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How information technology automates and augments processes: Insights from Artificial-Intelligence-based systems in professional service operations

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Abstract

This study contributes to the technology management literature on the effects of IT on operations processes by examining the use of systems based on Artificial Intelligence (AI) in professional services. The paper builds on key concepts on AI, information systems, professional work, and professional services operations management. A model is developed to explain how AI-based systems combine with humans to do work, both automating and augmenting the work of the professional, leading to process improvement and extension of the service offering. The study uses case-based research in two law firms and two accountancy firms using AI-based systems. It shows that AI-based systems are used selectively, mainly on high-volume, back-office tasks, across the sequence of stages in the professional service process—diagnosis, inference, and treatment. Automation using AI relieves professionals from repetitive tasks, while AI achieves augmentation by buffering professionals from low-value activity, making their expertise scalable and providing new analytical insights. System use can improve performance in delivering core professional services and enable service extension into additional, high-value advisory work. The model and research approach have potential implications for other emerging areas of technology management in OM.

KEYWORDS

artificial intelligence, customer contact, expertise, information technology, professional services

1 | INTRODUCTION

The deployment of information systems based on artificial intelligence (AI) in professional services is a recent example of technology being used in product and service delivery processes in operations. Some commentators argue that information technology (IT), and in particular AI, will have profound implications for professional work, and may even render professionals unnecessary (Susskind & Susskind, 2015). Specifically in the legal services sector, Susskind (2017) suggests that, in particular, small and medium-sized firms who do not embrace new business structures and technology will not survive: "I do not see much of a future (beyond 2020) for most traditional small [law] firms in liberalized regimes" (Susskind, 2017, p. 64). Others are less extreme in their

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predictions. For example, Remus and Levy (2017) suggest that the effect of AI adoption on job security in legal services will continue to be more modest, because of the intrinsic need for "unstructured human interaction," which technology is unable to accomplish.

If operations management (OM) is about "managing work to produce valuable results" (Browning, 2020), then a pressing theoretical and managerial concern of the present era is how IT and human workers combine to do that work. In relation to AI, Von Krogh holds that "a fundamental research topic for management scholars is … what decision-making authority can or cannot be delegated to intelligent machines … and what are the effects on task performance?" (Von Krogh, 2018, p. 405). Professional services are an extreme (as well as economically important) setting in which to pose this question, because of the supposedly central role of human expertise in their delivery. More generally, in OM, professional services have typically been considered low-volume, high-variety, high-customer-contact, customized processes, dependent on professional expertise and discretion (Collier & Meyer, 2000; Silvestro et al., 1992), and therefore unlikely to be susceptible to automation. Many prior IT deployments in operations processes have taken over repetitive tasks performed by less skilled workers. The use of AI-based systems in professional services, however, raises the prospect of using IT to perform knowledge-intensive work previously seen as the exclusive preserve of highly skilled, human workers.

In this paper, therefore, we examine AI-based IT use in professional service operations (PSOs) processes, specifically in law and accountancy. We pose the following research questions:

> **RQ1.** How are AI-based systems currently used in law and accountancy professional service firms' (PSFs) operations processes?

> **RQ2.** How does the use of AI-based systems in law and accountancy PSFs' operations processes automate and augment professionals' work?

> **RQ3.** How does the use of AI-based systems affect the competitiveness and scope of the service offered to clients in law and accountancy professional services?

> **RQ4.** How do profession- and firm-specific factors affect the use of different types of AI-based systems in PSOs?

We find We find that AI-based information systems are used at input, processing, and output stages of PSOs, and both automate and augment the work of human professionals. Our contribution to the literature on Technology Management (TM) in OM is to show how automation and augmentation can lead, directly and indirectly, to both improved performance of existing operations and extension into new service offerings. We combine empirical and theoretical insights to develop a model of these phenomena. Although we restrict our immediate focus to the particular case of AI in these two professions, we contribute more widely to TM by revealing the many direct and indirect ways in which the use of IT in the execution of core service delivery processes affects those processes and the scope and nature of the services provided to customers. This contrasts with much of the existing TM literature, which seeks to quantify the effect of IT adoption on aggregate performance, without inquiring into how the effects come about.

In the next section, we review key concepts concerning AI use in organizations, outline our approach to conceptualizing technology in organizations and processes, and review selected literature on professional services. We then set out our research method, before presenting our findings from four PSFs. We develop a model of AI-based information systems in professional services, and discuss the implications of our research for technology management in OM and for PSOs management.

2 | LITERATURE REVIEW

2.1 | Forms and functions of artificial intelligence in organizations

As befits a focus on TM, we begin by outlining the forms and functions of the focal technology—AI—as used in organizations. One definition of AI is "a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan & Haenlein, 2019, p. 17). For von Krogh (2018), the functioning of AI systems relevant to organizations "entails task input (data: sound, text, images, and numbers), task processes (algorithms), and task outputs (solutions and decisions)" (Von Krogh, 2018, p. 404). This process-oriented conceptualization clearly aligns with an OM perspective.

Various technologies can be classified as AI. Several technologies most relevant to the applications we examine are defined in Table 1. Particular technologies can be categorized according to (a) how they work and (b) the functions they perform. Corea (2019) provides a useful categorization and mapping of AI technologies in this way. He identifies three broad AI technology paradigms:

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TABLE 1 Selected artificial intelligence definitions

Term	Definition	Source
Artificial Intelligence (AI)	a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation	Kaplan and Haenlein (2019, p. 17)
Robotic Process Automation (RPA)	A preconfigured software instance that uses business rules and predefined activity choreography to complete the autonomous execution of a combination of processes, activities, transactions, and tasks in one or more unrelated software systems to deliver a result or service with human exception management	IEEE Corporate Advisory Group (2017)
Expert System	an interactive computer-based decision tool that uses both facts and heuristics to solve difficult decision problems based on knowledge acquired from an expert	Buchanan and Smith (2003)
Machine Learning (ML)	a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty	Murphy (2012)
Natural Language Processing (NLP)	the processing and analysis of unstructured language data, essentially enabling computers to understand human language	Jones et al. (2019)

symbolic, statistical, and subsymbolic. Within these categories, particular AI applications use specific AI capabilities to perform functions in various problem domains: perception, reasoning, knowledge, planning, and communication. For example, expert systems use symbolic (or rules-based) logic to solve reasoning problems. In contrast, natural language processing (NLP) uses statistical approaches to solve perception problems, such as reading disparate sources of text.

Frameworks in the management literature concentrate on the functions that AI performs. Based on over 150 examples, Davenport and Ronanki (2018) identify three business needs that AI applications support: process automation, cognitive insight, and cognitive engagement. Process automation is the most common, and uses Robotic Process Automation (RPA) to automate both digital and physical tasks. Process automation examples include transferring, collating and reconciling data from various systems to update customer records with address changes, and extracting clauses of interest from multiple contracts using NLP. Cognitive insight applications use algorithms to detect and interpret patterns in large quantities of data, typically being trained on some of the data, so that the model improves as the AI is used more. Cognitive insight examples include predicting what particular customers will buy, identifying fraudulent behavior in real time (e.g., with credit cards), as well as some examples that are close to our research: extracting data on a large number of supplier contracts in procurement and, in auditing, examining much larger samples of documents (often 100%) than can feasibly be reviewed manually. Cognitive engagement applications include systems such as chatbots, based on NLP, being used to deal with routine enquiries from customers, for example to make product and service recommendations, and from employees, for example to handle requests for passwords or details of HR policy.

In the context of front-line service roles, Huang and Rust (2018) identify four "intelligences" in AI, broadly in the order of their development over time: mechanical, analytical, intuitive, and empathetic. This sequence exhibits parallels with Davenport and Ronanki's typology. Mechanical intelligence involves the execution of routine, repeated tasks, with minimal learning and adaptation. Analytical intelligence involves the processing of data, and learning from it to provide insightful information. Intuitive intelligence is "the ability to think creatively and adjust to novel situations" and is exemplified by the work of "management consultants, lawyers, doctors" (Huang & Rust, 2018: 159). Finally, empathetic intelligence is concerned with recognizing, understanding, responding to, and influencing other people's emotions. Empathetic intelligence is the most advanced form of AI and has arguably only rarely been achieved, and then only in limited ways.

The technologies in Table 1 are only a subset of AI technologies. Frameworks such as Corea's suggest that (a) other AI technologies exist that we do not encounter in our research and (b) still further AI technologies are conceptually possible, but do not exist in practice yet. In the spirit of "phenomenon-based theorizing" (Von Krogh, 2018), we concentrate on the technologies currently used. However, these wider frameworks for AI provide a basis for extending our contribution to the TM literature beyond the specific forms of AI-based IT we encounter.

2.2 | Conceptualizing information technology in organizations and operations

AI-based technologies are distinctive in some respects but, in many ways, we can analyze their application like that of many other forms of IT. Information systems scholars increasingly argue that research needs to move away from

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what Orlikowski and Iacono (2001, p. 123) call the "tool" view of the IT artifact, whereby IT is treated as an external, stable, black-boxed, technical entity "expected to do what its designers intended it to do." This tool conception neglects the interaction and mutual constitution between the technology on one hand and the organization, its processes, and end users on the other. It is also arguably the dominant approach in OM research, concerned as it often is solely with the effect of IT on operations outcomes and performance (e.g., Cao & Dowlatshahi, 2005; Dehning et al., 2007; Devaraj et al., 2007). This approach is suited to answering some simple kinds of research questions, but neglects others that are salient to organizational stakeholders and to researchers.

Barley (1986) showed that the introduction of technology occasions changes in functions, roles and interaction between staff, changes that are not and cannot be entirely planned or anticipated. Similarly, Markus and Robey's (1988) emergent perspective, and Orlikowski and Iacono's (2001) "ensemble" view both offer an alternative to the tool view of IT, seeing organizational structure and technology as mutually constitutive. Faraj and Pachidi (2021) see such views as increasingly necessary, given the proliferation of new organizational forms and new technologies and, like others, use the notion of affordance to understand IT in organizations (Anderson & Robey, 2017; Leonardi, 2007, 2013; Zammuto et al., 2007). Any artifact—for example, a piece of IT—has functional and material properties, which, when considered in relation to a user's goals, offer "distinct possibilities for action" (Leonardi, 2011, p. 153), which are termed affordances. Technology does not completely determine what users do, and the "possibilities for action" are taken up in different ways and to differing degrees from one setting to another.

In contrast, the accounts of AI such as that of Davenport and Ronanki, introduced earlier, while providing a basic scheme for classifying AI technologies, present a tool view of AI technology and take no account of such interplay. Furthermore, Davenport and Ronanki also mention particular forms of AI, such as RPA and NLP, but do not really consider the IT artifact in the sense of a "bundle[s] of material and cultural properties packaged in some socially recognizable form such as hardware and/or software" (Orlikowski & Iacono, 2001, p. 121). Organizations interact with AI-based IT artifacts, such as particular commercial software packages, not some kind of essentialized, disembodied "AI." This theme is touched upon in one of the only OM papers about the use of IT in professional services. Boone and Ganeshan (2001) examine the adoption of computer-aided design (CAD) technology in an engineering design firm. They find that productivity improvements are achieved by automating some tasks with CAD. However, these improvements are diluted because, by virtue of the capabilities of the CAD system, professional staff take on more tasks that were previously done by non-professional support staff, and the firm takes on more tasks that were previously subcontracted, thereby increasing task variety. A particular CAD system can automate some of the tasks previously carried out manually by the engineer but it may also present affordances in respect of other, related tasks that the engineers could perform, and which may or may not be part of their current job. A different CAD technology would comprise a different set of technological and other elements, and therefore offer different affordances—even though we would still classify it as "CAD."

This affordance perspective on IT suggests that, in researching the adoption of AI-based technologies in professional services (and elsewhere), we must be skeptical of accounts that see AI "tools" as neatly substituting for human labor, taking over discrete tasks or process stages. Davenport and Kirby (2015) recommend that AI-based systems should be seen as augmenting, rather than automating, the human execution of a task. Raisch and Krakowski explain that augmentation entails humans and machines "combin[ing] their complementary strengths, enabling mutual learning and multiplying their capabilities" (Raisch & Krakowski, 2021, p. 193). These authors use paradox theory to argue that automation and augmentation cannot be neatly separated from one another. Rather, the interdependencies between tasks in a process mean that automating one task alters the way humans interact with the technology, leading to possible augmentation of adjacent tasks as the automation "spills over" (Raisch & Krakowski, 2021, p. 197). We suggest that how this spillover takes place is a function of the affordance between a particular technology and particular users, rather than an inherent, stable property of the technology; it is also a function of the structure of the tasks in a process. Our contribution to the TM literature is to show how this interaction of particular AI-based technologies with tasks, processes and the workers and clients executing them leads to changes in operations processes and service offerings. We now turn to literature that helps us understand better such tasks and processes in professional services.

2.3 | PSOs management and the work of the professional

Within OM, PSOs have mostly been understood as highly customized, idiosyncratic processes that cannot be standardized or automated, and staffed by professionals who exercise great autonomy and resist any attempt to codify or manage processes. Consequently, beyond classifying them as such in our typologies of services (e.g., Collier & Meyer, 2000), we in OM have devoted little attention to them.

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There are some exceptions. Schmenner (1986, 2004) makes the general case that service processes—including those of professional services—can be made more productive by increasing standardization and achieving "swift, even flow." Heineke (1995), based on research in healthcare operations, contends professional services could benefit from the application of "operations management thinking" (Heineke, 1995, p. 267), and more recent work has begun to do that. Applying Schmenner's framework, Lewis and Brown (2012) show that many processes within a law firm are rather mundane and repetitive, not highly customized, and that even the more customer-specific are variations on processes used before for other clients. Brandon-Jones et al. (2016), examining management consultants, show that PSOs do not necessarily involve high customer contact. Rather, consultants do much of their work remotely from the client and the client prefers this, because it is less disruptive. Furthermore, levels of customer contact vary with the particular firm's strategy, and with seniority of consultant: senior staff interact with clients more, while junior staff such as analysts interact much less. Brandon-Jones et al. also question the general characterization of PSFs as low in capital intensiveness (Von Nordenflycht, 2010): firms in their study invest significantly in IT.

These OM studies suggest that, although PSFs exhibit some salient distinctive characteristics, they can still be understood using generic service OM concepts. The patterns of client interaction just discussed are consistent with customer contact theory (Chase, 1978), which holds that direct customer contact potentially undermines process efficiency, and so should be minimized. Where possible, tasks should be conducted in the back-office, using "traditional efficiency improvement techniques … to improve low contact operations" (Chase, 1981, p. 703). Sampson's approach to visualizing service operations (Sampson, 2012) develops Chase's theory, and distinguishes between direct interaction, surrogate interaction, and independent processing. By using surrogate interaction—acting on the customer's input, but not in co-present or synchronous interaction with the customer—operations can provide customer-specific service while mitigating the harmful impact of direct interaction on efficiency. Normative application of Chase's theory would suggest professional service process design in general, and the use of IT in particular, should be used to reduce efficiency-sapping direct customer contact.

As well as considering processes, it is important to identify the central tasks of professional work, so that we might consider how AI could be used in their execution. In OM, Harvey (2011, p. 153) suggests four professional service process stages: matching (connecting the client to the appropriate service provider), diagnostic, prescription, and treatment. He argues that the diagnostic and prescription stages are "the defining functions of professional work …" Similarly, Abbott (1988) identifies three parts of professional service practice—diagnosis, inference, and treatment:

> Diagnosis and treatment are mediating acts: diagnosis takes information into the professional knowledge system and treatment brings instructions back out from it. Inference, in contrast, is a purely professional act. It takes the information of diagnosis and indicates a range of treatments with their predicted outcomes. (Abbott, 1988, p. 40)

In other words, among other tasks professionals may undertake, it is inference that is <u>necessarily</u> the work of the professional. Further, Abbott's conception of information as an input into professional practice calls to mind Sampson and Froehle's Unified Services Theory (2006). This theory states that service processes involve significant inputs from the customer, and explains that the timing, quality and other performance characteristics of the "customer as supplier" in turn affects the performance of the service provider.

Although Harvey's and Abbott's models identify inference and expertise as essential ingredients of professional work, they do not explain what they are. Research on expertise, particularly in management decision-making, helps to answer this question. Dane (2010) proposes that individuals' knowledge consists of networks of interconnected schemas; schemas, in turn, consist of interrelated attributes such as facts, information, and concepts. Compared to those of novices, experts' knowledge networks have more schemas, consisting of more attributes, and with more interconnections between attributes and between schemas. These more developed knowledge networks make experts better able to associate new stimuli with familiar configurations of attributes (Chaffin & Imreh, 1997), and find shorter paths to solutions. Dreyfus and Dreyfus (2005), as part of their critique of earlier generations of AI, propose a five-stage progression from novice to expert. At the fifth stage, the expert abandons the conscious knowledge and use of rules, and does not deliberate concerning the problem situation and possible alternative actions:

> The proficient performer [stage 4], immersed in the world of skillful activity, sees what needs to be done, but decides how to do it. The expert not only sees what needs to be achieved; thanks to a vast repertoire of situational discriminations, he or she also sees immediately how to achieve the goal. (Dreyfus & Dreyfus, 2005, p. 787)

These insights into characteristics that distinguish professional and expert work provide a basis for enquiring in a

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more fine-grained way how AI-based technologies can or cannot be used in uniquely professional work.

Recent research by Sampson (2021) focuses on creativity and interpersonal skills as the critical characteristics that determine whether and how tasks in professional work can be automated using IT. Using a secondary dataset of job types classified according to the extent of training and preparation needed, he uses jobs in the highest category as a proxy for professionals. Based on this, he develops a framework of four forms of task automation: routine work, automated to allow self-service; interpersonal work, deskilled to allow completion by less expert workers; expert work, where IT is used to allow creative work to be completed in the back office; and interpersonal expert work, where IT is used to augment the work of highly skilled professionals. Our contribution builds on this typology using primary data to show, in a more nuanced fashion, how technology automates and augments tasks in these ways, but also restructures processes and leads to new service opportunities. How these general effects play out depends on the particular profession in question, as well as the wider strategy of the firm, and we explore these issues next.

2.4 | PSFs: types and strategies

Organization studies scholars have extensively researched PSFs (e.g., Empson & Chapman, 2006; Greenwood et al., 1990; Smets et al., 2017). Among other questions, these scholars have sought to find what is common to firms in all professions, as well as dimensions on which they differ. The defining characteristics of PSFs, according to Von Nordenflycht (2010), are high knowledge intensity, low capital intensity, and a professionalized workforce. The latter varies with the extent to which the particular profession has control over the domain of work undertaken. For example, while law has close control, in that only members of the relevant professional associations can practise, management consultancy has no unifying professional association and no such closure. In a subsequent analysis, Von Nordenflycht et al. (2015) identify knowledge intensity and customization as the two characteristics common to all PSFs.

Von Nordenflycht et al. (2015) also identify sources of heterogeneity that do not make a profession "more or less professional," just different. One of these is the nature of the knowledge base: normative (e.g., law), technical (e.g., engineering) and, combining the two, syncretic (e.g., accountancy). Scholars find that knowledge base is associated with organizational form and management: Malhotra and Morris (2009) argue that professions based on normative knowledge use partnerships, those based on technical knowledge are more likely to use bureaucratic management, and those based on syncretic knowledge use a mix. Malhotra (2003) and Malhotra and Morris (2009) also argue that professions differ in the extent to which they require face-to-face interaction with the client: lawyers can conduct a great deal of their work at a distance; auditors conduct significant parts of the audit process on the client's premises; engineers require close engagement with the client on the site where a project is being undertaken. Organization studies scholars focus on how this interaction difference influences whether the PSFs have geographically centralized or decentralized offices; clearly, there are also implications for OM.

While some characteristics are seen as inherent in particular professions, Von Nordenflycht et al. (2015) suggest that other sources of heterogeneity result from strategies pursued by firms within a profession. Maister (1993) distinguishes between strategies based respectively on expertise, experience, and efficiency (characterized respectively as "brains, gray hair, and procedure") (Maister, 1993, p. 22). Expertise-oriented work requires a "high percentage of senior professional time, due to the high diagnostic component in the work" (p. 23), whereas experience-oriented work requires "executing increasingly predictable (if still technically demanding) tasks" (pp. 24–25), and efficiency-oriented work emphasizes procedures for "low-risk, familiar types of problem" (p. 26), and less "heavy use of judgment" (pp. 26–27). Von Nordenflycht et al. comment that firms following Maister's efficiency-based strategy, with a focus on procedure, "face lower knowledge intensity and customization, and higher capital intensity" (Von Nordenflycht et al., 2015, p. 153). As such, it seems that even the defining sources of homogeneity among PSFs (knowledge intensity and customization) also vary to some extent.

Given these key dimensions of PSFs, and the central characteristics of professional work, we seek to understand how the adoption of AI-based systems affects how professional work is done. Taking a task perspective, and drawing on the affordance view, our research contributes to the TM literature by showing how technology affects the context and nature of operational processes and performance. Rather than treating the technology and associated process as a black box, and trying to determine the overall effect of IT on aggregate outcomes, we show how the interaction between technology and process allows automation and augmentation of professional work, leading to improved process performance and extended service offerings.

In our setting, the technology is AI-based, and the processes are executed by professionals and related staff.

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These specificities allow us to make especially important insights, as the professional services sector (compared to, say, manufacturing) has hitherto seen very little use of IT in core operations processes. This relative novelty of IT use in the sector allows us to examine the initial impacts of technology on operations in the formative and fluid stages of development and adoption. AI arguably has the potential to eat at the very core of the professional service process which is, after all, about processing often complex information and using expertise to provide advice. As such, examining AI use in professional services potentially raises more fundamental and existential questions about the relationship between technology and operations than we might encounter in settings, like manufacturing, with established infrastructures, norms, and established patterns for technology adoption. Our insights also represent an important contribution to the still relatively limited literature on professional services OM, by showing the implications of task-based analyses such as that of Lewis and Brown (2012) for the use of IT in professional services. Next, we explain the method we used to examine this especially fruitful research setting.

3 | METHOD

3.1 | Research design

We chose to research firms in law and accountancy. Although professions are very diverse (Von Nordenflycht et al., 2015), law and accountancy are often treated as archetypal, and are relatively widely researched, outside of OM. As such, we felt they would provide the best basis from which to explore a relatively novel phenomenon like the adoption of AI. Law and accountancy are also very important economically, and have been prominent in debates about the potential incursion of AI into professional work (Susskind & Susskind, 2015). Including both professions allows us to explore points of contrast, as well as common themes. Law and accountancy are based on different degrees of normative versus technical knowledge (Malhotra & Morris, 2009). In addition, law deals primarily with words, accounting with numbers, which may influence how AI-based systems can be used. Each profession has evolved and been shaped by the particular regulatory and wider institutional context in which it operates (Abbott, 1988).

We define our scope as UK-based firms with annual revenues of £25m–£250m. We chose these mid-tier firms because they are just beginning to adopt AI-driven technologies and offer potentially rich insights into adoption challenges and operations implications. These firms are interesting because they are big enough to be able to devote some resources to AI adoption, but not so big that they can simply invest many millions in their own in-house development of AI. In addition, if Susskind's (2017) prediction is at all accurate, the survival of many of these firms is at stake in their approach to technology adoption. Such firms are also relatively commonplace, which is important for the generalizability of findings.[1]

In choosing a case-based approach, we took our cue from Hayes, who, in relation to the "new economy" of the millennial dot-com boom, argued that OM scholars needed to begin by "exploring this new world case by case, gradually discovering where existing theory still provides guidance and developing new theory where it doesn't" (Hayes, 2002, p. 31). We are arguably in similar territory today regarding AI: Von Krogh (2018) suggests the use of AI in organizations is at a stage that makes it ripe for phenomenon-based theorizing. Furthermore, the use of IT of any kind in professional services has been researched very little in OM. For all these reasons, a qualitative, case-study-based approach (Ketokivi & Choi, 2014; Voss et al., 2002) was most appropriate.

Based on an initial scoping phase (see Appendix A), we selected two law firms (Law A and Law B) and two accountancy firms (Acc X and Acc Y), in which to conduct in-depth case research. These firms offer the opportunity to compare law with accountancy, but we chose them because they differ in other theoretically salient ways. We had established that they were using technologies incorporating different types of AI (such as machine learning and expert systems). The applications also encompassed both customer-contact and non-customer-contact tasks. Bearing in mind the notions of affordances and emergence in IT adoption and use, we also wanted to include use-cases that, at least ex ante, seemed to include instances of both more "off-the-shelf" and more purpose-designed instances of AI technology. Even within each profession, the firms differed in the competitive motivations shaping their efforts to use AI-based technologies, as well as facing different challenges and demands in working with clients.

Our research questions are mostly concerned with process-level phenomena. Many of our insights and consequent theorization concern so-called "use-cases," that is, the use of particular AI-based technologies to support particular tasks, within a part of the business. Other practice areas within the firm, meanwhile, remain completely untouched by the specific use-case. We therefore mainly focus, in our presentation and analysis of results, on use-cases of particular AI-based systems applied to particular service processes. Nevertheless, in some respects, firm-

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level phenomena are of interest and have a bearing on (and are affected by) the use-cases. This can also be understood as a multiple embedded case design, in Yin's terms (Yin, 2009).

3.2 | Data collection and analysis

Our semi-structured interview protocol (see Appendix B) was informed by our research questions. We also explored some aspects of the IT/AI innovation and organizational change process and its relationship to the roles and functions of the professionals and other staff involved. We began by interviewing senior staff, then individuals from different functions and levels of seniority, and with various perspectives on technology and AI, including professionals working on the day-to-day delivery of law or accountancy services. We conducted some interviews face-to-face on the firms' premises, some via video-conferencing, and interviewed certain individuals more than once. One of the authors conducted most of the interviews, but the other authors also participated in some. This interviewing approach engendered a common understanding of each setting, and a consistent approach to exploring beyond the basic semi-structured interview schedule. Taking account of occasional joint interviews, and multiple interviews with some individuals, we conducted a total of 51 interviews with 39 different people, ranging from 45 min to over 3 h in length (see Appendix C). All interviews were recorded and transcribed.

The interviews extended over several months, and we worked across the four firms in parallel. We coded the transcripts soon after the interviews, so the coding scheme developed as the fieldwork progressed, based on the codes from the scoping phase. This theme generation process enabled us to draw together data that had been elicited in various parts of multiple interviews, and coded in slightly different ways, so as to develop themes more explicitly informed by and aligned with OM concepts and theory. We conducted a small number of follow-up interviews to more fully understand and gather evidence about certain issues. Through this recurrent iteration between data, initial theoretical concepts, OM and related concepts that emerged as especially relevant, and then further data, we arrived at a data structure, as shown in Figure 1.

This data structure shows over 30 first-order themes drawn from the data on specific use-cases. These first-order themes are reduced to 14 more generic, but still empirically-rooted second-order themes. Finally, these are reduced to five aggregate dimensions (Gioia et al., 2013). Appendix D provides examples of quotations associated with our first-order themes.

4 | FINDINGS

4.1 | Outline of the case study firms

The four mid-tier case study firms and the use-cases we examined in each are summarized in Table 2. The firms all undertake matters or assignments across the range from the very small to the much larger—sometimes even within the same practice area. (In legal services, the term "matter" is used to refer to each piece of work for a client. Handling a matter usually involves multiple tasks.) Small assignments include thousands of personal injury claims for insurance company clients, or SME accounts preparation jobs that may each involve only 1 or 2 hours' work and fees of £2–3k. Large assignments include property portfolio and litigation matters for corporate clients or audits for larger corporations that each generate hundreds of thousands of pounds of fee income.

The use-cases examined were identified from secondary sources and from our scoping interviews. AI-based IT is, in all four firms, mainly used in what several interviewees called "point solutions"; that is, as relatively independent IT systems used for particular data-processing tasks, rather than major enterprise systems used across the whole firm or process. We do not present an exhaustive account of all IT use within the firms, just the use-cases summarized in Table 2. These provide opportunities to examine different forms and uses of AI, but also to seek replication (e.g., across the two uses of AI-based audit systems). The following sections summarize the findings according to the five aggregate dimensions of Figure 1, drawing on use-cases as appropriate.

4.2 | Complementary information systems

Using AI-based systems is facilitated by the standardization of some service processes and the integration of the AI-based and other information systems with those of external organizations, especially clients. Professionals are commonly understood to have enormous discretion in their work, yet we found that many PSF processes are quite tightly specified. For example, Law A uses a computer-based case management system into which, some 10 years previously, senior professionals had written over 500 "workflows," each specifying the sequence of tasks used for a particular type of matter. These tasks might include: requesting a document from an external agency, transferring a sum of money, or emailing a client. An individual lawyer's day, in some practice areas, consists of executing scores of such tasks across many matters, prompted by the case management system. Costing

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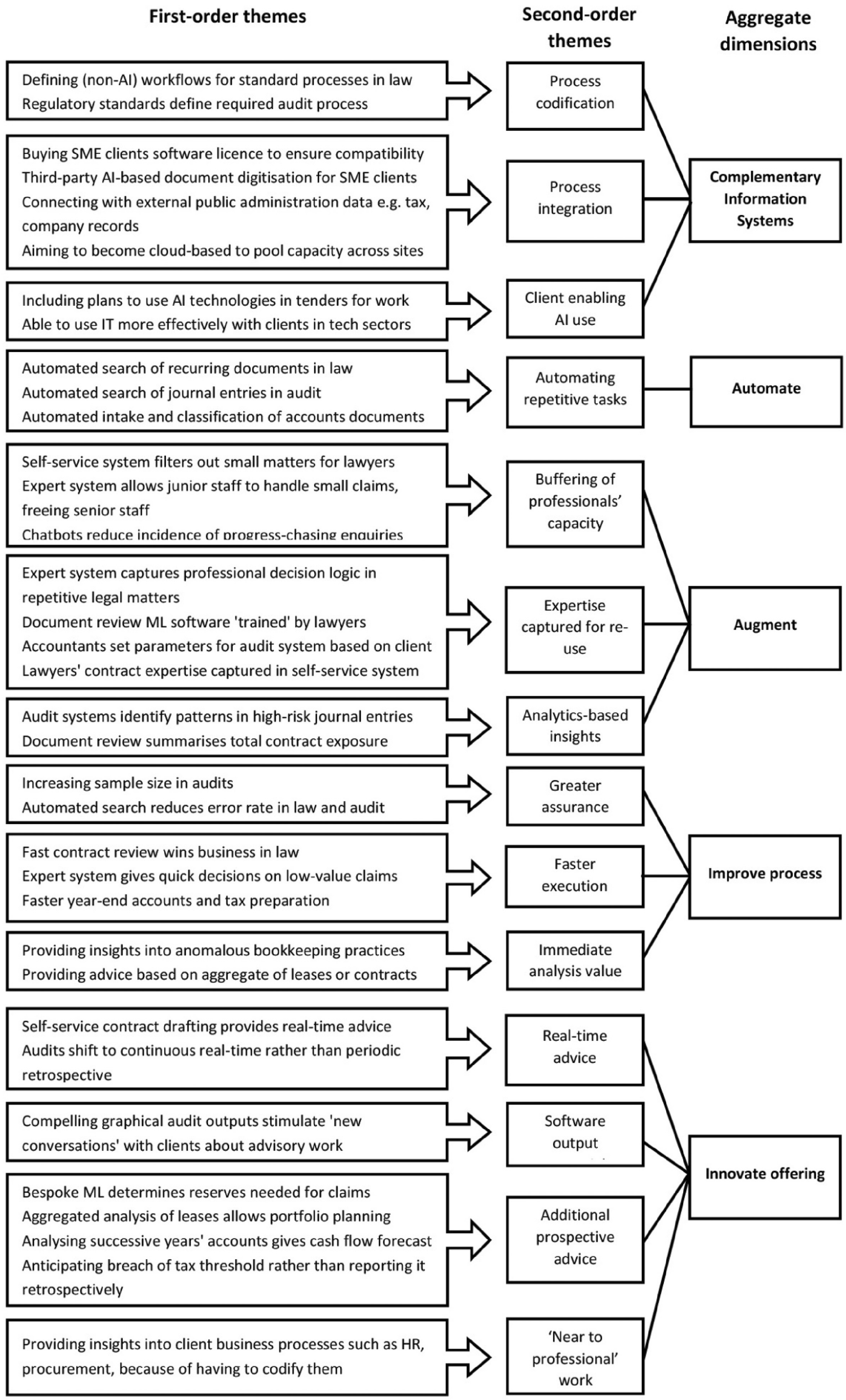

FIGURE 1 Data structure

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TABLE 2 Firms and use-cases

Firm	Annual revenue/ no. of partners	Firm characteristics	Use cases highlighted
Law A	£100m/140 partners	Over 100 years old, several UK locations. Full range of practice areas; strong background in insurance work. Matters range from 1 h to hundreds of hours' work, fees £2k–£700k+	• Document review using ML-based system • Small Personal Injury claims using expert system • Insurance reserves planning using bespoke ML-based application
Law B	£90m/129 partners	Relatively young firm (20 years), with explicit intent to innovate within the profession. Full range of practice areas, tend to serve technology-based clients and banks	• Self-serve contract review and drafting system based on NLP • Also use document review based on ML
Acc X	£25m/32 partners	Over 100 years old; several Northern England locations due to acquisitions. Diverse clients, from quite large to many SME, with fee income of £2–3k each per year. Strong audit and tax service lines. Desire to become a "cloud-based company"	• Audit system using some ML and NLP • Bookkeeping using an AI-assisted system • AI-facilitated data entry (outsourced to third party) • Cashflow forecasting app with AI functionality
Acc Y	£40m/55 partners	Over 100 years old; several Southern England locations due to acquisitions. Diverse clients, from quite large to many SME, with fee income of £2–3k	• Audit system using some ML and NLP (different system to Acc X) • Chatbots to handle routine progress-chasing enquiries from clients

Note: Annual revenue and partner numbers are indicative—adjusted slightly to obscure firm identities.

and billing are linked to this: lawyers record their time in 6-min units, accountants in 15-min units; if the client is being charged on a billable-hours basis, this time recording determines the eventual fee. In auditing, the UK Financial Conduct Authority specifies how audits should be conducted, including what data samples should be taken and what auditing tests should be applied. Within these absolute requirements, firms adopt particular industry standard audit procedures: for example, Acc Y uses the "Mercia" Audit Manual.

The accessibility of data from clients varies enormously. Some very small, unsophisticated client firms have rudimentary accounting systems, or none at all. Some clients are what one interviewee in Acc X called "carrier-bag jobs"—small business owners so poorly organized that they present the accountant invited to prepare a set of accounts with a disposable supermarket shopping-bag stuffed with randomly-ordered invoices, unopened letters from their bank, and other documentation. Most small firms are better organized than this, partly due to the availability of simple proprietary computer-based accounting systems. However, many such systems are available, and they are not mutually compatible, so significant effort is often required to convert data into the right format for the accounting firm's AI-based systems. As one interviewee put it:

> I think the data importation is the big bottleneck because … if the data isn't standard somebody has to spend a lot of time mapping the data through: that is highly inefficient. (Acc Y, IT and Operations Director)

To try to overcome this obstacle, Acc X pays a small monthly license fee for many of its smaller clients to adopt the system that Acc X uses, and provides a help-desk service to assist clients with the over 800 apps that are used in conjunction with this system. Acc X also uses a third-party supplier to digitize disparate accounting documents such as invoices and receipts, using AI-based technology. Interviewees at both Acc X and Acc Y also cited the growing need to connect seamlessly with public administration data concerning company records and taxation. Acc X managers intend it to become a "cloud-based company" so that data can be accessed and jobs be conducted from any of their offices, pooling capacity to provide greater flexibility.

Clients in certain industry sectors are especially attuned to using technology, and this further shapes the use of AI by the case study firms. A real estate solicitor at Law A commented that construction firm clients are more adept at organizing their documents and using routinized processes, because their own work requires formal systems and effective project management. Similarly, Law B's financial sector clients use technology very extensively, which in turn drives Law B's own adoption of AI-based systems. In some sectors, however, even large corporate clients are technologically backward:

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> ... it depends on the level of sophistication of the clients and, even acting for corporates, you can never assume where they're up to. I've seen large corporate entities and their estate management software is a pin in a wall, you know, on a map, with a little flag on. [Law A, National Head of Retail]

In sum, the degree of process codification and various forms of integration through complementary information systems underpin the use of AI-based systems.

4.3 | Automate

Automating repetitive tasks is a central function of many of the AI-based technologies we encountered. Law A uses a ML-based document review system to review large numbers of contracts or leases in relatively large projects. This process replaces the traditional method whereby a large number of junior staff work long hours and weekends to read hundreds or thousands of documents and mark up clauses and other features of interest, often under severe time pressure. In one such project, the leases had been prepared over several decades by many different law firms in various formats and using inconsistent terminology. Despite this inconsistency, Law A was able quickly to analyze thousands of leases, using NLP capabilities of the software, to identify critical clauses in the leases, summarize their implications, and alert professionals to any clauses that required further consideration.

Both Acc X and Acc Y use AI-based audit systems to automatically read clients' journal entries and other related data, and to identify entries of interest or concern, based on search terms and other parameters provided by the auditor. This automated identification replaces the process whereby accountants scroll through Excel spreadsheets comprising thousands of lines, trying to spot risky-looking entries. These AI-based systems automate both the repetitive uploading of multiple documents or other datasets, a process that can be classed as RPA, and the reading and interpretation of the content, using ML including NLP functions to handle legal documents or accounts information presented in disparate forms and using inconsistent terminology.

Although these key examples are explained briefly, automation is at the heart of the innovation we discuss here. The automation is achieved by capturing and using the expertise of PSF professionals, and provides the basis for augmentation, as well as improving the performance of the core processes and extending and improving the services offered. We discuss these three themes in the following sections.

4.4 | Augment

The AI-based systems we examined augment professional work by amplifying or concentrating the professional's expertise. They do this in part by releasing professionals' time by automating repetitive tasks, as already discussed. They also protect professionals' time by buffering them from clients. The AI-based systems capture professionals' expertise so that it can be more readily or widely used and enable quicker or better insights based on more advanced analytics.

Buffering is achieved by enabling clients to self-serve many of their own needs. Law B has partnered with an AI technology provider to develop a system that clients can use to examine and amend contracts drafted for or by their customers. Law B's best advice on how various contract clauses should be written is embedded in (or "baked in," as a Managing Partner put it) the AI-based system. Rather than seeking Law B's advice on each simple contract query, the client can self-serve for most, and pays a per-seat license fee rather than paying for each small matter handled. Clients then refer only the most complicated or unusual matters to Law B, providing Law B lawyers with only the more interesting, higher-value work, which is what most professionals want to do. The use of chatbots is another means of buffering. Law A and Acc Y use AI-based chatbots to filter and handle routine progress enquiries from clients, reducing interruptions and thereby increasing the effectiveness of high fee-earning, expert staff. Clients also have confidence that they can get answers to such routine questions at any time (e.g., outside of normal hours).

AI-based systems are being used to capture and replicate expertise in various ways. In collaboration with computer scientists at a university, Law A developed an expert system for assessing small personal injury claims. An interviewee at Law A explained the problem, and the intended solution:

> [junior staff] are quite diligent but they're afraid to make a mistake, so one of their responses to that is to try and nail a file to the ground. So, they investigate everything, everything, everything, everything, everything, just to- ... just to make sure that the offer of £3,200 is right, versus an offer of £3,400. But in the meantime, they've spent £5,000—I exaggerate—£5,000 worth of time to get to that 200 quid [pounds'] difference. Whereas, if you'd given it to a lawyer who'd been doing it for 20 years, he'd pick up the file and say, "Offer three-and-a-half grand, move on." And so, could we ...? The problem I was trying to solve is: can we help relatively inexperienced case-handlers come to

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> decisions more quickly? Win for us because we won't waste time on it; win for the client because the client measures us on how fast we get rid of these things. [Law A, Business Services and Innovation Director]

The expert system uses a sufficient but not necessarily complete set of information about the claim to determine whether a legal defense can be mounted and, importantly, what the argument for the defense would be (i.e., not just a simple, binary "defend/settle" decision). The system was developed through detailed interaction with domain experts at Law A, and by capturing, in the expert system, the reasoning embodied in existing firm handbooks and checklists. Using the system, less expert and less costly lawyers can handle claims as quickly and accurately as could much more expert ones. This capability is especially important when, as in Law A, the firm advises on thousands of relatively low-value claims.

In using an NLP-based system to review thousands of leases, as described earlier, Law A professionals' expertise is captured as they "train" the AI by manually reading and interpreting a small sample of leases and directing the system to identify and interpret clauses appropriately. The expertise of the trainer is important. Due to extreme time pressure, Law A initially assigned a mix of more experienced and more junior staff to conduct this AI training in parallel. This diversity of staff led to inconsistent AI training, hence "confusing" the AI-based system. Subsequent AI system training was conducted by fewer, more consistently expert trainers. To develop its AI-based self-serve contract review systems, Law B's experienced staff had to populate the system with general, sector-specific and client-specific suggestions and checklists concerning contracts and clauses. The system uses a form of NLP to locate clauses of concern, infer the risks associated with them, and provide advice and suggestions in "pop-up" boxes in situ as the client's staff draft a contract.

Interviewees at both Acc X and Acc Y told us that experienced partners could quickly identify areas of potential concern at the planning stages of an audit, based on prior knowledge of the client's business, and experience of a particular sector:

> All the partners have a sixth sense. Obviously, they've just been doing it that many years. If there was one thing you've missed in an audit, they don't even need to open the file before they know you've not done it. It's crazy, I can't ... don't know how they do it, they just do. [Auditor, Acc X]

It is this kind of expertise that auditors at both Acc X and Acc Y use to set search terms and sensitivity levels in the AI-based audit systems, and then to interpret the search results. Such AI-derived results are then combined with the auditor's expertise to probe further, for example, on why certain transactions are classified in particular ways, and whether the client's explanation is plausible to the auditor. In this way, the AI-based system both captures professional expertise for re-use and provides the basis for better-targeted further application of expertise.

AI-based systems also augment by providing quicker and better insights. For example, the ML functionality in an AI-based audit system allows the identification of patterns in posting of transactions. Frequent posting after office hours or at weekends can point to fraudulent or at least undesirable behavior (e.g., working excessively long hours). Rapid and exhaustive analysis of a large number of leases can quickly give clients a timely understanding of their exposure to legislative change or other risks. Presenting results in visually arresting and effective forms provides further benefits. For example, Acc X uses AI-based technology to produce interactive "heat-maps," which make it very easy to identify journal entries that are of interest because they are of high value or they combine particular pre-defined risk factors.

4.5 | Improve processes

The popular discourse on AI use in organizations concerns AI taking people's jobs away, by doing the same work at a much lower cost. In our research, this envisioned situation hardly ever turns out to be true. More often, the use of AI-based systems restructures processes rather than simply being substituted for human labor in an otherwise unchanged sequence of tasks, and results in improved speed or quality performance, rather than simply doing the same things more cheaply.

The expert system Law A uses for insurance claims controls costs by enabling relatively inexperienced and less expensive staff to make quick and appropriate decisions, based on only the key pieces of information. Importantly, though, using that expert system improves speed of handling. Also in Law A, using the ML-based document review system to analyze thousands of leases greatly improved speed, which was crucial, as the client needed urgently to understand the impact on its property portfolio of an imminent change in the law. Law A won this business—and was then given additional work—by delivering the necessary analysis in a short time-frame (2 weeks), which its competitors could not.

As well as speed benefits, AI-based systems can affect quality performance. For medium-sized and larger audit assignments, Acc X and Acc Y use their respective auditing systems to analyze 100% of a client's journal entries,

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rather than a sample, which is all that is feasible using a manual approach. Our interviewees commented that this more complete audit provides a general sense of assurance—to both auditor and client—because all the available data have been considered. The faster and deeper analysis enabled by the AI-based systems also provides the basis for providing clients with better advice on their core problems: richer understanding of business patterns and the ability to model alternative courses of action allow more valuable insights.

Despite these quality benefits, technology skeptics often raise questions about the accuracy of AI technologies. The basic lawyerly principle is to "get nothing wrong" (repeated many times across our law firm interviews): mistakes can have serious implications for careers. This principle leads to unease about using AI-based systems that have known and quantifiable levels of accuracy: a document review system will provide a certain percentage of errors, identifying for review some clauses that present no concerns, and missing others that would have been worrisome. Some search functions can be unsubtle; take this example from the use of an auditing system at Acc X:

> … recently we've done an academy [a type of school] and one of the directors' surname was Brown … the software can't recognise that that's a surname and it just pulls out every single transaction that's got a description that has "brown" in it. And because it were a school it had loads of transactions that said "brown," like brown paint and brown whatever … [Acc X, Senior Accountant]

Countering these acknowledged limitations of AI, many of our interviewees point out that humans make mistakes as well. Manually searching hundreds of documents late in the evening or scrolling through very large spreadsheets are not processes that lend themselves to zero defects. This is understood, but it is not explicit or quantified in the way that the error rate for an AI-based system is. These more explicit limitations of AI-based systems can become part of the argument against AI that are advanced by those professionals who are reluctant to adopt it.

Process performance also needs to be understood in the context of the changing fee regimes. The traditional billable hours model, whereby the client is charged according to the time used, is under severe challenge (Susskind & Susskind, 2015). In B2B law settings, clients are increasingly concerned about value-for-money in the services they buy. Many clients now use competitive tendering among approved suppliers, increasingly on a fixed-fee or capped-fee basis. In accountancy, services such as audit and preparation of accounts are basic statutory requirements for client firms, and often seen as a necessary chore, for which clients increasingly want fixed or capped fees. This heightened cost focus increases the incentive for the PSF managers to carry out work efficiently, by spending less time, and/or by using more junior staff whose cost per hour is lower. Improving quality, by providing greater assurance and improved insights based on the capabilities of the technology, allows these firms to maintain existing fees by effectively giving their clients more, for the same fee, while still requiring the same or less effort.

4.6 | Innovate offerings

AI-based analytics allow PSFs to provide valuable additional insights for their clients and extend their service offerings. Law A used AI-based systems to provide advice on specific problems with their property portfolios, as we have seen. But, once Law A has exhaustive data on the client's entire set of leases, it uses this data to advise the client on more proactive management of the portfolio. For example, knowledge of the break clauses (which indicate when a lease can be renegotiated) in an entire portfolio allowed Law A to plan and model the effect of various strategies for lease renewal and renegotiation, and advise the client accordingly. In both Acc X and Acc Y, as well as allowing the basic examination of transactions to satisfy the core requirements of audits, the use of AI-based systems to identify patterns of behavior, such as out-of-hours posting, can lead to HR-related insights for the clients concerning staff workloads and wellbeing.

Some additional service offerings extend further still beyond the core legal or accounting work. Law A used an AI-based system to assist a client in relation to its employment contracts. As a result, Law A was invited to provide a platform to provide and track training and development among the client's in-house legal staff. Law B interviewees referred to such offerings as "near-to-legal" work. One example was in procurement. To undertake an analysis of a client's procurement contracts, it was necessary to map and understand in detail the procurement processes, which meant that, as well as providing insights derived from AI-driven analysis of the contracts, Law B was able to provide consultancy on how to improve the procurement processes themselves.

AI technology can also bring additional tasks into the market domain, which can then generate new revenue for the PSF. Law A found that the use of an AI-based system to perform contract review on a client's many

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disparate leases ("all sorts of weird and wonderful stuff" [Partner, Law A]) makes it possible explicitly to define particular obligations that would previously have been too costly to isolate, and which the client would effectively have had to treat as an overhead:

> ... the cost of paying a big city firm to go through all their contracts and say where the risk is just too hard. And so it goes on the [client's] risk register ... Whereas with tools like [names software] you can kind of do it. [Law A, Business Services and Innovation Director]

Acc Y use their audit technology's analytics and reporting functionality to produce compelling and thought-provoking client reports, which serve as a basis for "starting new conversations" with clients about wider business issues, which adds value for the client and may lead to further remunerated advisory work. For example, identifying patterns in successive audits has allowed Acc Y to warn clients quite precisely of impending cashflow crises. Since the core process of auditing is tightly defined and increasingly commoditized, accounting firms increasingly seek to differentiate themselves, and earn revenue, through such related advisory services. As one interviewee put it: "Bye-bye compliance, hello advisory" [Acc X Data Analytics Manager]. The cumulative effect of this differentiation is that Acc X now interacts with more of its clients throughout the year, on a retainer basis, rather than once a year to complete an audit for a fixed fee. AI-based technologies are important in enabling this business model shift.

Not all uses of AI are about capturing, multiplying, and perpetuating existing expertise-based judgments. Some AI uses challenge them. Law A worked with a small computer-science-based company to develop a prototype ML-based system to estimate the reserves that their insurance company clients should hold, in anticipation of settling claims in progress. Holding too much or too little money can seriously affect insurers' financial performance. ML-enabled analysis of 2 years' past data on claims revealed that many factors that lawyers would consider irrelevant were in fact significant determinants of the size of the eventual settlement. Indeed, many of the factors that lawyers had set great store by, especially initial prognosis in personal injury claims, were actually far less important.

5 | DISCUSSION AND CONCLUSIONS

AI-based information systems have many actual and potential organizational applications in various sectors and processes (Von Krogh, 2018). We are arguably working in the "age of the learning algorithm" (Faraj et al., 2018), and basic descriptive and prescriptive accounts of the use of AI in organizations now exist in the literature (e.g., Davenport & Ronanki, 2018). AI use in professional services is particularly interesting because of the technology's potential to emulate or replace human intelligence in a sector characterized, according to prior academic work, by human judgment and high knowledge intensity. Yet, no-one has published primary empirical research on how AI-based systems are used in PSOs processes. We show how lawyers and accountants work in conjunction with AI-based information technologies to improve the execution of professional service delivery processes and extend and improve professional service offerings. These findings help contribute TM insights concerning the effects of IT adoption. As well as shedding light on operations and IT use in a neglected context, namely professional services, we also contribute non-intuitive insights into how technology used in operations interacts with human workers to change the structure, performance and scalability of processes, and to make enhanced and new services possible. These insights have potential applicability beyond our particular research setting.

We combine the theoretical perspectives introduced in our literature review with insights from our empirical findings in the model presented in Figure 2. At the heart is the ensemble between the particular piece of software, understood as an IT artifact partly comprising some aspects of AI, and the professional, possessing certain forms and levels of expertise. In this ensemble, the affordance of the IT artifact combines with professionals to do professional work (RQ1), in concert with complementary information systems and drawing on the data and knowledge appropriate to the profession in question. The functioning of the ensemble in turn enables some combination of automation and augmentation at task and process level (RQ2). Then, the combined effect of automation and augmentation is to enable some combination of improvement in the process, and innovation in the service offering (RQ3). These outcomes are achieved in interaction with the client, and are therefore dependent on the client's capabilities and their provision of data (cf. Sampson & Froehle, 2006). The emphasis in each instance depends on the substantive nature of the work (e.g., the volume-variety characteristics of the matters being handled) and the strategic emphasis of the firm (e.g., target sector or appetite for advisory vs. process work). The emergent potential of technology can drive strategy, as well as vice versa. In this way, we seek to provide a model combining the use of AI-based technology in executing core professional work tasks, with a

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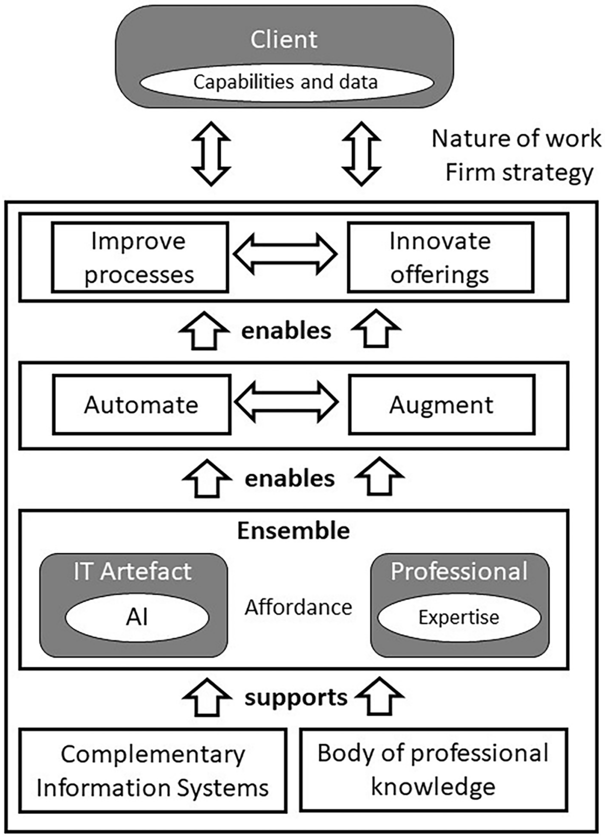

FIGURE 2 A model of AI-based automation and augmentation of professional service operations

contingency view taking account of different professions, and different firm strategies within professions (RQ4). The central concepts are drawn from theory. The relationships between the central concepts are elaborated based on our empirical findings and analysis.

In the following sections, we discuss our findings with respect to each of our research questions, which address the relationships between the main constructs of Figure 2.

5.1 | AI use in processes

Lewis and Brown (2012) show how, in law, service operations in particular practice areas can be broken down into sub-processes with different throughput and variety characteristics. The AI-based applications we saw are almost entirely "point solutions," applied selectively to such sub-processes. The point solutions are what McAfee termed "function IT," that is "IT that assists with the execution of discrete tasks" (McAfee, 2006, p. 145). Here we consider the tasks performed by AI-based systems in relation to the diagnosis, inference and treatment stages of professional service work (Abbott, 1988). The focus of much discussion on the role of AI in replacing human judgment might lead us to expect the AI used in professional services would mainly replace or emulate the inference of human expert professionals. In some ways it does, but AI-based point solutions also play a significant role in the diagnosis stage, by allowing disparate information to be brought "into the professional system" (as Abbott puts it), using RPA and NLP functions to do the distinctly unprofessional work of uploading documents, identifying what they are, and isolating the relevant content in a usable format. Using AI for these diagnosis tasks would be categorized as solving "perception" problems in Corea's framework (Corea, 2019). In OM terms, the AI-based functionality renders the variability in input format largely irrelevant, making higher volume and "swift, even flow" (Schmenner, 2004) possible in that process stage.

AI does play a part in inference, too. In supervised ML applications, the AI eventually supplants professional expertise at the micro level (e.g., judging, contract-by-contract, which clauses require further scrutiny), contributing to—but not fully determining—the eventual advice on what the client should do. Expert systems do, for relatively tightly-defined problems, complete the whole inferential "leap" between diagnosis and treatment, allowing less expert staff to "find a shorter path to a solution" (Chaffin & Imreh, 1997), partly emulating expertise as described by Dreyfus and Dreyfus (2005), whereby conscious deliberation becomes unnecessary in deciding what to do. However, in any but these tightly defined problems, AI-based systems only support the human professional. While the systems may quickly provide aggregated and summary assessments of a matter, often involving powerful graphical presentations, and sometimes model the implications of alternative courses of action, they do not determine what to do (e.g., which leases to renegotiate, or whether an audit has been passed). In Corea's terms, AI can do reasoning (Corea, 2019), some of it inferential, but the inferential leap to defining the treatment also requires the human professional. How AI does that in practice is a function of the affordance (Leonardi, 2011) offered by the particular AI-based system to the particular professional.

AI-based systems restructure tasks and can make some aspects of expertise scalable. Models such as Abbott's (1988) and, in OM, Harvey's (2011) place inference or judgment at the center of a sequence of process stages. At a high level of abstraction, these are powerful conceptualizations. However, at a finer level of detail, a manual document review or audit process does not contain one pure "inference event," but rather many small ones. Professionals intermingle the mechanical task of reading with occasional exercising of judgment about which clauses or transactions are of interest. Because

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these moments of professional judgment are inseparable from the brute mechanical process of reading one page after another, the (expensive) skilled professional is occupied with a task, most of which (e.g., turning pages, reading irrelevant text) is a waste of their time. AI-based systems effectively separate the brute reading task from the exercise of judgment. The professional then exercises judgment in a concentrated way; the lawyer by training the AI document review system; the auditor by setting parameters for the audit system, given their understanding and past experience of the particular client, sector and circumstances. In their forward-looking analysis of OM in the information economy, Karmarkar and Apte (2007) point out that operations must adapt to the fact that information is a non-rivalrous good. Expertise, if captured and made available using AI-based systems, effectively becomes information, and therefore also non-rivalrous. In this way, some expertise can be scaled via AI, because it has been separated from staff time or capacity, which is rivalrous (it can only be used once).

Although AI-based systems can help to automate data transfer from the PSF's client (cf. Sampson & Froehle, 2006), they do not automate the "front-line" service interactions described in the service management literature (Pemer, 2020; Singh et al., 2017), other than for very basic routine enquiries about the progress of work using chatbots. Huang and Rust (2018) associate "intuitive intelligence" in AI with the work of, among others, lawyers, but AI does not presently undertake this part of the PSF professional's work. Senior professionals are still central to the initial interaction with the client, as the point of contact for requests to undertake work, or as key figures in pitching for that work, then in meetings to define the scope of work and the practicalities of client access, data transfer, and staffing. It is noticeable that in all the use-cases, AI-based systems are used on problems that have already been narrowly defined between the PSF and the client. In terms of Abbott's model, basic diagnosis (e.g., as an insurance claim or set of accounts for auditing) is either trivially self-evident, or done by an experienced professional in conjunction with the client. (As Abbott says, "brokering is … a dirty business," which makes clients who can self-diagnose attractive [Abbott, 1988, p. 47]). In auditing, accountants spend lots of time—sometimes several weeks—on the client's physical premises, to "kick the tyres" [Auditor, Acc X] of the business, for example, conducting physical checks of capital equipment and inventories, and meeting with relevant functional staff. AI-based systems can then generate the key results of the analysis. But contextualizing the results and interacting face-to-face with the client to interpret and act on them—in other words, to define treatment—remains the preserve of the senior professional. It is also at this stage that professionals can identify opportunities for follow-up advisory work.

AI-based systems predominantly execute tasks in the back-office, not interactively with the client. The use of AI-based systems does not fundamentally change this. Even using traditional methods, most of these tasks would be back-office tasks. As Malhotra and Morris (2009) point out, much of the work in professions such as law can be done remotely from the client. In OM terms, the work lends itself to surrogate interaction rather than direct interaction (Sampson, 2012). (In accounting, there is some evidence that the use of AI, alongside complementary IT that collectively enables "cloud-based" operation, reduces the extent to which accountants need to be on their clients' premises[2] [cf. Malhotra & Morris, 2009]). AI in the form of chatbots or self-serve systems does change this back-office work, however, because as well as providing useful service to clients, these AI-based systems buffer the back-office processes from disruption (as theorized by Sampson (2021)), allowing greater process focus (Skinner, 1974). This elimination of efficiency-sapping direct client interaction is consistent with the theory of customer contact (Chase, 1981). As Sampson and Chase (2020) have recently suggested, however, the customer contact model itself needs to be revisited and revised to take account of customers' opportunity to interact with anthropomorphic devices such as chatbots and digital assistants.

5.2 | AI, automation and augmentation

AI-based systems, then, automate tasks throughout the process. Following the logic of classic OM process choice (Hill, 1985), the targets for automation are the higher-volume tasks that are standardized or can be rendered standardisable by the functionality of AI, which allows the technology to cope with variability, for example in document format or language use. Furthermore, high task volume makes the investment in technology and skills development worthwhile. Our contribution here is to show this pattern empirically via case study data, and to show the relationship between automation and augmentation. While the popular literature encourages managers to see AI as a way to augment rather than automate work, we lack a detailed understanding of *how* AI use can lead to augmentation. Davenport and Kirby (2015) stress the augmentation perspective, but are mainly concerned to tell us how workers can respond to the encroachment of AI into their work. Raisch and Krakowski (2021) very helpfully explore the interaction between automation and augmentation, and provide some examples of how augmentation is achieved,

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concentrating on examples where the analytical capabilities of AI provide new inputs for the exercise of creativity.

We complement this research with an OM-derived sensitivity to capacity and process focus, showing the role of AI-based systems in buffering and otherwise releasing professional's time. In some senses, this finding confirms empirically what Sampson (2021) theorizes, but we go further by identifying effects beyond the immediate task in question. Somewhat surprisingly, AI-based systems do not reduce professional-client interaction through their "intuitive intelligence" (Huang & Rust, 2018), but potentially increase it by releasing professionals' time, which can now be spent on different, value-adding advisory work. This work often exploits the analytical potential of the AI-based systems, combined with deeper understanding of clients' businesses. Augmentation of the PSF professional in this sense, then, arises from a combination of simply having more time to give to higher-value work and client interaction, as well as affordances of the AI-based systems that create new possibilities for insight and action. These research findings add an operations-based perspective on service innovation to the existing professional service OM literature.

5.3 | Competitiveness and the service offering

We see automation and augmentation as consequences of using AI-based systems that can then provide improved competitive performance. Our contribution here is to separate automation and augmentation as means from process improvement and the extended service offering as ends. The limited literature on professional services OM (Brandon-Jones et al., 2016; Lewis & Brown, 2012) is mainly concerned with revealing and explaining how the characteristics and managerial challenges of PSFs affect operations, rather than how PSF processes achieve competitive advantage. PSFs are under increasing pressure to reduce costs and offer more value. Global supply markets for routinized intellectual labor (cf. Leamer & Storper, 2001) have opened up, and so offshoring and technology-based process innovation are much more evident and theoretically salient. In the case studies we examine, innovation involving the use of AI-based systems improves performance in terms of the standard OM performance objectives (i.e., speed, quality and, in some cases, cost). But these competitive improvements were often not anticipated in specific terms. Rather, AI-based systems were often adopted in an exploratory way, based on a more general sense that the firm would derive benefit from the automation of repetitive tasks and from the analytic potential of the technology. Only subsequently did the particular competitive benefit—often for particular clients, segments or projects—become apparent.

Straightforward cost reduction was rarely evident. The labor cost reduction achieved by reducing the time spent by professionals in undertaking repetitive review tasks was often counterbalanced—at least in the short run—by the work required to make data accessible, to train the AI-based system, or the cost of using the AI-based system (usually via a per-document or per-seat fee). Furthermore, there is rarely a like-for-like comparison between an old system and a new AI-based system. Because of augmentation, the AI-enabled process is often different, often enhanced (e.g., the 100%-sample audit), so it is not just a matter of doing the same old task more cheaply. Competitive advantage on dimensions other than cost arise in rather general ways, for example the quality advantage of providing greater assurance through a fuller analysis of the client's data, but also in very specific ways, for example the speed advantage of being able to complete a particular contract review exercise under very severe time pressure.

AI-based systems also allow innovation in, and extension of, the PSF service offering. In some instances, the AI technology supports enhancement of essentially the same offering, for example by providing fuller and more immediate analytical insights arising from delivery of the basic service (e.g., an audit). These insights are supported by the affordances, such as routine reporting functions, of the particular AI-based system. Other extensions to the PSF's service offering are more radical. Although these extensions may be rooted in relatively routine or well-defined tasks (audit, say, or due diligence), the affordances of an AI-based IT artifact and an expert and open-minded professional provides the basis for greater augmentation and hence more opportunities for service offering extension. In this way, we build on the insightful framework of Sampson (2021) by considering the generation of new tasks as well as the automation of existing ones, and by showing how automation spills over into augmentation (Raisch & Krakowski, 2021).

In some instances, the new service offerings "just happen" (Menor et al., 2002) in an emergent fashion. In others, they are more deliberately designed. Openings for such PSF service extensions often come about during interactions between professional and clients, sometimes prompted and facilitated by the particular outputs (e.g., reports and dashboards) of the IT artifact being used. PSF managers must decide which additional service is to be included in the price for the basic service, and which is to be charged for separately. This dimension, known as bundling, is part of Normann and Ramirez's (1989) theory of the offering,

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which provides a basis for deliberately shaping a service strategy around novel offerings. In turn, new service offerings can change the subsequent service process. For example, using analytics to shift to pro-active management of a client's portfolio of property leases changes, in many ways, what the lawyer's role is, and how human and AI capabilities are deployed in accomplishing it thereafter. Choosing which clients to work with (Skjølsvik et al., 2007) may be an important part of steering the development of AI-based capabilities in particular directions.

5.4 | Contingency factors: professional knowledge base and firm strategy

Our research shows how some of the contingency factors identified in the PSF literature may influence AI adoption at task, use-case, and process level. By researching both law and accountancy firms, we have an opportunity to examine how these factors may affect the use of AI. Above all, it will be evident from the first-order themes shown in the data structure of Figure 2 that there is considerable replication across both professions. But there are also differences. The theme of achieving integration between PSF systems and those of other organizations was emphasized much more in the accountancy firms. This may be because the underlying knowledge base (Malhotra & Morris, 2009) is more technical and more numerically-based than in law, and processes are subject to industry-wide standards. These characteristics make audit susceptible to automation which, in turn, makes achieving integration (e.g., with clients) a more pressing concern. More generally, then, the degree of technicality of the knowledge base is likely to affect how AI-based systems can be used. Engineering has an even more technical knowledge base: work is governed by international standards, various regulations and, ultimately, the relevant underlying sciences. This technical knowledge base may mean that certain tasks in engineering are even more susceptible to AI-based automation.

As well as profession-related factors, the use of AI-based systems in a PSF depends on strategy at firm or, more likely, practice-area level. Practice areas focusing on high-volume, smaller assignments—based on efficiency, in Maister's (1993) terms—devote more attention to automating more steps in the overall process, and are more concerned with effective integration with complementary information systems, within and outside the firm. Practice areas focusing on fewer, larger assignments, where expertise and experience (Maister, 1993) are important, do use AI-based systems for certain repetitive tasks, but are more concerned with the augmentative effect of AI used in concert with the expertise and experience of more senior professionals, and less concerned with trying to achieve process integration with complementary information systems.

5.5 | Limitations, reflections and suggestions for further work

We believe this research presents new insights into the use of AI in medium-sized PSFs in law and accountancy and, by extension, the effect of technology on operations processes. However, there remain a number of limitations. While we have attempted to generalize to some extent to professions as such, we need further empirical work in professions other than law and accountancy, where different knowledge bases, institutional contexts and other factors will affect the use of AI-based systems in ways we cannot anticipate. Likewise, while we have written about "AI-based systems," we have not encountered every conceivable form of AI and so there are limits to our ability to generalize about the universal impact of AI as such. We consider it a strength of our research that we examine the use of the particular IT artifacts that we encountered, for these artifacts are what shape how processes actually change. However, we cannot always identify the particular forms of AI incorporated within them. As Rahwan et al. (2019, p. 478) note, "Industrial secrecy and legal protection of intellectual property often surround source code and model structure. In many settings, the only factors that are publicly observable about industrial AI systems are their inputs and outputs." Focusing only on the AI technologies we encountered also means that we do not seek to predict what might be. Nor do we examine AI developments in the R&D labs of major global PSFs, which might lead to different conclusions about which aspects of professional expertise will remain the preserve of human workers. As the novelist William Gibson put it, "The future is already here—it's just not evenly distributed."

While our focus on use-cases provides insights into the way AI-based systems impact particular processes and service offerings, we do not have systematic data on the overall effect of AI adoption on firm financial performance. Quantifying financial impact was not our aim and, anyway, it is probably too early to tell. But future TM studies could take a more aggregated view of the outcome of AI adoption and return on investment. This research would need to recognize that AI-based systems are often paid for on a "Software-as-a-Service" basis (e.g., fee per user, per client or per document analyzed), rather than as a one-off capital investment. The more significant investment is in human capital via developing users' skills and paying the staff in in-house technology or innovation groups. In this sense, conclusions about

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whether PSFs are or are not capital intensive (Brandon-Jones et al., 2016; Von Nordenflycht, 2010) must be drawn very carefully, if at all. The industry-specific measure of fee-per-partner might be a more relevant dependent variable in such studies, as it would indicate some of the effects of AI in making expertise scalable and more consistently used to do higher fee-earning work.

Although we touch briefly on some aspects of technology innovation and adoption processes, there is much more to know about these processes in the particular commercial, institutional, and cultural context of PSFs. We have mainly presented an account and analysis of what has been achieved, and its effect on operations processes. But this is not to suggest that the introduction and propagation of AI-based systems is straightforward and happens unopposed. Further research is needed to understand the obstacles to and processes of innovation and adoption in PSFs. Relatedly, our understanding of the way the technologies' affordances lead to particular operations improvements could be further developed by complementing our interview-based data with close, observational studies of professionals using AI-based systems in their work.

5.6 | Implications for PSF managers, and for technology management in OM

For managers of PSFs, our research shows that AI-based technologies can have indirect and not always obvious effects on operations processes and service offerings. Managers hoping for straightforward cost reductions may be disappointed, at least in the short term, but can also expect to gain competitive advantage on dimensions other than cost, and through new service offerings. Because many AI-based systems are used on a Software-as-a-Service basis, adoption does not require a do-or-die, step-change capital investment, but can be more incremental and exploratory, which suits the still-fluid and formative stage in the evolution of the technology market.

In the wider context of TM research in OM, we have developed a model showing how IT (in this case, AI-based IT) both substitutes for and complements human labor, something hitherto only modeled theoretically (Napoleon & Gaimon, 2004) or analyzed at a high level of aggregation (Peng & Zhang, 2020). Indeed, by focusing on IT used to do work in delivering services, we have sought to correct a tendency in recent years for technology management research to focus mainly on enterprise systems such as ERP, which are about planning and controlling operations processes rather than performing tasks in making products or delivering services. In classic operations strategy terms, the research focus has been on IT as an infrastructural decision area, not a structural one (Hayes & Wheelwright, 1984). IT—and, indeed, AI—is increasingly pervasive in production and service delivery processes (e.g., Industry 4.0 approaches in manufacturing). We therefore suggest that some of the insights here, and aspects of our model, may be relevant in many contemporary uses of technology in operations processes.

Furthermore, by examining the mechanisms through which AI-based systems affect operations processes and service offerings, we follow scholars such as Heim and Peng (2010), who argue that focusing only on overall performance outcomes means that we miss important insights into the full range of roles played by IT. The insights we achieve are in part consequences of our conceptualization of the IT artifact, not simply as a tool, with anticipated effects that we seek to measure, but as part of an ensemble mutually constituted with the professionals and processes with which it interacts. This approach has helped reveal the many indirect consequences of AI adoption in professional services. We suggest this approach, with the methodological choices it entails, will also be increasingly important in addressing other technology management questions in OM.

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ENDNOTES

[1] In both law and accountancy sectors in the UK, a few large firms are extremely dominant. In law, the top eight firms had annual revenues in 2019/20 of £1–2bn; the 20th had an annual revenue of £366m (The Lawyer, 2021). In accountancy, the distribution is even more skewed: the "Big Four" all have annual UK revenues between £2bn and £5bn; the fifth in the list has an annual revenue of £660m and the 20th only £54 (Accountancy Age, 2021). These huge firms are in many ways very different organizations to the vast majority of law and accountancy firms.

[2] This effect was accelerated during our study by COVID-19 restrictions, which made it necessary to conduct audits entirely

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remotely—even to the extent, for example, of auditing inventory in warehouses using video calls.

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APPENDIX A

A.1 | SCOPING PHASE

We conducted a scoping phase to increase our familiarity with relevant issues, terminology and themes within the domain, and to inform our choice of and approach to subsequent in-depth case studies. The scoping phase included some larger firms (i.e., those outside the mid-tier) and consisted of single interviews in 17 law firms, 13 accountancy firms, and four technology vendors, resulting in over 40 h of interview data. We complemented the scoping interviews with extensive examination of company websites, reading reports by relevant professional bodies such as the Law Society, and following relevant and authoritative publications and online forums such as Accountancy Age and LegalGeek. In particular, the scoping stage enabled us to identify AI deployments in different parts of the professional service process, and therefore to purposively sample firms—and thereby application examples—that would be most likely to generate potentially interesting contrasts and insights.

We conducted semi-structured interviews with individuals closely associated with AI adoption initiatives within their firms, holding positions such as "Chief Technology Officer" and "Managing Partner—Strategy and Development." We identified these through a combination of existing industry network contacts and by following up on publicly available reporting of particular adoption projects. These individuals were able to provide authoritative overviews of both the technological and organizational aspects of the firm's AI and IT initiatives. The research reported here was part of a larger project concerned with various aspects of AI adoption in law and accounting firms, including issues associated with organizational behavior, training, professional identity and careers. As such, the scoping interviews included a range of topics alongside the OM-specific concerns of this paper.

Open coding of the interviews led to over 40 high-level themes. These included many that were relevant to OM, although not explicitly theorized in OM terms, as well as others relating to issues such as changing professional norms, wider institutional barriers to AI adoption, or training, which are not central to the research questions we address here. One of the authors led on coding but we all coded selected interviews, compared our coding, then refined the approach to ensure consistency in coding and subsequent interpretation. This provided the basis for coding in the main in-depth study.

APPENDIX B

B.1 | INTERVIEW PROTOCOL

Interviewees had a variety of roles and positions, but fell into four broad categories: Managing Partner or other senior management; IT or Technology Director; lawyer/accountant (including trainees); Practice Area Head. The interview schedule was adapted according to role, then used flexibly to explore areas relevant in each firm and use-case. The following summarizes the key areas explored for each group.

1. All interviewees
   Explain job role, background, typical work activities.
2. Managing partners
   - Describe the business—size, services provided, clients, competitive & business environment.
   - Describe company strategy regarding AI and technology more generally; technologies explored, business case or rationale for adoption, other drivers for and forces affecting adoption, policy regarding encouraging adoption.
   - Describe client requirements and competitive value of AI-based technologies, including examples.
   - Describe immediate and longer-term developments.
   - Identify other staff to interview.
3. IT/Technology Director
   - Develop the discussion of role to explore relationship between technology and professional (law/accountancy) expertise and position within firm.
   - Describe general approach to identifying, developing, procuring technology.
   - Describe mandate within the firm, business case or rationale for adoption, organization and mechanisms for encouraging adoption.
   - Describe lawyers'/accountants' attitudes and aptitudes toward AI adoption and use, plus other internal adoption challenges/processes.
   - Describe client demands and roles in adoption; describe client benefits.

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- Describe and discuss examples/use-cases.
- Comment on performance improvements achieved.
- Describe immediate and longer-term developments.
- Identify other staff to interview, as appropriate.

4. Lawyer/Accountant
   - Develop the discussion of role to explore day-to-day activities, general technology use, client interaction, nature of expertise as a lawyer/accountant.
   - Describe involvement with, and/or use of AI-based systems in general.
   - Describe how AI-based systems are used within specific processes and tasks, giving examples, and extent of discretion and initiative in use of systems.
   - Describe client involvement and benefits, performance outcomes, consequences of AI use.
   - Describe training, motivation and incentives to use.
   - Explore views on future potential for AI use in general and within career.
5. Practice Area Head

   As for Lawyer/Accountant (depending on extent of "hands-on" professional work) plus:
   - Describe scope of work within team/practice area.
   - Describe whether and how AI use provides performance benefits within the practice area, giving examples/use-cases.
   - Describe and comment on technology and innovation support .
   - Describe whether and how AI innovation and use is encouraged, required or incentivized within practice area, including changing job roles within team and need for fee-earning.
   - Explore views on future potential for AI use in general and within jobs and careers of team.

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APPENDIX C

C.1 | INTERVIEWS CONDUCTED IN FOUR IN-DEPTH STUDIES

Firm	Position of interviewee	Number of interviews
Law A	Business Services and Innovation Director; Innovation Manager (joint interviews)	4
	Real Estate Solicitor	2
	Commercial Real Estate Partner	1
	Innovation Trainee	1
	National Head of Retail	1
	Commercial Property Lawyer	2
	Principal Associate	1
	Partner, Head of Built Environment	1
	Innovation Manager and Partner*	2
	Partner and Real Estate Lawyer	1
	Legal Engineer 1; Legal Engineer 2 (joint interview)	1 (total 17 with 13 people)
Law B	Managing Partner; Head of Digital Group (joint interviews)	2
	Operations Director	1
	Partner and Group Leader, Commercial Services	1
	Partner—Technology Practice	1
	Solicitor—Technology Practice	1
	Partner—Client Service Transformation	3 (total 9 with 7 people)
Acc X	Head of Auditing; Director (joint interview)	1
	Senior Manager 1	1
	Data Analytics Manager	5
	Outsourcing Senior Manager	1
	Senior Accountant 1	2
	Senior Manager 2	1
	Senior Accountant 2	1
	Partner	1
	Senior Manager 3	1
	Assistant Manager	1 (total 15 with 11 people)
Acc Y	IT & Operations Director	3
	IT Operations Manager	1
	Corporate Manager and audit AI specialist 1	1
	Corporate Manager and audit AI specialist 2	1
	Board Member and Service Line leader—Outsourcing and Payroll	1
	Audit Manager	1
	Partner	1
	Senior Partner and Board Member	1 (total 10 with 8 people)
	Total	51 with 39 people

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APPENDIX D

D.1 | THEMES AND EXAMPLE QUOTES

Note: we coded relatively large pieces of text, partly to retain context and nuance. One consequence of this is that quotes were often coded in more than one way but, for simplicity of presentation here, we associate each quote with one theme. This is an indicative selection.

Themes	Example quotes
Defining (non-AI) workflows for standard processes in law	... that's how the workflow works ... one of the partners wrote the workflows 10 years ago. [Commercial Property Lawyer Law A]
Regulatory standards define required audit process	Then we perform a calculation based on Mercia, the audit methodology that we use [Corporate Manager and Audit AI specialist 1, Acc Y] But actually the client in every case didn't actually mind what process we used as long as ... they were compliant with laws and regulations. [Partner—Acc Y]
Buying SME clients software license to ensure compatibility	So with Sage jobs there won't be any efficiencies because we are still having to take data out of Sage to put it into [names software]. So we've actually bought [names software] ledgers for all out clients. [Data Analytics Manager Acc X]
Third-party AI-based document digitisation for SME clients	But when you drop us off a bag of records we used to take a chargeable staff member's time—three, four days to type up, reconcile. Now we use Receipt Bank, we push it through [names software] and it automates an element of that process for us. [Data Analytics Manager—Acc X]
Connecting with external public administration data, for example, tax	But also there's the fact that [names software] tax will file your accounts with Companies House and your tax return with HMRC. [Data Analytics Manager—Acc X]
Aiming to become cloud-based to pool capacity across sites	... we want to be a cloud accounting firm ... We can utilise staff across the firm better ... [if] it's a [City 1] job, [City 1]staff manage it. It doesn't need to be like that. If we've got capacity in the [City 2] or [City 3] office we should be able to pick up any job. [Senior Manager Acc X]
Including plans to use AI technologies in tenders for work	... we've been criticized ... for not being technologically [advanced] ... So we knew that in this tender we had to pull out all the guns kind of thing to impress them ... [so] we developed a lease risk analysis product and basically we took what we know is important to [names client] and what we knew that we would be able to report on using [names AI-based software] [Commercial Property Lawyer Law A]
Able to use IT more effectively with clients in tech sectors	The surveyors have fantastic AI property management resources. They are ... they always have been ahead of the legal profession on it because it is their business, they have to have the most up-to-date systems to retain management contracts. [Commercial Real Estate Partner Law A]
Automated search of recurring documents in law	... they'd asked us to review I think it was 1,600 or 1,800 leases in six days or five days, which we couldn't do just by sticking people in a room and getting them to look at the leases. So we tried [names software] with I think it was 20 leases on different preference points that the client wanted us to look at and then we went from there. [Real Estate Solicitor, Law A]
Automated search of journal entries in audit	So it does all those sort of testing, looks for fraud, looks for strange ledger entry dates, i.e., something's put there on the last day of the month or perhaps a staff member seems to be doing a lot of transactions on a Sunday, is that normal? ... And then it says here's all the questions, here's all the outputs and here's where we think you should be looking at things. [IT & Operations Director, Acc Y]
Automated intake and classification of accounts documents	... the RPA stuff is about removing grit and friction from the system which makes everybody's lives easier, saves them time doing valueless work. And AI I think helps them do their job. At the end of the day quite a lot of what we do is people stuffy anyway. [Board Member and Service Line leader—Outsourcing and Payroll, Acc Y]
Self-service system filters out small matters for lawyers	Whereas, where I hope AI will move more rapidly, as we have tried to do, is get to the heart of what lawyers are doing, which is to provide legal advice. And so with this product, ... it allows you [the client] to get legal advice without the need to speak to a human. [Managing Partner, Law B]

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Themes	Example quotes
Expert system allows junior staff to handle small claims, freeing senior staff	I think there's always ways to add value to a client and help them improve their business and all the time you're doing that stuff at your desk you're not helping them in another aspect ... and this frees you up to do that. [Corporate Manager and audit AI specialist 2—Acc Y]
Chatbots reduce incidence of progress-chasing enquiries	... the chat bot will be like a gatekeeper just to make sure we're not answering questions that are rules-based ... So that actually just means they can get on with their jobs. At the moment they feel they're being asked questions that actually someone can pick up the book and read but they're too lazy to so they could ask the chat bot. [Board Member and Service Line leader—Outsourcing and Payroll—Acc Y]
Expert system captures professional decision logic in repetitive legal matters	... [junior staff] are quite diligent but they're afraid to make a mistake, so one of their responses to that is to try and nail a file to the ground. The problem I was trying to solve is: can we help relatively inexperienced case-handlers come to decisions more quickly? [Business Services and Innovation Director, Law A]
Document review ML software "trained" by lawyers	When we trained it [names software] would tell us where those clauses were, so we could just flick through them and say "yeah that's right" or "no that's not quite right." And then we'd go through it. So it would take us a lot less time ... [Real Estate Solicitor, Law A]
Accountants set parameters for audit system based on client	So it primarily analyses all the transactions by risk ... based on a number of control points ... things like the material value of the transaction, the double entry, the actual nature of it, the description whether that's risky. And then once summarised you can then investigate those high-risk transactions [IT Operations Manager –Acc Y]
Lawyers' contract expertise captured in self-service system	... it was quite a few solicitors, associates and partners who were involved in generating the advice ... it was as broad ranging as possible so that it was appealing to a wide variety of clients. [Solicitor—Technology Practice Law B]
Increasing sample size in audits	... it provides them with further comfort that the transactions and what's been posted by the finance director, the whole team has been through even more of a scrutiny than an existing audit. ... So they saw that as very much a positive. [IT Operations Manager—Acc Y]
Automated search reduces error rate in law and audit	B: I think we worked out it was something like 0.02% was the inaccuracy rate. So it was, so we came out of it thinking actually its accuracy that was the biggest advantage to using AI here. [Partner, Head of Built Environment Law A] ... automatically the risk of not spotting that journal as an error is massive because you have got a human person reading it. What [names software] allows you to do is put that data into the system and tell it to pick out everything that says error or adjustment or suspense account. [Head of Auditing, Acc X]
Fast contract review wins business in law	they basically said to us "We've got this deadline, we need this doing in this deadline—can you do it?" We had [names software] which we used a little bit but not a great deal ... I think we certainly did it quicker than we would have if we had 20 people sat in a room. [Real Estate Solicitor Law A]
Expert system provides reliably quick decision in low-value claims matters	Win for us because we won't waste time on it; win for the client because the client measures us on how fast we get rid of these things. [Law A, Business Services and Innovation Director]
Faster year-end accounts and tax preparation	We have a document that we call key audit findings ... using the graphs and the output generated from the software we would put those into the document so that the client can see visually the transactions by risk, the amount of transactions. [IT Operations Manager—Acc Y]
Providing insights into anomalous bookkeeping practices	... it's able to do things that I probably wouldn't have thought of doing, like checking dates. Because the computer knows what day of the week a date is, it's able to check things on a weekend, it's able to check things that are unusual times. So it ... I think it has expanded what we can look at. [Senior Manager, Acc X]
Providing advice based on aggregate of leases or contracts	... if you've got a huge estate like [names several clients] it must be difficult to keep track of what's going on, when all the leases are going to be coming up for renewal, when you've got break clauses or when you've got rent reviews ... it's a good tool to offer and say "Well, we know that on this site we've got 40 125-year leases" [Real Estate Solicitor, Law A]

(Continues)

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Themes	Example quotes
Self-service contract drafting provides real-time advice	The way the product works is that it reviews the document in question, it uses natural language processing to review any, identify any issues for it to consider. They may either be material or minor issues. And the help text that it generates would be based on the advice that a UK lawyer would give. [Partner—Client Service Transformation Law B]
Audits shift to continuous real-time rather than periodic retrospective	I'd have thought more real time audit is probably where we're headed with audits happening so far after a year end sometimes missing the boat on some quite high-profile cases. ... it will just free up the experts to do some different work rather than it taking over their role. [Audit Manager—Acc Y]
Compelling graphical audit outputs stimulate "new conversations" with clients on advisory work	I had one business that was particularly seasonal and the graph ... it was a proper visual representation of their data that actually they hadn't really seen despite having an awareness of it. And so that was surprising and a good talking point in the audit committee meeting with them. [IT Operations Manager—Acc Y]
Bespoke ML determines future reserve requirements for insurance claims	But usually you're pretty wedded to the range of that first [reserve] figure. So no client wants to be told to reserve £10,000 and it to be a £500,000 case ... if people were consistently chucking another £20,000 on because they just didn't like the figure and then it transpired that the claims were settling within the machine's prediction then we'd just be having a word and going you're using the system, its way more accurate than you. [Innovation Manager Law A]
Anticipating breach of tax threshold rather than reporting it retrospectively	So what we need to be able to do is (a) access their accounting records more regularly, we can perform checks on it, we can pick up ... Your clients expect a certain level of service from you. Like if we're using [names software] we can pick up the phone and go "Do you know you're just about to breach your VAT threshold?" [Senior Accountant 1 Acc X]
Providing insights into client business processes such as HR, procurement, because of having to codify them	I met with an organisation's general counsel last week and they talked about one of their issues in house, with in house teams is dealing with the continuing professional development of their in-house team and managing it. ... I came across a software product ... so I've got a client who's saying this is a problem for us, [and] I've got a solution that says we might be able to do this. [Business Services and Innovation Director Law A]

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