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Generative machine learning in professional work and professional service firms: a research agenda

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This paper addresses the need for an approach to theorizing professional work and professional service firms in the generative machine learning (GML) age. We develop an approach using insights from existing literature on digital, algorithmic, and artificial intelligence technologies. We seek to extend existing theories whilst also responding to the distinctive characteristics of GML and the implications for how we theorize change. We argue that an approach is needed focused on emerging and future interdependencies between professionals and GML, something that implies extending but also reimagining theoretical perspectives on expertise, work, and organizations.

Keywords artificial intelligence, generative machine learning, professions, expertise, professional work, professional service firms, professional work

INTRODUCTION

Professional work and professional service firms (PSFs) are intimately connected to digital technologies. From the earliest studies of disruptions through 'nonintelligent' algorithmic technologies such as Lotus Notes (Orlikowski and Gash 1994) and knowledge management databases (Brivot 2011), to more recent impacts of robotic process automation and artificial intelligence (AI) such as extractive and predictive machine learning (Cooper et al. 2022; Faulconbridge et al. 2024), studies have shown that professional work and PSFs are constituted through relations with technologies (Pakarinen and Huising 2025; Scarbrough et al. 2025). Earlier generations of algorithmic technology—i.e. technologies that operated through encoded procedures to transform input data into desired outputs through computational steps—are different from AI and machine learning in particular because of the absence of intelligent forms of agency. AI and machine learning mean the technology 'learns its own "rules" for linking the input data to the desired outcomes … [that] are not created by human actors and, in many cases, cannot even be explained by humans' (Kemp 2024: 619). This form of agency, based on statistical models that analyse and draw inferences from patterns in data to develop intelligence, is a step change from algorithmic technologies that were programmed and could be explained by humans.

Most recently, the rapid advancement of generative machine learning (GML) poses some new and fundamental questions (for an overview of the distinctive implications of GML, see Brown et al. 2024). GML is a step forward from AI based on extractive or predictive machine learning (i.e. machine learning that identifies, extracts, analyses, and predicts from existing data). GML and its ability to produce new text, images, and other forms of content in conjunction with large language models (LLMs) transforms machine learning into a tool that appears to be able to engage in the interpretative and advisory functions of professionals. Also, the ease of use due to design and controls utilizing natural language marks a distinct difference, democratizing access and use in ways that both enable professionals to adopt more easily and allow other occupations and lay persons to use technology for professional purposes (e.g. generating legal advice). As Glaser et al. (2021, 2024) argue, advances in machine learning thus require us to understand the 'biography' of the technologies driving change in terms of their design, operation, and effects, and to analyse the implications of human–machine collaborations for work and organizations.

The relatively recent rise to prominence of GML technologies such as ChatGPT and Microsoft's Copilot, alongside profession-specific, bespoke GML applications, means that adoption and the implications for professional work and PSFs are still emergent. Individuals and firms are experimenting before committing to use in day-to-day work (e.g. Womack 2023; Faulconbridge 2025), particularly given risk and ethical questions in relation to data privacy and consent, bias and fairness in outputs, including hallucinations, accountability for misuse or errors, and the potential for automation to erode expertise and reshape professional identity. Broader risks also include the use of generative systems for manipulation or disinformation, the tendency of firms to rely on self-regulatory ethics frameworks with limited enforcement, and the social and environmental costs of large-scale model training (Hagendorff 2020). Yet, in the short to medium term, GML is touted as a particularly disruptive technology. Some estimate that about 40% of current labour time in professional services (e.g. law) can be automated (Eisfeldt et al. 2023; Singh and O'Keeffe 2023). Others suggest the potential exists to reimagine ways of diagnosing and treating client concerns, with implications for the service offerings and in turn business models of firms (Armour and Sako 2020; Goto 2023; Faulconbridge 2025). Additionally, work that today is done by professional experts might in the future be done by paraprofessionals or other occupations, with much less education and field knowledge, or by anyone—in the case of extensively user friendly and intelligent systems (Susskind and Susskind 2015). Consequently, understanding what GML might mean for how we theorize professional work and PSFs is a pressing research agenda.

Theoretically, a starting point is to recognize how GML might be incorporated into professional work and PSFs and the implications for some of the distinctive features of such work and organizations. In the existing literature, three distinctive features have been highlighted as key (for an overview, see Brown et al. 2024). First, professional work is understood as distinctive because of its basis in expertise embedded in individual professionals. A key starting point for theorizing professional expertise is Abbott's (1988) study, in which he highlights the diagnosis, inference, and treatment work carried out by professionals. The jurisdiction of a profession is shown by Abbott (1988) to be tied to the way individual professionals can claim the expertise needed to diagnose, infer, and treat when encountering a client's needs. Across different professions, the nature of this expertise is heterogeneous (Malhotra and Morris 2009), but crucially, structures how work is conducted and by whom. This includes settlements within professional ecologies that organize the system of professions and the competition and cooperation between them (Abbott 2005; Seabrooke and Tsingou 2015). The rise of GML requires an understanding of how this technology acts and interacts with professionals and the impacts on how expertise emerges (Glaser et al. 2024; Scarbrough et al. 2025). What are the implications for how we conceptualize expertise, and in turn, what are the implications for how professionals claim jurisdictions through their work?

Second, the link between professional work, professional identities, and how professionals respond to new technologies has been shown to be critical. The different tasks associated with diagnosis, inference, and treatment are meaningful to professionals because mastery of their performance is associated with the demonstration of expertise and the creation of boundaries around professional jurisdictions (Currie et al. 2012; Huising 2014; Bryan and Lammers 2020; Kellogg 2022; Faulconbridge et al. 2025). In addition, the apprenticeship model typically adopted in professions forms identities tied to learning and the performance and mastery of key tasks (Pratt et al. 2006; Nelson and Irwin 2014; Anteby et al. 2016; Beane 2019; Chen and Reay 2020; Jonsson et al. 2026). An understanding is, therefore, needed of the potentially acute disruptions associated with GML, given the technology's ability to automate, mimic, and transform key tasks. How should changing professional work tasks, experiences of and responses to these changes, associated identity disruptions and reformation, and the implications for learning and, again, professional boundaries be studied?

Finally, third, the distinctive modes of organizing and governing PSFs are important when considering how digital technologies are adopted and their effects. Whilst there is not a singular model adopted by all PSFs (see, Empson and Chapman 2006; von Nordenflycht 2010), approaches typically prioritize organizing that enables professionals to produce and deliver expertise by drawing on their individual insights and knowledge. This typically involves approaches designed to provide professionals with autonomy in their work (Mintzberg 1979; Newell et al. 2002). At the same time, governance is often through collegial forms, manifested in partnerships or approaches that mimic partnership, the intention being to give professionals degrees of influence over decision-making that corporate bureaucracies do not. Such approaches have been possible in many (but not all) contexts because PSFs have typically had low capital intensity and hence limited need for external investment, whilst the systematization of production processes has been deemed unnecessary due to the reliance on the expertise of individual professionals (Empson and Chapman 2006; von Nordenflycht 2010). The distinctive form of PSFs raises questions about how GML will interact with and play a role in reconstituting organizational structures designed to enable autonomy (Kronblad 2020; Faulconbridge 2025). Relatedly, the implications for the business models of PSFs (Armour and Sako 2020), ways of delivering client services (Coombs et al. 2020; Paluch and Wirtz 2020), and organizing innovation (Goto 2023) need to be examined. How will GML be challenged by and challenge the distinctive approaches to organization and governance adopted in PSFs?

In the current moment, the need for an approach sensitive to the specificities of professional work and PSFs poses, however, a conundrum. Alongside the inevitable lag between technological breakthroughs such as GML and published research studies, many studies use illustrations from professional work but without firmly placing the analysis in the context of our theoretical understanding of the professions, professional work, and PSFs (see e.g. Cardinali et al. 2023; Sundaresan and Guler 2025). Thus, conceptualizations risk being de-contextualized and based on studies that privilege the technology over the institutional, organizational, and situated specificities of professional work. This is a risk because, as Stark and van den Broeck (2024: 9) note, the impacts of digital technologies, including AI, 'cannot be assumed in advance but depend[s] on national, institutional, and organizational structures as well as cultural and interpretive practices'. Similarly, Pakarinen and Huising (2025) argue that de-contextualized analyses risk ignoring the relational dynamics between professional work and technology, which need to be central to understandings of how machines are incorporated in professional work and equally important into explanations of 'what machines can't know'.

Our purpose in this paper is to address the need for an approach to understanding the impacts of GML on professional work and PSFs that builds on and extends existing theorizations of professional–technology interdependencies. By interdependencies, we mean the 'system of interactions' (Anthony et al. 2023, p. 1680) and networks of collaboration (Pakarinen and Huising 2025, p. 2062) between professionals and technology; in our analysis, this relating to interactions and networks between professionals and GML technologies. We ask: *how can insights from existing literature on digital, algorithmic, and AI technologies in professional work and PSFs be extended to inform approaches to future research examining interdependencies with GML*? By examining insights from existing literature and extrapolating the implications for future research priorities, we identify the kinds of contextualized questions that need to be asked about professional work, PSFs, and the adoption, interdependencies with and impacts of GML. The challenge when taking this approach, as Glaser et al. (2021, 2024) remind us, is to not lose sight of the specificities of the technology, in our case, how GML differs from other forms of digital technology and machine learning, and to take seriously the interdependencies emerging from interactions between the technology and the situated context of professional work and PSFs. This means that studies of earlier generations of algorithmic and AI technology provide sound theoretical foundations to examine the effects of GML, if questions are asked about how the engagement and relations between professionals and technology are likely to evolve because of the distinctive forms of agency associated with GML.

Our approach, therefore, is to begin by considering how pre-existing questions about professions–technology relations raised by earlier generations of digital, algorithmic, and AI technologies are now more pertinent as change becomes quicker and more extensive as a result of GML's distinctive characteristics. But we also consider how the questions are potentially transformed by the kinds of situated human/professional–machine interdependencies that are emerging. In taking this approach, we follow Hinds and von Krogh (2024: 2) who argue that 'it is not the technology (GML) itself that requires interrogation, but the relations and functions it performs and how those evolve'. Specifically, it is the way professional work and PSFs build relations with GML and the experiences of and responses to these relations that need to be understood and theorized. We outline the questions that can build such theorizing in relation to the topics of professional expertise, professional, and PSF responses to GML.

RESEARCH BACKGROUND

Generative machine learning

Machine learning is one form of AI technology. Its roots go back to the 1950s and are associated with systems that can learn without being explicitly programmed (Samuel 1959). These systems are based on statistical models that analyse and draw inferences from patterns in data. As its name suggests, machine learning becomes 'intelligent' through a learning process as more data are integrated to develop models that are increasingly sophisticated. As computing power increases and greater quantities of relevant data can be integrated, the systems enhance their ability to learn.

One of the key features of machine learning is the way 'systems are set a task, and given a large amount of data to use as examples of how this task can be achieved or from which to detect patterns. The system then learns how best to achieve the desired output' (The Royal Society 2017: 19). There are two main forms of learning processes. Supervised learning involves datasets being labelled by a human, the labels identifying what the data represents. For example, a sentence in a legal contract is labelled to identify it is an example of a break clause. Or a transaction in an audit record is labelled as being an example of how suspicious activity appears in a ledger. As the machine learning digests multiple labelled examples, it identifies common patterns in the data that are indicative of the category (e.g. break clause), allowing it to recognize and/or produce examples in the future. Unsupervised learning occurs without the involvement of a human. It involves the machine identifying for itself common statistical patterns and clusters in data, these patterns and clusters then being used to make predictions. The key difference between supervised and unsupervised learning is, therefore, the process through which 'intelligence' emerges. In the former, the human aids the development of 'intelligence' through the labelling of data. In the latter, the machine forms its own 'intelligence based on the patterns and clusters identified which act as the basis for interpretation.

Machine learning is either extractive or generative. Extractive machine learning, as the name suggests, allows information to be extracted from large datasets. Typically using supervised learning, extractive tools speed up the process of analysis, for example, when an accountant wants to identify suspicious transactions as part of an audit, or a lawyer wants to identify clause types in a bundle of contracts. When extractive machine learning is used, the algorithm does not produce new data. It allows the professional to identify relevant data. Nonetheless, in its extractive form, machine learning is still providing interpretations of the data. Based on the statistical associations identified through the learning process, machine learning infers from patterns what is relevant and irrelevant, in a way that is black-boxed and thus not visible to the professional using the tool. Hence, while an accountant for example knows which transactions have been identified as potentially suspicious, they cannot know why they were selected, which transactions were close to being selected and ultimately not selected because statistical correlations were not strong enough, etc. It is also not possible to know what may have been selected if the learning process had digested different datasets.

Most recently, and based on unsupervised machine learning, easy to use GML has become widely accessible, such as ChatGPT and Microsoft Copilot. GML can be defined as 'a class of machine learning technologies that can generate new content—such as text, images, music, or video—by analysing patterns in existing data' (Brynjolfsson et al. 2023: 5). Crucially, unlike extractive machine learning, GML generates new data by remixing and recombining existing content when given relevant prompts. Its outputs are not extractions from existing datasets. Rather, it generates content, such as documents containing text, graphs, images, and analysis that typically a professional would produce for their clients, using the remixing and recombing of content in response to prompts from a professional.

To date, much of this discussion about how GML is or might be used has been at the micro level, concerned with tasks. Predictions concerning the use of technologies such as ChatGPT are that it will be most helpful in generating first drafts of documents:

> ChatGPT has the potential to enhance the productivity of knowledge work through various mechanisms, such as simplifying the information search process, but I predict that its most significant impact will be to provide a competent first draft for our most common written knowledge tasks. (Michael Wade, writing on knowledge work productivity in Dwivedi et al (2023))

Determining how to use GML tools in the accomplishment of tasks, what the division of labour should be, and how the machine and human work should be coordinated is, thus, a recurring theme. Dell'Acqua et al (2023) distinguish between 'cyborg' and 'centaur' approaches. The cyborg approach integrates human and machine learning capabilities at a very fine-grained level—for example, machine learning might create a first draft of a sentence in an email, and the human amends it. The centaur approach sees a more distinct division of labour at a higher level of aggregation—for example, the machine learning might be asked to provide a summary of multiple documents on a given topic, which the human then adapts to suit a particular purpose. These divisions of labour take place at what Dell'Acqua et al. (2023) call the 'jagged frontier' between machine learning capabilities and human capabilities. By this, they mean that machine learning reaches surprisingly far into the zone of tasks we might suppose humans to be uniquely capable of in some instances, while at the same time having surprisingly low capabilities in respect of other tasks that we might consider relatively easy to automate. The frontier is ever-changing, as well as jagged and, of course, some humans are more capable than others. Mollick (2024: 130–136) suggests another typology of tasks at the frontier: 'Just Me' tasks, Delegated tasks, and Automated tasks. Just Me tasks do not involve machine learning technologies; Delegated tasks are assigned to the machine learning, but carefully checked; Automated tasks are assigned to the machine learning, but not checked.

The effect of GML on productivity and quality is, unsurprisingly, also a key concern. Some argue that less skilled humans benefit more from the use of GML than do more skilled humans. Studies show large reductions in the disparities of productivity and quality among knowledge workers undertaking writing tasks[1] (Dell'Acqua et al. 2023; Noy and Zhang 2023): by using generative mean learning, everyone can perform above average, so to speak. This has potentially major implications for the capacity and roles of professionals—perhaps especially more junior ones, whose typical tasks are more directly affected by the initial uses of GML and hence whose productivity and quality can most immediately be improved, within the bounds of the current capability of the particular technologies. It does not, though, tell us much about how GML might be adopted in the situated context of professional work and PSFs and how this might result in new interdependencies that change how we theorize, amongst other things, professional expertise, identities, and organizations. Indeed, revealing the uncertainties, other research suggests that it is those in the middle of the skills range (not junior apprentices, not senior masters) that are likely to build the strongest relations with GML (Allen and Choudhury 2022). This uncertainty reveals why understanding the questions underlying a research agenda on GML in professional work and PSFs is so crucial.

GML in the professions

The potential of machine learning to profoundly affect the professions has long been recognized (Abbott 1991; Susskind and Susskind 2015). Since the latter years of the 2010s, the long-contemplated promise of AI to undertake the work of experts has finally begun to be fulfilled through the release and adoption of GML applications that support the execution of particular tasks in professions such as accountancy and law. A body of work, including studies in the *Journal of Professions and Organizations*, pays attention to particular occupation- and organization-specific issues related to extractive machine learning. Such issues include, e.g. the adoption and use of machine learning in PSFs (Faulconbridge et al. 2024), and how that, in turn, might lead to changing business models (Armour and Sako 2020; Rodgers et al. 2023), threats to professional and organizational identities (Goto 2021; Klimkeit and Reihlen 2022), increased boundary work and jurisdiction reconfigurations (Köktener and Tunçalp 2021; Faulconbridge et al. 2025), and intensified sensemaking among the professionals (Goto 2022; Scarbrough et al. 2025). It also examines how machine learning, which is 'more encompassing, instantaneous, interactive, and opaque' (Kellogg et al. 2020, p. 366) than previous generations of technology, makes outputs inscrutable (Anthony et al. 2023; Faulconbridge 2025), this being a key consideration when considering the risks and ethical questions for professional work and PSFs.

Coupled with the development of LLMs that allow question-and-answer style prompt interfaces, GML applications have transformed the possibilities and impacts of AI in the professions beyond the extractive machine learning examples documented to date (Briggs and Kodnani 2023; Villasenor 2024). For example, GML is a general-purpose technology that can be applied across multiple use-cases, whereas extractive machine learning was often developed and applied as a 'point-solution' focused on a very specific task (Spring et al. 2022). This is illustrated by the way GML and LLMs can automate analysis reports, scrutinize data, and make inferences

[1] Academic readers involved in teaching and assessment may be familiar with this phenomenon: all of a sudden, all written assignments (where ChatGPT has been used), even those by weak students, are of what would have been an above average standard, at least in terms of structure and writing quality.

in relation to a range of different tasks within and between professions (Zhang and Kamel Boulos 2023). In medicine, this means diagnostic test results can be scrutinized and initial conclusions drawn. In law, summaries of document datasets can be produced, and reports automated that identify the main findings of due-diligence work. The production of drafts of contracts, filings, court rulings, etc. can also be automated (Villasenor 2024), albeit with a risk from hallucinations that need to be checked for by human professionals (Milmo 2023).

To illustrate the potential of GML across tasks and contexts, Table 1 provides a summary of the kinds of uses that are either predicted or actively being trialled at the time of writing. In all of the examples, combinations of technology developers and professionals have purposefully set about incorporating GML into professional work to develop specific use-case solutions. Sometimes this involves developing bespoke applications of GML, sometimes it involves deploying general-purpose technologies like Microsoft Copilot for a specific use case. Importantly, in all cases, it results in new interdependencies between professionals and GML, the implications of which need to be understood as part of the future research agenda we set out below.

The key motivation for analysing the characteristics of GML is, therefore, to consider how the distinctive differences in possibilities and effects compared to algorithmic technologies and extractive machine learning can be understood. However, the literature on technology adoption in professional work reminds us that it is not only the characteristics of the technology that matter. It is also the response of professionals and interactions with 'human attributes such as language, habits, beliefs, and perceptions' (Salijeni et al. 2021: 534). Of concern are the new machine–professional interdependencies that come to define professional work and forms of organization in PSFs. Underlying such concerns are questions about AI agency, this being a research theme in, amongst others, the fields of psychology (e.g. Pagliari et al. 2022) and information systems (Dattathrani and De 2023). The scope of this paper does not allow for a full recap of these discussions. However, noting the relevance and impact of 'conjoined' (Murray et al. 2021) human and AI agency is essential to the research agenda we develop. Interdependencies imply interaction networks that result in professionals and GML acting together.

Specifically, the research agenda we set out below seeks to identify the most pertinent research questions to address about the interdependencies emerging and likely to emerge between GML, professional work, and PSFs. Our ambition is to provide a framework for studying and theorizing in the age of widespread emergence and use of GML, in advance of the development of a body of empirically informed research. Our approach, like Hinds and von Krogh (2024: 10), builds on a range of existing theorizations to understand some of the key 'forces in and around organizations that accelerate and arrest' change. We ask how GML as a force interacts with the distinctive characteristics of the work of professional experts (Heimstädt et al. 2024; Pakarinen and Huising 2025) and the organizations they operate in (Armour and Sako 2020; Goto 2023). In doing this, we consider three levels: the *field level* and the implications for *professional work and expertise*; the *individual and group level* and *how professionals respond to GML*; and *the firm-level* in terms of the *organizing of work in PSFs*. Analytically, we consider the three levels separately whilst recognizing their interrelatedness as changes at one level are tied to changes at other levels.

Reflecting debate over the years about the definition of a profession, we recognize that 'old' and 'new' professions and PSFs (Dent and Whitehead 2002; Muzio et al. 2013) display different features. Von Nordenflycht (2010) addresses this differentiation by separating 'new' professions into two categories of technology developers (e.g. biotech) and neo-PSFs (e.g. advertising) and then separating 'old' professions into two categories of professional campuses (medicine) and classic PSFs (e.g. architecture). In line with the contents of this journal and the different empirical foci that have emerged depending on whether profession is interpreted in a narrow way or more broadly, we consider examples from both 'old' and 'new' professions. In particular, we are alert to the distinctive features of the 'old', which are regulated by the state, have a formally regulated workforce, typically rely on stronger forms of the collegial professional trustee logic (Freidson 2001) and typically have a preference for the professional partnership as a mode of governing organizations (Empson and Chapman 2006). We recognize that the features of 'old' professions, and variations between professions within the 'old' categories (e.g. accounting versus law), alongside variations between 'old' and 'new' professions (and variations within the 'new' professions category) all matter when considering interactions with GML technologies. We, therefore, seek to build a framework of questions and priority foci that can be applied across professions, rather that developing definitive articulations of how GML will impact any specific profession. We draw on insights from a broad range of literatures considering the implications of AI but also other digital and algorithmic technologies for professional work and PSFs. This approach allows us to capture insights into the kinds of questions that

Table 1 Example uses of GML in professional work.

	Applications in professional work
Client self-service (chatbots and virtual agents, multilingual support, automated document drafting)	Accounting firm tax guidance: guidance about the elements of tax codes that apply to a particular client (Acenteus 2025) Law firm client triage processes: ascertaining the types of services a client is likely to need and summarizing applicable law and approaches to address particular client needs (see https://tipsaccelerator.co.uk/case-studies/leveraging-ai-to-enhance-access-to-justice-in-matrimonial-services/) Law firm bespoke client-facing chatbot: to both signpost prospective new clients to sources of guidance and advice services, as well as collecting personal data to inform the lawyer's decision about whether to onboard that client or refer to another firm (see https://tipsaccelerator.co.uk/case-studies/leveraging-ai-to-enhance-access-to-justice-in-matrimonial-services/) Medical triage questionnaires: to gain insights into diagnosis and advise on investigations and potential treatments (IntuitionLabs 2025) Bank self-service account management: deployment of conversational AI to help clients with transaction inquiries and risk assessments, improving customer loyalty and reducing churn, for example NatWest's 'Cora' Chatbot (FinExtra 2025)
Research	Financial market research: GLM used to summarize key trends and cases summarized to inform advisory services (Bank of England 2024) Litigation/regulatory risk analysis: analysis of the specifics of a client's situation against a backdrop of similar cases and outcomes (LexisNexis 2022) Database analysis: GML used to rapidly analyse vast databases of relevant material (e.g. statutes, case law, and regulations; tax laws; medical research and protocols). Used to surface relevant precedents/laws/cases (The Law Society 2024)
Document summarization and communication	Professional reports: GML summarizes lengthy documents, helping professionals to quickly identify key issues and communicate findings to clients in clear and easy to understand language (see https://tipsaccelerator.co.uk/case-studies/fbc-manby-bowdlers-transformation-through-ai-powered-property-diligence/)
Real-time compliance	Monitoring changes in laws and standards: systems monitor changes and alert professionals (e.g. accountants and lawyers) to relevant updates (The Law Society 2025)
Predictions	Law firm budget tracking: using GML to improve quoting for billable hours work and projecting budgets for client projects (International Bar Association 2025) Law firm forecasting: leveraging past cases and GML to forecast the probability of success in litigation or regulatory matters and supporting lawyers in making recommendations about whether to proceed, settle, or adjust legal strategies (LexisNexis 2022) Accountant analytics: using large datasets from financial statements, transactions, and the market to identify trends, anomalies, or compliance risks enabling improved tax strategies, and identification of cost-saving measures or investment opportunities (Acenteus 2025) Medical treatment responses: Leveraging past responses to predict improved and individualized treatments (IntuitionLabs 2025)

(*continued*)

Table 1 Continued

	Applications in professional work
Recommendations	Law firm documents: GML is used to draft new contracts tailored to a client's needs, quickly iterating based on client feedback and legal requirements (see https://tipsaccelerator.co.uk/case-studies/fbc-manby-bowdlers-transformation-through-ai-powered-property-diligence/) Accountant financial scenarios: accountants use GML to model financial scenarios (e.g. the impact of regulatory changes or new investments), the modelling informing advice to clients about financial management strategies (Wolters Kluwer 2025) Medicine: standard operating procedure/clinic decision pathway guidance applicable to a patient case (IntuitionLabs 2025)
Report generation	Law firm contract review: GML automates the review of contracts, identifying risky clauses or inconsistencies and suggesting alternative language based on legal best practices (see https://tipsaccelerator.co.uk/case-studies/fbc-manby-bowdlers-transformation-through-ai-powered-property-diligence/) Accountant financial reports: use of GML to draft financial reports, audit summaries, and management letters, allowing accountants to focus on interpreting results and advising clients on strategic decisions (Wolters Kluwer 2025) Medical reports: assembling radiology diagnosis reports (IntuitionLabs 2025)

Source: Authors' field research.

need to be asked, extended and reimagined when examining GML.

PROFESSIONAL WORK AND EXPERTISE

Expertise—the specialized ability to accomplish tasks within a specific domain (Eyal 2013)—is central to professional work and PSFs. Codified expertise and esoteric knowledge are usually considered at the core of professional work, where knowledge is the primary input, mechanism, and output (Newell et al. 2002). While such expertise was traditionally institutionalized in human professionals (Abbott 1991), extant literature highlights how digital technologies are reshaping claims to expertise (e.g. Abbott 1991; Eyal 2013; Pettersen 2019; Lester 2020; Heimstädt et al. 2024; Pakarinen and Huising 2025; Scarbrough et al. 2025). With the advent of agentic systems and GML, these dynamics are becoming increasingly salient. New computational actors now make claims to expertise in, for example, accounting, medicine, and law—domains historically controlled by human professionals (Hinds and von Krogh 2024). In this context, what constitutes expert agency—and who or what can legitimately claim it—is being challenged (Dattathrani and De 2023; Pasquale 2023).

To understand the potential impacts of AI, scholars have highlighted the importance of analysing the 'system of interactions' (Anthony et al. 2023, p. 1680) or the 'assemblages or networks of various actor types' through which expertise is produced (Pakarinen and Huising 2025, p. 2062). Crucially, 'agency emerges from the interplay within assemblages, which include data, algorithms, routines, and decisions' (Glaser et al. 2024, p. 2750). It is, then, the interdependencies between professionals and GML that need to be the focus of analyses. Accordingly, agency cannot be ascribed in advance to either the human professional or a GML application. Instead, it is distributed and accomplished through ongoing interaction (Latour 2005). Perspectives differ on how machine learning technologies and their potential abilities are and will be woven into the fabric of professional knowledge work and expertise (for an overview, see Pemer 2021; Acemoglu et al. 2022). Here, we consider several of the key perspectives and what they imply for a research agenda on GML in professional work and PSFs.

One perspective on changing expertise has been to highlight the variety of tasks professionals and PSFs are engaged in (e.g. Köktener and Tunçalp 2021; Faulconbridge et al. 2024; Pakarinen and Huising

2025). Scholars have noticed how professional knowledge manifests itself through acts of diagnosing a problem, inferring a solution, and providing treatment (Abbott 1988; Faulconbridge et al. 2024). Professional jobs are, therefore, 'bundles of tasks' assembled under an administrative title (Cohen 2013: 432). Hence, it has been argued that whilst tasks can be 'automated', jobs are 'informated' by AI integrated with human professionals, given the inability to automate all tasks (Zuboff 1988; McKendrick 2018). This has led to a focus on which diagnosis, inference, and treatment tasks might be automated, which are untouched, and what new tasks emerge in an informated approach. Faulconbridge et al. (2024), in a study of extractive machine learning in accounting and law firms, suggest that changes occur mainly to diagnosis tasks, with machine learning enabling the search, sorting, and categorizing of data previously completed by junior professionals. Crucially, however, while this means that inference and treatment tasks are not directly affected by machine learning, with diagnosis processes sped up and refined, the way that professionals engage in inference and treatment work indirectly changes. Extractive machine learning changes professionals' abilities and creates new tasks associated with interpreting and applying the insights from machine learning. Such focus relates closely to debates about the automation-augmentation paradox (Raisch and Krakowski 2021). Automation refers to the completion of certain tasks by machines without human input—what was referred to earlier using the work of Mollick (2024: 130–136) as delegated tasks. Augmentation involves collaboration between humans and machines to enhance how a task is completed. We referred to this earlier using the work of Mollick (2024: 130–136) as delegated tasks. Augmentation is often focused on when professional work is discussed. However, augmentation is inherently entwined with automation, which in turn means more fundamental transformation to professional work than might be anticipated as automation is accommodated and responded to. These studies point, then, to the importance of examining how interdependencies between professionals and GML will produce both predictable but also more unpredictable changes to how expertise emerges and deployed in professional work and PSFs. New assemblages that develop will result from the replacement of professional tasks by GML, the preservation of some tasks, and the invention of new tasks for both humans and machines.

A different perspective approaches questions about the incorporation of AI into professional work and PSFs by examining the deficits and limits of AI technologies as well as its capabilities. Studies that focus on the deficits of machine learning emphasize the tacit nature of professional knowledge and the political and organizational context in which such work occurs. It is argued that professional work contains 'an ability to integrate facts and values, the demands of the particular case and prerogatives of society' (Pasquale 2019: 75). Therefore, the complex problems regarding diagnosis, inference, and treatment, solved by professional knowledge workers, are complex to solve through machine learning (Pettersen 2019). Similarly, Pakarinen and Huising (2025: 2058) propose that the relational and client-oriented nature of professionals' work makes it difficult to automate because both the production and application of expertise involve interactions that allow the incorporation into decision-making of situated considerations in relation to 'history, context, configuration, or enactment'. They, therefore, argue that professional jobs are like Gordian Knots with machine learning unable to address the entanglements between different aspects of professional work. Such ideas extend the arguments of Fleming (2019), who emphasizes the limited likelihood of AI taking over jobs due to political, socio-economic, and organizational forces that shape activity. Fleming introduces the notion of 'bounded automation', which depicts the difference between the rational, financially viable, and the actual political and organizationally mediated automation likely to take place. Understanding the nature of professional work and jobs allows us to understand better what leads to 'bounded automation' in the socio-material context of professions such as accounting, law, and medicine.

Within the deficit orientation, studies also examine the extent to which machine learning can mimic or reproduce what professionals' knowledge provides clients. Lebovitz et al. (2022) point to the challenge of measuring professionals' knowledge work and the similar difficulty in measuring the performance of machine learning in such contexts. They point to the differences in the evaluation systems for machine learning, where ground truth labels are applied, and expert work, where know-how is essential. Their work shows that narrow measures of machine learning performance, which only capture 'know what', are an inadequate basis for evaluating whether to use technologies, because the benchmarks omit the component of 'know-how' so crucial in professional work. Anthony (2021) similarly studies how algorithmic technologies are validated by employees with a limited understanding of the underlying black-boxed nature of algorithms. Based on a two-year inductive case study of analytical technologies across four investment banks, she shows that two main paths are taken: (1) partitioning, where the juniors perform the analysis and the seniors interpret the results, or (2) co-construction, where the juniors assemble and interpret results and seniors interpret and provide feedback. While the first approach implies that employees largely accept the black-boxed nature of the algorithms, taking them for granted without understanding them, the employees and organizations engaging in co-construction are more questioning and want to understand the impact of the algorithmic technologies. As well as enabling better-considered advice to be given, the co-construction approach also enhances the juniors' expertise and career trajectories and allows the deficits of the technologies to be identified. This highlights the importance of recognizing the deficits of machine learning when considering how it will be adopted, but again shows that analysis must account for the new interdependences between humans and machines. Ways of working, the expertise of a human professional, and approaches to serving clients will be reconfigured by both what GML knows and what it does not know, and how professionals accommodate and adapt to such deficits as well as the opportunities.

Indeed, other studies focus more squarely on the way the capabilities of AI technologies are accommodated by professionals. Some suggest that AI technologies will likely shape an 'attended automation' that results from a human–machine synergy (Zhang and Kamel Boulos 2023). Others stress new competencies emerging by focussing on higher-level tasks (Law and Shen 2025). Yet, most studies within this perspective again point out how machine learning technologies may change professional work by automating some tasks, augmenting others, and creating new tasks for professional workers (e.g. Pemer 2021; Faulconbridge et al. 2024; Law and Shen 2025). As such, a focus on capabilities leads us back to the same place as a focus on deficits: the future interdependencies between GML, professional work, and PSFs.

In sum, literature on professional knowledge and work highlight the importance of an approach that sees human professionals working alongside and with GML as a form of conjoined agency (Murray et al. 2021). Professionals, alongside those developing GML technologies, will find ways to automate and augment work. To understand how such changes emerge requires consideration of the specificities of professional work and jobs, and the characteristics of GML simultaneously. Understanding and accepting 'what machines can't know' (Pakarinen and Huising 2025) and how this is compensated for in augmented/informated approaches to professional work will be critical when considering interdependencies and conjoined agency. Such perspectives align with a system-level or a relational assemblage perspective on professional work, where several authors (e.g. Murray et al. 2021; Glaser et al. 2024; Pakarinen and Huising 2025) suggest that new technologies should be conceived of as actors in a relational network of interactions rather than as a replacement for actors. This argument about the role of machines as an actor in professional work is a key step in bringing professional work and GML together and conceptualizing a future research agenda for studying relational assemblages of diagnosis, inference, and treatment. Such an approach highlights an important focus for future research on the how to evaluate the knowledge outputs of GML technologies on the one hand and the human expert on the other hand? Moreover, how can understanding the outputs of technologies and humans together help us retheorize the systems of professional practice in an era of GML?

Such questions also have broader implications for learning processes, education, and training (e.g. Beane 2019; Wach et al. 2023; Villasenor 2024; Jonsson et al. 2026). Core questions regarding this concern how the interdependencies between professionals and GML might enable but also undermine learning processes seen as crucial for the generation of expertise. On the one hand, it has been suggested, for example, that GML can enable the development of a digital client 'twin' that can enable students to practise handling cases and clients, including adverse and alternative outcomes (Habarurema et al. 2025). Such interdependencies can enable learning that results in new ways of assembling expertise. For example, Raisch and Fomina (2023) suggest that AI agents can help develop different forms of insight and learning depending on whether they are used autonomously, sequentially or interactively in work, professionals thus needing to learn how to approach such different ways of collaborating with GML. On the other hand, technologies have been shown to potentially disrupt learning processes when they alter key tasks and work practices assumed with expertise development. Anthony (2021) describes how the black boxing effects of AI can lead to worse outcomes when professionals do not scrutinize and understand the outputs of key technologies, junior professionals being particular acutely affected by such black boxing. Sundaresan and Guler (2025) similarly suggest that experiential learning is diluted when algorithms and AI are used in decision-making without scrutiny, reflection, and questioning, this having long-term implications for individuals and organizations as expertise is weakened. Theorizing learning, apprenticeship, and the mastery of expertise in professional work and PSFs thus needs to be extended to consider the different ways that interdependencies with GML enable and undermine learning, the tactics professionals develop to ensure optimal outcomes, and the risks and responses to them.

A key priority for future research is, then, to theorize professional work, knowledge, and expertise in ways that examine the interactions between what machines can know, what they cannot know, and how machines and human professionals together reproduce systems of professional expertise. As we discuss below, how this reinvention occurs is not, however, only dependent on interactions between the particularities of professional knowledge and the agency of machines. As Brown et al. (2024) argue, broader socio-political and economic factors also matter.

PROFESSIONALS' RESPONSES TO GML

The way professionals respond to the potential for technologies to change work and the services offered to clients is another important dimension to consider when examining the effects of GML. This is not only associated with the capabilities or deficits of machines discussed in the previous section of the paper. Political factors are also important as professionals respond to technologies in ways influenced by their interests, priorities, and principles, and also the relationships with technologies that emerge during their adoption.

One of the most prevalent topics in the literature is the tendency for negative responses by professionals to technological change. For example, it has been pointed out how 'epistemic technologies' that (re)configure knowledge production, like AI with its black-boxed status, may be viewed as compromising core aspects of professionals' work (Pachidi et al. 2021; Scarbrough et al. 2025). In addition, professional status has been shown to influence responses to such technologies, with higher-status individuals potentially resisting or appropriating technologies in unforeseen ways (Anthony 2021). Furthermore, ethical dilemmas and controversies are ever present (Wach et al. 2023). From data security to awareness of the 'hallucinations' associated with GML, professionals and their regulators need the ability to minimize the risks of using GML and to understand how to supervise and recognize accountability for the outputs of generative systems (Villasenor 2024; Faulconbridge 2025). Often responses to such risks involve professionals avoiding, being negative about, and critiquing new technologies (McPeak 2018). How might we understand such responses as part of a process of producing new interdependencies between professionals and GML? The existing literature identifies theorizations of four types of responses through studies of algorithmic and extractive machine learning technologies that need to be extended to consider the implications for relationships and interdependencies between professionals and GML.

First, there are questions about well-documented technology aversion in the professions (Allen and Choudhury 2022). When new technologies threaten to disrupt established roles and work practices, professionals respond strategically to preserve their interests (Kellogg et al. 2020; Pachidi et al. 2021), often in the form of contest and resistance (Raviola and Norbäck 2013). Given the potential impacts of GML, an important question is whether and why its implementation is being met with resistance. For instance, while it has been suggested that GML will lead to decreased headcount in PSFs, as fewer professionals are needed, particularly at the junior levels (Sampson 2021), recent studies indicate that use might also increase headcount, due to business growth (Law and Shen 2025). Taking inspiration from Goto's study (2022) on professionals' sensemaking and sensegiving processes around AI, it is important to remember that professionals will make and give sense to GML as part of the process of building new interdependencies. Their sensemaking will be shaped by and shape the interaction between professionals and GML, and this, in turn, might have recursive effects on interaction with other groups of professionals (Scarbrough et al. 2025). Perhaps, as identified in studies of extractive machine learning (Pemer 2021; Goto 2023; Faulconbridge et al. 2025), professionals will identify opportunities and embrace the technology in controlled ways. Or perhaps, as Anthony (2021) notes, when delving into the 'black boxing' of algorithmic technologies, the opacity of AI systems' inner workings and the lack of transparency will create trust issues and concerns about professional responsibilities and ethics that provoke hesitancy and resistance to use (see e.g. Remus and Levy 2017; Hagendorff 2020; Seethamraju and Hecimovic 2023; Eisikovits, Johnson and Markelevich 2024; Trincado-Munoz et al. 2025).

A second theme relates to effects of and on professional identity. Professional identity is recurrently said to answer the questions of 'who we are' and 'what we do' as professionals (Pratt et al. 2006). In particular, there is a strong connection between professionals' work and their identities (Anteby et al. 2016). Consequently, changes to the work of professionals because of machine learning can disrupt identities, leading to efforts to conserve existing identities or 'park' existing identities and produce new ones (Nelson and Irwin 2014; Chen and Reay 2020). There are also recursive effects to explore:

professional identity can impact how professionals enact their work in response to digitalization (Pemer 2021), but the use and interpretation of technology can also reconfigure professional identity on a collective level (Goto 2021). In particular, as GML can be used not only for diagnosis, but also for inference and treatment (Abbott 1988), generating reports, advice, and predictive analyses, the question of 'what we do' as professionals becomes more complicated to answer. Professionals may seek to use GML to automate routine tasks whilst staying in command of the analytical and advisory tasks, perhaps seeing GML as a colleague (Einola et al. 2024). For example, Pemer and Werr (2025) show how auditing firms engage in creative accumulation to develop the skills needed to keep up with technological developments and the use of machine learning in ways that feel controlled by professionals and unthreatening to identities. Hence the adoption of GML, whether perceived as leading to the deskilling of professional work (Sampson 2021; Eisikovits et al. 2024) or an opportunity to reinvent professional work (Reay et al. 2017; Faulconbridge et al. 2024), seems likely to be part of a process that results in professional identities becoming entangled with how GML is and is not used, this entangling in turn having effects on the kinds of interdependencies between machines and humans that emerge.

A third theme is the protection of professional jurisdictions and boundaries. Professions protect their financial and political interests through systems of closure and boundaries that restrict access to certain types of activity (Freidson 1970; Johnson 1972; Larson 1977). Boundaries 'define a profession's access to material and nonmaterial resources such as power, status, and remuneration' (Bucher et al. 2016: 498). They also separate different professions and differentiate between professional and nonprofessional work. New technologies can disrupt boundaries when they allow nonprofessionals to perform what was previously defined as professional work (Petrakaki et al. 2016) or when they unsettle boundaries between different professions (Faulconbridge et al. 2021). In response, professionals can respond by 'boundary work' (Langley et al. 2019), which involves 'purposeful efforts of professional groups and their members to influence the boundaries between professions' (Weber et al. 2022: 2). Faulconbridge et al. (2024) highlight the way the boundaries of professions can change when forms of extractive machine learning allow new types of services. As some tasks are automated by machine learning, new tasks emerge that use the outputs of AI to inform new services and domains of expertise that a profession colonizes. Similarly, Waardenburg et al. (2022) illustrate how 'algorithmic brokers', a new group established to help dissolve and overcome knowledge boundaries within an organization, unintentionally created new boundaries between technology developers and the users. Relatedly, Stark and Van den Broeck (2024) argue that as algorithmic practices are unmediated, enabling clients to interact directly with GML instead of with professionals to access expertise, professional jurisdictions become circumvented and lose importance.

An important question is, then, how GML technologies potentially play a role in the processes of reshaping and disrupting boundaries and how professionals enact and respond to such disruptions. The way that boundaries evolve will also have implications for the financial and political interests of professions and relationships with other professions, occupations, and GML itself (Bailey et al. 2022; Hinds and Von Krogh 2024). We may see professionals seeking to protect and maintain existing boundaries as a defensive move against GML and the threat that machines or 'nonprofessionals' working with machines can deliver previously protected services. This could also mean that professionals seek to redefine and extend their boundaries, potentially through competition with other professionals in ways that redraw the ecological settlement between different professions. Indeed, relational approaches to professions (Abbott 1988, 2005; Eyal 2013; Seabrooke and Tsingou 2015) remind us that it is the way different groups of professionals coexist, cooperate, and complement one another that results in both recognition of claims to expertise and settlements that define the jurisdictions of different groups. The adoption of GML seems likely to both disrupt and lead to evolutions in the system of the professions and the landscape of PSFs as GML becomes an important actor in systems of the professions.

A fourth theme in the literature, in part related to questions about boundaries, is the effects on collaborations between professionals and other occupations (i.e. nonprofessionals). While a stream of literature has highlighted professionals' unwillingness to collaborate, seeing it as threatening their professional identity (Ahuja 2023) or creating unwelcome dependencies on related professionals such as e.g. digitalization consultants and technology suppliers (Cardinali et al. 2023), another stream illustrates how professionals work with other occupations in ways that are strategically beneficial (see e.g. Currie et al. 2012; Huising 2014; Bryan and Lammers 2020; Kellogg 2022). These collaborations can result in role configurations that are acceptable and beneficial to all the actors involved, leaving professionals with work that they perceive as valuable and meaningful (Rodgers et al. 2023). For example, Faraj et al. (2018) explore how AI reshapes organizational practices, fostering new forms of collaboration and altering traditional ways of understanding expertise. This shift, together with the increased use of GML in decision-making (Stark and Van den Broeck 2024), involves the emergence of new dynamics and collaborative frameworks, where AI plays a role alongside professionals and other actors. In particular, responses to the growing role in PSFs of 'technologists'—those with the skills needed to install, operate, and maintain GML systems—need attention as technologists move from the status of professional support worker to active agent in the production of legal advice and work processes (Glaser et al. 2021; Pemer 2021; Goto 2023; Faulconbridge et al. 2024). Further, these new groups of 'technologists', 'translators', or 'algorithmic brokers' can change established hierarchies and status relations in PSFs (Waardenburg et al. 2022; Faulconbridge et al. 2025; Pemer and Werr 2025). More studies are, therefore, needed to explore how GML creates the conditions for new kinds of collaboration or competition between different professions and occupational groups, and how the knowledge asymmetries between GML and humans, on the one hand, and professionals, 'technologists', and other occupational groups, on the other hand, influence trajectories of change.

Summing up, extant research highlights how new interdependencies between professionals and GML will be influenced by and influence a range of situated factors relating to the specificities of professions and professional work. Research needs to extend theorizations to account for how interdependencies between professionals, their work, and GML are mediated by and change contestation and resistance linked to identity, the un- and resettling of boundaries, and relationships between professions and occupations. The next section of the paper, therefore, considers in more detail how the organizational context in which these interdependencies and professional responses emerge—the PSF—will shape and be shaped by the adoption of GML.

ADOPTING MACHINE LEARNING IN PSFs

As noted earlier, PSFs adopt particular institutional and organizational logics because of how professional work is shaped by individual expertise. In turn, governance and management structures mediate the expression of professional agency and also approaches to technology adoption (Cooper et al. 1996; Faulconbridge and Muzio 2008; Empson et al. 2015; Hinings et al. 2018; Brown et al. 2024). Understanding the implications of the distinctive features of PSFs for how interdependencies with GML emerge and how in turn PSFs themselves evolve is, therefore, crucial. We consider four interrelated areas relevant to theorizations of PSFs: business models; organization and governance; innovation; and client interactions. When considering these areas, we remain alert to both the distinctiveness of PSFs but also variations within the category, such as between 'old' and 'new' PSFs (von Nordenflycht 2010), and the potentially variable effects across different organizations.

Business models, broadly conceived, are concerned with how value is created and captured (Teece 2010), i.e. including operational questions about how processes are configured, encompassing decisions about what expertise is made available to clients and how. In this light, the adoption of GML requires re-examination of how firms configure and distribute tasks and how authority and responsibility are organized. Armour and Sako (2020) argue that machine learning opens the possibility of new business models oriented around scalability, routinization, and process efficiency. For instance, legal operations, stressing efficiency and routinization, become a new focus as efforts to incorporate legal technology require new ways of organizing work. A focus on legal operations could displace formerly judgment-intensive activities as machines are incorporated into professional workflows, particularly in the early stages of professional diagnosis and inference, e.g. drafting, summarizing, and synthesizing documents. Whereas earlier generations of technology were often viewed as tools for use by professionals, GML and its ability to combine, mix, and generate new material means machines participate not merely as a tool but as an actor, generating texts, patterns, and outputs that feed into subsequent human action. In this way, GML acquires a form of conjoined agency (Murray et al. 2021) within the operational core of PSFs that requires reflection upon and extension of existing theoretical understandings of the role of technology. The incorporation of GML alongside human professionals also means questions need to be explored in relation to the emergent balance between the humans and machine and likely implications for the size of the professional workforce, leverage ratios (junior/senior split), capital intensity of firms as they invest in GML, and ultimately offering and modes of delivery of services to clients. Underlying all of these changes will be adjustments to the costs and pricing structures of firms—for example, will the billable hour survive in legal work?

Such questions are important because, as Armour and Sako (2020) note, transformations in business models are often accompanied by shifts in organizational form and governance. Often this is posed as a question about the move from the classic professionalism and partnership (P^2) model to more corporate and hierarchical models that better accommodate technology governance and investment (see also Smets et al. 2017), or more recently as virtual network firms based on digital platforms (e.g. Skjølsvik and Breunig 2018). Developing this theme, Kronblad (2020) revisits Von Nordenflycht's (2010) typology of PSFs to suggest that machine learning adoption weakens the link between knowledge intensity and professional exclusivity. If knowledge becomes more codified and GML assumes larger roles in producing professional outputs, firms may become more capital-intensive and less dependent on highly professionalized workforces. The traditional basis of professional authority, grounded in esoteric knowledge and institutionalized credentials, is challenged by new hybrids of human–machine production. From an agency-theoretic perspective, this creates novel forms of distributed agency within the firm that governance structures need to respond to: decisions and actions are now outcomes of interactions between professional judgment and nonhuman generative systems. This raises a profound question: are PSFs potentially 'no longer special', in the sense that they no longer need to be governed by professionals, partnership, and in ways distinct from other organizations (Kronblad 2020: 519)?

Studies of earlier generations of technology suggest that the evolutionary, sedimented, and hybrid approaches (Cooper et al. 1996; Smets et al. 2017) adopted in PSFs in response to other challenges and opportunities are most likely to emerge. For example, Coombs et al. (2020) point to the need, alongside investment in technology, to consider complementary investments (c.f., Teece 1986), principally in human skills and capabilities, with new conjoined agency between humans and machines needing to be facilitated. Meyer et al. (2020: 154) argue that 'complementary, complex skills wherein human capital and AI build each other to increase the firm's knowledge stock of both forms of intellectual capital will provide sustained competitive advantages to PSFs, particularly those in B2B PSF sectors'. These examples suggest that, just like professionals need to find ways to accommodate GML and reinvent their work practices, PSFs need to find ways to organize and govern that are responsive to interdependencies between GML and human professionals. This will include addressing questions about workforce composition, i.e. whom to employ alongside professionals, in what roles, and how to evaluate and develop them. Do firms prioritize hiring individuals with hybrid competences, those able to work effectively with and through AI systems, or develop parallel groups of AI specialists and professionals who cooperate and collaborate?

Cumulatively, such considerations raise further questions about how PSF organize around multifunctional teams and alternative career models (Rodgers et al. 2023); bear in mind that 'teams' in this instance might better be understood as assemblages that incorporate both human and nonhuman actors. Organizational theorizing must, therefore, account for how distributed agency across human–technology teams alters authority, collaboration, and accountability structures and in turn ways of governing whether through partnership or other forms (Empson and Chapman 2006). The effects are likely to differ depending on starting points, e.g. between 'old' and 'new' PSFs, and also within categories, such as between alternative business structure (sometimes private equity owned) and traditional partnership PSFs. Crucially, though, across all contexts, GML and its ease of access and use are changing who is involved in the production and delivery of professional services. Faulconbridge et al. (2024) note that 'technologists'—those with knowledge and skills needed to use AI effectively—are increasingly part of both producing and delivering advice to clients in law firms with collaboration between technologists and lawyers being key to accommodating AI in work processes. Dodgson et al. (2022) similarly found that in accounting firms AI is leading to increased workforce diversity with over 3,000 employees at PricewaterhouseCoopers working in technology, resulting in experimental ways of working as accounting professionals and technology specialists find ways of working together to adopt AI. Such developments have implications for power dynamics within PSFs as technologists become critical to the success of firms, alongside professionals, thus potentially unsettling assumptions about autonomy, control, and status.

Relatedly, GML also necessitates reconsideration of how PSFs structure innovation itself. Goto's (2023) concept of 'anticipatory innovation', i.e. a shift towards more top-down, corporate approach to innovation, suggests that larger PSFs are developing formal structures to integrate emerging technologies. Yet innovation is not solely a structural matter. Dodgson et al. (2022) emphasize the need for distinctive leadership practices and the creation of intellectual and experimental spaces—both conceptual and physical—to promote innovation. Whether PSFs adopt centralized, top-down management to set polices and principles for adoption or enable bottom-up, practice-led experimentation is a key site of organizational contestation and part of changes to governance in PSFs. Decisions around top-down standardization versus local adaptation are also shaped by contextual factors such as sectoral regulation, internal epistemic cultures, and firm-level risk tolerance (Hinings et al. 2018; Coombs et al 2020). In practice, firms may oscillate between containment strategies, where GML is carefully circumscribed within policy frameworks, or exploratory approaches, where professionals are encouraged to experiment with cyborg-like assemblages (Dell'Acqua et al. 2023; Mollick 2024). What all this means for the PSF as an organizational form and the number of 'variants' of PSF compared with those already recognized in the literature (Empson and Chapman 2006; Malhotra and Morris 2009; Von Nordenflycht 2010) is thus a crucial pathway for extending theorizations of the PSFs in the GML age.

Finally, GML also potentially reconfigures the interface between PSFs and their clients. For professionals, the relationship with the client has always been sacrosanct (Anderson-Gough et al. 2000) and fundamental to relational expertise whereby interactions with the client allow the generation and application of expertise in ways that are effective, contextualized, and supportive of the client's interests (Pakarinen and Huising 2025). Studies of other technologies have also shown that professional–machine interdependencies often emerge in response to the perceived needs, best interests, or demands of clients (Bourmault and Anteby 2023; Pemer and Werr 2025). In many ways, then, GML will lead to the persistence of the eternal question of whether to compete on cost and process efficiency enabled by technology or on differentiation through distinctive client service and interactions with human professionals. GML will, though, also be different because it can potentially play a role in both types of offering, depending on how it is used alongside human professionals. For instance, GML tools may generate draft reports that professionals work from and adapt before delivering to clients, and/or support chatbot-style client exchanges directly with clients who consume the outputs of GML (see Table 1). PSFs will need to decide whether to choose between one approach or another or to combine them. Indeed, some argue that GML has the potential to dramatically improve customer experience and service quality, as well as productivity, all at the same time (Paluch and Wirtz 2020). Will this be harnessed to enable high-skilled professionals to focus on inter-personal, creative, and bespoke service activities (Coombs et al. 2020; Paluch and Wirtz 2020) that sit alongside GML-enabled client self-service? And with what implications for both understandings of professions-client relations and ways of organizing PSFs to deliver such hybrid arrangements? The route forward is not yet clear, but GML presents at least the possibility—at the jagged frontier discussed earlier—that some client interaction tasks can be delegated to technology, depending on decisions about how to adopt. But, perhaps counterintuitively, this might further the commitment of professionals to relational expertise (Pakarinen and Huising 2025), as well as the more commonly hypothesized outcome of professionals being replaced by machines (Susskind and Susskind 2023), if ways of combining human and machine agency are developed.

Organizations are, however, conscious about the negative effects that new interdependencies between professionals and GML might have on service provision. Flavián et al. (2022) found that, specifically when customers worry about the harmful consequences of technologies, they might avoid making use of the service provided. With GML and the ethical, data security, and 'hallucination'-related issues discussed earlier, such concerns are very real. As Meyer et al. (2020) warn, technology adoption must be not only technically competent but also strategically appropriate to avoid the alienation of clients. The boundary, therefore, between productive delegation, collaboration, and interdependency with GML and inappropriate substitution is constantly being redrawn, shaped by organizational learning, client feedback, and professional norms. This evolving boundary will be important as PSFs navigate in common but also differentiated ways depending on their starting point—e.g. old versus new PSFs; alternative business structures versus traditional partnerships etc.—towards new ways of organizing and governing, feeding back into the discussions above of business models, organizational forms, and governance.

Overall, then, studies indicate that GML can be expected to disrupt the business models of PSFs, challenging current economic models, organizational strategies, and governance. New ways of approaching innovation, resulting in changes to services and potentially new ways to engage and interact with clients, will further feed into adjustments to how PSFs are organized. All of this will emerge as interdependencies between professionals and GML redefine core features of PSFs as organizations, requiring extensions of theorizations of PSFs to account for continuity and change associated with organizations that are defined by the dynamics of GML–professional–client relations (Scarbrough et al. 2025). It seems likely that diversity within the PSF category will grow—influencing and resulting from how interdependencies with GML develop. Most crudely, this might involve variations between 'old' and 'new' PSFs. More subtly, variations between firms with, amongst other things, different funding (e.g. partnership equity versus private equity) and governance (e.g. full partnership versus approaches mimicking partnership but delegating authority to management boards versus corporate hierarchies) arrangements will need theorizing. GML is, then, likely to be a key actor in the next stage of the evolution of PSFs and thus needs to be central to how theorizing of PSFs is extended and reworked.

DISCUSSION—THEORIZING GML IN PROFESSIONAL WORK AND PSFS

This paper aims to address the need for an understanding of how to approach theorizing emerging interdependencies between GML, professional work, and PSFs. We reveal the ways that the situated contexts of professional work and organizations will both affect how GML is responded to by professionals and be affected by new interdependencies that emerge. Specifically, building on research that argues that professional work will be distributed in a network of actors that include GML, human professionals, institutions, organizations, clients, and others (Glaser et al. 2021, 2024; Heimstädt et al. 2024; Pakarinen and Huising 2025; Scarbrough et al. 2025), we expand discussions beyond the specificities of machine learning as a technology and consider ways of theorizing some of the key interactions between the technology and situated field, individual/group and firm level contexts.

Table 2 outlines how in our three interrelated areas of focus—professional work and expertise (field level), professional responses (individual/group level), and PSFs (firm level)—existing questions about the impacts of digital technologies need to be extended and reworked to account for the specificities of GML. Underlying the analysis in Table 2 is an approach that recognizes the need to conceive of GML as a technology that interacts with professional work and organizations in ways that are distinctive compared to earlier generations of algorithmic technology (Glaser et al. 2024; Hinds and Von Krogh 2024; Stark and Van den Broeck 2024).

Table 2 begins by exploring how understandings of expertise need to evolve. Recognizing the role that GML will play in relational assemblages means considering the interactions between different actors and the factors influencing interactions. For example, as Glaser et al. (2021) argue, understanding interactions between what technology providers imagine and design into GML applications (whether in generic applications like Microsoft CoPilot or more profession-specific applications) and the way professionals and other actors encounter and conceive of the deficits and/or possibilities to work with GML will be important. These interactions will influence how GML is incorporated into expertise assemblages and also how we come to understand the future role of human professional expertise. Similarly, the way different diagnosis, inference, and treatment tasks evolve in interaction with GML could be an important starting point for analysis. Indeed, it will be important to explore whether distinctions between diagnosis, inference, and treatment tasks and relatedly between automation and augmentation remain useful as new interdependencies emerge between professionals and machines. The discussion in Table 2 about expertise reveals, then, the need to extend theorizations in ways that help us understand the form, claims to, and exercising of expertise in the GML age.

Table 2 also considers how professional work will evolve. As an epistemic technology, GML will play a key role in reconstituting how professionals work to generate and apply knowledge for and to their clients. This reconstituting role has implications for professionals, given the need to respond to the black-box nature of the technology and associated risks. How to theorize the interdependencies between professionals and GML in ways that reveal the factors influencing the depth, role, and impact of interdependencies, including any variations between different types of professional work (e.g. accountants versus doctors)? It also means that combinations of evolving professional identity, boundary constructions, relations with other occupations, as competitors or collaborators, and the need for technological expertise in professional work will affect how professionals embrace, resist, and seek to control the use of GML. Professions will themselves be reformed by combinations of these reactions and the new interdependencies that emerge. This will occur in dialectical fashion with the evolutions in expertise assemblages outlined in Table 2. For instance, competitive, collaborative, configurational, and intertwined boundary work (Langley et al. 2019; Faulconbridge et al. 2025) seems likely because of the way GML unsettles expertise claims and forms of work that underlie ecological settlements between different professions and occupations. An approach is needed, then, to extend and redirect theorizations to offer both a generic approach for analysis across professions, but also insights into variations emerging between professions and types of professional work.

At the same time, PSFs as organizing entities will play a role in and be affected by the adoption of GML. Extending and (re)developing understanding of the business model of firms, how this translates into differentiated roles for professionals and other occupational groups, and new means of delivering advice to clients will be crucial. Relatedly, the need to (re)configure PSFs to allow the use of GML and the implications for

Table 2 Implications of GML for theorizing professional work and PSFs.

	Expertise assemblages	Professional work assemblages	Firm assemblages
Key theoretical perspectives from studies of earlier generations of technology	Expertise as relational—multiple actors interacting to assemble and claim expertise (Abbott 1991; Eyal 2013; Anthony et al. 2023). Implications for 'what machines can't know' when relational dimensions get lost in algorithmic logics (Anthony 2021; Pakarinen and Huising 2025) Professional work as comprised of multiple interrelated tasks with differing roles for technology (Zuboff 1988; McKendrick 2018; Faulconbridge et al. 2024), raising questions about automation-augmentation dynamics (Raisch and Krakowski 2021) The deficits and opportunities for delegation to technology that inform approaches to incorporation into work (Lebovitz et al. 2022; Mollick 2024) and how these affect perceptions of the technology (Allen and Choudhury 2022; Scarbrough et al. 2025)	Technology reconfiguring existing work assemblages (Chen and Reay 2020; Anthony 2021), particularly when epistemic technologies change knowledge production (Pachidi et al. 2021; Scarbrough et al. 2025) Contestation and resistance when work that is valued, meaningful, tied to identity, and claims to expertise is disrupted (Raviola and Norbäck 2013; Nelson and Irwin 2014; Kellogg et al. 2020; Yang et al. 2024) Sensemaking and adapting to the way technology reconfigures work (Pemer 2021; Goto 2022), professional boundaries (Waardenburg et al. 2022; Faulconbridge et al. 2024), and relations with other occupations (Huising 2014; Faraj et al. 2018; Bryan and Lammers 2020)	Technologies configure operational tasks, value capture, and client offering in ways that challenge assumptions underlying how PSFs organize (Smets et al. 2017; Armour and Sako 2020; Kronblad 2020) The human staff constitution of firms and teams within it are challenged when technologies remove the need for some skills and create a need for new skills (Waardenburg et al. 2022; Rodgers et al. 2023) Technology inspires and requires greater coordination of tasks, processes, and roles with implications for organizational governance (Armour and Sako 2020; Rodgers et al. 2023) Client interactions and service delivery modes challenged with questions about what to deliver, how to deliver it to clients, and the role of interactions between human professionals and clients (Flavián et al. 2022; Susskind and Susskind 2023)
Theoretical questions posed by GML	How do GML work alongside other actors in the assembling of expertise? And what are the implications for understandings of human expertise and its forms, locus, and distinctiveness What parts of the diagnosis, inference and treatment process—does GML impact most, and does the distinction between the three hold? What does the mix of tasks for human professionals look like when GML is used? What variations emerge between professions/types of professional work? Is automation-augmentation a useful distinction, or are different ways of conceptualizing the assemblage of machine–human actors and agency needed? What will assemblages in which GML acts and interacts with professionals look like? How will machines and	How to theorize the responses of professionals to the agency of GML, its effects as an epistemic technology with black-box characteristics, and the implications for the socio-materiality of professional work? How do responses vary between professions, types of work, and PSF forms? Do different groups of professionals (e.g. juniors versus seniors) respond in similar or dissimilar ways to GML, and if they do, what invokes the different responses? How do professionals understand their role in an assemblage of human–machine relations and in evolving professional	How to theorize the changing business models, organization, and governance of PSFs when GML is a key component of expertise production and delivery, both directly and indirectly in client interactions? How useful is the 'old' and 'new' professions distinction in understanding variations between firms? Is the distinction dissolved in the GML age? How to theorize the relational interdependencies between professionals and other occupational groups within PSFs when GML blurs boundaries? What are the implications of more coordinated innovation, work process design, and technology adoption

(*continued*)

Table 2 Continued

	Expertise assemblages	Professional work assemblages	Firm assemblages
	professionals work in ways that synergize strengths and compensate for one another's weaknesses?	ecologies/boundaries? And what does such hybridity mean for theorizing professional identity? What are the boundary work implications of GML as the content generated, and new opportunities afforded to different groups who work with GML to claim expertise, potentially challenge existing jurisdictional claims of professionals? And how might this agency of GML reorganize professional ecologies? What do revised theorizations of professional ecologies mean for how we understand linked ecologies in which different groups cooperate and collaborate? How does GML create new collaboration and/or competition—for example, involving those who design, manage, and operationalize GML technologies?	approaches, necessitated by GML, for the continued evolution of P^2 and the distinctive governance of PSFs? How do the implications vary between firm types and why? Which PSFs will find (and which will struggle) to evolve their business models? Will evolution be within existing firms or through new firm types that emerge 'born-AI ready'?

governance and some of the key principles underlying P^2 forms of governance, and professional autonomy in particular, raises questions about how to (re)theorize the PSF as a distinctive organizational form. Which forms of organizing become less common, extinct, or superseded? How will variety within the PSF category develop, and how will different varieties (e.g. 'old' versus 'new' PSFs; partnerships versus corporate forms) evolve? What kind of organizational forms might supersede the forms we currently find? These kinds of questions render theorizations of the evolution of the P^2 approach (Smets et al. 2017) more important than ever.

Whilst Table 2 presents the three areas separately, there are also key interactions between the three levels, given that changes to expertise can invoke and result from changes in professional work: firm assemblages being similarly intertwined with any changes to expertise and work. Table 2 seeks, then, to provide the starting point for asking new questions about conjoined agency (Murray et al. 2021) between GML and professional expertise, work, and firms, and about the implications for the (re)development of existing theoretical perspectives to take account of the recursive forms of change that emerge.

CONCLUSIONS

By examining the way that the distinctive characteristics of GML can be understood by extending existing theoretical approaches to expertise, professional work, and PSFs, we provide a way of studying the future of the professions in the GML age. Our approach seeks to take seriously the many factors that will influence the emergence of interdependencies between human professionals and GML. Our discussion highlights that, on the one hand, we can theorize change as an extension of the change already witnessed with digital, algorithmic, and extractive machine learning technologies. However, our discussion also shows that, on the other hand, the way we theorize change must be sensitive to the specificities of GML and the changes likely to emerge as interdependencies emerge between GML and professional work and PSFs that have distinctive consequences.

Limitations

The arguments in this paper are limited by the paucity, at the time of writing, of empirical studies of GML in professional work and PSFs. Existing theory provides pertinent questions, foci, and analytical frames. But revisions to theory will require responsiveness to currently hard-to-predict evolutions that, as they emerge, should be historicized but also used as the spur for generating the next iteration of theorization. The approach here, focused on three levels (field level and knowledge; individual/group level and professional responses; firm-level and the organizing of professional work), also creates a somewhat artificial split between the different levels of analysis. As understanding of the impacts of GML evolves, greater consideration will be needed of the systemic implications of changes that cut across the different levels. This will mean posing questions about how changes to knowledge, work, and PSFs together have implications for power relations, boundaries, and fundamental understandings of expertise and professions. Returning to foundational debates, such as those inspired by Abbott (1988) about the system of the professions and Eyal (2013) about expertise will be required to account for the implications of GML as an actor that configures and reconfigures the role, practices, and status of professions and experts in society.

Our analysis here and the framework outlined in Table 2 provide the building blocks for developing an understanding of the changes likely to emerge that can inform such wider reflections on the systemic nature of change and the implications for theorizing professions and organization.

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Data availability

Due to ethical and commercial issues, data underpinning this publication cannot be made openly available.

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