WORKING PAPER SERIES

# DIGITAL TRANSFORMATION IN A WHITE COLLAR FIRM: IMPLICATIONS FOR WORKERS ACROSS A CONTINUUM OF JOBS AND SKILLS

Elisabeth B. Reynolds, MIT IPC and DUSP

Anna Waldman Brown, MIT IPC and DUSP

Frank Michael Ryan, MIT IPC and TPP

MIT Work of the Future Working Paper 14-2021

June, 2021

MIT INDUSTRIAL PERFORMANCE CENTER

400 Main Street, E19-733, Cambridge, MA 02139

# DIGITAL TRANSFORMATION IN A WHITE COLLAR FIRM: IMPLICATIONS FOR WORKERS ACROSS A CONTINUUM OF JOBS AND SKILLS

**Elisabeth B. Reynolds, MIT IPC and DUSP**
**Anna Waldman Brown, MIT IPC and DUSP**
**Frank Michael Ryan, MIT IPC and TPP**

**May, 2021**

## I. Introduction

For service-oriented, white-collar firms, the process of "digital transformation" began years ago, but the pace has accelerated as new AI/machine learning technologies have advanced (Matt, Hess, and Benlian, 2015; Frey, 2019). In many cases, there is a sense that firms are behind and need to "catch up", though catch up to what remains somewhat elusive. New technologies go hand in hand with shifting operating models and management styles, such as the introduction of Agile and Industry 4.0 (Orlikowski, 2010; Davenport and Westerman, 2018). All of this leads to varying degrees of transformation across service-oriented firms. As customers' demands became more volatile, product development timeframes shortened, and machine learning algorithms improved, businesses responded by developing more adaptive and dynamic strategies that focused on "responding to change over following a plan" (Highsmith and Cockburn, 2001; Beck et al., 2001).

The following case study provides a window into one multinational insurance firm and its digital transformation pathway. The firm is a large, well-established company and operates in 30 countries. The focus of this case is not on the technology *per se* but on how its adoption and integration have affected particular jobs across a continuum of jobs and skills in the firm, as well as what steps the firm has taken to ensure some of its workers have the right skills to adjust to the changes taking place. White-collar work, where there are a higher percentage of workers with four-year college degrees, provides an important case study of understanding how new software-based automation technology (rather than physical robotics) may affect jobs and skills for higher-educated workers, of which there are many more than in traditional manufacturing jobs. It also provides a window into how middle-skills jobs in clerical and administrative positions continue to shrink (Autor, Katz, and Kearney, 2006) with the introduction of automated technologies such as robotic process automation (RPA).

Concerns about the future of work in services and white collar employment have increased in recent years as the power and potential of automating algorithms have focused on tasks that have traditionally been perceived as the domain of "knowledge workers," and thus less prone to automation or substitution than more routine, lower-skilled jobs (Brynjolfsson and Mitchell, 2017; Manyika et al., 2017; Autor, 2015). Several studies of white collar automation point to the displacement of managerial positions with higher cognitive requirements (Dixon et al., 2020, Autor, Katz, and Kearney, 2006) perhaps because today's "smarter" technologies require fewer managers to supervise increasing numbers of workers (Moulds, 2018). Several reports (Lund et al., 2019; Muro, Whiton, and Maxim, 2019; BLS, 2020) calculate that mid-level white collar jobs– especially those requiring lower education levels– represent several of the largest categories subject to automation and worker displacement as shown in Figure 1:

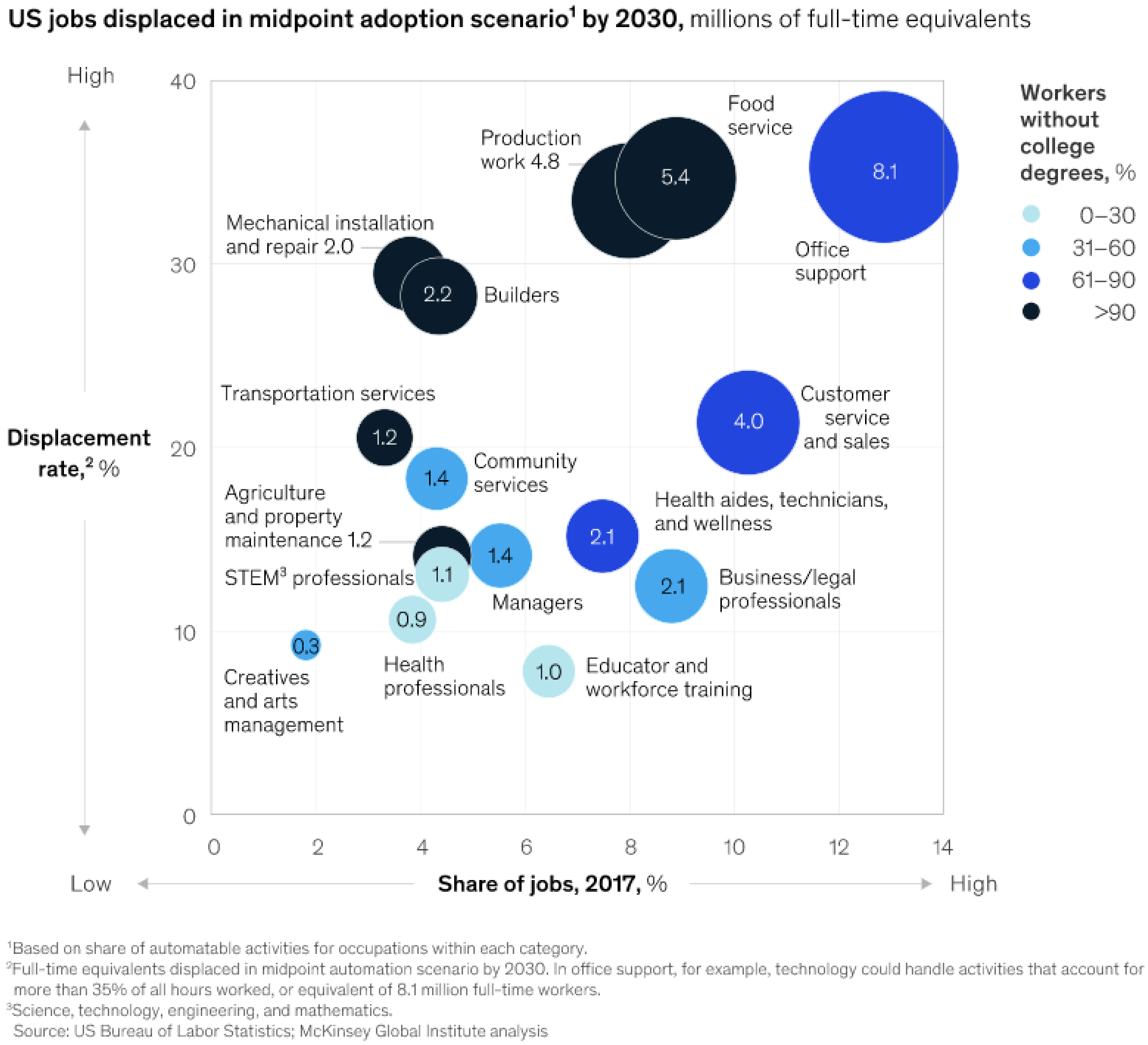


*Figure 1: Estimated US jobs displaced by 2030 by occupational category, via Lund et al 2019*

This paper is based on research conducted between the spring of 2019 through the summer of 2020. Approximately 25 semi-structured interviews were conducted with firm employees across IT, HR, the legal claims department, and the help desk and training department. Data regarding the Bootcamp training program was provided by the firm and analyzed by MIT researchers.

The outline is as follows. Section II discusses the drivers of digital transformation broadly. Section III discusses how the firm is building its AI capabilities within its technology team and how they identify problems where AI can be applied. Section IV examines three examples of the application of AI-related technologies, first in the case of legal services within the firm, the second with frontline insurance agents, and the third within the internal help desk. Section V looks at a particular case of upskilling with an internal training program to develop more software developers within the firm. Sections VI summarizes overarching themes from the case studies, and Section VII concludes with suggestions for future work.

## II. Drivers of Digital Transformation

What does digital transformation actually mean? In the words of Davenport and Westerman (2018): "Digital transformation is an ongoing process of changing the way you do business. It requires foundational investments in skills, projects, infrastructure, and, often, in cleaning up IT systems. It requires mixing people, machines, and business processes, with all of the messiness that entails."

A number of factors have driven firms toward increasing digitization of information and services, starting with the changes in software and technology platforms that have created greater power, speed, insight and reach in business operations. These new technologies not only help improve the efficiency and impact of current operations, but also create opportunities for firms to better link their business strategy to actual technology capabilities, in addition to opening up new business products.

The emergence of cloud computing, for example, has transformed the way businesses now collect, store and use data. The increase in computational power has led to far greater amounts of data that can provide important insights about customers, quality and general operations. Technological evolution and the pace at which it is happening are other major motivators for firms to invest in digitalization. And given how virtually everything done in sophisticated firms relies upon computers, there is significant opportunity to transform every corner of operations.

For the insurance firm in this case study, all of its software has changed over the past three to four years. As one of the leaders in the firm underscored, "Our business *is* technology; there isn't a separation now." In general, the firm needs more people who are technically oriented. But with a tight labor market before the pandemic (2018-2019), the firm decided to reskill and upskill some of their existing workforce, rather than hiring all new software engineers – who were hard to find and/or knew little about the firm's actual operations.

In conjunction, the firm moved from having several large, proprietary vendors of software technology (such as IBM and Microsoft) to a more piecemeal solution of tens of different, smaller software platforms (some of which were actually acquired by the firm) to avoid putting all their eggs in one corporate basket. While this strategy allowed for more customizable solutions and helped the firm retain power over its own capabilities, it has been challenging for the IT department to integrate all these diverse software packages into its workflow, while figuring out how to navigate a host of different technical problems across different platforms.

### *The Promise Versus Reality of New Technologies*

The firm has implemented a variety of new automation technologies, including some machine learning (ML) algorithms that could debatably be classified as artificial intelligence (AI), but firm managers were quick to point out that the promise of "a new dawn of AI" with significantly different capabilities from past technologies has not yet materialized. Like many other firms, this firm was aware of a host of predictions around the potential for large-scale automation, such as Frey and Osborne's (2017) conclusion that 47% of all US employment was "potentially automatable over some unspecified number of years, perhaps a decade." But that has not been their experience. No doubt, ML-enabled chatbots have substantially saved time and money by answering questions to the internal IT Help Desk as well as in customer service. And Robotic Process Automation (RPA) has increased efficiencies in back office work and replaced some workers (60+ workers in 2018). However, it has not delivered what was envisioned from the outset:

> *All the consulting firms did a huge disservice to firms like ours by telling them they could save billions with these new AI functions. We've used some of this, but it hasn't been dramatically impactful. Why is that? Our processes are not homogenous to the degree that we previously thought. For example, we thought we could automate processes 1-9, when actually it was just 2-4. So the case for these new programs has probably been oversold substantially.*

The nature of many jobs, even those that appear to have significant routines, turn out to be more heterogeneous than fully appreciated. While tasks can be replaced, it is harder to replace jobs as a whole.

Another key challenge when facing these new digital automation technologies is that they often replace old routines, but then lock the company into an expensive system that proves less flexibility than before:

> *By automating older functions, we are in some ways stuck with those functions. For example, if we take an old claim engine and automate it, we are stuck with the old claim engine. And the slightest changes in that claim engine to make it better will not enable it to be automated. Automation therefore works best on old, non-changing technologies. That is basically our situation with automation. And this experience has been repeated with many large companies.*

Of course, chatbots and RPA are arguably not representative of AI *per se*. Machine learning and decision-making technology do present more dynamic potential, and can generate new insights that have to date not been possible. But this is largely due, in the eyes of one of the lead technologists at the firm, to the increasing computing power that can process massive amounts of data, not necessarily new capabilities in AI. This technologist also notes, "do we really know how neural networks process data?" For much of machine learning, we are often not clear how ML arrives at certain conclusions or choices. As has been pointed out in many cases (Brynjolfsson and Mitchell, 2017), ML requires considerable data preparation and cleaning, and even the most "objective" datasets are likely to encapsulate human bias.

“We are in the first inning” of developing truly insightful AI, he says. Another senior IT leader put it this way:

> *We’re at the infancy of what AI and ML can bring to the insurance industry. We are tinkering, we’re seeing a level of success but really we’re just scratching the surface of how AI and ML are capable of disrupting the industry. It’s not just about the technology– in fact, I think the technology is more advanced than we can handle. It's more about the capability of our business to develop the problem statements that we want to achieve from AI and ML and then determining, how do we execute a learning journey? We lack the maturity in coming up with what’s possible.*

## III. Building Firm Internal AI Capabilities

To actually put to use AI technologies and build capabilities within the firm, the composition and organization of the tech support teams needed to change. They pivoted from having separate groups of software engineers and call center workers to building two integrated “squads” of 5-6 people made up of call center workers, software engineers, one or two data scientists, and machine learning experts.

Our use of the term AI throughout this paper refers specifically to the ML algorithms and advanced statistical analysis that many of the firm’s employees referred to as AI. The process of “teaching machines to make decisions” or “deep learning” lends itself well to predictive analytics—which, in the insurance business, can be very useful when assessing claims. This use of machine learning would not qualify as general artificial intelligence; instead, these algorithms rely on very specific and well-defined boundaries in order to effectively solve problems. According to one of the team members, “We’re decades, if not centuries, away from general AI in my opinion.”

The firm spent two years shoring up the foundations for ML by building an R computing platform that can create the capabilities for experimentation in data science work. The secure platform allows the company to work with its own team or with outside teams from consultants or academics to experiment on real-world data in a cyber environment.

The first step to engaging AI capabilities in the firm is to find a relevant problem to address. This is not as straightforward as one would think and requires not only the IT team to engage but firm employees within different units to imagine how this technology might help with their work. This is not something that comes intuitively to the average worker, but often can be gleaned with the help of data scientist experts engaging with firm workers. The firm brought an interdisciplinary team together to develop a set of parameters for what would be a great AI project. The team decided that any new project must answer the following questions:

1. Is there a business pain point we’re trying to solve?
2. What is the dollar value of the business problem? 100s, 1000s, millions?

3. Is there leadership enablement? Has leadership bought in to the idea?
4. Is the *business*, not the leader ready?

On the latter point, it was emphasized that often, from a cultural point of view, a business unit isn't open to the use of AI because they don't believe it can really help. Predictive models, for example, are often perceived to fail and thus an AI model that is using data to generate better predictive analytics is met with some skepticism.

> *The biggest bang for our buck is when there's a human who knows that ML can really help somewhere—and they're willing to fight the good fight. The [Firm] is very risk-averse, so every time someone says we've got ML, people get uncomfortable.*

Once these questions are answered, the critical fifth step is generating the data for analysis. The data must meet a certain quality, and be accessible as well as accurate. If this can be assured, then an experiment or pilot is launched. The "data science lifecycle" begins with understanding how the particular business unit operates and how the data fits into their work. From there, the data is mined, cleaned, and explored. Data scientists are needed for the exploration and also for the next steps that require predictive modeling and feature engineering (the process of identifying and extracting specific properties – features – that could help develop a machine learning model). Finally, once the team has something it believes can be useful to a particular group or department, it looks to deploy it. This is the most challenging step. As one of the engineers commented, a model is completely useless if you don't use it:

> *How do we deploy these into actual decisions– say a report that people use, or integrated into our pricing mechanism?*

The potential for use of AI in predictive analytics is significant in this industry. An AI model can quickly bring together the right pieces of information to provide insight into probabilities and make recommendations as to what steps should be taken - "90% of the time, you should do X because in five out of eight cases, this is what has happened." Clearly, this kind of capability will dramatically change how claims occur in the future. One of the largest areas of potential use is in insurance pricing because of the high volumes of relevant data. In auto, for example, the introduction of telematics – chips you put in your car that measure multiple dimensions of your driving experience – has and will profoundly change the insurance pricing model for auto insurance. They are working on collecting data from peoples' cars 200 times per second. It can be from various sources - the micro-movements of the pedal of the accelerator, to the speed of turning, to whether the driver is distracted. The tradeoff is that you might pay for insurance by the mile but a chip will be installed in the car that emits data constantly, making the driver's performance more exposed to scrutiny. In addition, privacy concerns can be raised because the data can track a car's longitude and latitude, i.e. where it is at all times. This kind of private information represents a significant tradeoff for better insurance pricing tools.

The issue of the ethical use of all of this data is a new area where the firm is exploring and developing protocols. Clearly, this new amount of data raises serious ethical questions about client's privacy. "How do we empower data scientists and professionals while protecting our policyholders' privacy?" Data security is of paramount importance given the private nature of the data they are collecting.

The firm's innovation-focused Data Lab has introduced ML for several projects across the company, experimenting in a variety of different departments and applications. Data scientists from the lab seek out issues across the firm that could benefit from machine learning and data analytics, then work in coordination with employees within relevant divisions to prototype and develop solutions. The Lab's work in image processing and pattern recognition is being used for a variety of tasks, from the relatively straightforward to core firm competencies.

For example, the firm's communication team has approximately 350,000 photos in their personal repository, and the corporate office used to spend many hours combing through all these images to find, for example, photos of particular executives standing together. The Data Lab coordinated with the Corporate Communications Office to develop an image recognition tool using Python and AWS which can search for and identify requested images within minutes, across more than 5 terabytes of photos.

Another example involves working with the firm's claims management teams on insurance risk assessments that produce risk algorithms for individual customers, as well as pattern recognition for commercial insurance pricing and synthesizing data for financial investments and bond trading. The Data Lab essentially tries to correlate insurance claims with specific, business-related variables and data obtained through public sources of information and third party integration– especially telematics from insured private vehicles. This allows the firm to develop new rating algorithms for pricing both individual and commercial insurance. "Avoiding risk means we'll still insure, but we'll price effectively. You worry less when you know more."

In the next section, we explore how the rise of accessible big data and advanced data analytics are shifting the day-to-day jobs of workers within the firm, as well as the firm's workforce as a whole.

## IV. How Technology is Changing Jobs at Every Point on the Continuum

Perhaps not surprisingly given the type of work of the firm, most of the cases of new technology adoption described in this paper and by firm employees use ML/AI capabilities that are largely complementary to human capabilities, while the core functions of business units still rely heavily upon human workers whether due to the customer-facing nature of the business or the complexity of the work. Insurance is a data and knowledge-driven business. No doubt, technology has been a catalyst to both the reduction of jobs in some areas (business analysts, customer service workers) as well as the slowing of hiring rates. These jobs involve employees in both higher educated and lower educated roles. But where automation has been introduced, it has led more to the shedding of tasks and reorientation of work than to a wholesale eradication of the job itself.

Below we describe three cases of adoption of new ML technology: one in the case of an in-house legal team, one with front-line insurance agents, and the third related to the firm's internal help desk, which pilots new technologies for subsequent use by its customer call centers. These cases provide a window into the range of ways in which new technologies are changing the nature of workers across a spectrum of activities in the firm.

## Case Studies

### A. Legal Strategic Services

The Legal Strategic Services department was officially created in 2006, but it's grown in both size and amount of work over the last 15 years. The department interacts with between 4000-5000 different external law firms across the country, and deals with around $1.1 billion in legal fees and expenses annually. The department employees 20-30 auditors, who are mostly former attorneys and former finance people who decided to pick up auditing. They all have bachelor's degrees, and most are post-graduate attorneys. These auditors read through thousands of legal bills to catch discrepancies and ensure that the firm only pays for the right claims. All their bills are electronic, and for the past number of years the firm has uploaded these digital bills into a computer system for auditors to inspect line-by-line. Due to the complexity of legal reimbursements and regulations, which vary by state law in addition to what different law firms deem acceptable, there could be substantial variance across auditors.

The idea for Legal Services' AI model – which became one of the first implementations of AI across the firm – didn't come from any of their own attorneys. Four years prior, the legal department's predictive modelling team started using data from their bills to predict how much the firm might need to pay out for specific large claims. Once their model was deemed successful, they decided to apply this kind of model to their own data and their own auditors. The volume of data required to develop any meaningful prediction on legal bills was enormous, so the predictive modelling team turned toward machine learning algorithms to tackle the question.

Their pilot project for this ML model determined whether or not photocopying was an allowed expense on legal bills. Different states have different guidelines, and the firm has 12,000 different claims professionals typing up unstructured data from legal bills which results in a wide variety of different terminology ("duplicating" vs "photocopying" vs "Xeroxing"). Their first task was to bring three different teams together: the data scientists (who knew how to manage the data), the technology people (who wrote the algorithms), and the auditors. The firm's data scientists had never been so close to auditors or technologists before, while the technologists had never had to normalize against both structured and unstructured data. The auditors were skeptical about the entire process, and 40-50% said that it would never work since lawyers had been doing this for ages and the AI would never be smart enough. Only 10-15% of auditors initially welcomed the technology.

After convening all the auditors, the data scientists and technologists realized they would need to normalize their internal parameters because the auditors themselves wouldn't always agree on the same course of action. One bill from one law firm had 20-25 different parameters, including which claim, which state, which law firm, which types of activities were done, and which auditor was checking over the bill. As soon as the data science team sat down to start normalizing the data, they ran into a roadblock that couldn't be solved through technology alone.

> *Our auditors themselves weren't calibrated in the way they're thinking! This is the difference between a pure white-collar job and an assembly job. In the white collar job things differ by work units, whereas in the blue collar it's standardized.*

Once the developers mapped out how auditors approached their tasks, they found eight different clusters of decision-making. The data scientists then had to spend eight months on calibration in close coordination with the auditors, to bring all their disparate opinions together into a single, semi-standardized cluster. The very existence of this "calibration program" ended up increasing the firm's savings by forcing all the auditors to sit down and devise standardized auditing procedures, since the algorithm provided a neutral, consistent third party around which the auditors could calibrate their work.

The team's next challenge was that their model only got access to the data *after* the bills were paid, which rendered its decisions useless:

> *We needed to re-organize our process engineering in place, which was harder to do than create the AI itself. We had a champion here who knew there was a better way to do this.*

They discovered their model was only 13% accurate– but even this small gain could save an additional $10,000 annually. After presenting to the firm's CEO, the team got some more runway to keep improving upon their algorithm, and eventually worked their way up to 85% accuracy.

Even then, the auditors were still displeased:

> *They'd say, the model is wrong and the data scientists agreed because it's wrong 20-30% of the time– but then the auditors realized it was actually right 80% of the time!*

The AI team's key question became, how much additional money could be saved above and beyond the auditors? They decided to put the AI at the tail-end of the bill-auditing process, so the auditors could continue their normal work and then the AI could provide a final auditing step and potentially unlock additional savings that humans had missed. This led the auditors to realize that the model was doing something above and beyond their own capabilities, and gradually they started trusting the technology more.

Within six months of implementation, the model pumped out $1 million of extra savings and the firm is estimating a total savings of $3-4 million for the rest of the year as they add new capabilities. The team hopes that the combination of human and machine auditor can eventually save over $120 million as auditors will have the time to move on to more complex work while the AI takes over automatable tasks. The operations team within Legal began on improving this model full-time, and the rest of the department was "100% on board."

Future work for this department includes graph neural networks, which can automatically recognize that language such as "photocopying" and "duplicating" refer to the same task. They're also working on sentiment analysis and voice recognition to see if a caller is angry, or to run particular algorithms whenever someone mentions, for example, a specific make of car:

> *It's been a learning experience– 4 years ago until now, we've seen an entire business transform. An entire cultural change, that's where the passion comes in.*

### B. Frontline insurance agents

The jobs of consumer-focused insurance and customer service agents have changed considerably in the past ten years, although the number of jobs and degree of personal interaction hasn't shrunk by as much as executives had originally anticipated. It turns out that many of today's customers still want high-touch interactions with insurance salespeople, but they also expect streamlined and user-friendly self-service options ("direct to consumer"). Over time, the firm anticipates being able to shrink the number of customer service agents as customers become more tech savvy and more comfortable with online transactions– but the number of employees within the firm's Direct Response Center (humans on the phone) has remained constant as have the number of actual insurance agents in bricks-and-mortar offices.

> *There's a reduction of the mundane tasks, but shifting to the more knowledgeable and experienced workers to solve more complex problems. This will [ultimately] shrink the workforce. We're also growing at the same time so there won't necessarily be fewer workers.*

Instead of selling exclusively in person or over the phone, the firm has adopted an "omni-channel approach": a hybrid model of online, on the phone, and in-person sales. The firm can sell insurance direct to consumer via their website, but if you get confused online you can call the customer service center and they can pick up from where you left off online. They also sell through agents in brick-and-mortar shops around the country, both with direct firm employees and independent insurance agents. Ten years ago, the firm expected to see in-person agent jobs fade away and more direct-to-consumer activity. But they have seen little change in the percentage of their in-person agents even as direct-to-consumer has grown. Despite only being used by a fraction of customers, the existence of self-service options lets agents spend more time selling insurance to those who want in-person interactions.

Technology has dramatically affected the agent's job in terms of making certain tasks much more efficient while also providing much more insight into existing or potential customers. For example, the time required to sign up new customers has decreased drastically. Historically, agents used to print out forms and carry around a "suitcase of documents" that needed to be signed and mailed back to the firm, but today much of this is automated through a combination of online processing (e-signatures) and third party data integration.

> *We know where you've lived, how many cars, accidents you've had, how many kids. During the quoting process, we fire off third party integrations to the DMV, to credit scores, to various other third parties who give us a tremendous amount of integration so we barely need to ask anything.*

On the service side, the firm is gathering so much intelligence about their policies and claims that they can often anticipate customers' questions before they even call in. The firm uses ML algorithms to help understand what customers may be calling about, and agents will receive advice and guidance about likely scenarios as soon as the system recognizes who's calling:

> *Our policy systems are talking to our billing and claims system, so we are 98% sure you're calling about billing because we know your payment is due in x days. This could be through automated IVR or a human, saying, "are you calling about your payment that's due soon?" We can even say, "would you like to move that payment by a week?" and fire alerts to service representatives saying, here's the customer need and here's what you're allowed to provide to them.*
>
> *If your daughter has just reached the legal driving age, we can say, "hey, happy birthday to your daughter! Would you like to add her to your policy?" And we'd know if you've already bought another vehicle or not.*

The firm also knows where customers are within their insurance claims process due to interactions with, for example, automotive repair shops and glass companies in the case of a car accident, and they can send proactive communications accordingly.

Overall, these innovations have allowed agents to spend less time with customers today, but the time they do spend is "better and more quality time." Agents spend more time on the sales experience and educating consumers, and less time servicing claims and onboarding. The onboarding process has also become more efficient– perhaps it takes half an hour today to sign up rather than what used to take an hour ten years ago, and often customers can complete the entire onboarding process on their own. At the end of the day, price is the key deciding factor for personal insurance so the firm has also been forced to increase productivity in order to keep pace with competitors.

The actual skills needed on the job– such as a firm handshake and good communication skills– haven't changed much. As one of the senior leaders for North America who oversees personal insurance products said, "I'm a big believer that emotional intelligence is as or more important than other types of intelligence," a quote that resonates with recent research that underscores the value of "social skills" relative to STEM skills in today's labor market (Demming, 2017). Today's agents do need to be more tech savvy and be familiar with using a tablet and various insurance apps. But these do not necessarily require new degrees or significant training to acquire. On the other hand, there is a new need for PhD-trained data scientists who can work behind the scenes on sophisticated ML and data integration projects such as the significant push into telematics. The company expects over time the number of customers who are comfortable working without any human interaction will increase, but as of today, they've seen relatively little movement in this direction over the past decade. In the meantime, ML technologies and automation are making their customer-facing workers much more productive, increasing their number of customers, and consequently, their sales and commissions.

### C. From Help Desk to Help Hub

The firm's Help Desk deals with 500,000 internal tech support issues annually, across 4,000 different software applications. Most employees tend to have 2-3 incidents a month, which adds up quickly for a company of 70,000 people. This volume of requests has made the help desk an ideal pilot location for the firm's experiments with new technologies, which can be tested on the firm's own employees (referred to here as help desk customers) first before rolling out to the firm's actual customers around the world.

This department's experiments with data science began in 2017, when they first created a control center to deal with their data. The IT call center receives an average of 2,500 calls per day across the company, and customer service agents have under 2 minutes to fill out a drop-down survey about how their call went. These surveys and other customer success metrics resulted in a large volume of data, which the firm had not yet been able to fully utilize until they started implementing ML algorithms. The Help Desk also had 10,000 pre-written knowledge articles for their agents to use for problem solving, which facilitated the process of automating simple tasks.

Their primary driver for new technologies was to transform the call center into a "true omni-channel experience," where people who needed technical support would first go to the firm's online help hub and try self-help options, chatbots, or AI-in-the-loop chat conversations before having to pick up the phone and spend an employee's time on inefficient, in-person problem-solving. A 15 minute help desk call costs about $20 of staff time, which is appropriate for a broken laptop that needs complex troubleshooting, but very high for a simple password reset or door entry authorization. When the help desk gets a queue longer than 20 people, employee utilization decreases rapidly.

The team's goal for 2020 is to go from 80% phone calls to 40% calls, with the other 60% of interactions fully solved through digital interactions. The team was about halfway there in July 2020, and had just kicked off a marketing campaign to persuade people not to call them. Deflecting calls to chat (whether human or AI) has proven especially useful for company acquisitions, since text-driven chat combined with embedded information about a customer's computer system can facilitate smooth integration with all the different systems forced on the technical team during mergers. Chat has also been better for people working from home during the pandemic, who may need to get outside the firewall or onto external video call platforms before solving their technical issues.

To accomplish this, the tech support center developed two interdisciplinary “Innovation Squads” of about six people each, with product owners and former help desk workers along with data scientists and developers recruited from across the company. One squad is focused on bot tech and automation, and the other develops the online help desk portal. These squads built all their own bots starting in May 2019. They rolled out a plan for increasingly complex virtual interactions from basic chatbots, to AI-in-the-loop chat systems, to data-enabled predictive problem-solving before a customer even needs to explain their issue.

*Evolution of chatbots*

The firm made an effort in 2017-2018 to introduce chatbots throughout the ecosystem, which consisted mostly of chatbot user experience design rather than advanced AI. These bots allowed employees to “ask questions where they already are,” such as on Facebook Messenger. In 2018, the help desk introduced its first chatbot for high-volume, low complexity tasks: an off-the-shelf password reset bot using Amazon Web Services Lex. They added other simple tasks that could quickly improve their KPIs, such as calendar sync, and managed to bring the cost per call down from $20 to $1.50 or even $0.75 for these automatable tasks.

Nonetheless, tech support managers have realized that chatbots aren’t for everyone– especially when they try to introduce chatbots to the firm’s external customers:

> *Tons of customers just want to talk to a human on the other line. There are still many, many people though who feel that they need to bind their insurance policy with a person on the phone.*
>
> *Our customer experience numbers have gone up because people can get to their answers faster. We got mixed reviews initially from consumers—"I’m going to keep hitting 0 until I get to a human”—but now the chatbots are improving.*

Overall, chatbots allowed the tech support team to slow down hiring and centralize support teams even as the firm grew– but the introduction has not resulted in any layoffs.

> *Chatbots have impacted jobs by consolidating locations, and they’re allowing more scale. We’re #5 in the US for P&C and we want to double our size in next few years and get to #3, but we’re not going to double our staff.*

Over the past year or two, the help desk has moved from binary AWS chatbots to “agent-driven chat,” where it’s unclear to the customer if you’re talking to a bot or a human. Behind the scenes, humans dealt with complex problems and sent simpler tasks over to the chatbots.

Next, the firm plans to move over to fully-embedded AI in the same channel as tech support professionals.

> *I want to bring the AI right to where you're doing your job. In the contact center world, I might be able to solve much of what you're doing with an AI doing 60% of the work in the same channel as the human. Our ML algorithms learned our taxonomy by training on 1 year of data, and now they're even better than humans.*

By July 2020, these successes had already allowed the help desk to maintain a flat number of employees while the volume of service has gone up by 15-20%. The director of customer relationship management estimates that if around 300,000 out of 500,000 annual tech support issues are eligible for automation, and they can get 30% of those issues automated, that will free up 30-40 people while replacing a 9am-5pm agent with a bot that is available 24/7.

## V. Reskilling for software engineering after the transition to Agile

While the previous cases provide examples of how the introduction of new technology has changed the nature of work and specific jobs, there is another important dimension to this transformation related to training. While some jobs are changing and the rate of hiring might be declining, there are also jobs being eliminated. We include a case study here to highlight how the firm has handled the wholesale elimination of occupations and transitioned workers either within or out of the firm.

Between 2016 and 2018, the firm's shift to an Agile software development model resulted in 2,134 employees being threatened by a firm-wide "Reduction in Force" or RIF: the elimination of a position with no intention of replacing it. Most of these RIF-eligible workers were analysts and project managers for project managers, as shown in Figure 4. When the firm switched to a more collaborative and iterative development paradigm in which engineering teams figured out technical requirements themselves, analysts were no longer needed to produce requirement documents for new or revised products.

In contrast to the Waterfall model where specialized teams worked on separate phases of the development process, Agile introduced a need for smaller, multi-disciplinary employee groups that collaborate on new products more efficiently, bridging the gap between the IT and business arms of the firm. Instead of the Waterfall method's in-depth planning phase with business systems analysts and other analysts at the beginning of a project, Agile methodologies were designed with the primary aim of being open to changing requirements over time and to encourage constant feedback from the end users. Rather than following a series of rigidly predefined steps, development was carried out in iterative cycles of designing, building, and testing, with the goal of each iteration to produce a Minimum Viable Product: a version of the desired product, with just enough features to satisfy early customers and provide feedback for future product development (Moogk, 2012). Each iteration was intended to be small and easily manageable to be completed within a couple of weeks only. The firm traded the certainty of knowing its exact end product ahead of time for the freedom to iterate and build upon a process that helps them figure out how to get to their end goal: “We had to move away from multi-year, billion dollar programs that promised nirvana three years from now.”

As Agile teams are typically smaller and highly cooperative in order to facilitate quick decision-making and multiple design iterations, all team members, including software engineers, need to be well-versed in both the business context and technical constraints. Strong people skills, such as effective verbal communication and the ability to work within a team, are also a must for all team members so that they are able to fluidly cooperate with one another. Furthermore, the need for Agile teams to be co-located, in order to facilitate seamless communication between members, has meant that all employees involved in the software development process were (at the time) required to live within a commutable distance of one of the firm’s four “technology hubs” within the United States– which was not the case before the transition.

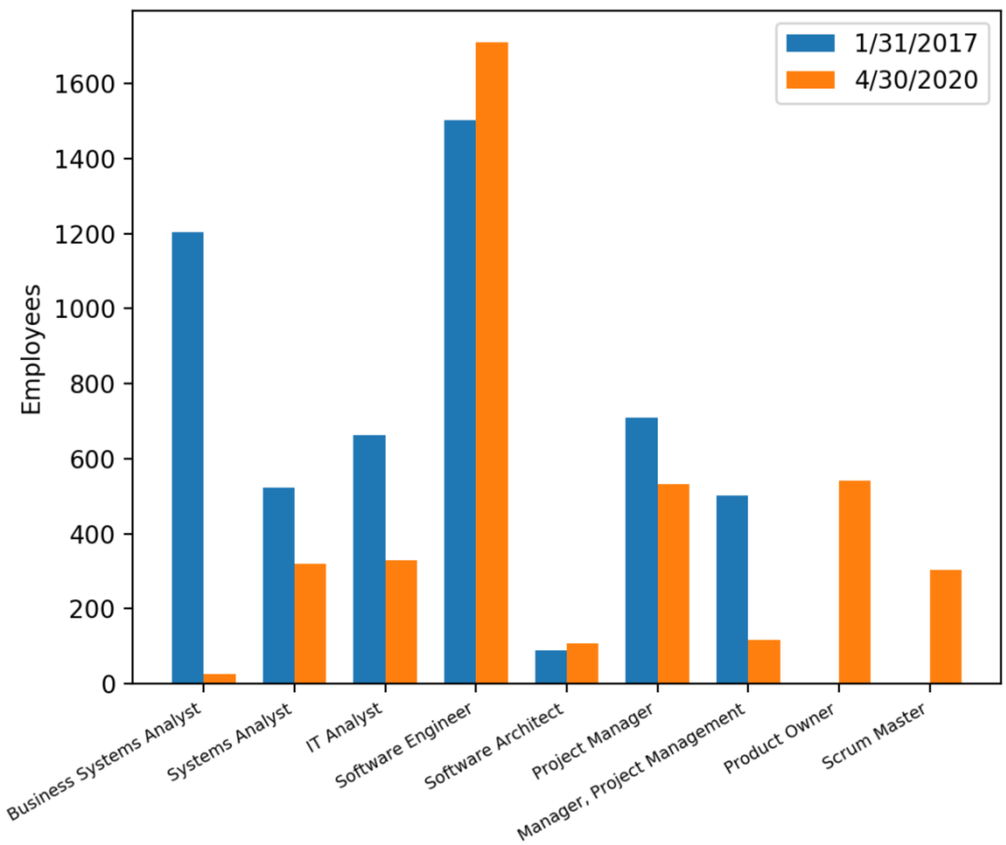

*Figure 4: Workforce shifts during Agile transformation*

The digital transformation that accompanied the transition created a demand for technically focused skill areas within the firm, including back-end and front-end software development, User Interface/Experience Design (UI/UX), and data science. Instead of firing all their obsolete workers and attempting to find new, expensive software developers from outside the firm, the firm decided to run an intensive three-month code school that we will call “Bootcamp,” which allowed reskilled employees to take a year to settle into new technical positions before being evaluated.

This pathway only worked for a small portion of those whose jobs were at risk, but for those who participated, it had relatively successful outcomes.

As shown in Table 1, 61% of these RIF-eligible employees remained in the firm. Among those who stayed, 51% applied for other positions within the firm without formal reskilling, and 10% completed the company's Bootcamp.

*Table 1: Outcomes for RIF-eligible employees*

| **Overall RIF-Eligible** | **Outcome** | **Percentage** |
|---|---|---|
| *61% of RIF-eligible stayed, of which: (1,301)* | Applied for another role | 51% |
| | Did not apply for other role | 39% |
| | Completed Bootcamp | 10% |
| | | |
| *39% of RIF-eligible left the firm, of which: (832)* | Retired | 4% |
| | Left for personal reasons | 7% |
| | Left for work reasons | 18% |
| | Involuntary termination | 70% |
| | | |
| *23% of RIF-eligible applied to Bootcamp, of which: (490)* | Accepted to program | 34% |
| | Accepted but did not attend | 2% |
| | | |
| *8% of RIF-eligible participated in Bootcamp, of which:* | Left firm involuntarily | 5% |
| | Left firm voluntarily | 14% |
| | Didn't complete program | 19% |
| | | |
| *6% of RIF-eligible graduated from Bootcamp, of which:* | Moved to programming-relevant role | 86% |
| | Left firm involuntarily | 2% |
| | Left firm voluntarily | 4% |

All company employees were eligible to apply for Bootcamp, regardless of their job title, length of tenure at the company and whether they were RIF-eligible or not. One fundamental objective was to find new roles within the firm for employees whose jobs were particularly under threat due to skill obsolescence, and another was to better utilize existing employees by integrating knowledgeable analysts into technical teams.

Most Bootcamp participants and managers deemed the program a considerable success for both the company and reskilled employees. The firm's own cost analysis found that terminating a RIF-eligible participant cost the firm on average $2,596 in severance costs and new hiring expenditures, whereas putting a RIF-eligible employee through the program and later employing them in a new position actually saved the firm $37. Program graduates were also 10 percentage points (90% vs 80%) more likely to remained employed at the firm 18 months after beginning the program, as compared to externally hired software engineers. Several retrained employees who completed code school reported feeling especially valued for their prior business specific expertise, even though they were new to programming:

> *I kind of operated as a middleman because I had the best of both worlds with the technical knowledge and the business knowledge, so I could almost translate between the business and my team.*

Nonetheless, younger employees and people with more coding experience (who were often younger) had a distinct advantage in the program– and were far less likely to be RIF eligible to begin with. RIF-eligible employees had worse outcomes from the program, both in terms of post-program job grade and likelihood of remaining in a program-related role, compared to non-RIF-eligible employees. Prior coding experience was the greatest indicator of a participant's success on the program, and participants with prior coding experience were both awarded higher job grades and were more likely to remain in a role that was related to their coding program.

As mentioned, Bootcamp was only able to accept one-fifth of applicants– and the program ended amidst a flurry of additional interest from throughout the company. The firm made plans to continue with similar technical reskilling programs in the future, but several Bootcamp participants acknowledged that they had many colleagues who were disappointed that they couldn't attend. The firm also has an extensive program for tuition reimbursement, and many employees– both Bootcamp graduates and others– have taken advantage of free university and community college classes to learn new technical skills.

## VI. Overarching themes from the cases

These examples from one multi-national firm highlight the multiple ways that AI-related technology as well as firm reorganization due to new business operations model like Agile are changing the nature of work, including the tasks and skills within specific jobs and occupations. These cut across different units within the business as well as educational and wage levels among workers. Below we highlight a few overarching themes that emerge from these cases.

### *1) Time saving and hiring slowdown*

Even relatively rudimentary ML implementation has already saved years of employee time, leading to a hiring slowdown as teams didn't require additional staff despite business growth and acquisitions:

> *How much time have we saved by implementing these ML examples? In one month, we saved about a month of time for the image recognition. Legal one was about 18 months.*

In the case of the legal team, managers found that their initial narrative of using technology to replace entire teams of people was “uninformed”:

> *We had two stories, one uninformed story which was, “if the model can do anything, we don’t need auditors.” That’s what people wanted to hear in very big meetings, but what we found was exactly the opposite.*

After the legal team introduced their bill-auditing AI, they had to hire five more people to deal with the increased number of alerts coming from the model’s improved discrepancy detection. The team still needed final human auditors to go through manually, and human auditors working in collaboration with the model were able to unlock “much greater” savings than just auditors or the model alone.

### *2) Employee Enablement*

Several managers across different departments concluded that new technologies enabled workers to focus more on what humans do best– human interactions, problem-solving, and other higher-value-added tasks that they didn’t have time for before the adoption of new technology and/or Agile development.

Most employees didn’t initially see this as a benefit and resisted the change to their familiar tasks, although many learned more about their own capabilities through the process:

> *The nervousness comes because people think the job will remain the same– they don’t realize they’re much more capable than pressing one button every day. We business leaders have to go convince our employees to go beyond their own capability, but they don’t realize this yet.*

Eventually, most workers realized that technology would displace the boring grunt-work of looking at bills, resetting passwords, and other routine yet high-volume tasks.

> *It’s all changing our workforce to be more customer-centric, more personalized. “This isn’t about tech support, it’s about employee enablement.”*
>
> *The auditors are happy they can perform a higher level job and actually help their customers even better– one person told me, “thank you, now I feel this was worth it because I went to school to actually help claim managers handle litigation, not just look at bills!”*

### *3) Predictive Problem-Solving*

Across the firm, data scientists are driving a shift from reactive problem-solving to prediction and prevention– leading employees to spend more time on solutions rather than identifying problems. On the insurance side, as mentioned above, salespeople and claims agents are provided with instantaneous information (often via third party integration) about why customers may be calling– so they can get right into discussing insurance details without having to gather personal information. In the IT department, one data scientist has been tasked with predicting a systems outage and then preventing that, and proving there would have been an outage if they hadn't intervened. The Help Hub is developing personalized solutions for customer employees, such as API "collectors" that sit on all employees' devices and provide information such as type of device, operating system, and latency scores.

> *Because of what we've built, agents don't have to wait for you to react, but rather they can tap you on the shoulder immediately and say, "oh hey, the network is slowing down on your computer. Can I clear your cookies for you?"*

### 4) Continuous Learning, Upskilling and Embracing Technology

The firm's digital transformation has led to a need for continuous learning and capacity building. Lundberg and Westerman (2020) note the rise of the transformative "Chief Learning Officer" across corporations, to encourage their employees to develop new technical skills as well as introducing a more creative, problem-solving mindset across the firm. In order to support employees for more advanced tasks and problem-solving, the tech support department had to create new tiers in their job ladder and establish new formal and informal training programs (including their own departmental version of Bootcamp). "If we don't keep folks both trained and interested," said the tech support manager, "we'll fall behind."

Even though tech support agents have very little time outside of work for upskilling, their managers have realized that they need more technically-competent workers before they can start upgrading their technology.

> *It's a tall order, but we're looking for folks who are flexible, who learn and adapt, who aren't afraid to learn more about tech. We're pushing the whole concept of, "you don't think you're technical? Don't be afraid to dig in, we've got tools that can help you."*

Yet this type of problem-solving role isn't for everyone, and the tech support managers found that some of her staff just wanted to show up, do their routine work, and go home without putting in the extra effort. These are the folks who may be forced to find jobs elsewhere as the firm becomes more fully digitized and human jobs are better optimized for cross-team communication and problem-solving.

> *I fully expect we won't be able to get everyone onboard, and some folks will be left behind because they're not interested in this super-agent philosophy. They're just too comfortable doing what they've always been doing… they don't have the right mindset.*

Unlike the historical trend of siloed departments with their own protocols and acronyms, the introduction of machine learning and Agile development have required collaboration across departments and channels– just as individuals need to become competent outside their own areas of expertise. This firm's data scientists are collaborating with others, with a different department doing their code review. Data scientists were also the first to introduce AI to the legal team, by discovering a potentially useful model that the lawyers and auditors hadn't even considered.

This demand for collaborative generalists has been a challenge for tech support workers who consider themselves "subject matter experts" in their own fields:

> *If we want to stay ahead of tech, we need to retain this channel-specific knowledge but get people out of their comfort zones.*

To pursue a more flexible and collaborative project management style rather than their "traditional, top-down" approach, the tech department decided to reorganize internally following the Agile framework– allowing for more worker input and self-directed teams:

> *As a manager I was nervous about this at first, because different teams would be able to drive their priorities and have their own sprint planning.*

Nonetheless, as described above, the newly-created "squads" used their newfound independence to devise creative strategies and technological experiments to improve customer experience across the board.

## VII. CONCLUSION

Overall, this study demonstrates the critical value of keeping humans "in the loop" of the digital system; the firms' algorithms are most accurate when humans consistently provide feedback rather than introducing complete automation. With the exception of the now-redundant business systems analyst position, the firm consistently automated specific *tasks* (easy helpdesk requests, bill auditing, looking up personal facts for insurance sales, etc.) rather than entire *jobs*, improving efficiency while leaving incumbent workers with more time to attend to customers or solve trickier problems. While they may be slowing the hiring in certain occupations, there was relatively little direct substitution occurring:

> *What we are seeing right now is a transformation of how we do things, but not a replacement of people. We are seeing demands for new skills and organizations, but not large-scale replacement.*

While it may not be large-scale replacement, demand for new skills is occurring and creates job insecurity for a certain subset of workers. Automation caused most of these jobs to generally increase in skill requirements and decrease in tediousness. Across the skills continuum, these digital transformations and related organizational innovations required workers to spend more time on creative problem-solving and/or customer service. While this may be a valuable outcome for the incumbent workers who are willing to adapt and prefer less menial work, firm managers alluded to a sizeable cohort within the firm who may be left behind. The important question is how white collar workers are positioned to weather these changes and maintain their relevance through these technological transformations. What happens to the workers who refuse or are unable to adapt to a more dynamic and creative environment? Importantly for firms when there are tight labor markets, how can they retain displaced workers (along with these workers' embedded company knowledge) through reskilling? And what happens to the smaller, more locally-based insurance firms that cannot afford to adopt new technologies and upskill their workers at the rate of their larger competitors?

Despite a history of in-depth, granular studies on jobs and automation across diverse fields, recent contributions to the literature largely abstract away from firm-level explorations. Instead, today's macro-economic studies primarily assess technological change through the application of econometric models and large-scale surveys. Yet firm-level studies such as this provide a valuable lens into the inner workings of technology adoption, by drawing upon explorations at the meso level of individual technologies, team managers, and the workers themselves who are figuring out how to collaborate with algorithms on a daily basis.

***References***


Autor, D. H., 2015. Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, 29(3), pp. 3–30.

Autor, D. H., Katz, L. F., Kearney, M.S., 2006. The polarization of the US labor market. *American Economic Review*. 96(2), pp. 189-194.

Beck, K., Beedle, M., Van Bennekum, A., Cockburn, A., Cunningham, W., Fowler, M., Grenning, J., Highsmith, J., Hunt, A., Jeffries, R. and Kern, J., 2001. Manifesto for agile software development.

Brynjolfsson, E., and Mitchell, T., 2017. What can machine learning do? Workforce implications. *Science*, 358: pp. 1530–1534.

Bureau of Labor Statistics (BLS), 2020. Occupational Outlook Handbook. Available from https://www.bls.gov/ooh/. [Accessed September 2020.]

Davenport, T.H. and Westerman, G., 2018. Why so many high-profile digital transformations fail. *Harvard Business Review*, *9*, p.15.

Deming, D., 2017. The Growing Importance of Social Skills in the Labor Market, *The Quarterly Journal of Economics*, vol 132(4): pp. 1593-1640.

Deming, D.J., 2017. The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, *132*(4), pp.1593-1640.

Dixon, J., Hong, B. and Wu, L., 2020. The Robot Revolution: Managerial and Employment Consequences for Firms. *NYU Stern School of Business*.

Frey, C. B., & Osborne, M. A., 2017. The future of employment: how susceptible are jobs to computerisation? *Technological forecasting and social change*, *114*, pp. 254-280.

Frey, C.B., 2019. *The Technology Trap: Capital, Labor, and Power in the Age of Automation*. Princeton University Press.

Highsmith, J., & Cockburn, A., 2001. Agile software development: The business of innovation. *Computer*, *34*(9), pp. 120-127.

Lund, S., Manyika, J., Segel, L. H., Dua, A., Hancock, B., Rutherford, S., & Macon, B., 2019. The future of work in America: People and places, today and tomorrow. McKinsey Global Institute.

Lundberg, A. and Westerman, G., 2020. The Transformer CLO. *Harvard Business Review*.

Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Ko, R. and Sanghvi, S., 2017. Jobs lost, jobs gained: Workforce transitions in a time of automation. McKinsey Global Institute, pp. 150.

Matt, C., Hess, T., & Benlian, A., 2015. Digital transformation strategies. *Business & Information Systems Engineering*, *57*(5), pp. 339-343.

Mitchell, T., & Brynjolfsson, E., 2017. Track how technology is transforming work. *Nature*, *544*(7650), pp. 290-292.

Moogk, D.R., 2012. Minimum viable product and the importance of experimentation in technology startups. *Technology Innovation Management Review*, 2(3).

Moulds, J., 2018. Robot managers: the future of work or a step too far? Guardian Media Group, USA.

Muro, M., Whiton, J. and Maxim, R., 2019. What jobs are affected by AI?: better-paid, better-educated workers face the most exposure. *Metropolitan Policy Program Report*.

Orlikowski, W., 2010 January. The sociomateriality of organisational life: considering technology in management research. *Cambridge Journal of Economics*, Volume 34, Issue 1: pp. 125–141.