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Using algorithms to improve knowledge work

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Abstract

We explore how organizations leverage algorithms to improve knowledge work in contexts where the tasks require skilled work, as distinct from routine tasks that have traditionally been the focus of academic enquiry. Drawing on a multiple-case study of four business areas in a multinational energy firm undergoing a digital transformation, we find that contrary to what the literature predicts, tasks that require skilled work can also benefit from the adoption of algorithmic solutions. To benefit, business areas engaged in two distinct pathways for transforming knowledge work. The first focuses on automating a specific task, replacing human activity with algorithms in a single task. The second involves re-engineering an entire process, whereby sequences of steps adjacent to the task at hand are redesigned on integration of an algorithm. We find that these pathways have different effects on the ability to improve knowledge work, suggesting that alignment between the task and the pathway chosen is crucial to realizing any improvement. We also find that the ability to sustain any improvement depends on the adjustment of the knowledge regime—the practices and structures that sanction knowledge. Building on these findings, we propose a general process model for the adoption of algorithmic solutions in knowledge work. In the wider context of the future of work debate, our findings challenge the prevailing notion that a task's skill requirements determine the extent to which knowledge work can be improved by algorithmic solutions.

KEYWORDS

future of work, knowledge work, machine learning, process improvement, robotic process automation

HIGHLIGHTS

- When using algorithms to improve knowledge work, there are two choices: to automate a given task or to re-engineer the entire process.
- Re-engineering the process tends to yield greater operational improvements.

- Socializing and validating the algorithm's outputs tend to increase their acceptance.

1 | INTRODUCTION

The digital transformation of organizations is reshaping the nature of knowledge work—a type of work that requires human expertise to make meaningful decisions that add value for organizations (Bechky, 2006; Davenport, 2015; Staats et al., 2011; Starbuck, 1992). Key to this transformation is adopting "modern algorithmic solutions" (Angelopoulos et al., 2023), formally defined as systems that autonomously learn from data and mimic human decision-making (Angelopoulos et al., 2023; Bailey et al., 2019; Bailey & Barley, 2020). Examples include machine learning (ML) for predictive modeling, as well as generative artificial intelligence (AI) systems like Claude and ChatGPT. Hereafter we will refer to these solutions simply as "algorithms." Across sectors that include law, healthcare, and manufacturing, organizations have widely adopted algorithms to transform knowledge work, and in turn, create a competitive advantage by reducing costs, enhancing quality, speeding up delivery, and/or improving the safety of knowledge work performed in organizations (Sako et al., 2022; Sampson & dos Santos, 2023; Senoner et al., 2022; Spring et al., 2022).

However, the effectiveness of algorithms in realizing these benefits is still widely debated (Brynjolfsson et al., 2019). Prevailing economic studies suggest that algorithms can boost productivity in routine work, but they may not have the same effect in knowledge work (e.g., Autor et al., 2003; Autor & Salomons, 2018; Frey & Osborne, 2017). The argument is that human skills crucial for knowledge work, such as creativity, social intelligence, and dexterity, may withstand automation. Hence, emerging sociological and learning studies on the practical use of algorithms under the labels of "learning algorithms" (Faraj et al., 2018), "modern epistemic technologies" (Anthony, 2018), "intelligent technologies" (Bailey & Barley, 2020), and "artificial intelligence" (Lebovitz et al., 2021), tend to focus on the implications (and perils) of algorithms for how experts build their understanding of a topic to make decisions (Anthony, 2018; Lebovitz et al., 2021; Waardenburg et al., 2021). One of their concerns is that replacing human expertise with algorithmic solutions may hinder learning and performance in the long run (Balasubramanian et al., 2022). The question that remains, and that is the focus of our investigation, is how an organization can adopt algorithmic solutions to create and sustain improvements in knowledge-intensive tasks that require skilled work.

In response, we conducted a multiple-case study focused on the adoption of algorithmic solutions in a multinational energy firm, hereafter referred to as *ACME*. Our study encompassed four distinct business areas within ACME, representing Davenport's (2015) segments of knowledge work: business services (as "transactional work"), internal audit (as "collaborative work"), maintenance (as "integrative work") and drilling engineering (as "expert work"). Each area was a case study designed to explore how variation in actual skills, tasks, and knowing practices influence technological change—a variation otherwise obscured in occupational databases (Bailey & Barley, 2020). Within each case, we identified one or two significant projects involving ML and robotic process automation (RPA) algorithms. These projects served as focal points to examine the subsequent transformation of knowledge work and its impact on operational performance. To build our cases, we conducted 55 semi-structured interviews over 2 years with staff and managers of these business areas. Additionally, we supplemented our data through detailed notes from participant observations and analysis of internal performance reports.

Our research contributes to the wider debate on the digital transformation of work, giving scholars and practitioners a better understanding of how organizations create and sustain operational improvements with algorithms in knowledge work involving skilled decision-making (Angelopoulos et al., 2023). Specifically, we make three key contributions. First, we challenge the perception that task skill requirements dictate the extent of algorithmic improvement in knowledge work. Instead, we argue that any improvement depends on how organizations transform the work in which tasks are embedded. This expands on the notion that technologies intertwine with organizational norms, rules, and practices (Faraj & Pachidi, 2021; Orlikowski & Barley, 2001), with benefits depending on transformations being seen in context. Second, we advance a novel perspective on technological change by identifying a model of algorithm adoption with two pathways: (1) "automating the task" by substituting human activity within a specific task, and (2) "re-engineering the process" by redesigning adjacent step sequences. We found that these pathways produce different outcomes for creating and sustaining operational improvements: While the reengineering pathway generally leads to greater operational improvements, there is evidence that the task automation pathway is often preferred as it matches institutional inertia and is simpler to implement. Finally, we connect process improvement and knowing-in-practice literature to explain how improvements are created and sustained depending on the transformation pathway that organizations follow. We conclude by discussing how our findings can inform managers on how to deliver the best outcomes promised by algorithmic use.

2 | THEORETICAL BACKGROUND

2.1 | The role of algorithmic solutions in improving knowledge work

Since the second half of the 20th century, knowledge work and technology have become central themes in organizations (Barley & Kunda, 2001). Unlike manufacturing labor, knowledge work involves primarily mental rather than physical effort (Bechky, 2006), manipulating knowledge and information to create value for the firm (Davenport, 2015; Starbuck, 1992). Formally defined, knowledge work requires the "ability to draw distinctions, within a collective domain of action, based on an appreciation of context or theory or both" (Tsoukas, 2005, p. 123). This work[1] plays a pivotal role in various occupations, including healthcare professionals (Harvey, 2016), software developers (Staats et al., 2011), and financial analysts (Cetina, 2010). In these contexts, knowledge is "(…) the critical input in production and primary source of value" (Grant, 1996, p. 112). Integral to knowledge work is technology, which shapes the practices through which workers construct, refine, and disseminate knowledge (Anthony, 2018; Bailey et al., 2010; Cetina, 1999). Commonly cited examples include drug discovery (Dougherty & Dunne, 2012); strategy-making (Kaplan, 2011), and product development (Kellogg et al., 2006).

With the rise of novel algorithmic solutions, especially those built on artificial intelligence, organizations are increasingly exploring how best to use these tools to enhance knowledge production, aiming for greater efficiency and competitive advantages (Armour & Sako, 2020; McAfee & Brynjolfsson, 2012). Algorithmic solutions are computer-programmed procedures designed to emulate decision-making (Kellogg et al., 2020) and differ fundamentally from traditional technologies (Bailey et al., 2019; Bailey & Barley, 2020; Benbya et al., 2021): they learn to make predictions from existing patterns in data (Agrawal et al., 2018), which minimizes the need of codifying tacit organizational knowledge into explicit rules. Prominent examples include ML and RPA algorithms. The ability to learn and, potentially, act, autonomously expands the spectrum of roles that algorithmic solutions play in organizations (Angelopoulos et al., 2023), offering a wider range of possibilities to improve knowledge work.

These possibilities can be understood from three distinct perspectives. The first perspective is economic, viewing algorithms as replacements for workers in tasks or, in some cases, jobs (Arntz et al., 2016; Dellot et al., 2019; Manyika et al., 2017; Muro et al., 2019). Algorithmic solutions are posited as a cornucopia of automation opportunities that bring about uniform effects in the labor market, resulting in similar organizational structures and work patterns across various organizations. For instance, Frey and Osborne (2017) argue that algorithmic solutions expose 47% of current employment to a high risk of computerization. From this perspective, the improvement of knowledge work involves reducing labor input or enabling labor arbitrage, such as automating back-office tasks (Lacity et al., 2016; Lawrence et al., 2016) and professional duties (Spring et al., 2022; Susskind & Susskind, 2016).

The second perspective is sociological, considering algorithms as interconnected with organizing (Faraj et al., 2018; Faraj & Pachidi, 2021; Huysman, 2020). Drawing on contingency theory (Thompson, 1967; Woodward, 1965) and technology studies (Barley, 1986; Orlikowski, 1992), scholars argue that algorithms are entwined with organizational norms, rules, and actors (Faraj & Pachidi, 2021); this can result in two organizations encountering the same solution realigning roles and structures in different ways (Barley, 1990). From this point of view, organizations improve work when they use technology to align structure and function (Hayes & Wheelwright, 1979a, 1979b). For example, organizations may strategically restructure work, enhancing certain tasks while simplifying, automating, or centralizing others (Sampson, 2021).

The third perspective is informed by a learning lens that regards algorithms as possible blocks to learning and performance when used injudiciously in knowledge work (Balasubramanian et al., 2022; Choudhury et al., 2020). This viewpoint stresses that people often mistakenly treat algorithmic outputs as objective truths, disregarding that algorithms are trained on expert judgments that contain uncertainty and flaws (Lebovitz et al., 2021). Furthermore, it highlights the challenges people face in validating the quality of algorithmic outputs, as opaque calculations and assumptions underlie them (Anthony, 2018). For instance, radiologists using AI solutions experienced greater diagnostic uncertainty when AI recommendations diverged from their judgment without explanation (Lebovitz et al., 2022). While organizations may create roles to interpret and translate the outputs of algorithms, unintended consequences can emerge, like substituting personal views for algorithm explanations (Waardenburg et al., 2021). Such issues further limit the usefulness of algorithms in knowledge work.

2.2 | A "knowing-in-practice" view of improving knowledge work

While economic, sociological, and learning perspectives have been instrumental in understanding the digital transformation of knowledge work, they fall short in explaining when organizations succeed or fail to harness algorithmic solutions to improve knowledge work. To bridge this theoretical divide, we borrow a theory from organizational studies known as "knowing-in-practice." This theory views knowledge (or "knowing") as an ongoing accomplishment located in social practices (Nicolini, 2011; Orlikowski, 2002; Tsoukas, 2005). Rather than considering knowledge as a static capability or an individual trait, it is seen as an ongoing achievement that continually evolves as people engage in normatively structured practices (Hadjimichael & Tsoukas, 2019; Orlikowski, 2002; Østerlund & Carlile, 2005). We consider this perspective as particularly relevant for examining the operational performance implications of utilizing algorithms due to its focus on practical and empirical observation.

We focus on two specific aspects of knowing-in-practice: first, knowing-in-practice encompasses the recognition that intelligently performing work hinges on both the individual's factual knowledge (the so-called "know-that") and the individual's accumulated expertise (the so-called "know-how") rooted in social and tacit practices (Lebovitz et al., 2021; Ryle, 1949). For instance, project managers "know that" following risk identification procedures is essential for a successful project delivery. At the same time, project managers also need to "know how" to assess and communicate potential risks, grasp contextual uncertainties, and navigate the intricate dynamics with the project team. This process goes beyond mere rule-following and involves integrating subsidiary elements (e.g., effective communication) and focal awareness (e.g., project risks) (Polanyi, 1967; Tsoukas, 2012). The interplay between "knowing that" and "knowing how" plays a pivotal role in harnessing the potential benefits of using algorithmic solutions in knowledge work. This points us to the challenges that organizations may face when codifying situated knowledge into algorithms, often resulting in the development of algorithmic solutions that overlook critical contextual aspects and ultimately fail to yield the desired performance improvements (Choudhury et al., 2020).

Second, adopting a knowing-in-practice perspective involves acknowledging that knowing how to perform a task is embodied in individuals' skills (Dreyfus, 2014; Hadjimichael & Tsoukas, 2019; Sandberg & Tsoukas, 2011). Through continuous practice (repetition), people develop skills as they train their bodies "to relate in certain ways to the world" (Tsoukas, 1996, p. 17). These skills are honed by participating in occupational communities, where individuals internalize legitimate forms of action and norms that define how to work (Hutchins, 1995; Lave & Wenger, 1991). This includes assimilating a shared purpose, vocabulary, and a set of values that guide and legitimize their actions (Kellogg et al., 2006; Wenger, 1999). A knowing-in-practice perspective recognizes that skills represent people's collective, shared taken-for-granted ways of doing things, which are difficult to capture in algorithmic solutions.

Previous studies have suggested that certain skills such as creativity, social intelligence, and manual dexterity are difficult to codify into algorithms (Frey & Osborne, 2017). Creativity, the ability to generate novel and valuable ideas (Amabile, 1983), is important in knowledge work to understand and explore problems with variable inputs, processes, or outputs (Schmenner, 1986). Designing customized services or dealing with uncertainty requires creativity (Kellogg & Nie, 1995; March, 1991; Staats et al., 2011), especially in contexts involving risk-bearing decisions (Harvey, 2016; Schmenner, 1986). Social intelligence, involving navigating social situations by recognizing cues, understanding emotions and intentions, and responding appropriately, is critical for knowledge work that requires high customer engagement (Brandon-Jones et al., 2016; Lewis & Brown, 2012). It enables customer problems to be diagnosed and solutions to be suggested (Abbott, 1988; Schmenner, 1986; Silvestro et al., 1992). The quality of the solution depends heavily on the service provider's ability to interact and gather the necessary information to identify and understand the client's specific problem. Finally, manual dexterity, coordinating movements of fingers or hands to manipulate and assemble objects is essential for building skill and obtaining legitimacy at work (Beane, 2019; Sergeeva et al., 2020). Thus, in practice, creativity, social intelligence, and dexterity remain skills that are highly valuable but challenging to codify into algorithms (Sampson, 2021).

2.3 | Synthesis

The literature highlights the potential for organizations to adopt algorithms to improve knowledge work, while also raising concerns about undermining organizational learning and the creation of value (Anthony, 2021; Balasubramanian et al., 2022; Lebovitz et al., 2021). We explore this tension by incorporating insights from distinct perspectives discussed above. From economic studies, we recognize that algorithms affect tasks rather than entire occupations, as some tasks are more amenable to automation (Acemoglu & Autor, 2011; Autor et al., 2003). From sociology studies, we acknowledge that these tasks are situated in organizational contexts, with similar algorithmic solutions transforming work in different ways, and with different consequences for operational performance (Bailey et al., 2019; Bailey & Barley, 2020; Faraj & Pachidi, 2021). From learning studies, we recognize that any transformation in the way organizations produce knowledge may affect learning and performance (Lebovitz et al., 2021).

Incorporating these insights into a "knowing-in-practice" perspective, we empirically explore whether, and how, knowledge-intensive tasks can benefit from algorithmic solutions. This involves recognizing a key challenge that has traditionally been theorized as impeding the use of algorithms in knowledge work. That is, performing a task requires a combination of factual knowledge ("knowing that"), practical expertise deeply rooted in social practices ("knowing how") (Lebovitz et al., 2021, 2022), and embodied skills (Sergeeva et al., 2020). Given the exploratory nature of our study, we kept a broad research question: how can an organization adopt algorithmic solutions to create and sustain improvements in knowledge-intensive tasks? Considering the digital transformation underway in an energy company, we identified different ways to adopt algorithms, their success (or failure) in improving the productivity and quality of knowledge work, and residual effects on experts learning. Our analysis enabled us to develop a theory for managers to navigate the digital transformation effectively.

3 | METHOD

3.1 | Research context and design

This research draws on a 2-year comparative multiple-case study within ACME, a multinational energy firm. ACME represents an ideal research context due to its reliance on professionals and experts engaged in knowledge work. Here, engineers, accountants, and petrophysicists work together in business areas to produce, trade, and deliver energy products, including hydrocarbons, lubricants, and low-carbon energy. Moreover, the context is appropriate because ACME was undergoing a digital transformation, with algorithmic solutions emerging as a strategic priority. The leadership team allocated US$1bn per year to capture, incubate, and scale projects that used these solutions. As such, this context provided ample opportunities to gather data and elicit cases on how various business areas used algorithms to transform their knowledge work, and the consequences of this transformation for operational performance.

The case sampling logic we settled on was theoretical (Miles & Huberman, 1994), and drew inspiration from Davenport's (2015) categorization of knowledge work into four segments. We worked with our main contact at ACME's R&D, who oversees the digital transformation across the organization. With his guidance, we selected four business areas that represented each segment of Davenport's taxonomy: business services (transactional), maintenance operations (integrative), internal audit (collaborative), and drilling operations (expert). Our contact had over 15 years of experience collaborating with diverse ACME business areas on innovation projects. His deep understanding of work in different areas was key for selecting cases that exemplified Davenport's segments. Studying these embedded cases within the same company allowed us to control for contextual factors affecting technological adaptation, including strategic orientation, aspirations, recruiting, governance, and technology policies (c.f. Eggers & Kaplan, 2009; Tripsas & Gavetti, 2000). Since ACME leadership expected all areas to engage with the digital transformation and adopt new algorithms, we could exploit similarities to isolate the effect of our variable of interest (Bechky & O'Mahony, 2015).

The four business areas selected were well suited to this study for several reasons. To begin with, knowledge plays a critical role in fashioning services across these areas. Staff rely on mastering technical and professional expertise to deliver key services like constructing deepwater platforms and auditing anti-bribery programs. Second, business areas provide a good opportunity to generalize findings to a broader population, as they in effect operate like most medium-sized private service organizations. Work is organized into tasks and conducted by groups of specialists who serve a wide range of customers. Finally, the business areas exhibit salient tensions in digital transformation. These include balancing pressures to adopt algorithms against staff resistance. Thus, we argue that business areas offer a rich setting to study the adoption of algorithms in knowledge work. Here, we briefly present the context of the four sampled business areas, laying the groundwork for this study.

3.1.1 | Case 1: Business services

The first case was built based on the business services area, which provided ACME with credit management, customer service, and human resources services. Because of the nature of services offered, staff working in business services have diverse backgrounds, typically, in finance, engineering, management, and economics. Some staff are also hired based on equivalent experience rather than education. Business services staff usually conduct standard work in the front and back offices. They work in large business process outsourcing centers, and operate according to documented instructions compiled in standard operating procedures. For instance, in credit management services, they perform activities to assess the borrowers' ability to repay a loan according to the instructions in the accounts receivable standard operating procedure. While staff in this area must be able to communicate effectively, their work does not depend on collaborating with others. Because work, in this case, was routine and primarily governed by standard operating procedures, we argue that business services fit the characteristics of Davenport's transactional knowledge work segment.

3.1.2 | Case 2: Maintenance operations

The second case was built based on the maintenance operations area, which provides asset management services to ACME, including assessing the condition of machinery, developing maintenance procedures, and troubleshooting equipment issues. Staff in this area, known as "maintenance workers," are typically junior and mid-level specialists, technicians, schedulers, planners, and coordinators. They are responsible for both planned and emergent work. Planned work involves regular maintenance activities to prevent unexpected asset breakdowns, while emergent work focuses on addressing initial faults to minimize downtime. Although maintenance workers have some discretion, they must also adhere to vendor recommendations and maintenance standards (e.g., ISO 55,000 and 13,374) to ensure compliance with legal, technical, and safety requirements.

Social intelligence skills play a crucial role in maintenance work. When a fault occurs, maintenance workers communicate with plant operators to gather information and diagnose the cause and location of the issue. This includes identifying potential exposure to corrosive, toxic, flammable, or other hazardous substances, as well as determining if the repair work needs to be conducted at heights, underwater, or in confined spaces. Collaboration and effective communication remain crucial during the actual repair work. Once a team of three to four maintenance workers is assigned to fix the fault, they communicate with the control room and other stakeholders to prevent the unintended restart of machinery around the affected area while maintenance workers are still working on it. Good understanding of social cues and trust among the team are vital to coordinate repair work and understand the emergent risk. Given the importance of standardized practices and collaboration in maintenance work, this case aligns with Davenport's integrational segment of work.

3.1.3 | Case 3: Internal audit

The third case was built based on the internal audit area, which provides independent financial and technical assurance services to ACME, including verifying the appropriate operation of accounting processes, governance mechanisms, and internal controls. Because internal audit offers both financial and technical assurance, members of this area (hereafter referred to as "internal auditors") had different backgrounds, such as accounting and chemical engineering. The common denominator is that to become internal auditors, aspirants must master high levels of expertise; they must be skilled and seasoned professionals with a demonstrated command of regulations (e.g., the Sarbanes-Oxley Act), standards (e.g., the Generally Accepted Auditing Standards), and codes (e.g., the code of ethics). Such financial or technical prowess allows internal auditors to examine, verify, and judge if the organization is operating in line with mandatory legal guidelines and technical standards.

In addition to being subject matter experts, internal auditors rely on social intelligence skills to do their job. Each year, internal auditors perform circa 200 audits spread over eight auditing rounds. In each round, a team of internal auditors (three to nine people) work together to write an audit's terms of reference and internal controls testing plans. They then collaborate with members of the auditee function (e.g., human resources) to execute such plans and produce reports of findings that outline risk areas and recommendations to improve the auditee's operations. Communicating effectively allows internal auditors to build trust with auditees and ensure the right evidence is collected and analyzed, thus helping them ensure that the audit findings capture the auditee's operations in the best way. Whenever irregularities or risks to the organization's growth or reputation are identified, internal auditors liaise with the chief auditor who conveys them to the board of directors. For these characteristics, we considered this case as an exemplar of Davenport's collaborative segment of knowledge work.

3.1.4 | Case 4: Drilling operations

The fourth case was built on the drilling operations area, which provides global drilling support services to the organization, including defining the scope and activity of wells, overseeing the operation of wells, and designing fracturing and stimulation treatments. Staff in this area (hereafter referred to as "drilling engineers") are predominantly mid- and senior-level mechanical engineers, chemical engineers and petrophysicists who have an in-depth knowledge of drilling and completion operations. Before joining this area, candidates must demonstrate seasoned experience in dealing with a variety of practices and assets for drilling onshore and offshore wells; they must have at least 5 years' drilling experience, prove command of practices for drilling in subsea reservoirs, and understand managed pressure drilling equipment—specialized arrangements of rotating control devices, choke manifolds, and other apparatuses that control the pressure in the wellbore. Their extensive experience grants drilling engineers a high level of discretion. Some expert senior drilling engineers, for example, are responsible for designing tailored fracturing and stimulation treatments for oil and gas wells with unconventional environmental conditions around the globe. These designs depend on acumen, as drilling engineers draw on past experience with similar wells to analyze technical and regulatory dimensions that may impact the safety and cost-effective operations of the present well. For these characteristics, we matched this case with Davenport's expert segment of work.

ACME's bid for digital transformation led these four areas to adopt algorithms, making them meaningful cases for understanding how organizations used algorithmic solutions to improve knowledge work. We gained access to study these areas and collected data, including interviews, observations, and archival records, to understand how algorithms affected their operational performance. The data collection and analysis strategies are presented below.

3.2 | Data collection

3.2.1 | Interviews

Between November 2019 and October 2021, we conducted 55 semi-structured interviews with staff in the business service ($n = 18$), maintenance operations ($n = 11$), internal audit ($n = 15$), and drilling operations ($n = 11$) areas. These interviews, lasting an average of 75 minutes each, were conducted either in private rooms or via Zoom. We interviewed staff in both leadership and non-leadership roles, representing diverse backgrounds including engineering, accounting, and data science. Interviews served two purposes. In the first round, we aimed to characterize knowledge work within each business area. Interviewees were asked to provide detailed descriptions of their work, quantifying the level of skilled performance required for various tasks on a 10-point Likert scale. For example, we enquired about the degree of creativity, social intelligence, and dexterity to accomplish these tasks. We further asked them to qualify their skilled work and the perceived fit for using algorithmic solutions in the given task (see Appendix B). In the second round of interviews, our focus shifted to understanding how algorithms were employed within each area, and their implications for improving knowledge work. Interviewees were asked to elaborate on specific projects involving algorithmic solutions, identifying the tasks in knowledge work that were affected, and examining the resulting consequences for operational performance (see Table C1 in Appendix C). We conducted interviews until we achieved theoretical saturation, increasing the validity of our findings (Glaser & Strauss, 2017).

3.2.2 | Observations

To complement our interviews, we drew on participant observations. We visited each business area multiple times between November 2019 and March 2020. These visits took the format of one-week participant observations, apart from one COVID-related exception. The first author was given a desk, training on the field, and permission to contact anyone in the organization. We participated in day-to-day knowledge work activities, such as maintenance planning meetings, in which engineers discussed short- and long-term asset management projects to ensure complex plants run on time; or internal audits, where auditors interviewed corporate employees in, for example, human resources, to identify potential risks and recommend how to address them. These observations were designed to complement our interviews by capturing aspects that participants may have struggled to articulate during interviews (Barley & Kunda, 2001). Thus, we used them to create "thick" descriptions of how participants draw on tacit knowledge to carry out their work (Bechky, 2006; Orr, 1996). The focus of observations was twofold: to capture how the areas adapted knowledge work around algorithmic solutions, and to build a more comprehensive picture of how professionals and experts create and share knowledge before and after infusing algorithms at work. We made our research overt, and maintained a journal with notes about the business area's practice, keeping a separate journal for recording experiences, anxieties, and reflections from fieldwork to minimize contaminating data with biases (De Rond & Lok, 2016). By visiting each area multiple times, we built a rapport with participants and minimized the risk of reactivity.

3.2.3 | Archival data

After the national lockdown was instigated in March 2020, we paused the observations and began collecting archival data as ACME operated a work-from-home policy. This included operating procedures that governed the practices in each of the four business areas, and internal reports that captured the impact of automation projects on the company's performance. These documents helped us understand the effects of algorithms in the four segments of knowledge work. Table 1 summarizes the data collection across the different business areas.

3.3 | Data analysis

Our analysis was inductive, iterative, and comparative. The aim was to elaborate theory on the adoption of algorithmic solutions and transformation of knowledge work by detecting patterns in and across cases. As the foundation for this analytic strategy, we used the constant comparative method (Glaser & Strauss, 2017). Over various iterations, we read and coded the interview transcripts and observational notes, looking out for similarities and differences in the adoption of algorithms across the four business areas. These iterations took place over three main stages of analysis: understanding current knowledge work, identifying the knowledge work transformation process triggered by algorithmic solutions, and explaining differences in outcomes in the adoption of algorithmic solutions. These stages are detailed below.

3.3.1 | Stage 1: Characterizing current knowledge work

First, we analyzed interview transcripts and field notes to construct narratives that portrayed how knowledge work was done in the four areas before algorithmic solutions were introduced. Using these narratives, we compiled a list of tasks performed by staff in each business area, considering a task as a discrete activity contributing to the production of goods or services (Acemoglu & Autor, 2011). This task list included "planning the terms of reference of an audit," "processing clients' purchasing orders," and "investigating issues on fracturing and stimulation." At this point, it became apparent that some narratives describing ostensibly identical tasks actually varied based on the specific context in which they were enacted. To capture these *variations* (Bailey & Barley, 2020), we coded tasks by contextualizing them within the job where they were performed. For instance, narratives related to "planning an audit's terms of reference" were categorized into two distinct tasks, recognizing the differing activities and skill requirements for compliance-based versus risk-based audits.

Next, we focused on analyzing tasks as skilled work. We coded each task in our list using five dimensions: the degree of creativity, social intelligence, manual dexterity, repetition, and perceived suitability for automation with algorithms. The purpose here was not to provide a quantitative assessment but to observe any meaningful patterns between these dimensions and the applicability of algorithms. We used this to deepen our analysis of the knowledge work in each business area, as an intermediate step toward building our case studies. At this point, we sent a case write-up to the business areas' senior directors to validate and refine the cases. Directors had 10 or more years of experience and had a high level of understanding of the work in their respective areas. We asked them to confirm that their respective area accurately exemplified the Davenport knowledge work segment we had matched them to. Additionally, directors provided feedback enriching the task analysis of the work performed in their area. These cases formed the foundation for our subsequent analysis of how the adoption of algorithmic solutions transformed the nature of work across these business areas.

3.3.2 | Stage 2: Identifying knowledge work transformation

In the second stage of the data analysis, we examined a subset of successful and unsuccessful projects that involved algorithms to understand the process of transforming knowledge work. We identified seven projects across the four business areas that included the application of ML, RPA, and logic-based algorithms, which are summarized in Table 2. For each of these projects, we then interviewed the professionals and experts involved, the developers who built the algorithm project, and the managers who sponsored and oversaw it. To build up descriptive abstractions from interview notes and field observations on algorithm projects, we used NVivo and applied the constant comparative method, following the

TABLE 1 Description of cases and data collection.

Business areas characteristics						Data collection		
Area	Knowledge work segment	Degree of expertise	Degree of collaboration	Work characteristics	Examples of tasks in this case	Informants	Interviews ($n = 55$)	Additional data collected
Business services	Transactional work	Low	Low	Work is repeatable, reliant on formal rules and easily structured in process terms. Workers have low discretion	Issue credit cards for customers Process clients' procurement orders Input purchase orders into ERP systems	Data scientists (9) Automation group director (1)	18	Observational notes Standard procedures, press releases, industry reports
Maintenance operations	Integrative work	Low	High	Work is repeatable, reliant on formal rules and easily structure in process terms. Workers rely on tight integration across functional boundaries	Prepare asset maintenance plans Collect data about assets' performance Prepare detailed reports on maintenance effectiveness	Maintenance workers (9) Functional Manager (1) Deputy Manager (1)	11	
Internal audit	Collaborative work	High	High	Work is improvisational and judgment oriented. Workers rely on tight integration across functional boundaries	Test the design and operating effectiveness of controls Prepare detailed reports on audit findings Plan the audit terms of reference for compliance-based and risk-based audits	Financial Auditors (4) Operational Auditors (5) Data Scientists (2) Audit Managers (1) Functional Manager (2)	15	
Drilling operations	Expert work	High	Low	Work is improvisational, judgment oriented, and dependent on star performers	Design fracturing and stimulation treatments for offshore wells Design fracturing and stimulation treatments for onshore wells Prepare and manage the completion team to ensure the acidizing treatments are done effectively	Drilling Engineers (6) Data Scientists (2) Functional Manager (1)	11	

TABLE 2 Descriptions of projects involving algorithmic solutions across cases.

Area and project	Project description	Improvement
1. Business services: Credit card onboarding	An effort to use RPA algorithms to automate the credit card onboarding process.	Yes: time reduction and cost savings
2. Business services: Credit card locking	An effort to use RPA algorithms to automate the decisions of locking or unlocking customers' credit cards.	Yes: time reduction and cost savings
3. Maintenance operations: Maintenance scheduler	An effort to use logic-based algorithms and ranking systems for generating and updating preventive maintenance schedules.	Yes: time reduction
4. Internal audit: Anomalies in financial transactions	An effort to train and deploy rules-based and machine learning algorithms for testing the effectiveness of controls in compliance-based audits and discovering anomalies in financial transactions.	Yes: time reduction and minimizing risk
5. Internal audit: Risk reports for directors	An effort to use machine learning algorithms (topic modeling and Latent Dirichlet Allocation) to recognize natural language from audit reports and prepare quarterly summaries for ACME's directors.	No
6. Drilling operations: Drilling optimization	An effort to use reinforcement learning algorithms to automate drilling onshore and offshore.	Phase A—No Phase B—Yes: cost savings
7. Drilling operations: Mini frac calibration	An effort to use reinforcement learning algorithms for calibrating a "mini frac" on an offshore well. (A "mini frac" is a small fracturing procedure to observe the behavior of the fracture system, and to calibrate the main hydraulic and stimulation treatment.)	Yes: time reduction and risk reduction

Abbreviation: RPA, robotic process automation.

guidelines suggested by Gioia et al. (2013). Because we assumed that informants were "knowledgeable agents" who could describe the implementation of algorithmic projects as well as explain resulting changes in their work, we allowed first-order codes to emerge from quotations and observational notes. This initial coding followed a line-by-line approach (Charmaz, 2006). Then, applying axial coding (Corbin & Strauss, 2008), we built up descriptive theoretical categories that captured similarities and relations in first-order codes. Finally, we distilled and mapped the relationship between these themes to develop stages that explained the transformation of knowledge work. The result of this second analysis stage was a grounded theory model of the adoption of algorithmic solutions in knowledge work. The resulting data structure that served as the basis for our findings is presented in Table C1 in Appendix C.

3.3.3 | Stage 3: Explaining differences in outcomes in the adoption of algorithmic solutions

In the final data analysis stage, we explored the variance among different mini cases when it came to using algorithms in knowledge work tasks. Our focus was on understanding how the transformation of work affected the ability to improve operational performance. We started by looking at how different pathways of transforming work made it possible to use algorithms effectively in tasks requiring skilled work. Then, we compared whether these pathways of transformation also led to changes in how knowledge was validated, shared, and sanctioned. Although it would also have been interesting to examine the role of organizational actors in the transformation of knowledge work, such an analysis lay beyond the scope of this study.

4 | FINDINGS

4.1 | Barriers to using algorithmic solutions when improving knowledge work

At ACME, staff in the four business areas engaged deeply in knowledge work. They performed tasks that required them to draw meaningful distinctions by understanding the nuances of their practice and ACME's unique context to create and maintain energy-related products and services most effectively and efficiently. To do this work, staff spent several years accumulating experience (know-how), mastering codified procedures specific to their areas (know-that), and developing improvisational and embodied skills.

This process involved learning in communities (Brown & Duguid, 1991), whereby staff embraced the business area's distinctive language (Schön, 1983) and adhered to its legitimate ways of working (Lave & Wenger, 1991). For instance, junior internal auditors invested time in learning ACME's unique acronyms, like "CoW," which denotes "Control of Work." They also spent time practicing alongside expert auditors, learning that actively listening to, rather than accusing, auditees was crucial for successfully executing tasks like "testing and design of controls." Moreover, as junior auditors continued to practice, they gained organizational knowledge, comprehending the rules governing ACME's operations and the authorities responsible for sanctioning these rules. Mastering the community language, embodying valid ways of working, and internalizing ACME's procedures, led internal auditors to a deeper appreciation of the system of ideas that underpinned auditing functioning. This gave them a solid foundation to use categories and make appropriate distinctions to engage in knowledge work.

As ACME's leadership embraced the new digital transformation strategy, it inevitably placed mounting pressure on the business areas to follow suit. While the staff in these areas were eager to demonstrate their support for the strategy, they could not help but be concerned about the potential implications of algorithms on their roles. They feared that their hard-earned skills might become redundant or lose their significance within the organization. Moreover, skepticism prevailed regarding the accuracy and reliability of algorithms, particularly in tasks that demanded nuanced decision-making and contextual understanding—tasks in which staff took great pride in their ability to navigate complex situations, relying on their intuition, experience, and creativity. While acknowledging that algorithms offered cost savings for certain tasks, they argued that implementing them in certain areas would prove to be time-consuming, financially inefficient, and ineffective. Because of our interest in knowing in practice, we focused on understanding how skilled work affected the business areas' ability to use algorithms to improve knowledge work.

4.2 | Effect of skilled work on the ability to use algorithmic solutions

Tasks relying on skilled work hindered taking full advantage of the productivity benefits offered by algorithms. Staff reported that highly creative, socially intelligent, or manually dexterous tasks were associated with lower effectiveness when applying algorithms, as shown in Figure 1. Most staff agreed that using algorithms in creative tasks was less challenging than in tasks requiring social intelligence. The results were less clear for manual dexterity, since most knowledge work tasks studied required no manual dexterity beyond typing. However, in the few cases where manual dexterity was needed, organizations struggled to effectively incorporate algorithms.

A central factor contributing to the limited applicability of algorithms to tasks requiring social intelligence is their integral role in the process of "sensemaking" within knowledge work (Weick, 1995). These tasks involve making collective sense of situations that are confusing, ill-defined, ambiguous, or unexpected (Maitlis & Christianson, 2014). Examples include understanding emergent risks in deepwater drilling, the impact of new data protection regulations, or potential failures of previously unmaintained assets. In such scenarios, explicit documentation of operational procedures is often inadequate, inaccurate, or irrelevant. Consequently, individuals rely heavily on their social intelligence skills to manage these intricate tasks proficiently.

The results shown in Figure 1 challenge the conventional thinking that specific skills impede the computerization of tasks (c.f. Arntz et al., 2016; Frey & Osborne, 2017). Instead, it shows pronounced heterogeneity in the ability to use algorithms in tasks requiring skilled work. Even highly creative and socially intelligent tasks can benefit from algorithms, the figure shows. By studying seven projects where ML and RPA were applied in different business areas, we reveal a set of transformational practices. These practices helped improve highly skilled, knowledge-intensive tasks across the studied business areas.

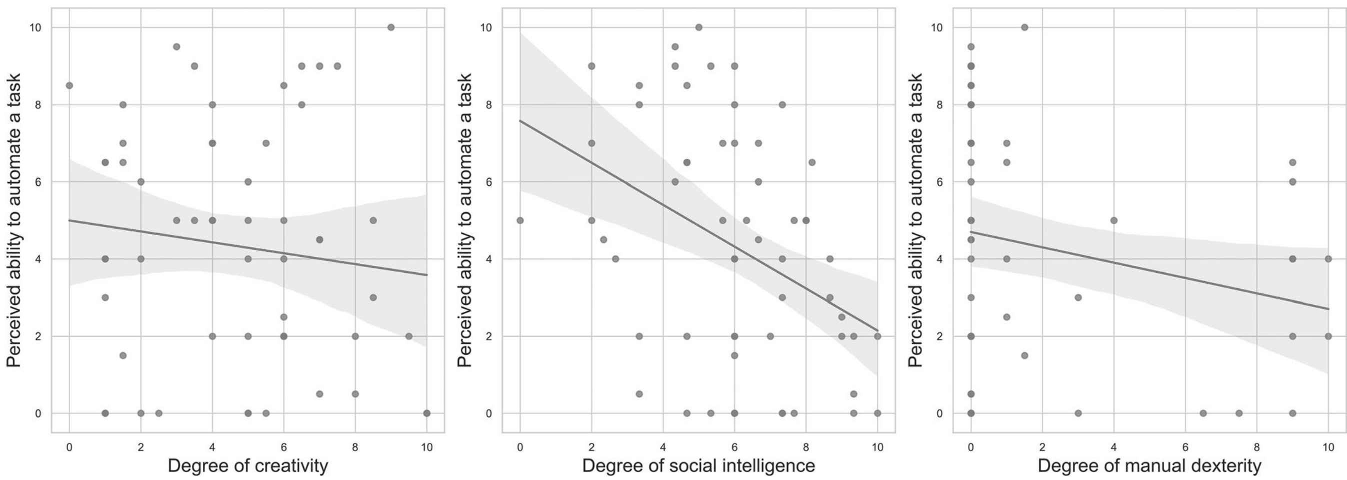

FIGURE 1 Perceived ability to use algorithms in different tasks, plotted against the skill levels needed to complete those tasks. Skill requirements in each task were evaluated on a continuum using a Likert scale with 10 as the highest level of skill needed. The data for this figure was derived from interviews with staff at each business area and our direct observations of their work.

4.3 | Transforming knowledge work to use algorithms

Our examination of the cases highlighted two distinct pathways business areas followed to transform work using algorithms. In some instances, they chose the "automating a specific task" pathway, which involved substituting humans with algorithms on a single-task basis. Conversely, other cases followed a pathway of "re-engineering the entire process," entailing the redesign of sequential steps surrounding the task to incorporate algorithms.

4.3.1 | Task automation pathway

The first pathway of knowledge work transformation revolved around the automation of specific tasks. This pathway was found in four projects and occurred mainly in internal audit and maintenance operation areas. In each case, efforts to reshape the practice were channeled toward discrete units of work, focusing on factors like task repeatability and standardization. For instance, staff in these areas often undertook task categorization into well-defined and ill-defined cases, standardizing activities that demanded creative expertise, and separating work into cognitive and physical labor (hand and brain) components. We discuss these practices below (Table 3).

Standardizing tasks

Business areas that transformed knowledge work by automating a specific task tackled the demand for skilled work by standardizing tasks. This practice served to confine the level of creativity required to execute the task, achieved by encapsulating the practical know-how within standardized operating procedures. This subgroup demonstrated active engagement in ACME's organizational learning initiatives, participating in workshops involving internal and external stakeholders to glean industry best practices. For instance, in the case of internal auditors, they embraced a continuous improvement mindset, capturing valuable insights and streamlining their testing methodology. Collaborating with ACF, an external auditing firm, they standardized ACME's auditing practice to align with industry norms. Standardizing their approach to auditing allowed them to "… have consistency for testing" (Senior Auditor 1); "…ensure that we test everybody in the same way so that we've got benchmarks that we can review" (Audit Manager).

By assimilating external and internal knowledge into their operational framework, these auditors paved the way to integrate algorithms into their practice. This shift involved substituting the need for creative design in audit test plans with standardized alternatives, enabling the deployment of algorithms for tasks such as document automation. This approach resonated through statements like "We're not doing everything differently every time" (Senior Auditor 2), and "We might make some tweaks and modifications to it, depending on the nature of the area we're looking at or what the focus is… But at the core of it, it's a standardised testing approach" (Operational Auditor 4).

Separating "hand and brain"

Another practice that business areas used to modify specific tasks was "separating hand and brain" (Drilling Engineer 2). In response to challenges in automating tasks requiring both physical and cognitive skills, drilling

TABLE 3 Transforming work by automating a specific task.

Area and project	Nature of work before algorithm adoption	Practices for transforming work	Operational outcomes
1. Maintenance operations: Maintenance scheduler	The maintenance scheduler weekly prepares a document outlining upcoming maintenance tasks. The document includes details like task types, priority, deadlines, and assigns workers. The scheduler compiles preventive and corrective tasks into a spreadsheet by poring over manuals and fault logs. Collaborating with internal and external staff is crucial. The scheduler communicates with workers for emergent faults, managers for worker availability, and operations team to negotiate maintenance times to avoid disrupting production. Due to constant changes and potential spare part unavailability, the schedule often undergoes revisions, taking about 4 days to finalize.	Standardizing tasks. The maintenance scheduler established standardized metrics, including a ranking system for maintenance requests. This transformed the nature of the task. Instead of relying on intricate social intelligence, the task transitioned to routine social interactions, aimed at gathering inputs for creating the schedule.	Improvement by reducing the time to complete the task. Standardization facilitated the creation of a VBA algorithm for generating maintenance schedules. The algorithm recalculates the maintenance activities that need to be done that week, reducing the execution time of this task.
2. Internal audit: Inconsistencies in financial transactions	During internal financial audits, auditors work together with the auditee team to collect and analyze accounting records. They check for mistakes, regulatory issues, and if proper accounting practices are being followed. This involves using sampling, testing, and checking financial statements. They also ask questions and confirm information with external parties. Being socially aware is important for a successful audit. Auditors build trust with auditees, helping to find evidence and investigate incidents. Social skills also help auditors understand verbal and non-verbal cues, for example if someone seems unconcerned or uncomfortable discussing a topic. These cues can signal financial problems and	Categorizing tasks. Auditors categorized their testing activities into financial and engineering groups. Standardizing tasks. Then, they established standardized protocols for ensuring consistent SOX compliance audits based on industry best practices.	Improvement by reducing time and minimizing risk. By categorizing and standardizing, the internal audit team could use a data scientist to build an algorithm for SOX compliance tests. This helped gather evidence for SOX audits faster. Also, they checked all transactions closely (instead of just some) to find mistakes, which lowered the chance of legal problems.

TABLE 3 (Continued)

Area and project	Nature of work before algorithm adoption	Practices for transforming work	Operational outcomes
	suggest a need for further investigation.		
3. Drilling engineering: Drilling optimization (Attempt 1)	The drilling process begins once the site is ready and necessary permissions are in place. It involves creating a hole, known as the wellbore, to the desired depth. Measurements and samples are taken to assess reservoir productivity. The well is then completed by adding casing and tubing to prevent collapses and allow oil and gas to flow out. Drilling can happen on land or on offshore rigs. Both methods require skilled workers with geological knowledge, the ability to manage drilling processes, and an understanding of the mechanical and technical aspects of drilling equipment.	Separating hand and brain. Engineers utilized sensors and communication tech to dislocate physical labor from cognitive knowledge tasks in drilling operations. Standardizing tasks. The area hired petrophysicists with doctorates to create standardized protocols for estimating ideal drilling paths and pressures.	Failure. Through transformation practices, engineers aimed to consolidate the intricacies of drilling within a reinforcement learning algorithm. However, the task was closely linked to the drilling simulation, which acted as a bottleneck, hindering the realization of benefits from the algorithmic solution.
4. Internal audit: Risk reports for directors	Every quarter, internal auditors provide ACME directors with a condensed version of important audit findings and identified risks. To make this summary, a team of auditors collaborates to analyze and simplify 50 audit reports. This involves social intelligence as auditors discuss how various risks from different parts of the business might come together. Also, it involves translating knowledge—auditors need to remove technical terms and details from the original reports and turn them into clear PowerPoint slides with visuals and explanations. The goal is to help directors understand and focus on specific risks.	Standardizing tasks. Internal audit delegated the project to ACF. Internal auditors standardized all the previous year's audit reports, as well as the equivalent report findings.	Failure. ACF used standard reports to train an NLP algorithm to make risk summaries for directors. However, the algorithm created summaries that pointed out incorrect risks, as it focused on guiding management in the wrong direction. This led to stopping the project because of inaccurate and possibly confusing results.

Abbreviations: NLP, natural language processing. VBA, visual basic for applications.

engineers separated work into manual ("hand") and cognitive ("brain") components. Unlike traditional divisions of labor, this separation sought to facilitate automating the task's cognitive component. For example, a division was established between fracturing experts handling mental tasks (designing fracturing treatments) and those performing physical tasks (well completion). Sensors, algorithms, protocols, and satellite communication enabled real-time data transmission, connecting well completion teams at well sites with fracturing specialists in remote control rooms. This led to further specialization, disconnecting fracturing specialists from the physical work. In turn, this paved the way for using algorithms for some of the fracturing specialists' tasks. The new real-time data streams flowing into the communication rooms were used to feed ML models that imitated decisions previously made by specialists.

Categorizing tasks into "well-defined" and "ill-defined"

One final practice embraced by those transforming knowledge work through task automation involved task categorization. This practice entails classifying tasks, formally or informally, based on whether they involve familiar or less common scenarios. For instance, in business services, tasks were differentiated between those that demanded social intelligence for collecting data from established sources, structures, and systems, and those requiring the untangling of "ill-defined and emergent situations" (Data Scientist 3). Although both cases relied on trust and effective communication, participants agreed that the former involved familiar and relatively consistent scenarios, requiring minimal true intelligence. A prime illustration was collecting information from clients and colleagues to populate fields in customer relationship management software like Salesforce.

Categorizing tasks into well-defined and ill-defined groups was useful for pinpointing areas where algorithms could potentially enhance efficiency. It identified instances where tasks were well-defined but being carried out in what participants termed a "quite old school way" (Data Scientist 1), and still relied heavily on human intervention. By categorizing tasks, organizations could identify opportunities for using algorithms to streamline information flow across diverse systems, facilitating collation, manipulation, and validation of information, ultimately enabling more efficient knowledge work.

4.3.2 | Process re-engineering pathway

The second pathway of transformation focused on re-engineering the process. This pathway emerged in four out of seven projects, primarily within the fields of business services and drilling engineering. In these instances, the emphasis shifted toward processes—clusters of activities that convert inputs into desired outcomes. Put simply, organizations that pursued this pathway directed their efforts toward overhauling the entire process so that they could use algorithms in embedded tasks. Staff in these areas were concerned less with the question of skills and more about reconfiguring the way the organization transformed resources into services. Some practices deployed by those following this pathway included controlling for process variation, adding steps for assuring algorithmic outputs, and eliminating non-value-adding activities. Below, we describe these practices.

Identifying and controlling process variation

Business areas re-engineering their processes to use algorithms engaged in a practice for identifying and controlling the process variation. Process variations happen when the conditions and features of a process change, making the process less consistent. These variations matter because they can disrupt the effectiveness of algorithms in the workflow. A data scientist in the business services sector mentioned in an interview that processes that "(…) have a lot of different rules to go through and variations make the logic more complicated, and that's where you could struggle with the success rate of technology" (Senior Developer 2). To mitigate this problem, data scientists took the initiative to work with users beforehand to understand variations in inputs (like interacting with clients through different channels), conversion processes (such as different decision-making approaches among experts), and output (for instance, customizing products or services for specific clients). By pinpointing the sources of variation, they identified ways to manage and control it before incorporating algorithmic solutions.

A good example of this practice involves a project in the business services area to incorporate algorithmic solutions in locking and unlocking credit cards based on customers' transactions, payments, and credit information across platforms. At first glance, the task seemed like simple automation of data collection. But soon, the business services area realized that the activity had many potential variations and interdependences that risked the project's success. Specifically, the algorithm logic became complicated as credit card payments came from different intermediary banks, which used different data formats and processing times. Variation further increased as developers added non-payment-related transactional data and rules to minimize defaulting risk. One senior data scientist noted, "[Locking and unlocking credit cards] has been very tricky. It has a lot of dependencies on all sorts of different [payment] processes… it was quite complicated in terms of looking at all aspects before you make a decision to lock a customer." To deal with the inherent variation in locking or unlocking customers' credit cards, data scientists interviewed and conducted workshops with owners of the credit card process to map tasks, inputs, and dependencies involved in locking and unlocking credit cards. The results of these workshops included entity relationships and process maps that ironed out potential variables and variations in activities that might influence the decision of locking or unlocking a customer. This, in turn, allowed business services to create more complex algorithm solutions that bridge identified process variations, reducing service times to lock and unlock credit cards in real time.

Eliminating non-value-added activities and artifacts

Re-engineering the process sometimes involved eliminating activities and artifacts that were not adding value to the product or service offered. Organizations realized that some activities and artifacts in their processes limited their ability to reap benefits from algorithms—even if these were once deemed necessary. This practice involved questioning outdated assumptions and long-established rules that were bottlenecks in the process.

Consider the project for using algorithms on credit card onboarding in the business service area. The team decided to automate parts of this process using a combination of RPA and computer vision. Credit card onboarding was a multistep process involving tasks such as credit checking, rating, and issuing physical credit cards. When they began thinking about using algorithms to redesign the credit onboarding process, staff in business services began questioning the need for using physical credit cards. While physical cards had for decades traditionally been deemed necessary for the process—as a token of identification and security for customer transactions—it also increased the lead time of the card onboarding process, making them "lose business"—as some staff put it. The business services area decided that a physical card was the main bottleneck in the process, and so decided to allow users to load a digital card via their phones. Eliminating the need for physical cards and automating the due diligence checking process enabled business services to onboard new customers almost within a day (rather than a month).

Adding steps for algorithms' output assurance

Another practice involved in re-engineering the process that revolves around building a capability to assure output quality. As the name indicates, this practice entailed redesigning work by adding extra steps to the process to assure the quality of knowledge created by algorithms. Consider, for example, the project to use reinforcement learning to automate the calibration of mini fracs in offshore wells—a task considered to require high levels of creative thinking that involved characterizing a well by causing a short fracture in the formation before the main fracturing treatment (see Table 4 for more context). In this project, drilling engineers sought to use a reinforcement learning algorithm to explore different types of calibration and select the solution that best matched the well's characteristics in the shortest possible time. The algorithm imitates the mental processes of the expert who designs the fracturing treatments; it runs multiple scenarios until it finds a combination of parameters that match the well's pressure system. If the mini frac is poorly executed, it can cost ACME several millions; therefore, the process was redesigned so an expert could review the calibration, approving or adjusting it according to their expertise. In this case, the algorithm did not completely replace the need for creative thinking. The team remained responsible for discovering the problem and defining goals and appropriateness criteria to measure the quality of the algorithmic solution.

4.4 | Adjusting the knowledge regime

In addition to transforming the work, some business areas adjusted their knowledge regimes. We based our construct of a knowledge regime on the works of Pachidi et al. (2021) and Howard-Grenville and Carlile (2006), and define it as the combination of social, material, and discursive arrangements that govern the specific practices that actors use to learn and perform their work; the structural arrangements that inform which actors have authority over how knowledge is produced; and the valuation schemes that sanction how experts shall understand new information. Below we provide a few examples.

4.4.1 | Shifting structure and authority arrangements

When staff focused on redesigning the process through which the knowledge was transmitted, they ended up reorganizing the area's structure and authority arrangements. In some cases, this reorganization stemmed from employing new staff skilled in process mapping, data analysis, or software development. This led to new structures like parallel organizations focused on scaling algorithmic solutions. For example, IO was created parallel to the business services function to provide "automation-as-a-service" to staff in business services. IO was composed of developers offering three core services: advisory and consulting, end-to-end DevOps, and federated automation solutions. The workflow at IO was organized in scrum sprints, during which developers partnered with staff in business services who had ideas on redesigning their work around algorithmic solutions. As a result, business services morphed into a biparty rectangular organization within ACME—which differed from traditional matrix and heterarchical structures. This also changed authority arrangements within the business services area. Staff lost jurisdiction to developers and reported not only to their functional head, but also to the scrum masters. Decisions on where and how to use algorithmic solutions were distributed across both business services and IO.

Other cases also experienced shifts in structure and authority arrangements after transforming their work to use algorithms. Auditors automating data collection and analysis for auditing tests found themselves needing to create an internal data analytics team, with associated new roles to support auditors on an on-demand basis. Similarly, drilling engineers described that transforming work to use algorithms led to new organizational interfaces, which altered who needed to be consulted for a project as well as who was involved in making drilling-related decisions.

> (…) prior [to the adoption of algorithms], in my particular case, I was in drilling… and knew the community quite well. We knew who the key stakeholders were and whom we had to engage with. There were not too many interfaces. Whereas now, a lot of us are having to find, okay, who are the new interfaces? Now we kind of engage with [the cybersecurity team], so, key architects and additional security people are involved in my work.
>
> (Drilling Engineer 1)

4.4.2 | Altering schemes for evaluating new knowledge

New ways of working with algorithmic solutions also affected the mechanisms for learning and valuing knowledge. Before the implementation of algorithms, if a specialist gave a judgment, the quality of that judgment was rarely questioned; they were experts whose credentials and past experiences granted them the legitimacy to make decisions. When algorithmic projects were launched, however, this norm changed. Those developing algorithmic solutions put significant efforts toward quantifying the quality of the algorithmic outputs. One senior engineer working on projects Alpha 1 and Alpha 2 shared that such quantification emerged because staff using algorithmic solutions needed metrics to decide how and when to trust the algorithmic recommendations to avoid damaging the quality of the service offered. "On the first half of the year, we are doing some hardware in loop testing—potentially testing on rigs—making sure we have some extensive tests ahead of our first deployment" (Senior Engineer 2). The testing emphasized translating the quality of knowledge into metrics, such as the accuracy and the coefficient of determination of the algorithmic recommendations. While at the beginning this quantification was only applied to the recommendations produced by algorithms, eventually experts started thinking about their own recommendations, in the same way, extending the quantification of the quality of knowledge from algorithms to engineers and petrophysicists too.

In addition to this shift to quantification of the quality of constructed knowledge, knowledge workers also altered their learning practices to accept intractable algorithmic recommendations. At the beginning of Alpha 1, for example, engineers were concerned about the effects of being unable to explain calibration recommendations made by the reinforcement learning algorithm. As time progressed, however, they focused less on understanding intractable algorithmic recommendations, and more on embedding boundary conditions in the algorithm to ensure that recommendations were safe:

> Working with a black box algorithm may be challenging for some and may be easy for others. And that will depend on the project… On Alpha 1, we will connect to the rig control system. So, it's going to be good. But you also got to have some faith in it that it does the right thing. We've got sort of safety parameters around it. So, it would never go badly wrong, but you will never know why it's recommended a certain set of parameters over other certain parameters.
>
> (Senior Engineer 3)

Accepting unexplainable algorithm recommendations prompted engineers to alter how they evaluate knowledge. They compensated for the lack of explanation by monitoring whether the recommendations looked adequate. For example, drilling engineers focused on developing tools to display the algorithmic recommendations and allow experts to compare them to expected results.

> Now if we have the reinforcement learning algorithm that comes up with a solution that's calibrated, and you can see the two curves, an expert can say with one look, "That's a good or that's a bad calibration", right? It doesn't matter what the parameters are. Again, there's an end to that, which they can be within. The expert says "I can do better than that, or actually, this is good enough"… So, in that scenario, the fact that

TABLE 4 Transforming knowledge work by re-engineering the entire process.

Area and project	Nature of work before algorithm adoption	Practices for transforming work	Outcome
5. Business services: Credit card onboarding	This process starts when a customer applies for a credit card. A team of knowledge workers conducts various checks across credit, resource planning, and customer systems to decide card approval. While some parts are automated, others need manual calls and data collection, relying on some degree of social intelligence. After gathering information, the team approves or rejects the application. For approved cases, a physical card is issued, activated by users for use. This process, involving multiple software interfaces, often took over a month, causing delays for customers. The customer onboarding process usually took around 30 days	Identifying and controlling process variation. Experts hired to map and validate the credit card onboarding process. Eliminating non-value added. The team questioned the need for physical credit cards and changed internal rules to let customers use virtual cards instead.	Improvement by reducing time and cost. Transformation practices help record different ways of doing things and remove obstacles to establish a process that's backed by an RPA algorithm. Onboarding turnaround decreased from 30 days to a couple of days.
6. Business services: Credit card locking	Business service analysts place locks on customers' credit cards due to reasons like suspected fraud or unusual spending. They manually review databases, looking for timely payments and suspicious transactions. Some inspections involve scheduling calls with database owners for financial info, requiring negotiation skills to prioritize these requests. This ensures prompt locking and unlocking of credit cards. Despite these efforts, the turnaround for locking and unlocking customers was significant, increasing the risk for business services.	Identifying and controlling process variation. The team interviewed process owners and created entity relationship and process maps for the credit card locking process.	Improvement by reducing time and cost. Process maps aided in crafting multiple RPA algorithms, resulting in quicker customer lock and unlock procedures and reduced costs. Executing this project was tougher due to numerous variations in requests and checks, which involved different systems. Incorporating extra logic to handle these requests raised the tool's intricacy and upkeep demands.
7. Drilling operations: Drilling optimization (attempt 2)	The drilling process begins once the site is ready and necessary permissions are in place. It involves creating a hole, known as the wellbore, to the desired depth. Measurements and samples are taken to assess reservoir productivity. The well is then	Removing non-value added. Experts revised drilling process, removing unnecessary work. Adding steps for knowledge assurance. Various metrics were used to measure the validity of algorithmic recommendations in drilling,	Improvement by reducing cost. A reinforcement learning algorithm was introduced to find the "optimal" drilling speed, while ensuring temperature and pressure remain on a prespecified and safe window. This allowed

(Continues)

TABLE 4 (Continued)

Area and project	Nature of work before algorithm adoption	Practices for transforming work	Outcome
	completed by adding casing and tubing to prevent collapses and allow oil and gas to flow out. Drilling can happen on land or offshore rigs. Both methods require skilled workers with geological knowledge, the ability to manage drilling processes, and an understanding of the mechanical and technical aspects of drilling equipment.	including the coefficient of determination. Also, an interface was created to allow the operations control team to validate in real-time if algorithms were performing appropriately. Identifying and controlling process variation. The team pinpointed simulation software as a significant obstacle for implementing algorithms. They brought the software into their environment to address this variation.	more junior expert drilling engineers to do the job.
8. Drilling operations: "mini frac" calibration	Fracturing underwater is seen as very complex. The team must create custom solutions and adapt them to deal with different conditions in the well and the sea environment. They work on subsea reservoirs that are 25,000 ft. under the sea, and they need to think about storms that could affect their work on the vessels they use. If things go wrong, it could cost ACME millions, which even experienced experts worry about. Because they can't see directly into the well, they use special techniques to understand the reservoir, including "mini fracs" to see how fractures behave and decide how to adjust the main fracturing process. They also draw on their past experiences and run through different scenarios to be prepared for any issues.	Removing non-value added. Drilling engineers compressed the process of fracturing and stimulating wells and simplified the methodology to drill.	Improvement by reducing cost and risk: Simplifying the process made it possible to use reinforcement learning algorithms to design fracturing and stimulation treatments. These algorithms helped the team speed up the mini frac process. Eventually, drilling engineers questioned the need for doing a mini frac, so they merged it with the main fracturing and stimulation treatment activities.

> it's a black box it's actually less important because you can see the output.
>
> (Drilling Engineer 2)

Because of the intractable recommendations, engineers lost their ability to learn from doing the job. In the case of Alpha 2, they could no longer build causal links between parameters and pressure outputs. To overcome this problem, they dislocated learning in time and place. That is, they created simulated environments whereby engineers could train and play with different parameters of calibration to see the effects on the fracture pressure.

> That enables you to prepare your mind. Just like how I go to bed and think about how the job looks like that particular well we did

> five months ago and, so expect this pressure to climb at this rate... Right. So [the simulator] can enable us to look for those patterns ahead of time. And you have a lot more confidence in that pressure match because we have automated that calibration piece.
>
> (Drilling Engineer 2)

4.4.3 | Updating the skill requirements

Finally, organizations that adjusted the knowledge regime, engaged in practices to update the skill requirements to do the work. For example, engineers in the drilling case argued that Alpha 2 empowered less experienced engineers to carry out fracturing treatments, thereby minimizing service variability and improving process resilience and endurance. Before using algorithms, only a limited pool of experts felt comfortable with designing hydraulic treatments. One senior advisor commented that many junior engineers "(...) are afraid to stick their neck out into the unknown," which negatively affected the number of recruits for drilling roles, and so, the endurance of drilling operations. By implementing Alpha 2, the drilling organization empowered junior engineers to do the fracturing treatments, as the following statements illustrate:

> The automation, really psychologically, is a crutch that [junior engineers] can hang on while they're still making the key decisions (Drilling Engineer 2); and
> (...) it's an aid to them in the proper decision-making (Drilling Engineer 3); and
> (...) it's basically enabling [junior engineers] to make the right decisions and not end up in a space where the well is messed up (Drilling Engineer 1).

Some business areas went beyond adjusting internal job skill requirements—they influenced skill development in their entire fields. The drilling engineering department, which maintained strong ties with universities for research and recruitment purposes, motivated professors to update the curriculum of their engineering schools so graduates had data science skills straight out of university. "When [students] finish their engineering degree to come to industry, they should have some knowledge of data science, machine learning techniques, artificial intelligence, and coding" (Drilling Engineer 2). By updating curricula to align with the abilities needed for algorithmic solutions, these departments hoped to ensure incoming engineers could contribute to successful projects from day one.

4.5 | Operational consequences of the transformation pathway choice

Participation in these transformation pathways resulted in three significant outcomes for the operational performance of knowledge work. First, it enabled organizations to employ algorithms for tasks that were previously reliant on specialized expertise and embodied skills. Second, it influenced long-term performance by shaping the learning opportunities inherent to algorithmic integration. Third, it impacted the performance of subsequent algorithmic projects by steering business areas onto path-dependent trajectories.

4.5.1 | Consequences for enabling algorithms in skilled knowledge work

Our case studies revealed the active roles played by the two transformation pathways in facilitating the use of algorithms within business areas, even for tasks that previously demanded skilled work. The nature of knowledge work across these business areas was intricate, context-dependent, temporal, and situated (Brown & Duguid, 1991; Lave, 1988). Thus, the effectiveness of this work hinged on individuals' embodied skills, their accumulated experience (know-how), and their mastery of organizational protocols (know-that). By engaging in either of the transformation pathways, business areas employed practices to address the challenges posed by knowledge work. For example, they decreased the need for embodied skills and specialized expertise by standardizing how tasks were executed. This approach subsequently paved the way for identifying and refining data, enabling algorithms to effectively recognize work patterns and imitate expert judgment. This is not to say that the know-how of a practice can be captured into know-that, as these two aspects are mutually co-constitutive (Tsoukas, 2012). But through these practices, business areas translated certain simplified components of practitioners' expertise into new procedures that empowered algorithms to undertake work relying on skilled work.

Beyond making it easier for organizations to use algorithms in tasks that require skilled work, we found that the two transformation pathways had different effects on the resulting operational performance, as shown in Table 5. Business areas that introduced algorithms in knowledge work by automating a specific task were

TABLE 5 Consequences for operational performance based on the transformation pathway.

Pathway	Project	Success	Failure
Re-engineering the entire process	Business services: Credit card onboarding	x	
	Business services: Credit card locking	x	
	Drilling operations: Drilling optimization (Phase B)	x	
	Drilling operations: Mini frac calibration	x	
Automating a specific task	Internal audit: Anomalies in financial transaction	x	
	Maintenance operations: Maintenance scheduler	x	
	Internal audit: Risk reports for directors		x
	Drilling operations: Drilling optimization (Phase A)		x

less likely to see the benefits compared with those that re-engineered the entire process. At first, automating a specific task might seem like a reasonable way to change work. It can help reduce the risks of new technology and make algorithms feel less intimidating to staff, compared with more radical changes (Truelove & Kellogg, 2016). However, there are risks involved in this approach. This pathway did not work well when the task not only demanded skilled work but was also tightly coupled or involved a lot of variations in inputs and outputs. In such situations, just changing a task is not enough, and a broader approach to changing the entire process is necessary.

4.5.2 | Consequences for learning and long-term performance

We observed that, when adopted, not all the algorithmic solutions triggered a readjustment of the knowledge regime, which had consequences for the individuals' ability to learn. A discernible contrast emerged between the two transformation pathways, as shown in Table 6. Business areas that overhauled knowledge work through process re-engineering consistently adjusted the knowledge regime. This level of transformation was too substantial, necessitating a reconfiguration of learning approaches and knowledge validation practices. Conversely, areas that modified knowledge work by changing specific tasks only adjusted the knowledge regime in one case. As this approach involved a direct substitution of human labor with algorithms in a single task, individuals underestimated the potential impact of not enacting this action on their learning. The presumption was that since algorithms were handling the task, there was no need for staff to engage with their outputs or operational methods.

Neglecting to adjust the knowledge regime was particularly problematic because it risked the long-term operational performance of the business area, impeding knowledge transfer, and even causing its destruction. For example, relying on algorithms to replace humans in generating weekly maintenance schedules progressively limited opportunities for maintenance workers to learn through experience. They found themselves acknowledging a lack of understanding about creating these schedules without the assistance of computers. Some even expressed concerns about being clueless if the person overseeing the algorithmic scheduler were to leave the organization, given that she was the only one experienced in handling it. Thus, introducing algorithms without adjusting the learning practices led to a process of knowledge self-alienation, wherein workers saw their knowledge as unfamiliar or alien. Furthermore, it posed challenges to knowledge transfer. Maintenance workers no longer possessed the necessary information and skills to address emerging issues tied to these schedules, and conveying these insights effectively to other staff beyond their organization became problematic.

4.5.3 | Consequences for using algorithms in subsequent projects

Our cases showed that algorithm projects create path dependency, steering business areas toward consistently employing a specific combination of transformation pathways and algorithmic solutions over time. This had important effects on how well future algorithmic projects improve business area operations. Path dependency resulted from existing investments in specific technologies and cognitive frames that favor established interpretations of technology use. This posed both positive and

TABLE 6 Consequences for operational performance based on the transformation pathway.

Pathway	Project	Adjustment of the knowledge regime: Yes	No
Re-engineering the entire process	Business services: Credit card onboarding	x	
	Business services: Credit card locking	x	
	Drilling operations: Drilling optimization (Phase B)	x	
	Drilling operations: Mini frac calibration	x	
Automating a specific task	Internal audit: Anomalies in financial transaction	x	
	Maintenance operations: Maintenance scheduler		x
	Internal audit: Risk reports for directors		x
	Drilling operations: Drilling optimization (Phase A)		x

negative implications for operational performance. In some cases, path dependency allowed organizations to enjoy the cost advantages of creating economies of scale, as the cost of reusing algorithms in other knowledge work was significantly lower. Consider, for example, the case of the business services area. After initial success using RPA, they used their current infrastructure as a scaffold to create and deploy circa 240 more RPA solutions across the area. In other cases, path dependency had negative implications; it prevented organizations from realizing the need for a different algorithmic technology or pathway for automating other knowledge work.

One example that illustrates the negative consequences of path dependency involves a project within the internal audit area tasked with creating risk reports for directors using natural language processing algorithms. This project failed, as internal auditors adhered to their familiar approach of automating a specific task instead of restructuring the entire process. At the project's inception, the internal auditors opted to employ algorithms to automate a specific task: the creation of audit report summaries. Their choice was influenced by their prior focus on adjusting particular tasks in past projects, but implementing it led to unsatisfactory outcomes. An analysis of the reports created by the natural language processing algorithm used revealed its confusion when encountering variations in terminology, including multiple acronyms employed by ACME, ultimately decontextualizing the audit's findings. Words such as “cow,” which could refer either to the animal or in ACME's lexicon, “Control of Work,” were not differentiated. This lack of contextual understanding resulted in convoluted risk findings. Further variations that confused the algorithm stemmed from the differences in language used by engineers, who run operational audits, and accountants, who run financial audits. After several iterations, the audit team asked ACF to separate operational and nonoperational audits to control some language variations between these two contexts. This adjustment improved the performance of the algorithms, indicating that a comprehensive process redesign for constructing audit reports, segregated by audit type, could have yielded more robust knowledge production.

5 | DISCUSSION

5.1 | A qualification on the role of skills

A key question guiding this paper was how organizations harness algorithms to improve knowledge work, particularly skilled tasks. Our research at ACME provided key insights: we found that skills are not the main determinant of whether knowledge work tasks benefit from algorithms. Instead, improvement depends on how established work practices are transformed. This finding contrasts with prevailing research that suggests skilled tasks resist productivity gains from new technologies like algorithms (c.f. Acemoglu & Autor, 2011; Arntz et al., 2016; Autor, 2015; Frey & Osborne, 2017; Sampson, 2021). While skills like creativity, social intelligence, and dexterity presented complexities when accommodating algorithms, our investigation shows that they did not stop business areas from gaining benefits. For example, drilling engineers used reinforcement learning algorithms to successfully calibrate customized fracturing and stimulation treatments, previously needing creative judgment. Similarly, workers in business services successfully used RPA algorithms for credit card onboarding, which needed social intelligence. The requisite skillsets initially posed barriers to algorithmic integration, yet through transformation practices, these barriers were surmounted or circumvented. Thus, an important insight is that to understand technology change, we need to look at the organizations' capability to transform knowledge work processes. As novel algorithms like generative or multi-modal AI will enable automating more complex tasks and processes, this point will only increase in importance (Alavi & Westerman, 2023).

Our theoretical contributions demonstrate how organizations achieve operational improvements by implementing algorithms within skilled knowledge work through transformative processes. To do so, we establish a connection between the literature on process improvement and knowing-in-practice. In the remainder of this section, we abstract from our empirical observations of business areas to offer a general model of how organizations adopt algorithms, and with what consequences for operational performance. We then explore how this model contributes to existing research and theorize the circumstances under which algorithms drive and sustain knowledge work improvement. We conclude by presenting the limitations of our study and opportunities for future research.

5.2 | A process model of algorithmic adoption

In this section, we draw on our findings to present a model of algorithmic adoption, depicted in Figure 2. Unfolding from left to right, our model begins with overcoming the inertia of established working practices, where workers repeatedly evaluate algorithms to negotiate on adoption, motivated by occupational values, personal ambitions, and fears, as well as institutional pressures (though this stage was out of scope, see Bechky (2020) for related discussion). Once an organization has agreed to adopt algorithms, the model progresses into the actual work transformation, following two pathways that we have called "automating the task" by substituting human labor with algorithms and "re-engineering the process" by redesigning sequences of steps upon integration of an algorithm. The model concludes with the "adjustment of the knowledge regime," a stage that involves modifying the structures that sanction knowledge, and the legitimate ways of learning. Importantly, not all transformations reached this stage, which impacted the extent of algorithmic improvement. In the following, our discussion focuses on elaborating on the in-scope stages of transforming work and adjusting the knowledge regime to understand how organizations can realize performance gains from algorithms in knowledge work.

Our findings reveal two pathways for accommodating algorithms that yield varying outcomes for task performance: "automating the task" and "re-engineering the process." The first pathway focuses on substituting a specific human task with an algorithm, as maintenance workers did in creating an algorithmic scheduler. This automation pathway can deliver performance benefits by standardizing and constraining the task, reducing the need for accumulated experience. However, this pathway faces two inherent challenges. First, it only succeeds when the task is loosely coupled and less variable. Second, the subtle substitution of one task overlooks the necessity of adjusting knowledge regimes to ensure learning from algorithmic outputs. These twin challenges hamper the instantiation of operational improvements. And even when organizations realize improvements, the pathway poses long-term performance risks by limiting ongoing learning and adaptation.

In contrast, the second pathway focuses on re-engineering the entire process to accommodate algorithms, as engineers did in developing personalized fracturing treatments. The process re-engineering pathway can deliver performance improvements by addressing potential variations in inputs and removing non-value-adding steps. Although this transformation pathway demands stronger stakeholder buy-in and appears more daunting initially, it not only enables operational improvements to be created but also sustains them. Given the larger scope of transformation following the re-engineering, it triggers an adjustment of the knowledge regime that enables human learning from algorithmic outputs. For instance, adjustments to drilling regimes, empowered engineers to enhance frac pack efficiency while maintaining control over knowledge quality and learning.

Importantly, the choice of pathway is also influenced by path dependency. Business areas that first implement algorithms through task automation tend to stick to that approach for subsequent projects, even when it proves challenging. Transitioning to process re-engineering instead was difficult despite greater long-term benefits. We argue that this is because past adoption of algorithms creates opportunities for people to align new technologies to existing practices, shaping change through self-reinforcing patterns over time (Ciborra, 2006; Leonardi, 2011; Pentland et al., 2022; Taylor, 2001). Thus, while multiple transformation pathways may exist in theory, in practice operational requirements and historical patterns constrain business areas to follow just two dominant routes.

5.3 | Improving the outcome of adopting algorithmic solutions

Our study raises important questions about how to instantiate the improvement of knowledge work with algorithms. A key finding from our study is that

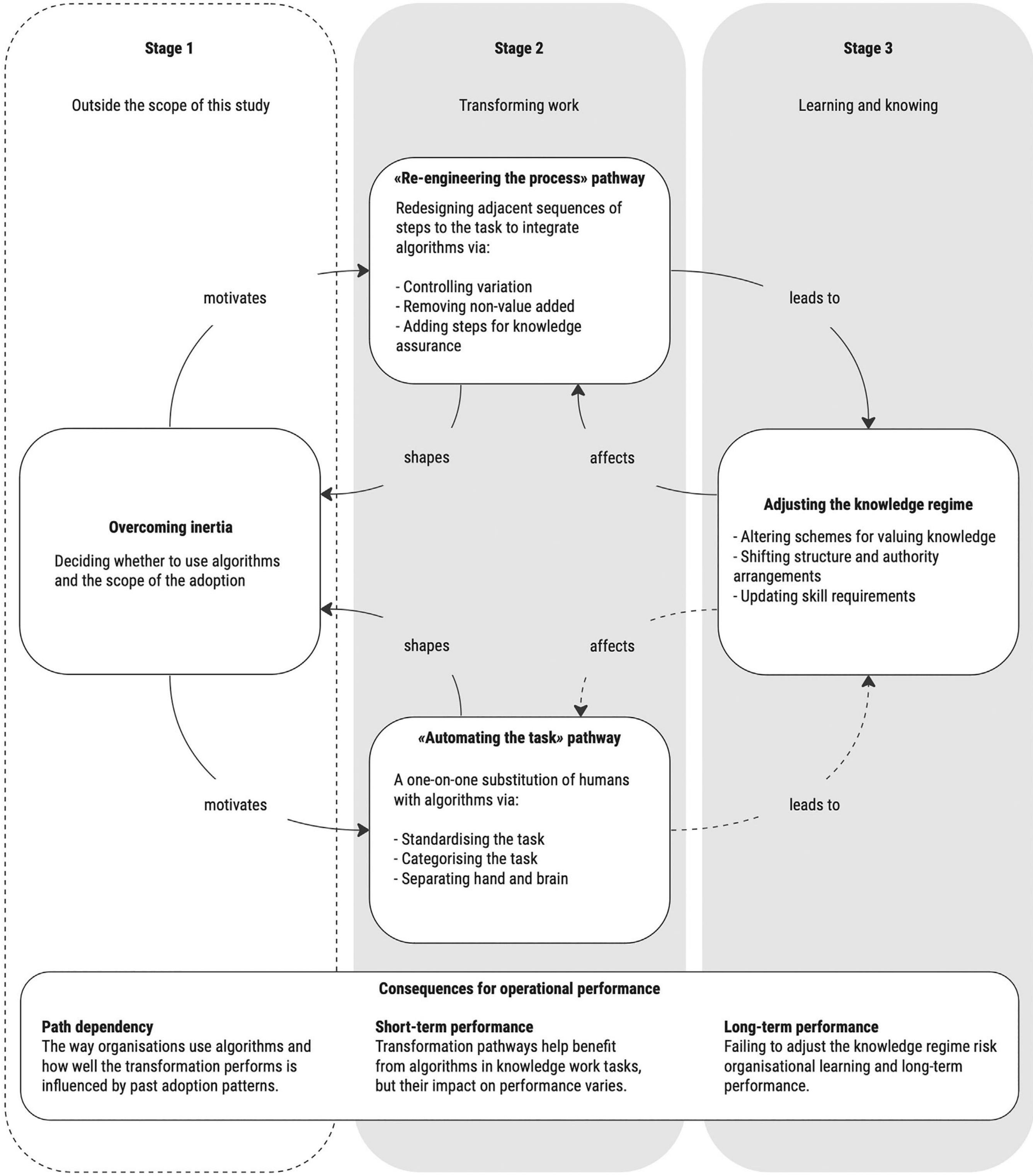

FIGURE 2 A process model of the adoption of algorithms in knowledge work.

algorithms do not inherently deliver operational benefits; instead, these benefits materialize when they are seamlessly integrated into established work practices. Projects that chose the process re-engineering pathway proved more successful in generating operational improvements. The success of process re-engineering can be attributed to the fact that these business areas were better able to grasp how individuals actually carried out their work. They comprehended people's underlying assumptions, the norms guiding how knowledge was created, validated, and shared, the significance of specific acronyms, the potential variations in job tasks, and how people adapted to these variations. In essence, process re-engineering allowed business areas to capture not only explicit knowledge but also the valuable tacit know-how that might otherwise have remained hidden. By capturing this tacit knowledge, business areas acquired the insights necessary to redesign their work practices in a way that considers or transforms these hidden understandings, ultimately ensuring the quality of the algorithmic outputs. In the task automation pathway, this outcome was less likely to occur. Business areas on this route were more prone to overlooking these nuanced and tacit understandings, which in some cases resulted in work transformations that were flawed or incompatible with established knowing practices. In turn, the projects proved to be less successful. Thus, we propose:

> **Proposition 1.** *When incorporating algorithmic solutions, redesigning entire business processes leads to greater improvements in operational performance, compared with only automating a specific task within a process.*

We argue that to enhance the likelihood of successful algorithm adoption in knowledge work, organizations can benefit from what we term "work triaging"—conducting a preliminary assessment of the work where the algorithm will be deployed, to determine the most suitable transformation pathway. This could involve evaluating work tasks in terms of their degree of coupling, extent of variation, and frequency of repetition. This approach may be facilitated by mapping the knowledge work process, identifying resources, dependencies, and subsequent steps. Additionally, the triage process can explore the modality of its input variations, such as how information in knowledge work is acquired to form meaningful decisions. By triaging work, organizations can decide whether a straightforward substitution of humans with algorithms for a task is feasible, or if further adjustments to the process or inputs are needed before implementing algorithms. Thus, our findings support what Sampson and dos Santos (2023) proposed analytically.

This proposition also raises important questions about how organizations may overcome the path dependency created by previous algorithmic projects. We have established that the transformation pathways organizations choose for integrating algorithms into knowledge work play a key role in achieving operational improvements. However, as highlighted earlier, successful endeavors can lead to path dependency. When transformation pathways misalign with the specific task's requirements, failure can follow. For instance, internal auditors' historic reliance on practices tailored to automating single and discrete tasks proved inadequate for incorporating NLP algorithms into the creation of audit reports. These practices prevented internal auditors from realizing that such a task demanded re-engineering the entire process to handle high levels of variation in the inputs and outputs. It is conceivable, if not likely, that the opposite scenario could occur as well: organizations accustomed to re-engineering entire processes might struggle to seize quick wins through algorithmic substitution in tasks that merely require the direct substitution of humans for algorithms. Thus, alignment between tasks' requirements and transformation pathways are crucial for creating operational benefits from algorithms.

5.4 | Enhancing the acceptance of algorithmic solutions

Our findings also raised questions about the acceptance of performance improvements derived from algorithms. Key to that is the need to alter how organizations evaluate knowledge as they adopt algorithms. Knowledge and action are intertwined (Orlikowski, 2002); thus, incorporating algorithms into established practices transforms "knowing how" to operate, needing organizations to evolve how they assess the quality of insights, recommendations, and decisions from human-algorithm work, to ensure the legitimacy and appropriateness of the knowledge produced. Altering the schemes for evaluating knowledge can be intricate as experts seek to protect the jurisdiction of work by keeping their expertise tacit (e.g., Abbott, 1988), preventing formalizations of their ways of working, and making judgments. Yet failing to adapt to the reality of new practices involving human-algorithm collaboration can negatively impact operational performance, both short term and long term. Consider auditors building NLP algorithms to streamline risk area identification. They failed to create appropriate ways to assess if the risk areas identified by the NLP algorithm were the right ones, resulting in misleading reports on resource prioritization for risk mitigation. They could have prevented this situation if new schemes for evaluating knowledge grounded in the new contextual practice had been in place. These schemes could have helped them understand that evaluating the contextual relevance of NLP risk areas was more important than NLP accuracy.

In addition to validating the algorithmic outputs against appropriate schemes, effective human-algorithm collaboration requires organizations to socialize algorithmic outputs (e.g., decisions, suggestions, summaries) and lessons learned. Unfortunately, knowledge sharing in many organizations has been subsumed into sharing memos or knowledge bases. This is ineffective for validating algorithm outputs. For one, algorithmic black boxing is as much a technical problem as it is social (Anthony, 2021); workers may accept algorithmic outputs unquestioningly, enabling diffusion of misinformation or inappropriate decisions. This becomes amplified by remote working that promotes individualistic learning, which can lead to imbalances in the expertise needed to critically evaluate algorithmic outputs. Mitigating these risks requires a more active form of knowledge sharing where algorithm outputs and lessons learned are validated in participative groups. This can take the form of sharing stories and anecdotes of failures and successes with algorithmic outputs. These stories help workers engage in collective sensemaking and facilitate human learning by acting as a live "repository of accumulated wisdom" (Brown & Duguid, 1991). For example, a discussion among auditors of the NLP algorithm's flawed risk analysis could uncover the need for separating audits into their contexts (e.g., finance and engineering) to improve risk area identification. Thus, we suggest increasing acceptance of algorithm recommendations requires evolved evaluation schemes and socializing outputs—both lessons learned and decisions taken—to promote continuous learning. Therefore, we propose:

> **Proposition 2.** *When incorporating an algorithmic solution, socializing and validating the algorithm's outputs leads to greater acceptance of its recommendations.*

Broadly, the need to validate and socialize algorithm outputs highlight an important insight: considering the knowledge regime when engaging in process improvement is vital. Thus far, research on process improvement has focused on cycles like Plan-Do-Check-Act (Deming, 1982), which tend to focus on objectifying work into sequences of tasks to identify opportunities for improvement, implement changes, and measure their impact. However, our study underscores the need to simultaneously consider work processes and learning practices. That is, learning considerations should not be limited to the check/study stage of this cycle, but must also consider the knowledge that occurs during process execution (the practice). In our cases, organizations unable to adapt learning practices, evaluation approaches, or authority structures—the knowledge regime—could not benefit from algorithms. Some managed temporary improvements but struggled to sustain them, rendering algorithms ineffective.

5.5 | Sustaining the improvements derived from algorithmic solutions

The ability to sustain the improvements is the ultimate metric of success in process improvement. Key to understanding how to sustain improvements is to acknowledge that tasks not only constitute work but also shape and reshape learning (Orlikowski, 2002). Our analysis shows projects that adjust their knowledge practices are more likely to realize operational benefits when implementing algorithmic solutions. This is because implementing algorithms requires reshaping work practices, which inherently modifies how people acquire knowledge and skills. Reshaping work practices determines which skills become relevant, which practices support learning, and how knowledge quality is evaluated. If it is not managed thoughtfully, organizations run the risk of having employees whose expertise and skills are no longer aligned with the evolving practices, rendering them, no matter how intelligent and experienced they may be, unable to contribute effectively to the process. Adjusting the knowledge regime mitigates this risk. It prompts organizations to assess whether their methods for validating knowledge outputs (e.g., reports, presentations, analysis) remain valid and, if not, to identify suitable alternatives. It also ensures the establishment of new structures for recognizing and promoting new skills. This helps the company to sustain operational performance improvements realized through integrating algorithmic solutions. Hence, we propose:

> **Proposition 3.** *When incorporating algorithmic solutions, adjusting the knowledge regime increases the organisation's ability to sustain improvements in operational performance.*

In this context, integrating process improvement and knowing-in-practice offers a new lens for studying algorithmic adoption in skilled work. This lens suggests that the challenges like opaque algorithmic recommendations (Lebovitz et al., 2022; Waardenburg et al., 2021), hidden epistemic assumptions within algorithms (Anthony, 2018; Lebovitz et al., 2021), stem from failures to understand people's work and how it shapes knowledge. This insight is key as organizations increasingly adopt algorithms to automate decision-making amidst continuous digital transformation (Angelopoulos et al., 2023).

6 | LIMITATIONS AND FURTHER RESEARCH

As with all case-based research, the generalizability of our findings is a prominent concern. Our cases aimed for naturalistic generalizability (Pratt et al., 2006) rather than statistical generalizability, drawing insights from unique cases rather than common ones. Care must thus be taken when transferring these findings. For example, our findings may not apply to contexts involving artistic creativity, as it differs from the cognitive and deliberate creativity observed in the business areas studied here. Importantly, the two pathways we identify may not represent the full range of transformations possible across all contexts. Further research could uncover additional pathways, practices, and outcomes associated with algorithm adoption in diverse contexts like professional services, open-source software, R&D labs, and more.

A key limitation stems from budget and time constraints that led us to focus only on knowledge practices and skill requirements of knowledge and the changes made to transform knowledge work. We did not examine other potentially influential factors like status, experience, unionization, and organization type that may impact algorithm adoption. It may well be that professionals in service firms may strategically construct narratives to protect their agency and knowledge work; or expert aversion to algorithms may hinder long-term benefits. Two open questions remain: how do experts with different characteristics construct, resist, and react to organizational algorithmic work redesigns? And how do these social processes moderate algorithmic performance gains? We pose these for future research.

In the wider context of the digitalization of operations, the use of algorithmic solutions in knowledge work will likely become more prevalent as technology advances further. Recent advances in multi-modal and generative AI systems are likely to spark further adoptions of algorithmic solutions to contexts that are so far deemed not to be automatable, and so further challenge our present assumptions about their impact. As the well-cited work of technologist Roy Amara tells us, at the point of technological innovation we are very likely to underestimate the effects that new technologies will have in the long term (Boucher & Amara, 1977). Developing a deeper understanding of how organizations can effectively create collaborations between humans and algorithms will thus be critical for the field of Operations Management.

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ENDNOTE

[1] Although the terms "work" and "processes" are closely related, we acknowledge some key differences between them. "Work" primarily emphasizes the concrete, dynamic, and situated activities that an individual engages in as part of earning a living (Barley, 1996; Barley & Kunda, 2001; Orr, 1996). On the other hand, a "process" refers to a sequence of steps designed to transform inputs into economic outputs (Holweg et al., 2018). While there are instances where an individual's work may encompass an entire process, in modern organizations processes are often divided among different individuals. Consequently, we take care to avoid equating knowledge "work" and knowledge "processes."

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APPENDIX A

INTERVIEW PROTOCOL FOR PHASE I

Part I: Characterization of work

1. Please tell me about your role in three sentences.
2. How many years have you worked with the company?
3. How many people are you responsible for?

Part II: Characterization of knowledge work tasks and perception of fit for algorithmic solutions

4. What are the five main tasks in your work? And how often do you do them?

From a to e, please rate each task on a 0–10-point scale according to the following dimensions. 0 means that the dimension (e.g., standardization) is NOT present (e.g., the task is not standard at all), and 10 means the dimension is fully present (e.g., the task has been completely standardized).

a. How standard is this task? Please explain your answer.
b. How much social intelligence is required to complete this task? Please explain your answer.
c. How much creativity is required to complete this task? Please explain your answer.
d. How much manual dexterity do you need to complete this task? Please explain your answer.
e. In your view, how suitable are algorithms (ML and RPA) for this task? And why?
f. What technologies do you currently use to support this task?

Part III: Perception of algorithms' potential

5. Where do you see, in general, the greatest potential for algorithms within your area? Why?
6. Specifically, what role do you see for RPA? For ML? in your area?
7. Is there anything you would like to add?

APPENDIX B

SEMI-STRUCTURED INTERVIEW PROTOCOL FOR PHASE II

Part I: Description of projects using algorithmic solutions

1. Tell me about project “X”:
    - How did the project start?
    - What technology are you using? And why?
    - What was the aim of the project (e.g., knowledge work task)?
    - Who executes it?
    - Who is involved?
    - What is the status?

Part II: Algorithmic solutions and organizing

2. How did you adopt algorithmic solutions?
    - What steps have you taken to use algorithmic solutions in your work?
    - What has worked?
    - What hasn't worked?
    - What changed?
    - What obstacles have you faced and how did you overcome them?

Part III: Algorithmic solutions and operational performance

3. Tell me about a positive experience automating work with algorithms.
    - What was the project about?
    - What was the impacted task?
    - How did the project improve knowledge work?
    - What were the impacted areas (e.g., quality, delivery, cost, morale, safety)?
    - How did you measure success?
4. Tell me about a negative experience automating work with algorithms.
    - What was the project about?
    - What happened?
    - What was challenging about the project?
    - What were the impacted areas (e.g., quality, delivery, cost, morale, safety)?
    - What is the status of this project?

APPENDIX C

TABLE C1 Data structure.

First-order codes	Second-order practices	Overarching dimension
• Maintenance operations: looking out for repeatable and predictable tasks to activate algorithms • Internal audit: Classifying whether tasks require social intelligence for information gathering or for dealing with emergent situations (informal)	Categorizing tasks	Automating the task
• Internal audit: Constraining creative tasks to ensure audit testing is consistent across audits • Deploying reinforcement learning to bridge the gap on the physics and art of fracturing on soft rock	Standardizing tasks	
• Business services: Automating keystrokes to enter information in applications (transactional applications) • Maintenance operations: Separating maintenance activities into planning and execution	Separating hand and brain	
• Drilling operations: Automating fracturing onshore is easier because the wells behave in a standard way • Business services: Identifying standard and static activities in credit card onboarding • Standardizing work around drilling to deploy project Beta	Identifying and controlling the process variation	Re-engineering the processes
• Drilling operations: adding steps for experts to review the hydraulic treatment calibration suggested by an algorithm • Business services: Creating dashboards for monitoring algorithms over time • Business services: Assigning analysts to monitor the performance of RPA bots	Adding steps for assuring output quality	
• Business services: Adjusting policies for using virtual credit cards • Business services: Eliminating the need for issuing physical credit cards • Drilling operations: Compressing the drilling process by incorporating the mini frac into the main hydraulic and stimulation treatment	Eliminating non-value-added activities and artifacts	
• Drilling operations: Dealing with new interfaces at work • Internal audit: Engaging with the data analytics team to run audit tests • Drilling operations: Reorganizing teams based on staff expertise with the Bonsai platform	Shifting the structure and authority	Adjusting the knowledge regime
• Drilling operations: Using machine learning to look for patterns ahead of time and learn what was going on • Drilling operations: Accepting that reinforcement learning does not need to provide explanations to provide value to the firm • Business services: Testing models extensively before deploying	Altering practices for learning and valuing knowledge	
• Drilling operations: Using algorithms to empower engineers without specialized knowledge to run mini fracs • Business services: Automation improves the standardization of a process and decreases the need for experienced workers	Updating the skill requirements	