (ABSs) and lawtech solutions providers. Respondents were spread widely in terms of years of experience, with the year of qualification ranging from 1965 to 2019. Table 2 presents descriptive statistics for our sample.<sup>218</sup>

[Table 2 about here]

### B. *Univariate Results*

In order to investigate our first hypothesis, the relationship between AI deployment and multidisciplinary teams, Table 3 presents a cross-tabulation of results from Questions 10 and 13 of our survey. Question 10 asked respondents about their use of AI-assisted legal technologies; respondents

---

<sup>215</sup> Participants were recruited through an email invitation from the Law Society, with a link to the online survey. The survey was hosted using the Qualtrics platform, and the questions were piloted on a small number of respondents before finalizing the questions.

<sup>216</sup> We discarded 74 responses that were incomplete or where the respondent did not verify that they were a practicing lawyer; the total including these was 427. Amongst the valid responses, some respondents did not answer all the questions, reducing the number of observations in some of our quantitative analysis.

<sup>217</sup> Initially, 10,000 randomly-selected lawyers were sent an anonymous link to the online survey to complete. The survey link was then shared with the Law Society’s Technology and Law Committee and through the Law Society’s social media channels to solicit further participation from Law Society members. In order to increase survey participants, and to diversify the nature of the respondents, subsequent survey invitations included those aimed at under-represented groups of respondents, such as members of the Law Society’s 40,000-member Junior Lawyers Division.

<sup>218</sup> A descriptive overview of the survey responses can be seen in our report published jointly with the Law Society: Sako, et al. 2020.

were invited to select one or more from a list of potential use-cases (or “other”).<sup>219</sup> As can be seen from the column totals in Table 3, 163 respondents (50%) indicated that they used one or more AI-assisted legal technology, whereas 164 did not (50%). Question 13 asked respondents about the expertise of the persons with whom they worked on a day-to-day basis to get legal work done. They were invited to select one or more from a list, of which two represent persons with traditional legal human capital (lawyers and paralegals), whereas the others represent other types of human capital relevant to the deployment of an MDT. We use responses to this question to categorize a respondent as working in an MDT if they indicate that they work on a day-to-day basis with one or more persons whose expertise is not traditional legal knowledge, namely “legal project managers”, “process mapping experts”, “data analysts/data scientists”, and “IT / legal innovation experts”. The rows in Table 3 show that, by this classification, 97 (30%) of respondents indicated that they worked in an MDT, whereas 230 (70%) indicated that they did not.

[Table 3 about here]

The cross-tabulations reveal that respondents who use AI-assisted lawtech are twice as likely to work in an MDT (65/163, or 40%) than those who do not use such technology (32/164, or 20%). A Chi-squared test confirms that the two variables are clearly not independent.<sup>220</sup> This provides initial support for Hypothesis 1.

With respect to Hypothesis 2, the relationship between MDT assembly and organizational type, Table 4 presents a cross-tabulation of whether respondents work in an MDT (derived from Question 13 of the survey, as explained above) and whether they work in a traditional law firm, organized as a partnership, or not (Question 3 of the survey). This shows that respondents who work in law firm partnerships are less likely to participate in an MDT (62/225 or 28%) than those who do not work for a partnership (34/97 or 35%). This is suggestive, but the difference is much more modest than in Table 3, and a Chi-squared test fails to reject the null hypothesis that the variables are independent.<sup>221</sup> Consequently, we do not find support for Hypothesis 2 in the univariate comparison.

---

<sup>219</sup> We told respondents that by “AI-assisted” we meant “technology that uses an expert system, machine learning, and/or deep learning.” (see Appendix, Q10).

<sup>220</sup>  $\chi^2 = 15.289$ ,  $p = 0.000092$ .

<sup>221</sup>  $\chi^2 = 1.4795$ ,  $p = 0.2239$ .

[Table 4 about here]

### C. *Multivariate Results*

We now explore whether these univariate results are borne out in a multivariate setting. We might expect, for example, that a respondent's stage of career or career aspirations might affect their willingness to use AI-assisted legal technology or to work on a regular basis with non-lawyers.<sup>222</sup> Older lawyers, or those whose role or career expectation is partnership in a law firm, might be expected to be more conservative in their attitudes to these matters. Similarly, it might be expected that familiarity with computer systems in general might make it easier for respondents to learn how to use AI-enabled systems, so we might expect a relationship between utilization of these systems and of AI-assisted legal technology.<sup>223</sup> Moreover, respondents who have received training in legal technology may be expected to be better able to make use of AI.<sup>224</sup>

[Table 5 about here]

Table 5 presents regression results on the determinants of MDTs. In Models (1) – (3), the left-hand side (dependent) variable is whether the respondent participates in an MDT, derived from Question 13 of the survey. Because this is a binary variable, a logistic regression is appropriate. Models

---

<sup>222</sup> These factors are captured, respectively, by Questions 20 (years since qualification), 4-7 (current role), and 19 (career aspirations) in our survey.

<sup>223</sup> Use of computer systems generally is captured by Question 9 of our survey, which asks respondents to indicate which of the following, if any, they use in their current role: “accounts / time management”; “document / knowledge management”; “CRM / marketing / tender document creation”; “document automation / matter workflow” / “extranets / deal-rooms” / “other”.

<sup>224</sup> Training in legal technology-related skills is captured in Question 11 of our survey, which asks respondents to indicate which of the following, if any, they have received training lasting for a day or longer in the previous 3 years: “software packages used by your employer” / “software coding” / “data analytics” / “digital literacy” / “ethical issues raised by the use of AI / technology” / “innovation techniques” / “legal issues raised by the use of AI / technology” / “process re-engineering” / “project management” / “design thinking”.

(4) – (6) are OLS,<sup>225</sup> using a left-hand side (dependent) variable that reflects respondents’ *openness* to participation in MDTs, as opposed to their actual participation. Question 14 in the survey asks respondents to indicate the extent to which they agree or disagree with the proposition that “[l]awyers need to become familiar with multiple non-legal technical specialisms, such as data science, project management, and design thinking.” Respondents’ answers fall on an ordinal scale of 1-5, ranging from “strongly disagree” to “strongly agree”.

The primary right-hand side (explanatory) variable in each case is whether the respondent works in a law firm or not. We control for years since qualification, the number of non-AI legal technology solutions used by respondents, whether the respondent uses AI (which we know from Table 4 to be correlated with MDT participation) and the number of legal technology training sessions received by the respondent in the previous 3 years.

The coefficients for the variable of interest in Table 5—“works for law firm”—are negative and statistically significant in each of the models, with the level of significance at 95% in models (1) – (3) and 99% in models (4) – (6). This is consistent with Hypothesis 2, indicating that MDT assembly for legal work is less common in law firms than in corporations. The coefficients for number of non-AI legal technology solutions used are positive and statistically significant in all specifications, suggesting that technology use generally is associated with MDTs. As expected, the coefficients for respondents’ use of AI-enabled lawtech are positive and statistically significant in Models (2) and (3), but they are not statistically significant in Models (5) and (6) capturing respondents’ openness to MDTs. The coefficients for years since qualification are negative and weakly statistically significant in Models (4) – (6), but not significant in Models (1) – (3). The coefficient for the number of legal technology training sessions received in the previous 3 years is positive and (weakly) statistically significant in Models (3) and (6).

[Table 6 about here]

Table 6 presents logistic regression results on the determinants of AI utilization. The left-hand side (dependent) variable is whether a respondent

---

<sup>225</sup> As the dependent variable in these models is an ordinal ranking, the OLS assumption of a continuous cardinal variable may be violated. As a robustness check, we also ran ordinal logistic regressions, for which the results were qualitatively similar. We present the OLS estimates because of their relative ease of interpretation. Further specifications are available on request.

uses any AI-enabled legal technology.<sup>226</sup> Our primary right-hand side (explanatory) variable is whether the respondent participates in an MDT. We also include as control variables whether the respondent works in a law firm, the number of years since qualification, the number of different non-AI lawtech solutions the respondent uses, the number of instances of lawtech training received by the respondent in the previous three years, and whether they aspire to a “traditional” legal career.<sup>227</sup> As can be seen, the coefficients for “works in MDT” are all positive and strongly statistically significant (at the 99% level) in all specifications. This is consistent with Hypothesis 1 and shows that the univariate results in Table 3 are robust to taking into account the effects of organizational form, age, role, training and deployment of other technology.

Overall, these results are consistent with both Hypothesis 1 and Hypothesis 2. We should of course understand their limitations. The key variables of interest are likely to be endogenous: there is two-way causation with respect to Hypothesis 1, as MDTs facilitate AI deployment, but AI also causes or necessitates MDTs. We are consequently unable to make any causal claims about the relationship between the variables in our data, but nevertheless the results do show correlations consistent with our hypotheses. These findings raise important questions for the work of lawyers, the way in which law firms seek to make use of AI, and the structure of the legal profession, to which we now turn in Part IV.

#### IV. IMPLICATIONS

Our empirical research has yielded robust insights into the emerging pattern of deployment of AI-based technology in legal services. Specifically, our mixed-methods evidence demonstrates that the deployment of AI is facilitated by multi-disciplinary teams, and that corporations rather than law firm partnerships are more conducive to the creation of multi-disciplinary teams. But what are the implications of these findings? In this Part, we explore the implications at three levels of analysis. First, for individual lawyers: how will their work and careers be affected? Secondly, for law firms: what are the main considerations in AI deployment if fee-sharing with,

---

<sup>226</sup> This is derived from Question 13 of the survey, as described above.

<sup>227</sup> This is captured by having selected the following answer to Question 19: “I hope to continue with a ‘traditional’ legal practice career progression, to become partner, managing partner, etc.”

and ownership by, non-lawyers are permitted? And thirdly, for the legal profession: in what ways will augmentation by AI change the jurisdictional boundary of the legal profession?

A. *Lawyers*

Much of the professional literature about the future of legal work focuses on the concept of the “T-shaped lawyer”.<sup>228</sup> The idea is that in order to embrace technological change, future professionals will need to have not only a deep grounding in their core discipline (the stem of the “T”), but also a breadth of more superficial engagement with a range of other technical disciplines (the cross of the “T”).<sup>229</sup> The assumption is that this greater range of expertise will be necessary to facilitate effective multidisciplinary teamwork making use of technology. Our results suggest an important qualification. For legal services professionals, the configuration of the “T” – the width of the cross-disciplinary expertise versus depth of “own” disciplinary expertise – will vary depending on whether they are functioning as consumers or producers of technology-enabled legal services. This in turn has implications for training and career progression.

1. Classical advisory roles: augmented by technology

Our results suggest that for the foreseeable future there will continue to be a need for human lawyers working in classical advisory roles. The technological limits of today’s AI,<sup>230</sup> and the use-cases in which it is capable of being deployed,<sup>231</sup> suggest that for the foreseeable future its deployment

---

<sup>228</sup> See, e.g., R Amani Smathers, *The 21st century T-shaped lawyer*, 40 LAW PRAC. (2014). Peter Connor, *The T Shaped Lawyer*, Legal Business World, Dec 22, 2017 (<https://www.legalbusinessworld.com/post/2017/12/22/the-t-shaped-lawyer>);

<sup>229</sup> The term appears to have originated in the computer science community, to describe the way IT professionals would need to be able to interface with domain-specific knowledge (David Guest, *The Hunt is on for the Renaissance Man of Computing*, THE INDEPENDENT, Sept. 17, 1991, at 12), (describing a professional profile “equally comfortable with information systems, modern management techniques and the 12-tone scale”) then being deployed more widely to characterize the need for professionals to be able to operate in multidisciplinary settings (see, e.g., TM Karjalainen, et al., *Educating T-shaped design, business and engineering professionals* (Cranfield University Press 2009); T Hensen & B von Otinger, *Introducing T. Shaped Managers, Knowledge Management’s next Generations*, HARVARD BUSINESS REVIEW (2001); Sergio Barile, et al., *Structure and dynamics of a “T-Shaped” knowledge: From individuals to cooperating communities of practice*, 4 SERVICE SCIENCE (2012)., before ultimately being used in the context of the legal profession.

<sup>230</sup> See *supra*, Section I.B.

<sup>231</sup> See *supra*, Section I.C.



will focus on work that is repeatable. This will leave one-off or “tailored” legal work such as complex litigation and complex transactions with idiosyncratic features—be they M&A, corporate financing or restructuring—will continue to require the traditional expertise of human lawyers. AI is in this respect a recent application of a more general regularity in the impact of technology on the work of lawyers.<sup>232</sup> However, an additional nuance about the scope of AI’s useful application is the continued importance of human lawyers for client interactions. To some degree, even where legal services work is carried out by an automated system, there will be a continuing need for human lawyers to be able to explain and interpret the results for end-users or clients.

For lawyers pursuing these traditional roles, the quality of work will likely increase, as the more tedious and repetitive tasks are automated. Moreover, while AI systems will substitute for lawyers in some tasks, this is likely to increase the productivity—and hence the value of the human capital—of the lawyers whose service offerings are augmented by the AI. Lawyers working in these augmented roles will primarily be *consumers* of legal technology. They will need to learn enough to master the interfaces with their technical systems, and to explain the strengths and weaknesses of these systems’ analysis to their clients. This will require, at a minimum, some appreciation of the way in which machine learning works, how performance is benchmarked, and the appropriateness of different benchmarks for particular contexts.<sup>233</sup> However, these systems are, as we saw,<sup>234</sup> being developed so as to be as readily accessible to non-technically trained lawyers as possible.<sup>235</sup> Moreover, it is likely that platform vendors or operators will have personnel on call available to give specialist advice about the strengths and weaknesses of the analytic results, who can support the lawyers relying on them in preparing for a client call. Consequently, the increase in necessary breadth of skills for lawyers who consume AI-enabled legal services is likely to be modest; rather, their value will continue to lie in their deep disciplinary

---

<sup>232</sup> See, e.g., SUSSKIND. 2000. In the context of AI specifically, see Marc Lauritsen, *Toward a Phenomenology of Machine-Assisted Legal Work*, 1 RAIL (2018).

<sup>233</sup> See *supra*, text to notes xx-xx.

<sup>234</sup> See *supra*, text to note xx.

<sup>235</sup> As one interviewee put it:

“I don’t think lawyers should code or need to code. I think what they do need to do, to future-proof themselves, is thinking about the breadth of interpersonal skills and be curious and willing to adapt, less from a technical perspective, more from a how they interact and how they work and are continually changing.” (Interview 39).

expertise.<sup>236</sup> While demand will continue for traditional lawyers, career opportunities are likely to be less certain. A reduction in overall numbers of roles, coupled with increasing rewards for those remaining, suggests an ever-more-competitive tournament for those pursuing traditional partnership opportunities.<sup>237</sup>

## 2. New multidisciplinary roles: augmenting technology

At the same time, there will be new roles for persons with legal training as part of multidisciplinary teams augmenting the technology. Persons with legal human capital working in these roles will likely be *producers*, rather than simply consumers, of AI-enabled legal services. We deliberately do not label these persons as “lawyers”, for two reasons. First, the work that they do may look quite different to that of lawyers in traditional legal advisory roles. Their job titles are likely to be different to reflect this – roles such as “legal engineers”, and “legal product experts”, cropped up in our interviews.<sup>238</sup> Second, it is unclear to what extent the professional license to practice law, as opposed to simply some relevant legal knowledge—likely coupled with relevant non-legal expertise—will be required to perform these roles.<sup>239</sup>

Training to perform these new roles will need to reflect their multidisciplinary focus.<sup>240</sup> Some will be primarily based on legal expertise—captured in the idea of the “T-shaped” professional—others will require a wider mix of skills.<sup>241</sup> All personnel working in multidisciplinary tech teams will, however, require at least a sufficient common vocabulary of each other’s disciplines so as to be able to collaborate together effectively.<sup>242</sup>

---

<sup>236</sup> In this respect, they are likely to remain closer to what is sometimes called an “I-shaped” model of professionalism: see, e.g., Sergio Barile, et al., *Service economy, knowledge, and the need for T-shaped innovators*, 18 WORLD WIDE WEB, 1185 (2015).

<sup>237</sup> Galanter & Henderson, STAN. L. REV., (2007); William D Henderson, *From big law to lean law*, 38 INTERNATIONAL REVIEW OF LAW AND ECONOMICS (2014).

<sup>238</sup> See *supra*, Table 1.

<sup>239</sup> Of course, some of the individuals taking up these roles will be legally qualified; our concern here is whether this will be necessary to perform the roles.

<sup>240</sup> See generally, Vaclav Janecek & Rebecca Williams, *Education for the Provision of Technologically Enhanced Legal Services* (Oxford University 2020).

<sup>241</sup> A study of a very large-scale dataset of recruitment advertisements suggests that employers in the legal services sector are increasingly seeking to recruit both MDTs will consist of disciplinary experts who are able to work together in a complementary fashion. Adam Saunders, et al., *Lawyering when the Law Becomes Machine-Learnt: Mapping LegalTech Adoption and Skill Demand*, in THE LEGALTECH BOOK (Sophia Adams Bhatti, et al. eds., 2020).

<sup>242</sup> Janecek & Williams. 2020.

These new roles will offer a multiplicity of career paths for appropriately-skilled individuals. These include working from the outset in corporate legal departments some of which (e.g. at Cisco) are offering traineeships; working as legal operations directors at law firms or legal departments; working as law firm innovation managers, then moving onto ALSPs or lawtech startups.<sup>243</sup> The question of whether individuals working in these new roles will need to be legally qualified also relates to the regulation of legal services firm, and the boundaries of the profession, which we now consider.

### B. *Law Firms*

As we have seen,<sup>244</sup> the ABA's fee-sharing prohibition, which has the effect of requiring lawyers to organize in partnerships with other lawyers, is increasingly viewed as a barrier to the adoption of digital technology and access to affordable legal services. Our empirical findings suggest that lawyer-only partnerships struggle to deploy AI-enabled legal technology as producers, relative to in-house corporate legal teams or ALSP law companies. Law firms' disadvantage has two key dimensions rooted in their mono-disciplinary partnership structure: they are relatively slow to make necessary strategic decisions for efficient implementation, and they face challenges recruiting and motivating the necessary non-legal talent to augment the technology.<sup>245</sup> At first blush, these findings appear to provide clear support for relaxation of the fee-sharing rule. However, closer examination reveals a more complex picture.

Our case study and survey evidence is from the UK, where the partnership form is no longer mandated for law firms. The UK's Legal Services Act of

---

<sup>243</sup> As one interviewee explained:

“[I]f you look at the growth of jobs for legal professionals ... my understanding is [that] the in-house area is far outstripping the law firm market, right? So, more and more ... the growth and size of in-house legal departments is ... accelerating compared to the growth of law firms generally. Then, when you layer ... law companies on top of that, it's very clear that career prospects for new legally-qualified individuals coming out of ... law school needs to include ... legal operations, in-house legal practice, law companies, as an option.” (Interview 45).

<sup>244</sup> *Supra*, Section II.A.

<sup>245</sup> Our findings further suggest the corporate form has corresponding advantages across both dimensions.

2007 overhauled the regulation of legal services in England and Wales,<sup>246</sup> with multiple objectives of promoting the public interest, protecting consumer interests, improving access to justice, and promoting competition among providers of legal services.<sup>247</sup> A cornerstone of the new regulatory framework was the permission for lawyers to establish entities with lay (non-lawyer) ownership, management, and investment, known as “Alternative Business Structures” (ABSs).<sup>248</sup> There are now nearly 1,200 licensed ABSs, as against a total population of over 10,000 law firms.<sup>249</sup> About half of these ABSs have transformed from law firm partnerships,<sup>250</sup> and a sizeable number have consequently changed the way in which they raise finance, to invest more in technology and innovation.<sup>251</sup> However, the vast majority of these law-firm-to-ABS moves have been very small firms whose clients are individuals rather than businesses.<sup>252</sup> While there have been one or two high-profile restructurings of larger incumbent law firms that focus on the

---

<sup>246</sup> Within the United Kingdom, there are in fact multiple legal jurisdictions, the most significant of which is England and Wales. Scotland and Northern Ireland are separate jurisdictions, which were outside the scope of the reforms: Legal Services Act (UK) 2007, § 212(1).

<sup>247</sup> See Legal Services Act (UK) 2007, § 1(1) (setting out “regulatory objectives”). See generally, Clementi. 2004; John Flood, *Will There Be Fallout from Clementi: The Repercussions for the Legal Profession after the Legal Services Act 2007*, MICH. ST. L. REV. (2012); Myles V Lynk, *Implications of the UK Legal Services Act 2007 for US Law Practice and Legal Ethics*, 23 PROF. LAW. (2015).

<sup>248</sup> Legal Services Act (UK) 2007, Part 5.

<sup>249</sup> The Solicitors Regulation Authority (SRA) keeps a register of licensed bodies (ABS). As of February 8, 2021, the total was 1,163. See <https://www.sra.org.uk/solicitors/firm-based-authorisation/abs/abs-search>

<sup>250</sup> Evaluation: ABS and investment in legal services 2011/12-2016/17 – Main Report (2017). (56% of respondents to survey of ABSs had offered regulated legal services prior to becoming ABSs).

<sup>251</sup> In 2014, SRA found in a survey that 27 percent of ABSs changed the way their business was financed, and that investment was most often sought for entry into technology, to change the services offered, and for marketing. See SOLICITORS REGULATION AUTHORITY, *Research on alternative business structures (ABSs): Findings from surveys with ABSs and applicants that withdrew from the licensing process* 17 (May 2014),

<sup>252</sup> LSB, Evaluation: ABS and investment in legal services 2011/12-2016/17 – Main Report 16-17. 2017. (most common areas of practice for ABSs are consumer-facing fields such as wills, trusts and probate and real estate conveyancing; mean number of principals for licensed ABSs was 7.2).

corporate sector, such as DWF<sup>253</sup>—which underwent an IPO in 2019—these have very much been the exception.<sup>254</sup> Consistently with this, all but one of the law firm case studies we recruited for successful implementation of AI involved firms that were organized as partnerships.<sup>255</sup> This raises an obvious question: why have these law firms not embraced the opportunity to restructure as ABSs, given the disadvantages we find the lawyer-only partnership form faces in implementing AI?

Inertia might be a possible explanation,<sup>256</sup> but this becomes decreasingly plausible over time, and it is now a decade since the opportunity to switch to ABS first became available.<sup>257</sup> Our analysis and results suggest, on the other hand, an economic explanation for large law firms' continued adherence to the partnership form despite the advantages of the corporate form for deploying technology. The professional partnership is a very effective form for recruiting and motivating the human capital associated with traditional legal advisory work. Such human capital is highly mobile. So long as it remains valuable, the partnership form in turn is a valuable complement to it, which would be lost by switching to the corporate form.

Our findings suggest that the implementation of AI in legal services will increase the value of the human capital of traditional legal advisers who *consume* the output of AI-enabled technologies in the performance of their work. For law firms whose human capital predominantly falls into this category, the benefits of the partnership form will actually increase, rather than decrease. And large law firms who serve corporate clients will have more valuable aggregate pools of human capital than small firms who serve individual clients.

---

<sup>253</sup> Following the restructuring, the pre-existing law firm became a subsidiary of the new public company, with some law firm partners and other non-lawyers becoming directors of the parent public company. The law firm can harness multi-disciplinary teams hosted by the corporate parent. See Prospectus for Offer of Ordinary Shares and admission to listing on the Official List and to trading on the main market of the London Stock Exchange. (2019). See Armour & Sako (2020) for further details on DWF as PLC.

<sup>254</sup> Aulakh & Kirkpatrick, *INTERNATIONAL JOURNAL OF THE LEGAL PROFESSION*, (2016).

<sup>255</sup> This does not appear to be simply an artefact of sample selection. Amongst our survey respondents, who were all practicing lawyers, only 12 worked in organizations that were ABSs, as opposed to 236 who worked for traditional law firms: Sako, et al., 20. 2020.

<sup>256</sup> Law firms exhibit documented conservatism in decision-making: see, e.g., Aulakh & Kirkpatrick, *INTERNATIONAL JOURNAL OF THE LEGAL PROFESSION*, (2016). See also *supra* Section II.B.

<sup>257</sup> The new regulatory regime became effective from the beginning of 2011: see LSB, Evaluation: ABS and investment in legal services 2011/12-2016/17 – Main Report 10. 2017.

At the same time, the pattern of AI adoption—and indeed technology adoption more generally—has been very much skewed towards larger firms, because of the economies of scale.<sup>258</sup> ALSPs meanwhile have chosen to become ABSs in order to practice law directly. For example, law companies such as Elevate and UnitedLex operate as ALSPs in the UK.<sup>259</sup> Also, the Big Four accounting and audit firms all have their legal wings – Deloitte Legal, EY Legal, KPMG Legal, PwC Legal – approved as ABSs.<sup>260</sup> This enables them to practice law in areas – tax, regulatory, government investigation – that are complementary to their audit and accounting practices. Their sheer size gives them resources to invest in technology, including AI. Important for our discussion, given career opportunities for lawyers and non-lawyers to be promoted to partner, is the ease with which MDTs can be crafted to manage the AI pipeline.

This implies a pattern of deployment of AI in legal services *organizations* that closely complements the division we identified in legal services *work*: traditional law firm partnerships that focus on giving (human centric) legal advice, in so doing *consuming* some AI-enabled legal services as inputs; and corporate in-house teams and/or independent law companies that focus on *producing* technologically-enabled legal services. The appropriate organizational form will be a function of whether the value of the (traditional) legal human capital that is augmented by technology is greater than the value of the AI-enabled technology.<sup>261</sup> For a law firm with a traditional legal advisory business model, the value of their traditional legal capital is likely to be greater. For a firm specializing in the deployment of legal technology (i.e. an ALSP law company) or the in-house team of a large corporation, the reverse is likely to be true.

Of course, this does not imply that producers of AI-enabled legal services will necessarily work in different organizations from the consumers of these

---

<sup>258</sup> See *supra*, Section II.B.

<sup>259</sup> See ElevateNext UK Limited, <https://elevateservices.com/elevatenext-uk-legal-practice/> (last visited Feb 5, 2021); Elevate also has a law firm called ElevateNext with its main office in Chicago, <https://elevatenextlaw.com/> (last accessed Feb 5, 2021); UnitedLex has a law firm, Marshall Denning, as part of its portfolio companies, operating in both the US and UK, <https://www.marshalldenning.com/> (last accessed Feb 5, 2021).

<sup>260</sup> Solicitors Regulation Authority (UK), Register of licensed bodies (ABS): <https://www.sra.org.uk/solicitors/firm-based-authorisation/abs/abs-search> (searches conducted Feb 5, 2021). (Deloitte LLP licensed May 31, 2018; Ernst & Young LLP licensed Nov 28, 2014; KPMG LLP licensed Oct 1, 2014; PricewaterhouseCoopers Legal LLP licensed Jan 30, 2014 and PricewaterhouseCoopers LLP licensed Aug 15, 2016).

<sup>261</sup> This would be net of the cost of the multidisciplinary human capital that is necessary to produce the AI-enabled legal services.

services. Within a corporate in-house team, there will often be both; outside law firms have the option to acquire technology companies as subsidiaries, and as we have seen,<sup>262</sup> ALSPs may (where permitted) recruit practicing lawyers. Firms may be expected to combine all aspects of the value-chain for AI in legal services in this way where the associated friction between their human capital needs and their organizational form is less than the costs of contracting with another firm.<sup>263</sup> Yet even where such combination occurs, the choice of overall organizational form can be expected to complement the recruitment, co-ordination and motivation of the personnel associated with the most valuable assets for the business, be they human capital or technological capital. Doing both under one roof, while not impossible, requires clarity around the scope of the legal profession, as well as aligning organizational structure to business model combinations.

Reforms to the fee-sharing prohibition are now under way in some US states—specifically, the introduction of regulatory “sandboxes” in Arizona, California, and Utah.<sup>264</sup> These have largely been motivated by a wish to improve access to affordable legal services and to justice, particularly for individuals – what is Henderson terms the “People Law Sector”, in contrast to the “Organization Client” sector.<sup>265</sup> Relaxing the restrictions on fee-sharing and ownership by non-lawyers in such a way as not to cause consumer harm is the key aim of the state-level regulatory sandboxes. Our findings and analysis have two pointers worth noting for those engaged in such sandboxes, from the perspective of the Organization Client sector. First, the UK experience suggests that, in itself, the lifting of restrictions on lawyer-only ownership is likely to have an incremental, rather than a transformative, impact on the delivery of legal services for business clients. Large incumbent law firms are unlikely to reorganize as corporations, simply to improve their deployment of technology. Second, with the advent of MDTs, AI deployment complemented by multi-disciplinary human talent management will likely

---

<sup>262</sup> *Supra*, text to notes 259-260.

<sup>263</sup> We analyze these “make or buy” contracting issues over legal technology in a companion paper: John Armour, et al., *Contracting for Legal Technology* (2020).

<sup>264</sup> See ARIZONA 2019. Task Force on the Delivery of Legal Services: Report and Recommendations. Supreme Court, State of Arizona; CALIFORNIA 2020. State Bar of California Task Force on Access through Innovation of Legal Services: Final Report and Recommendations. State Bar of California; UTAH 2019. Narrowing the Access-to-Justice Gap by Reimagining Regulation: Report and Recommendations. Utah State Bar Working Group on Regulatory Reform.

<sup>265</sup> HENDERSON, W. D. 2018. Legal Market Landscape Report. Commissioned by the State Bar of California.

blur the boundary of legal services and related services markets. This will require greater clarity around the scope of the legal profession going forward.

### C. *The Legal Profession*

It remains an open question whether the rise of augmented lawyering will be capable of being accommodated within the existing institutional structures of the legal profession. The existing structure is that of occupational licensing, under which only licensed lawyers are authorized to practice law,<sup>266</sup> just as only licensed doctors can practice medicine. Inherent in the notion of “authorized practice of law” in the United States and “reserved activities” in England and Wales,<sup>267</sup> the legal profession has been highly successful in holding an exclusive claim to specific knowledge and expertise.<sup>268</sup> Exclusive jurisdiction rests on a claim to distinctiveness and differentiation of the package of professional knowledge.<sup>269</sup> However, this drive towards differentiation of expertise has also led to greater intra-professional specialization and splintering into multiple sub-professions.<sup>270</sup> These outcomes are not necessarily due to technology, but technology may trigger or accelerate disruption in the scope of occupational closure.<sup>271</sup>

This Article has focused on the impact of AI technology on legal services. In this context, the distinction we draw between lawyers as producers (providing inputs for the AI pipeline) and lawyers as consumers (using outputs from the AI pipeline) is useful in identifying possible scenarios for the future. It is evident that each scenario is populated by a different sort of legal professional (without pre-judging at this point whether she is called a

<sup>266</sup> See ABA Model Rules of Professional Conduct, Rule 5.5 (prohibiting persons not admitted to practice in a particular jurisdiction from holding out to the public or otherwise representing that they are so admitted).

<sup>267</sup> Legal Services Act (UK) 2007, § (defining “reserved legal activity”).

<sup>268</sup> See, e.g., Hadfield, *STAN. L. REV.*, (2007); Henderson. 2018; RHODE. 2004.

<sup>269</sup> ABBOTT, A. 1988. *The System of Professions: An Essay on the Division of Expert Labor*, Chicago, University of Chicago Press.

<sup>270</sup> For example, U.S. physicians now have 25 broad-certified specialties (encompassing over 125 sub-specialties), and solicitors in England and Wales have 54 specialties in different areas of law. See SCOTT, W. R. 2008. Lords of the dance: professionals as institutional agents. *Organization Studies*, 29, 219-238. It is a wonder that once admitted to the Bar, there is nothing stopping an attorney with one specialization – e.g., real estate law – to go into employment law, family law, class action suit, or other non-contentious areas of law.

<sup>271</sup> Other forces pushing to disrupt the traditional scope of professional activities include globalization and the associated intensification of competition: see, e.g., Kevin T Leicht, *Market fundamentalism, cultural fragmentation, post-modern skepticism, and the future of professional work*, 3 *JOURNAL OF PROFESSIONS AND ORGANIZATION* (2016); Smets, et al., *JOURNAL OF PROFESSIONS AND ORGANIZATION*, (2017).



“lawyer” or something else). Also, these legal professionals in different scenarios provide different things to their clients -- traditional legal advice, legal services or products, or integrated solutions (guaranteed solutions for trouble-free operations in some cases).

One scenario envisages a profession defined around human lawyers who are primarily legal experts. This is very much the current vision of the legal profession, and so can be thought of as a “baseline” scenario. For a profession defined in this way, practicing “lawyers” are only ever likely to come into contact with AI-enabled technology as consumers. Lawyers’ capacity to give legal advice may be augmented by AI providing more efficient and effective outputs, be they contract review and generation, TAR supporting discovery, or legal research. In so doing, the lawyers are assisted by other professionals providing technical support and will require minimal auxiliary training to interact with these other professionals. This scenario therefore entails only a modest incremental change in the activities of the legal profession, with the majority of lawyers interacting with AI and associated technologies only as consumers. A clear division of labor remains between lawyers who practice law and other professionals (data scientists, project managers, design thinkers) who support lawyers.

A second scenario incorporates the combined roles of lawyers-as-consumers and lawyers-as-producers of AI-enabled legal services. Combining the roles of producer with consumer implies that lawyers in varying stages of seniority are involved in choosing and labelling the data to train AI algorithms and evaluating the model performance, which they believe they can do well only by interfacing directly with clients to understand how best to fulfil their needs. The legal profession may endorse the producer expertise within its occupational boundary because it contributes to the effectiveness of their consumer role. This is the notion of “lawyer-coders”, the idea that the majority of lawyers should become familiar with how to use AI models, if not to learn how to code. In this scenario, lawyers have an extended remit not only to give legal advice, but also to take a more systematic perspective to providing integrated legal solutions to their clients.

A third scenario is the splintering of professionals beyond the traditional legal profession into multiple sub- or even new professions. While some lawyers may remain consumers of technology, new roles will be created that focus on the producer role for technology-enabled legal services, with an emergent specialization in legal operations, legal engineering, legal project management, legal products, and legal technology. Some of these occupational roles are already organized into a separate professional association. Notable is CLOC (the Corporate Legal Operations Consortium),

which sets out the twelve areas of competence in legal operations.<sup>272</sup> CLOC members have an understanding of legal practice (via a university degree in law for example) but are not necessarily licensed to practice law. Their day-to-day work is certainly not about practicing law. They are the emergent “hybrid professionals” in legal markets, but given the existing regulation, they will remain outside the legal profession.

We think that this third scenario is quite plausible if changes in professional regulation around what constitutes unauthorized practice of law (UPL) remain minimal or slow. A small number of stellar lawyers may remain lawyers-as-consumers, creating untold value for their clients. However over time, for the profession as a whole, value creation for clients will migrate away from lawyers-as-consumers to other legal professionals who combine (or specialize in) producer roles. The legal profession has a choice between two paths. One is to stick to the existing strict occupational closure which will exclude more and more professionals with some legal expertise. The other is to recognize *within* the profession some heterogeneity in specialization (e.g. in technology or business of law) beyond specific areas of law. This latter path is materially different from the paraprofessional route pursued by state bars which are exploring regulatory reform.<sup>273</sup>

## CONCLUSION

In this Article, we have focused on the “human dimensions” of change generated by the implementation of AI in legal services. We draw an important distinction between lawyers-as-consumers and lawyers-as-producers of AI-enabled legal services. This enabled us to analyze two relatively neglected types of impact of AI on what lawyers do. Instead of

---

<sup>272</sup> <https://cloc.org/what-is-legal-operations/>

<sup>273</sup> A paraprofessional is a person to whom a particular aspect of a professional task is delegated but who is not licensed to practice as a fully qualified professional. The state bar of California is exploring implementing “a new paraprofessional licensing program (such as a Limited License Legal Technicians program) that would allow nonlawyer individuals to render specified limited legal advice and services” (CALIFORNIA 2020. State Bar of California Task Force on Access through Innovation of Legal Services: Final Report and Recommendations. State Bar of California; page 5). Similarly, Arizona Supreme Court authorized in 2003 the certification of Legal Documents Preparers (LDPs) (ARIZONA 2019. Task Force on the Delivery of Legal Services: Report and Recommendations. Supreme Court, State of Arizona. Page 9), while Utah state bar certifies Legal Paralegal Practitioners (LPPs) (UTAH 2019. Narrowing the Access-to-Justice Gap by Reimagining Regulation: Report and Recommendations. Utah State Bar Working Group on Regulatory Reform.).

focusing exclusively on AI replacing lawyers' tasks, our investigation led to two further important impacts. Technology will augment the capabilities of human lawyers who use AI-enabled services as inputs to their work, meanwhile generating new roles for legal experts in producing these AI-enabled services. We document these new roles being clustered in multidisciplinary teams ("MDTs") that mix legal with a range of other disciplinary inputs to augment the operation of technical systems. We identify challenges for traditional law firm partnerships in implementing AI. Contrary to prior debate, these do not flow from constraints on finance to invest in technical assets. Rather, the central problems have to do with human capital: making necessary strategic decisions; recruiting, coordination and motivation the necessary MDTs; and adjusting professional boundaries of the legal profession. These findings have important implications for lawyers, law firms and the legal profession.

## APPENDIX: SURVEY QUESTIONS

*A. Preliminary screening*

Q1 Your answers will be completely anonymous; no personal data will be collected from you. Please review our participant information sheet (click [here](#) to view) and confirm you are happy to participate.

Yes, I agree to participate

Q2 Do you have a certificate to practice as a solicitor?

Yes

No

*B. About you and your organization*

Q3 What type of organisation do you work for? Please select all that apply.

Law firm

Accounting firm

Alternative business structure (ABS)

In-house legal department

LawTech solutions provider

If answer to Q3 is “Law firm”:

Q4 What is your current role? Please select all that apply.

Associate / assistant

Partner

Professional support lawyer

Managing / senior partner

Counsel

Other

If answer to Q3 is “In-house legal department”

Q5 What is your current role? Please select all that apply

Leadership role

Legal advisory role

Legal operations role

If answer to Q3 is “Accounting firm” or “Alternative business structure”

Q6 What is your current role? Please select all that apply.

Leadership role

- Legal advisory role
- Legal operations role
- Business development / product development role

If answer to Q3 is "LawTech solutions provider"

Q7 What is your current role? Please select all that apply.

- Leadership role
- Legal domain expert
- Business development / product development role
- Other

Q8 Do you have any of the following professional qualifications, in addition to being a solicitor? Please select all that apply.

- Other legal profession (barrister, licenced conveyancer, patent attorney etc)
- MBA
- Chartered Institute of Marketing (or equivalent)
- Project Management Institute (or equivalent)
- CFA (or equivalent)
- Other

*C. About your organisation's use of LawTech*

Q9 Which of the following do you - personally - use in your current role? Please select all that apply.

- Accounts / time recording
- Document / knowledge management
- CRM / marketing / tender document creation
- Document automation / matter workflow
- Extranets / deal-rooms
- Other

Q10 In which context (s) do you currently use AI-assisted legal technology? Please select all that apply. By "AI-assisted legal technology", we mean technology that uses an expert system, machine learning, and/or deep learning.

- eDiscovery / eDisclosure / technology assisted review
- Predictive analytics for litigation
- Due diligence
- Contract analytics
- Regulatory compliance

- Legal research
- Fee-earner utilisation analytics and / or predictive billing
- Other

*D. About your organisation's current LawTech training*

Q11 Have you received training - lasting a day or longer - in any of the following areas in the last 3 years? Please select all that apply.

- Software packages used by your employer (all types)
- Software coding
- Data analytics
- Digital literacy
- Ethical issues raised by the use of AI / technology
- Innovation techniques
- Legal issues raised by the use of AI / technology
- Process re-engineering
- Project management
- Design thinking

Q12 Please indicate the extent to which you agree with the following statements. (Strongly agree/ Agree/ Neither agree nor disagree / Disagree / Strongly disagree)

“I feel sufficiently trained in how to use new technology at work”

“I know whom to ask if I need advice on using new technology”

“I can confidently identify legal risks associated with using new technology”

“My organisation understands the challenges for lawyers brought about by new technologies.”

“Productivity at my organisation could be improved further by training lawyers in how to use new technologies.”

“My organisation captures data effectively, so that it can be used by legal technology.”

Q13 In your organisation, with whom do you work on a day-to-day basis, in order to get legal work done? Please select all that apply.

- Paralegals
- Legal project managers
- Process mapping experts
- Data analysts / data scientists
- IT / legal Innovation experts
- Other solicitors / lawyers
- Other

*E. Your future career*

Q19 Which of the following statements most closely describes your career aspirations?

- I have already reached a high level of seniority, and intend to stay “in post” until I retire.
- I hope to continue with a “traditional” legal practice career progression, to become partner, managing partner, etc.
- I am open to the idea of working for (or establishing) an alternative legal service provider.
- I am open to the idea of working for (or establishing) a LegalTech solutions provider.
- I am open to the idea of moving (or remaining) in-house.
- I wish to ensure my work-life balance by working as a contract lawyer on a project basis.
- Other

Q20 In which year did you qualify as a solicitor?

**Table 1:** Anonymized Interviewee Details

<b>Interviewee #</b>	<b>Organization ID</b>	<b>Interviewee Role</b>
1	Corporate A	X Counsel Technology, X and Governance
2	Corporate A	Transformation Director - Legal & X
3	Corporate A	Head of Legal X Management
4	Corporate A	Head of X & X Systems and Change
5	Law firm A	Director of Practice Development and Innovation
6	Law firm A	Assistant General Counsel
7	Law firm A	Director of Product, X
8	Law firm B	Managing Director, X
9	Law firm B	Principal X - Data & Predictive Analytics
10	Law firm B	Data Process & Application Scientist
11	Law firm B	Chief Information Officer
12	Law firm B	Head of R&D
13	Law firm C	Chief Legal Innovation Officer
14	Law firm C	Chief Legal Innovation Officer
15	Law firm C	Principal Associate
16	Law firm C	Global Head of X Architecture
17	Law Firm D	Chief Information Officer
18	Law Firm D	Director, Global X and New York – X Services
19	Law Firm D	Head of eDiscovery and Legal Technology, UK
20	Law Firm D	Partner
21	Law Firm D	Chief Legal Operations Office
22	Law firm E	Partner
23	Law firm E	Head of X Strategy
24	Law firm E	X of Knowledge and Innovation Delivery
25	Law firm E	Head of X
26	Law firm F	Business Services and Innovation Director
27	Law firm F	Partner and Innovation X
28	Law firm F	Solicitor
29	Law firm F	Partner
30	Law firm F	Principal Associate
31	Law firm F	Principal Associate
32	Law firm F	Partner
33	Law firm F	Partner
34	Law firm G	X Head of Legal Operations, Innovation Lead
35	Law firm H	Head of Innovation
36	Law firm H	Director of Knowledge & Innovation
37	ALSP A	Strategy & Operations Lead, X UK
38	ALSP A	CTO
39	ALSP A	Innovation and Ventures Lead
40	ALSP A	Manager, X
41	ALSP A	Assistant Director, X
42	ALSP A	Chief Data Scientist, X
43	ALSP A	Associate Director, Risk Advisory
44	ALSP B	X, Data Science & Innovation
45	ALSP B	VP, Innovation
46	ALSP B	Vice President and X, Digital Strategy & Solutions
47	ALSP B	General Counsel
48	ALSP C	Vice President Client Success
49	ALSP C	Chairman
50	ALSP D	CEO



51	ALSP D	Executive Vice President, X Legal Transformation
52	ALSP D	X, Digital Contracting and Commercial Solutions
53	ALSP D	X Vice President and General Counsel
54	ALSP E	Founder and CEO

**Table 2:** Variable Description and Descriptive Statistics

Variable	Definition	Survey Q (Appendix)	Min.	Median	Mean	Max.	Obs
Uses any AI-based lawtech	Binary variable, 1 = respondent lawyer regularly uses one or more type of AI-based lawtech	Q10	0	0	0.484	1	349
Works in MDT	Binary variable, 1 = respondent lawyer works on a day-to-day basis with non-lawyer professionals	Q13	0	0	0.297	1	327
Works for law firm	Binary variable, 1 = respondent lawyer works for a law firm partnership	Q3	0	1	0.688	1	343
Openness to other disciplines	Extent to which respondent lawyer agrees with proposition “lawyers need to become familiar with multiple non-legal technical specialisms, such as data science, project management, and design thinking.” (1 = strongly disagree, 5 = strongly agree)	Q14	1	4	3.711	5	342
Years since qualification	Number of years since respondent qualified as a lawyer	Q20	0	16.00	18.03	55.00	349
# Lawtech solutions used	Number of non-AI-based (“pre-AI”) lawtech solutions used regularly by respondent lawyer	Q9	0	3.00	2.72	4.00	349
# Lawtech training	Number of types of lawtech training (lasting a day or longer) respondent lawyer received in past 3 years	Q11	0	0.00	1.28	2.00	349
Partner or leadership role	Binary variable, 1 = respondent lawyer’s job type is “partner” (if works in law firm) or “leadership” (if does not work in law firm)	Qs 4-7	0	0	0.398	1	332
Traditional legal career aspiration	Binary variable, 1 = respondent hopes to continue with a “traditional” legal practice career progression, to become partner or managing partner.	Q19	0	0	0.172	1	344

**Table 3:** Cross-tabulation of use of AI-assisted legal technology and participation in MDTs

		Uses any AI lawtech		Row Totals
		No (Column percentage)	Yes (Column percentage)	
Works in MDT	<b>No</b>	<b>132</b>	<b>98</b>	<b>230</b>
		80.5%	60.1%	
	<b>Yes</b>	<b>32</b>	<b>65</b>	<b>97</b>
		19.5%	39.9%	
Column Totals		<b>164</b> 100%	<b>163</b> 100%	<b>327</b>

**Table 4:** Cross-tabulation of participation in MDTs and organisation type

		Works for law firm		Row Totals
		No (Column percentage)	Yes (Column percentage)	
Works in MDT	<b>No</b>	<b>63</b>	<b>163</b>	<b>226</b>
		64.9%	72.4%	
	<b>Yes</b>	<b>34</b>	<b>62</b>	<b>96</b>
		35.1%	27.6%	
Column Total		<b>97</b> 100%	<b>225</b> 100%	<b>322</b>

**Table 5:** Determinants of Multi-disciplinary teams

	<i>Dependent variable:</i>					
	Works with other disciplines			Openness to other disciplines		
	<i>logistic</i>			<i>OLS</i>		
	(1)	(2)	(3)	(4)	(5)	(6)
Works for law firm	-0.704** (0.285)	-0.642** (0.291)	-0.599** (0.293)	-0.351*** (0.127)	-0.343*** (0.127)	-0.331*** (0.127)
Years since qualification	0.006 (0.010)	0.008 (0.010)	0.011 (0.010)	-0.009** (0.004)	-0.009** (0.004)	-0.008* (0.004)
# Lawtech solutions used	0.368*** (0.099)	0.344*** (0.100)	0.280*** (0.104)	0.105** (0.042)	0.102** (0.043)	0.080* (0.044)
Uses any AI-based lawtech		0.932*** (0.261)	0.862*** (0.264)		0.068 (0.112)	0.040 (0.113)
# Lawtech training			0.165** (0.077)			0.059* (0.035)
Constant	-1.544*** (0.376)	-2.061*** (0.413)	-2.160*** (0.417)	3.831*** (0.161)	3.799*** (0.170)	3.767*** (0.170)
Observations	322	322	322	337	337	337
R <sup>2</sup>				0.045	0.047	0.055
Adjusted R <sup>2</sup>				0.037	0.035	0.040
Log Likelihood	-187.891	-181.283	-178.933			
Akaike Inf. Crit.	383.782	372.566	369.865			

*Note:* Data are responses to survey of solicitors in England and Wales conducted from November 2019-January 2020. Models (1)-(3) are logistic regressions of the likelihood that a respondent currently works on a day-to-day basis with professionals other than lawyers and paralegals; reported coefficients are logs of odds. Models (4)-(6) are OLS regressions of the level of support given by respondents to the proposition that “lawyers need to become familiar with multiple non-legal technical specialisms, such as data science, project management, and design thinking.” \* p < 0.1; \*\* p < 0.05; \*\*\* p < 0.01.

**Table 6:** Determinants of AI Utilization

	<i>Dependent variable:</i>					
	Uses any AI-based lawtech					
	(1)	(2)	(3)	(4)	(5)	(6)
Works in MDT	1.006*** (0.254)	0.982*** (0.256)	0.988*** (0.256)	0.931*** (0.261)	0.862*** (0.264)	0.887*** (0.267)
Works for law firm		-0.223 (0.250)	-0.232 (0.251)	-0.327 (0.265)	-0.297 (0.267)	-0.262 (0.280)
Years since qualification			-0.009 (0.009)	-0.008 (0.009)	-0.006 (0.009)	-0.009 (0.010)
# Lawtech solutions used				0.100 (0.089)	0.051 (0.093)	0.054 (0.093)
# Lawtech training					0.155** (0.076)	0.148* (0.077)
Traditional legal career aspiration						-0.287 (0.338)
Constant	-0.298** (0.133)	-0.143 (0.224)	0.028 (0.277)	-0.186 (0.337)	-0.306 (0.345)	-0.220 (0.354)
Observations	327	322	322	322	322	321
Log Likelihood	-218.410	-214.790	-214.248	-213.621	-211.476	-210.046
Akaike Inf. Crit.	440.820	435.581	436.495	437.241	434.952	434.092

*Note:* Data are responses to survey of solicitors in England and Wales conducted from November 2019- January 2020. Models (1)-(6) are logistic regressions of the likelihood that a respondent currently uses any AI-based lawtech. Reported coefficients are logs of odds. \* p < 0.1; \*\* p < 0.05; \*\*\* p < 0.01.