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Artificial Intelligence as Augmenting Automation: Implications for Employment

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Abstract

There has been concern that artificial intelligence may cause significant unemployment, but proponents say that AI augments jobs. Both of these positions have substance, but there is a need to articulate the mechanisms by which AI may actually do both, and in the process, transform the balance of work available. We examine economic studies of automation's impact on employment and skills, illustrating the favouring of nonroutine skills over the routine, and a hollowing-out of middle skill jobs. We then use case evidence of AI and automation to show how AI is augmenting automation to the same effect, allowing firms to modularize and control routine work. The remaining work tends to be nonroutine and low skilled (allowing for further replacement in the future), or high skilled. We illustrate the dynamic effects that occur when AI is combined with other key technologies, creating economies of scale and scope for firms. Through augmentation, the resulting employment structures may also have lower quantities of high skilled work. This depends on advances in AI, and its ability to replace more complex forms of work. We end with a call for more critical conversations between society and business, and on what business schools should teach.

Key Words

Artificial Intelligence, Employment, Automation, Augmentation, Replacement

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1. Introduction

In recent years, there has been great concern about Artificial Intelligence's (AI's) effect on employment. Observers have spawned concerns in the general public about which kinds of jobs and skills will be replaced, as well as discussed on how jobs could be transformed, and what new skills would be needed to work in this new 'Age'. Two views have emerged: the 'replacement' and 'augmentation' views. The research and evidence are usually based on cases and anecdotes, or assumptions that are skewed towards a particular view (e.g. of the technology's potential). Early studies promoted the 'replacement' view by showing that AI had a great potential to reduce employment in many categories (Frey and Osborne, 2017). Recently however, a slate of opinions from industry and business scholars have advocated an augmentation view in which AI complements human work, and in which humans have to upgrade their skills in order to fit in with the emerging work environments (Daugherty and Wilson, 2018; Davenport and Dreyer, 2018). Although both the arguments on replacement and augmentation are based on the technology's potential, they vary on their view of what happens to the work, since the augmentation view sees the core work tasks as being enhanced, while the replacement view sees the core tasks being replaced by automation. In practice, the technology complements and substitutes for skills, and the net balance depends on how the organization wields the two together. Indeed, Raisch and Krakowski (2020) recently argued for a more nuanced balance between the two perspectives, and on what organizations can do to mitigate the negative effects of AI as they embrace the positive effects.

Our view is that the business and economic perspectives have not been considered as well, and especially the dynamic effects. In this paper, to better understand how work may be replaced or transformed, we explore how AI is being used to enhance the automation of work and of organizations as a whole, and how this may create competitive advantages over time, as well as impacts to selected types of employment.[1] We will examine this with the use of examples from an extreme form of organization that is emerging - the digitally transformed firm - and its use of AI to automate the firm. To start off, in section two, we examine the literature on industrialization and employment. Economic studies show that as automation and information technology (IT) increased productivity, they tend to favour nonroutine skills and jobs, displacing routine work, and leading to shifts in employment structures. In section three, we develop a basis for understanding how newer AI technologies could displace routinized work. Using recent examples, we illustrate how "digitally transforming" organizations are embedding AI in a broader automation of work. In section 4, we account for the dynamic effects of this digital transformation on organizational competitiveness. When prospecting how further dynamics may play out, we consider how the combination of AI with other technologies creates additional capabilities for "digitally transformed" firms. These capabilities can create economies of scale and scope for the organization, and under certain conditions, can lead firms to favor employment structures with lesser amounts of skilled routine work, and more highly technical skilled work (albeit with smaller-sized teams).

Augmentation and Replacement

The recent debate about augmentation and replacement has stemmed from different perspectives in the literature. Inferring what AI could do across various occupational classifications defined by discrete tasks, a well-known study by Frey and Osborne (2017) found

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[1] To broaden the scope of and balance our investigation, we examined not only the augmentation view (as seen in Raisch and Krakowski, 2020), but also studies of the replacement view (e.g. Ford, 2015; Susskind and Susskind, 2015), some of which straddle the middle-ground. We also review economic studies on employment, technological developments, and secondary cases on industry to help theorize on AI's implications. One feature of our approach is its dynamic view of technological and organizational evolution, as seen recently in another view of AI in organizations (Iansiti and Lakhani, 2020).

that 47 percent of US employment could be at risk from AI (though much of it could have also involved the automation of tasks).[2] These studies were based on experts' assessment of whether the technology could replace tasks tied to occupational categories, based on how routine and replicable by machines (i.e. AI) the work could be.

Most recently, the opposing view has been put forward that AI augments jobs and tasks (Barro and Davenport, 2019; Raisch and Krakowski; 2020; Tarafdar et al, 2019). Many contemporary AI firms describe their products as improving productivity by removing routine and 'unnecessary' tasks within specific domains. Increasingly, AI has been used to tackle narrowly-scoped functions and tasks, ranging from market research to medical and financial domains. Many applications involve statistical data, but increasingly, other kinds of data, including images, are handled. While early companies often offered technology in search of a solution, the current trend has AI companies targeting specific tasks within a workflow, such as Cyft (which focuses on healthcare interventions), Uptake (which integrates the Internet of Things (IoT) and AI for industrial automation) and Numerai (which combines AI with blockchain technology). To exploit these deeper niche markets, the AI applications need to incorporate domain knowledge from experts. Deep learning also requires significant amounts of data for training. Increasingly, AI product firms also note that they are building platforms that clients can use to enhance work productivity, and increasingly, to integrate work activities. Recent academic views also embrace this augmentation view by emphasizing how AI enhances

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[2] Other studies follow the same tradition with the same type of data and methodology, e.g. Felten et al (2018) examined the impact of AI with the O*NET occupational database, which provides detail by tasks accomplished across a variety of occupations. In general, proponents of replacement note that advances in AI have the potential to disrupt much of the remaining human employment untouched from previous automation technologies, including manual occupations, services work, and back office functions. For instance, a number of driving occupations are at risk of disappearing (Ford, 2015).

personal efficiency or productivity (Agrawal, et al 2018; Barro and Davenport, 2019; Daugherty and Wilson, 2018). Since such views are often based on a narrow view of technology itself (usually focused on deep learning), and anecdotal evidence on the AI augmentation of tasks, they do not capture the potential changes to organizational capabilities and their employment structures.

2. Past Perspectives on Technology and Employment

A History of Productivity Increases

While replacement view studies of AI's impacts on employment rely on experts to assess the technology's potential impact in the future, we can examine historical periods for confirmation of an actual impact. The issue of technology's effects on employment have been a long-standing preoccupation. While technology has historically been considered a major force in transforming societies, studies of significant periods of industrialization show that the introduction of key technologies took years to impact on economic growth and productivity (Brynjolfsson and Hitt, 1996; Brynjolfsson et al, 2017; David, 1989). In part, this is due to the time needed for firms to transform themselves organizationally to take advantage of the technology. In many manufacturing sectors that saw significant automation in the 1980s, innovations such as flexible manufacturing systems and computer-integrated manufacturing reshaped both practices and skills. Manufacturing jobs were transformed into a mix of high and low skilled jobs, with many low skilled (typically manual) jobs being removed. Economic studies showed a mixed effect on jobs, as while some jobs were replaced by automation, new jobs were also created in other sectors. This could partly be attributed to automation creating new functions, and partly to the economies' move to a service or information economy (OECD, 2018).

When technology fosters productivity, the replacement or displacement of labor follows suit from those gains (Dedrick et al, 2003; Dewan and Min, 1997). In studies of the broader economy-wide impact of automation, routine work was the first to be automated and displaced (where economic studies typically categorized work into the dimensions of *routine* versus *non-routine*, and *cognitive* versus *manual* [Autor et al, 2003; Jaimovich and Siu, 2020]). [3] In addition to the ongoing automation of manufacturing, leaps in information technology during the 1990s also increased labor productivity in office environments. In the last few decades, administrative, secretarial and other routine jobs have been replaced by automation (Carbonero et al, 2018; Susskind and Susskind, 2015; Winick, 2017).[4] While as a whole, the loss of jobs is offset by the addition of jobs in other sectors (Nedelkoska and Quintini, 2018), much of the new work is not of the same income (Autor et al 2006). Computer-based automation is recognized for not only causing the loss of middle-income routinized jobs, but also for polarizing jobs into high and low waged jobs at the expense of middle-income ones (Jaimovich and Siu, 2019). These job polarisation studies describe the phenomena as the "hollowing out of the middle-paid, middle-skilled jobs in developed countries" (Nedelkoska and Quintini, 2018). While both anecdotal and sectoral evidence suggest that automation has displaced human work in the past (Susskind and Susskind 2015), economic studies also showed that automation impacted routine manufacturing and other jobs more than nonroutine ones in past eras (Autor et al, 2006). In a recent study of "jobless recoveries" (based on data up to just

[3] The routine, manual category refers to lower skill jobs, e.g. service occupations in the fast food industry. In contrast, the non-routine cognitive category refers to higher end analytical and other intellectual work, involving flexibility, problem-solving, and human interaction skills. In this framing, the occupational categories involving such work involve professionalized college degrees and occupations relating to management, business, and financial operations, as well as in professional and related occupations.

[4] While initial studies in the 1990s based on data from the 1980s did not yield a strong relationship between IT investments and productivity growth, later studies and meta-analyses concluded otherwise, in part because firms needed time to redesign their organizations and processes to take advantage of the new technologies. A similar effect is expected in the AI era (Brynjolfsson et al, 2017).

after the 2009 recovery), Jaimovich and Siu (2020) show that even the category of routine, cognitive work did not fully recover to their former numbers after the downturn. The broad trajectory of this is to be expected, given that firms will generally seek to routinize work. However, with advances in AI, some "nonroutine" cognitive work has also been shown to be replicable by AI, suggesting that previously untouched work may have risks of replacement in the future. Since historically, new sectors and jobs were also created in the wake of technological disruptions, the usual policy response involves creating workforce training programs to help displaced employees to seek new work (Illanes et al, 2018). However, workforce training was known to have mixed results in the past, and those who retrain may not get work that is comparable to the lost work (p. 11, Government Accountability Office, 2011). Furthermore, studies suggest that those on the lower-skilled end of routine manual work are unlikely to migrate upwards to the "cognitive" categories of work (Jaimovich and Siu, 2020). It should no longer be taken as a given that sufficient numbers of well-paying jobs can be created to replace future lost jobs.

The Transformation of Skills in Automation Eras

It is well-known that as new technologies transform work, they also change the skills required of tasks. The argument is that by making routine tasks "general purpose", information and communication technology allows better-skilled people to "make more creative and more productive use of it" (Nedelkoska and Quintini, 2018). This suggests that the remaining higher-skilled work is cognitively demanding, if not irreplaceable. However, job polarization studies suggest that while some of the remaining non-automated work are of the higher-skilled variety, other remaining work is of a more manual (nonroutine) variety. An opposing view in the 1980s held that the transformed manufacturing work was actually deskilled. The argument was that the tacit nature of human machinery operation was now replaced by the human operation of computerized machinery utilizing digital interfaces (Form, 1987; Zuboff, 1988). This has implications for the current debate on AI, since this itself is a procedural, and thus potentially automatable type of activity. In fact, many of the tasks that modern AI replaces in the realm of "cognitive work" were once tacit human tasks that have been reframed as pattern recognition problems solvable by AI.

There is still intellectually demanding work to be done. A large part of this occurs on the back end, involving the likes of programmers, data scientists, and "augmented" analytical tasks as found in marketing and other functions. As with manual work, when organizations shed labor to reduce costs and increase efficiency, not all of the "complementary" work that remains is rigorous, and the work that remains only does so because the AI cannot yet replace its tacit aspects. AI is already proving helpful in previously unassailable areas, including creative domains as art, design, and music, and AI programs have overcome experts in many complex games such as chess, go, and poker. In fact, AI has discovered game-playing strategies and design directions that even the best experts had not considered. These examples suggest that as AI enters more and more areas, its effects on employment may be complicated, as AI is capable of both, replacing "journeymen" levels of task, as well as augmenting them.

Types of AI and AI Capabilities

To better understand what causes AI to actually augment or replace work, we have to first, understand its characteristics, and second, to set it in an organizational context. It is common for firms to improve efficiency and productivity, but firms are finding that they can do much more when they connect AI to automation in the context of transforming their operations to digital ones. Many firms already depend on Web and IT environments, but digital transformation brings in new technologies, and treats software as a powerful, modular way to gain even more productivity advantages. AI acts as an amplifier on these effects. Where early automation was rule-based and guided by humans, one of the current goals has been to make automation autonomous or self-governing by way of AI.

The term 'AI' itself refers to many different kinds of technology (each suited to different applications). There are by now a wide variety of AI types addressed to different problems. Nowadays, much of the attention goes to deep learning, whose spectacular achievements have popularized the field as a whole. Deep learning evolved from artificial neural networks (ANN) (or just neural networks), one of the oldest streams of AI.[5] ANNs and deep learning are ideal for handling large amounts of data, and their ability to handle more complex data and problems is increasing. Most important perhaps is that they can evolve with continuous data inputs to reflect their changing environments. They can discover new features in the data, and thus, modify the rules (governing the AI's response to inputs) embedded within their structures.[6] Deep learning is successful at handling data and problems in domains as wide-ranging as finance and medicine.[7] Other AI techniques may be used for handling different kinds of problems. Problem domains involving human language require techniques that can recognize our "natural" forms of spoken language, also known as natural

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[5] Expert systems (procedural rule-based systems) were the first AI technologies to achieve commercial success, but it became too time-consuming to create each new application, as the rules for each had to be encoded anew for each domain and application.

[6] Advances in computing power facilitated their success at processing large-scale "unstructured" data sets such as social media (Gomez-Uribe and Hunt, 2016; Le et al, 2013). These bottom-up forms of AI excel at pattern recognition with huge amounts of data, but can be problematic in situations requiring contextual and other inferences from general knowledge. ANNs can misclassify phenomena if they falsely attend to features that show up strongly in the data, but that are spurious to the features needed for the actual taxonomical classification. Some infamous incidents including the misrecognition of tanks in trees (when the AI recognized the cloudy day as the defining feature in pictures, rather than the tanks themselves), or the recognition of a sofa as an animal.

[7] Deep learning AI is used in many other sectors, such as in online retailing (e.g. Amazon and Netflix's recommender systems), finance, and policing.

language techniques.[8] The problems encountered in domains such as service robots or warehouse inventory operations typically involve defining paths for robots, and may require some form of optimization – this is broadly classed as 'AI planning '.[9] In general, many AI products such as IBM's and Google's flagship AIs are composites of different AI techniques.[10] By now, many if not most AI systems involve learning in response to changing environments and input (data), often by using deep learning or machine learning techniques, but by no means does this mirror what humans do when we learn.

3. How AI and Automation will Impact on Work

3.1. The Scope of Automation

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[8] Natural language processing is a core technology for any AI needing to interact with humans using spoken communication. For other forms of human expression, such as the understanding of human expressions and emotions, computer and robotic vision in combination with pattern recognition techniques are used. When robots have to be aware of visual features in the external environment, such as is seen with in autonomous vehicles, computer vision is the key technology (and is itself based on image processing or pattern recognition technology).

[9] Planning, another long-standing and early application of AI, stems from operations research and mathematical methods used in production planning and optimization. Planning involves *"the task of finding a procedural course of action for a declaratively described system to reach its goals while optimizing overall performance measures"*. Planning continues to be used and developed today in robotics, by supplying the algorithms to provide more intelligent pathing. (IBM AI planning webpage [undated]. https://researcher.watson.ibm.com/researcher/view_group.php?id=8432. [accessed November 11, 2019]).

[10] For instance, the DeepQA technology underpinning IBM's Watson AI (that outcompeted human contestants on *Jeopardy!*) integrated natural language processing (to parse questions into more contextual form), and machine learning to weight the scores of candidate answers, amongst other technologies (Ferruci et al, 2013). Similarly, for DARPA's Grand Challenge to develop autonomous vehicles for urban environments, the 2007 winner, Carnegie Mellon's *Boss*, used perception, planning and behavioural software to enable it to predict traffic conditions, including other vehicle's movements.

To understand the impact of AI, we need to consider it within the evolving complex of automation and work. Much of a modern firm's operations are already located in what Brian Arthur coined "the second economy": an economy of "machines" exchanging and transforming information in automatic processes (e.g. by making transactions seamless, instantaneous and therefore "frictionless") (Arthur, 2011). The keys to this coordinated work are the software and algorithms that convert work processes into data and information flows.[11] AI transforms this automation even more. We use examples of digitally transformed firms like Amazon and Tesla to show how AI-augmented automation affects human work, and with examples like Netflix and AT&T to show how machines (i.e. AI and automation) have created new functionalities *above and beyond* human capabilities – ones that add to the firms' overall productivity.

While past economic studies indicated that automation generally did not replace nonroutine manual (or cognitive) work, this was premised on technologies at the time (Jaimovich and Siu, 2020). In past automated systems, knowledge had to be hard-coded for rule-based automation to be usable, and could not be reparametrized easily to fit to different work environments or conditions. However, with better algorithms capable of handling complex data, AI techniques such as deep learning can now handle a wider variety of cognitive work. We should consider how Zuboff's (1988) observation - that formerly manual work involving tacit knowledge was eventually replaced by automation and routinized forms of work – translates to the current day. It turns out that nonroutine work does not have to remain nonroutine in the same way, but can instead be transformed into a machine's "routine". The degree to which machines can handle tacit work depends on how much contextualization is needed. Machines are generally poor at recognizing context, so the narrower the domain (i.e.,

[11] These "informating" processes were seen in the early era of automation, and not only shaped how human work was performed in relation to computers, but shaped how people performed their work even in relation to their supervisors (Zuboff, 1988).

the less variable the contexts and the less commonsense or broad experience needed for a problem), the better their performance.

3.2. Examining the Augmentation of Tasks in a Broader Perspective

The augmentation view suggests that AI and human work will coexist, but it does so by focusing on how AI increases the productivity of tasks. We argue that we need to look beyond the level of a task or job. By increasing the productivity of a given employee, there are follow-on effects at the organizational level, such as how many such jobs are needed, and how many routine tasks accompanying the core work are replaced. For example, the most promising areas for augmentation has been in the medical field, where AI applications have long been used to assist doctors in diagnosis. Medical imaging provides an ideal application for AI due to the quality and structure of the data. In radiology for instance, AI is likely to replace the radiologists' task of scanning through stacks of images (usually for comparative analytical purposes). The work comprises a large part of what radiologists do, but is a taxing task for human eyes and minds: *"In many ways, deep learning can mirror what trained radiologists do, that is, identify image parameters but also weigh up the importance of these parameters on the basis of other factors to arrive at a clinical decision."* (Hosny et al, 2018). In the workflow for medical imaging, AI can "*increase efficiency, reduce errors and achieve objectives with minimal manual input by providing trained radiologists with pre-screened images and identified features."* (ibid). A recent meta-analysis showed that AI has now achieved parity with doctors and radiologists in the accuracy of diagnoses. In other cases, AI has been shown to be superior to human experts' pattern recognition abilities and judgement. The AI's ability to detect subtle features in data in algorithmically precise ways gives it an advantage over humans, and it is immune to inter-rater reliability errors.

The flipside is that the AI needs massive amounts of data for training, and is unable to exercise ethical and other human judgments. Furthermore, the software or AI cannot combine other qualitative information that doctors acquire (as from patient interviews) in diagnosing and recommending the correct course of action. While for the conceivable future, AI will still play an assisting or supporting role (Davis, 2019), one scenario suggests that the increase in efficiency of scanning will cause less radiologists to be needed. Debate has raged over whether AI will displace radiological and other medical jobs, and medical schools have seen drops in enrolment for the specialization of radiology. One health AI firm's CEO put it as a complementary effect: "*radiologists using AI will replace those who do not (use it).*" (De La Garza, 2020). In this augmentation view, the AI actually increases the productivity of the higher skilled (tacit) work, and offloads the lower skilled tasks onto the AI. While overall, this can correspond to less work being done by humans, the actual impact on employment is likely to vary according to the organization's workload. If the doctors are overworked and operating in resourced-constrained environments, such as in the UK's National Health Service, the AI's use might not impact on their employment, but serves an assistive role. If the hospital is organized as a production line and trust is placed in the algorithms to make decisions which are then communicated to the patient with a minimum of the specialist's input, fewer radiological specialists may be needed (Kaplan, 2015; Reardon, 2019).

3.3. Characteristics of AI-Augmented Automation in Digitally Transformed Firms

To address our thesis that AI further augments automation, we need to grapple with a second thesis that is in some ways more extreme: A digitally-transformed firm (or one that has almost all its operating capabilities in software) invokes the modularization of human work, then, coupled with technological progress, the modularized tasks may eventually face replacement. We further presume that in order to replace human work, the machines do not need to think in similar ways to humans, so long as their output matches the desirability of human-made outputs. To understand this, note Bezos' view of AI as the key to Amazon's growth across business functions: *"much of what we do with machine learning happens beneath the surface. Machine* *learning drives our algorithms for demand forecasting, product search ranking, product and deals recommendations, merchandising placements, fraud detection, translations, and much more. Though less visible, much of the impact of machine learning will be of this type – quietly but meaningfully improving core operations"* (Bezos, 2017). For example, a key function in firms like Amazon and Netflix with an online presence is the recommender system, which recommends content to users. These systems are the product of years of applied research into algorithms and models, now used for recognizing patterns in consumer preferences.[12] At heart, these systems involve the acquisition and analysis of continuous external data streams from customers' interactions with services. Software supports much of this automation and helps to integrate or link disparate systems. In the case of Amazon, the consumption data are electronically linked to other systems such as inventory and pricing. Thus, digital technologies transforms not only enterprises focused on digital services and content, but also gives enterprises the digital means to organize themselves and to connect to real world supply chains.

AI and Self-Governing Capability

One of the distinguishing features of AI is it provides a self-governing capability to itself and to automation in general. This was seen in the area of self-driving vehicles, referred to as an "autonomous intelligence", but has not been seen as much in other sectors yet (Garbuio and Lin, 2019). Whereas a traditional AI might regulate a system within pre-defined parameter ranges (much as a thermostat might), the nature of AI is changing, and modern kinds of AI such as deep learning can discover new features, which allows for an even wider range of

[12] Netflix's recommender system (in use since before 2005) also involves generating new models based on hypotheses of customer behavior, training the algorithms on historical data, making predictive estimates, and engaging in experiments to test the new algorithms against older ones (Gomez-Uribe and Hunt, 2016). Ultimately, these systems serve to make firms more efficient and productive. By combining analytics and models, Amazon and other firms create wholly new functions that do not have human equivalents in work.

operation. A second case involves communications network governance. AT&T had already automated its communications network's operations with rudimentary means of identifying breakdowns in the communications network, and these even autonomously assisted in repairs and rerouting traffic. In those systems, AI is embedded in what is termed a "software defined network", responding to a larger variety of different problem situations, identifying and solving failures, and conducting more complicated decision-making. This rudimentary intelligence governs network operations by pre-programmed (by humans) responses, what AT&T terms "policies", but AI capability continues to increase along with the network's degree of autonomy and "decision-making". As a leader in the practice notes: "*The real magic will happen when the AI has done this many times and keeps getting better at making predictions. It could even modify policies over time"* (Larson, 2016). In general, even though an automated system may be independently reacting and to operational conditions, human engineers are still needed for developing new models, and many current AI systems still operate according to prior-defined models of consumer behavior. In Amazon, it is the human developers which develop new insights on consumer preferences and algorithmic research which supports the creation of new conceptual models. However, the technology of of deep learning has the potential to do more. Given enough data, it can extract "new" features in the data, and so could create new models (although currently, that still happens with human help).

Automation as Monitoring and Controlling Human Work

One area that business programs historically train for is that of general management. Managers historically undertook monitoring, coordination and control functions for the workforce, and many jobs in contemporary firms are still of this type. Under certain scenarios, AI could have far-reaching implications for middle management employment. During the first era of automation, management was already being separated from the workforce by information technology (Zuboff, 1988), but management itself has steadily become routine work. In highly automated organizations, the remaining management functions involving the oversight of work are increasingly augmented by and patrolled by technology, with AI playing an increasing role as the monitoring and controlling "intelligence".

One corporate function that largely hinges on measurement and performance evaluation has been human resources management (HRM). With the advent of analytics, the application of AI becomes a natural next step. Even though humans still perform the bulk of certain tasks such as new employee orientation and training, many HRM activities such as recruitment, training and assessment increasingly take digital forms (e.g. simulation and gamification in training exercises). AI is already available for automating certain HRM tasks, but the next step will be the connection of assessment systems to AI, providing an extremely granular measure of task work.[13] While many firms had not yet used analytics in human resources (22% by one survey [Tambe et al., 2019]), an Amazon example shows how far this vision of HRM can be realized. Amazon effectively reshaped HRM by integrating the task of employee measurement into a broader automated system. Documents from a recent court case revealed that *"Amazon's system tracks the rates of each associate's productivity and automatically generates any warnings or terminations regarding quality or productivity without input from supervisors."* (Carey, 2018). In bypassing the traditional HRM function and even supervisors, the AI removes managerial oversight, creating a system that many may consider onerous.[14] This machine-led

[13] Some firms also offer blockchain solutions that allow for the fine-tuned management of human resources (PwC 2017). It is a short step further for such systems to capture and measure employee performance in even more automated ways. Invariably, more data also means more oversight of employees' activities.

[14] Amazon's law firm revealed how the system is used, in a recent court case over one employee (of several hundred fired in a given year from an Amazon facility in Baltimore) Lecher, C. (2019). How Amazon automatically tracks and fires warehouse workers for 'productivity', *The Verge*, April 25, 2019.

manner of coordination involves the AI in not only analysis, but also "planning" and optimizing performance. The speeds at which AI functions are now so much faster than humans that humans are increasingly "coordinated" within its automated workflow. All of this places limits on human agency, and creates a far greater degree of "automated" intrusiveness into employees' lives and rights than ever before (Tambe et al, 2019).

The Modularization of Work, Deskilling, and Replacement

The automation of discrete corporate functions is only a first step in the evolution towards the larger-scale use of automation in digitally transformed firms. A key point we will incorporate later is the idea that the modularization of work tasks will help facilitate automation across the broader organization. When manufacturing sectors were automated, at least three classes of tasks typically remain: manual tasks involving higher dexterity than computers can achieve, the human operation of computer controls via interfaces (to coordinate the new production system), and intellectual work that involves analytical and developmental activities (e.g. software development). As we will show, in the end, advancements in robotic vision and robotic manipulation will lead to more and more absorption of the first - the manual task work. The second – computer interface operation - is akin to the "deskilling" situations described earlier by Zuboff and other scholars. The augmentation view espouses that the third could expand, but as we will show later, under a different set of assumptions, even higher skilled (typically highly professionalized) work could be downsized.

The Replacement of Modularized Work

Tesla's experience is illustrative of the challenges of automating manual tasks. Tesla sought to fully automate its Model 3's factory to offset the costs and disadvantages to its costly product model, but the attempt failed: *"(the) robotic vision… the assembly line robots just couldn't*

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https://www.theverge.com/2019/4/25/18516004/amazon-warehouse-fulfillment-centers-productivity-firing-terminations (accessed November 15, 2019) *deal with unexpected orientations of objects like nuts and bolts, or complicated maneuvering between the car frame. Every such issue would cause the assembly line to stop. In the end, it was far easier to substitute humans for robots in many assembly situations."* (Kottenstette, 2019). It can be seen that the automated systems in Amazon's warehouses and Tesla's factories embed the remaining human work as circumscribed tasks in the overall work flow. We argue that this modularizing or circumscribing of tasks is a necessary prelude to their replacement by machines. In Amazon, the remaining manual work for humans to do consists of the "pickers" (of items off the shelves), the "stowers" (who replenish inventory on the shelves), and the "packers" (of boxes), where the pickers only act when the machines bring work to them. Baldwin's (2008) concept of modularity guides our interpretation of what seems to be happening: *In modularity theory, a module is a group of elements—in this case, tasks—that are highly interdependent on one another, but only minimally dependent on what happens in other modules (Baldwin and Clark, 2000: 63). By definition, modules are separated from one another by thin crossing points—in Simon's (1962) terminology, they are "near decomposable."* Essentially, by routinizing, then modularizing work, the digitally transformed firms are creating 'thin crossing points' between the modules of work – that is, clear cut interfaces between the circumscribed tasks that humans perform, and the wider automated workflow. Once the work tasks are circumscribed as such, they are not only measurable by automated means; the modularized tasks themselves are also more easily posed as technical problems for computer scientists and roboticists to solve, further increasing the prospect of more replacement of work.

Deskilling in the Modern Era and Business Imperatives

We have argued that digitally transforming firms will generally replace jobs with AI as part of a wider move to routinization and automation. AI may have a more transformative effect by automating work that has been circumscribed and modularized. In modern operations such as

Amazon’s and Tesla’s, robots are extensively employed in automated systems, and humans are mainly employed to monitor their operations or to undertake actions that the robots cannot reliably perform. However, the human work is subsumed to the automated system, and increasingly, a machine intelligence’s coordination and control, not unlike the manner seen with Chaplin’s hapless worker in *Modern Times*. While workers still do the picking operations, or the manual work of identifying exceptions and errors, this is only because the combination of human senses, skills and ability to contextualize circumstances are still superior to the machines’.[15] However, due to their superior information processing capability, machines have now taken over the analytical “thinking” parts of the work. With the exception of error identification, most of the remaining work of picking and sorting is routine manual labor, but since this is decoupled from the thinking and decision-making involving what to do (including after or before the activity), we could say that deskilling is at work. Another example of deskilling and AI replacement is seen in digital media firms such as Facebook or YouTube. These businesses require the screening of user-generated content for sensitive material. While this appears to require cognitive abilities and knowledge, it can also be framed as the identification of exceptions amongst repeated patterns. Recently, after office shutdowns occurring from the COVID-19 virus, the large social media firms quickly switched away from their human workforces to AI programs, illustrating the ease of replacing humans, and the potential of AI. More recently, Microsoft has also replaced the human journalists responsible for curating content on their MSNBC website with AI (Waterson, 2020). Recent advances in human-like text creation by the GPT-3 technology has also caught the journalism world’s attention.

[15] For instance, Amazon still needs human pickers because they can recognize exceptions that computer vision still cannot comprehend (unless it has a knowledge base of all such exceptions as well as patterns to match them). For instance, a human can recognize when a container is leaking fluids, whereas a machine might not be able to.

Comparing Human and Machine Ways of Thinking

The incessant advances in AI are causing the replacement of one human cognitive function after another. Many aspects of human work still require reasoning and other faculties, and AI cannot replace this human thinking. We are still far better than machines at acquiring and retrieving contextual knowledge, and many of our work processes still occur in idiosyncratic manner. However, this assumes that the machine has to duplicate our ways of working in order to replace humans. The computing paradigm essentially revolves around information processing, and great strides have been made on information acquisition, processing and contextualization for narrow domains. Machines can acquire information and process it at incredible speeds, and the application of the combination of sheer brute force computing with AI to various expert domains (such as autonomous vehicles) has proven a powerful combination. General human thinking processes have been more difficult for machines to replicate, and represent a challenge to AI experts attempting to create an 'artificial general intelligence'. One challenge to AI to replicate is the human ability to reason causally, which underlies the human basis for decision-making. While earlier generations of deep learning were initially only capable of modelling correlations, and not causal reasoning, recent theoretical developments in computer science have derived causal inferences from statistical data, and these are already being embedded in applications.[16] Another area is our human means of verbal

[16] The ability is to reason casually is potentially important, since causality is an important component to other forms of human thinking, including reasoning and scientific thinking. Causality is typically captured in branches of AI that use forms of knowledge representation to capture the structure of knowledge within a domain, e.g. predicate logic and knowledge graphs (based on mathematical graph theory). Commercial AI programs such as IBM's *Watson* store and retrieve knowledge in knowledge graphs, and conduct their reasoning with these and the help of other kinds of AI techniques. One of the challenges with ANN-based AI is that it captures data as correlations. A traditional ANN classifies patterns in the data, but the patterns are organized in relation to each other in spatial (e.g. vector) terms. In contrast, humans model the world, however, with causal inferences. The

and non-verbal communication. In areas like customer-facing work, the natural spoken language and facial expressions are critical means of communication., With advances in algorithms and sufficient brute force in computing, AI can theoretically replace if not supersede humans at many customer-facing and business decision-making tasks.[17] AI is not only replacing routinize work, but also *non-routine* human work. The AI does not need to replicate our thinking exactly in order to do better than us (Susskind and Susskind 2015). It just needs to create a similar output in a faster, more productive manner than humans. The remaining areas where humans still function better than machines are ones that involve the perception, acquisition, and processing of experiential and contextual knowledge. Human senses and sense-making of experiences are not replicable by any machines. The problem is, in the automated organization, these areas may be becoming ever smaller areas of work.

As noted earlier, it is a common expectation that digital transformation will increase the demand for highly-skilled technical professionals in areas like software and design (Seibel 2019). The augmentation view also suggests that jobs will require employees to learn new AI tools. Largely digital enterprises such as AirBnB, also require creative work such as design, but as noted earlier, these are not the typical transition paths for workers previously performing in the manual work lost to automation. As we show next, the economies of scale and scope

principles have been formulated by the computer scientist Judea Pearle and in part implemented in DoWhy, a casual inference software library established by Microsoft. The start-up Inguo now applies such reasoning in its deep learning algorithms.

[17] For instance, gesture recognition technologies and ontologies for human emotions now help AI applications to recognize human emotional and behavioral states from human facial expressions and body movements respectively. Previous generations of natural language processing (NLP) AI could not capture natural ways of communicating, but that is changing. NLP advances are helping make sense of human expressions of language. To capture even wider-spaced contexts, systems such as IBM’s Watson may combine NLP and knowledge graph ontologies.

arising from automation may reduce the numbers of technical personnel needed. Furthermore, there is an additional follow-on effect on employment as the new technologies grow more powerful, and as competitive advantages accrue to such automated firms.

4. Trends and the AI-Augmented Dynamics of Automation

Effects of Combining Technologies

AI's impact on work can have even broader effects over time, as the automated organizations restructure their work internally, and gain advantages in external competition. The first gains will come about from further technological recombination between AI and three other technologies: analytics (expanding on what was discussed earlier), cloud computing, and the Internet of Things (IoT). Cloud computing has been an important means for firms to scale their computing capability (Siebel, 2019). Firms acquire the needed computing capability through the cloud service provider only as their needs increase.[18] Hosting the firms' computing with the cloud service provider removes unnecessary hardware and maintenance costs from the firms, and provides more reliability and scalability given the firms' reduced responsibilities. Hosting on the cloud also allows smaller firms to adopt AI more easily (Garbuio and Lin, 2019). However, the costs and carbon emissions of training AI are not insignificant (assuming electricity from fossil fuels) (Schwartz et al., 2019).[19] A second disruptor - the Internet of

[18] While cloud computing benefits firms by making their IT operations more cost-effective, in general, the more a firm becomes software-based, the more it can become cloud-based. Seibel refers to five benefits to clients: *Infinite capacity* (i.e., resources), *On-demand self-service*, where users obtain computing resources as needed with ease, *broad access* (to resources), *resource pooling*, and *rapid elasticity* (resources being easily scaled up or down with the user's changes in demand).

[19] It has been estimated in recent research that training a large off the shelf deep learning AI (a representative called the Linguistically- Informed Self-Attention model) takes about $9870 worth of electricity to train (Schwartz et al, 2019). This is about 10.6 years' worth of electricity at a Tesla model 3's electricity cost (assuming a full

Things – refers to the trend to imbue equipment (e.g. Internet-accessible devices) with intelligence (Siebel, 2019). While only some consumer goods manufacturers have embedded IoT technology, IoT is becoming more common in complex products such as industrial machinery, infrastructure, and vehicles. The technology's potential is not fully realized, as the data is sometimes generated faster than firms can manage. IoT devices involve not only sensors and monitoring devices but also small-scale computing devices, making it possible not only for firms to know about the usage of their products on a continuous basis, but also for equipment to become more "intelligent", attaining some self-governing capability. In the case of consumer goods, the users' behaviors are tracked, giving firms the ability to discern future opportunities on potential consumer needs. Data can also help firms to know about device usage and failure patterns. Like aircraft engine manufacturers and other operators of complex machinery, Caterpillar embeds IoT in their construction equipment to enable a 'predictive maintenance', saving millions of dollars each year. These improve performance and efficiency by removing much of the manual work needed to inspect engines and other equipment each year.

While cloud computing facilitates AIs' manipulation of data, IoT is an additional accelerator to this as it pumps vast amounts of data into the evaluating AI or other systems.[20] Data is already sent to manufacturers on their equipment's real-time operations in the field. A

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charge each week). This is not even counting the cloud computing costs, which run anywhere from $103,000 to $350,000 for the same set of models.

[20] Start-ups now also operate their robots and peripherals from the cloud (that is, with their intelligence and software hosted on cloud resources), which removes the need for onboard hardware. This reduces the individual costs of robots, and make it easier for the robotics start-up to get traction in the market, and to service their customers (author's conversation with founder of a robotics start-up). Eventually, the lower cost per robot can encourage even more market penetration.

modern passenger plane's engine has numerous sensors sending data from the plane's communication systems back to the manufacturer for predictive (preventive) maintenance. A port's cranes will have hundreds of sensors gathering information on each crane and storing it for troubleshooting purposes.[21] The more sophisticated of systems may allow for a continuous processing of the data as it arrives, so as to improve the system's performance on the fly. An example of this combination of IoT and AI and interchange of information between individual units and the fleet are Tesla's vehicles. Tesla states: *Our networks learn from the most complicated and diverse scenarios in the world, iteratively sourced from our fleet of nearly 1M vehicles in real time.*[22] The learning and propagation of information on a global (i.e. fleet-wide) scale couples the notions of self-governance and system-level governance together.

What Underlies AI Scaling and Experimentation: Software, Platforms and Models

The automation of an enterprise or a facility such as Amazon's is facilitated by digital platforms. Platforms are usually based in software, but there are distinct features of the software platforms that imbue a digitally transformed firm with economic advantages (AirBnB, Uber and other platform firms being the obvious examples). The platforms' software-based characteristics that support the AI's augmentation of automation are: their ability to coordinate and automate work; their enabling of firms to run large numbers of experiments at scale; and their operating basis being in models (also a form of modularity). With regards to the first, the increasing number of platforms within a digitally transformed firm can cause challenges in their integration, especially if the automation is to become seamless. Firms will invariably seek to architect their

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[21] Author's conversation with lead data scientist for a container port.

[22] The AI then processes the data collected from the fleet as follows: *A full build of Autopilot neural networks involves 48 networks that take 70,000 GPU hours to train. Together, they output 1,000 distinct tensors (predictions) at each timestep.* https://www.tesla.com/autopilotAI, Tesla Autopilot microsite (Accessed April 8, 2020).

systems (i.e., platforms) to fit together by modular and other means. In AT&T, as multiple platforms came into being – one for each specialized function – the head of AT&T's development work noted, *"I can't just keep doing this one (i.e. platform) at a time. We need a foundation," said Mazin Gilbert. The carrier... (had) been using AI for decades in areas like call-center automation but developed it for each use as they came along. Now AT&T is pouring its AI smarts into a one platform that can be used with multiple applications… which the carrier built so it could roll out new services more quickly and efficiently"* (Larson, 2016).

The second platform characteristic, their experimental ability, allows firms to launch large numbers of experimental forays into markets, such as new digital content and marketing campaigns. It is common for Web-based and software firms to do A/B testing, that is, to run controlled trials of design interventions against one another. Firms like Amazon conduct (or in the case of Facebook, allow the conduct of) many more experiments daily on their websites, before rolling them out across multiple geographic locations. Firms like Amazon runs many thousands of e-commerce experiments over the course of a year on its platforms, making their platforms continuously running test beds. On Facebook, a trial can involve many different versions of an advertisement being tested on different segments of customers, each using different word choices and means of conveying the message. The effectiveness of these different word combinations can be validated by the ways in which users engage with "clicks" and "eye contact" (i.e., length of time spent on a page).[23] It is relatively easy to run large-scale experiments by automating the permutation of text, and for AI to be applied to analyzing the patterns in responses. In general, AI can process large amounts of statistical data - sometimes sparsely distributed across many seemingly unrelated dimensions - in ways humans cannot fathom. AI applications include financial institutions' tracking of illegal financial activity by

[23] The example was provided to an author by the director of an insurance company's innovation lab.

the processing of data - such as typical and atypical credit card uses for an individual and class of user – to detect unusual patterns of behavior.[24] As a predictive maintenance manager at Caterpillar Marine notes, *"There are relationships between pieces of data that the human eye just can't see – relationships about relationships about relationships* (Marr, 2017)*."*

Technically, AI is represented as models or algorithms in software. Unlike past statistical models, big data models capture a much more complete representation of the entire problem-solution situation. For instance, Netflix captures every part of a user's online behaviour using the algorithms in its recommender system. Netflix also relies on positive feedback (recommending users' preferences to other similar users), and rolls the algorithms out globally.[25] Seibel describes yet another notion of model: that of the conception of software as a model-driven architecture (representing an "*abstraction layer to simplify the programming problem"*). He decribes how this has driven productivity in software production: "*a model-driven architecture decreases the cost and complexity of designing, developing, testing, provisioning, maintaining, and operating an application by as much as 100 times or more."* (Seibel, 2019, pp 182-183). In fact, this conception of models in software is a manifestation of the earlier-discussed modularity. Modularity was at the heart of a firm's ability to reduce human work to problems that are solvable by machines. But software modularity also promotes recombination and reuse – two patterns of technological organizing that promote the productive use of software, and allows for economies of scope across different uses of the software.

In summary, software platforms not only possess economies of scale and scope, they power digital transformation by increasing the scope of automation across the entire organization. We will show that the integration of software, algorithms and automation with

[24] Based on an interview with lead member of a multinational bank's credit data group.

[25] Netflix for instance uses a set of algorithms based on statistical techniques and machine learning to tag each user's search patterns (Gomez-Uribe and Hunt, 2016).

AI fosters further advantages, and consequently, increasing returns (up to a point). While this complex of organizational activity augments and accelerates the human work modularly embedded within it, will this automated complex also increasingly displace the "natural" ways in which humans coordinate and do their work? The organization of human intellectual work is traditionally oriented around task coordination – something AI is adept at doing precisely – but also around the need to reconcile - via human means of communication - rich and differing views of the world - different ways of thinking about the world, or 'thought worlds' as it were. This leads to the follow-on question: If AI replaces all this human work, what do organizations lose out on?

The Shifting Character of Employment

We have laid out a theoretical picture of how firms accrue advantages from a more technical basis. To address the potential employment effects in digitally transforming firms, we examine a vignette. In Amazon, not only analysts and engineers, but also manual labor, were the recent job categories with the highest demand. However, the surge in AI and robotics and the modularizing of work makes each manual skill ripe for replacement on a modular, skill-by-skill, basis. Where humans once boxed and loaded pallets and carts, Kiva robots now work autonomously, and are monitored only for exceptions (Simon, 2020). Amazon aims to automate carts and vehicles to ever greater degrees, and recently acquired Canvas Technology, a start-up specializing in autonomous carts (as well as investing in an autonomous vehicles start-up); similarly Amazon just introduced carton packing and wrapping robots in select facilities (Wiggers, 2019). As one observer noted, *"start-ups and researchers are scrambling to overcome the many remaining technical obstacles. Amazon even sponsors an annual contest to encourage more innovation in the category."* (Wingfield, 2017). The incentives of the computer and engineering sciences and robotics firms, then, are to "solve" all the remaining manual work as "hard" technological problems.

While Amazon retrains workers to the new work, this work essentially involves following instructions on screens to manage the robots, or to react to exceptions (in ways that are also procedural in nature), in effect acting as a check on the robots' work. The history of automation involves gradual routinization followed by technological advancement and replacement or leveraging on fewer and fewer employees.[26] This may occur in other workplace settings as well. Looking towards the future, recent research that matched AI patents to job descriptions also suggests that some parts of the remaining white collar work – ones that are better paid and that require better educated workforces - are now some of the most at risk of being replaced (Muro et al., 2019).

Dynamics in the Marketplace: The Amazon Effect

The dynamic effect commonly observed is that e-commerce and other digitally transformed business models creating increasing returns via the various technological scaling mechanisms they use, often at zero to low marginal costs. The advantages of operating digitally allows them to outcompete conventional retailers and enterprises, both small and large, and causes an additional negative impact to overall employment. The most well-known example was of bookstores, which declined throughout the 1990s, but the effect also occurring in other sectors, retail and otherwise (e.g. Blockbuster at the expense of Netflix, Kodak at the expense of digital photography). This has not escaped policy-makers' attention: *"Steven Mnuchin, the Treasury Secretary, declared that Amazon has "destroyed the retail industry across the United States.""* (Duhigg, 2019). Conventional firms' employees suffer from pressure on wages, as witnessed by firms such as Uber intruding into the taxi companies' business. The counter argument used by Amazon has been to point to its tremendous growth in hiring employees. A similar perspective is raised by the augmentation view. Observers like Barro and Davenport (2019)

[26] Susskind and Susskind (2015) lay out a means for understanding how the organization of work changed over time in the legal, medical and educational professions.

use the term 'Partners in Innovation', while robotics uses the term "cobots" to describe systems of robots and humans working together. However, when we account for Amazon's expansion by examining other areas of the economy, a mixed picture emerges. A census count of employees in the books, periodicals and music stores retail sector show a decline in employment from 201,445 in 2002 to 97,904 in 2012 (the latest), the period when Amazon was showing early exponential growth.[27] An oft cited Amazon statistic is that they created 300,000 jobs in the several years' span since the introduction of robots in 2012 (Barro and Davenport, 2019). Simultaneously, however, Amazon also doubled the number of its robots from 100,000 to 200,000 in just one year –consisting largely of new systems that automated manual tasks. From these, Amazon was able to amortize the cost of just two new robot types in less than two years (Wiggers, 2019).

As the newer technologies being applied in Amazon continue to feed productivity increases across its various business, they cause employment per unit of value created to eventually decrease. As Amazon grows, it adds new business lines to its existing operations, creating competitive pressures on enterprises in other sectors of the economy. Facing this competitive situation, other companies will feel the need to engage in this arms race, where *"unless companies are willing to commit resources to AI technologies, they risk falling behind competitors in both productivity and quality."* (Barro and Davenport, 2019, p. 25). This organizational AI arms race raises productivity across the board, causing further employment losses in those sectors.

The Collapse of Barriers to Adoption

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[27] Firm statistics obtained from the US census: https://www.census.gov, https://data.census.gov (Accessed April 6, 2020). Amazon statistics obtained from Amazon Fulfillment Center microsite and Statista.com. https://www.statista.com/statistics/266282/annual-net-revenue-of-amazoncom/ (Accessed April 6, 2020); Amazon staff (undated).

As with any other innovation, a number of factors hold back the adoption of digital innovations, including their cost relative to low wage employees, their unproven nature, and general corporate inertia (including that of middle managers). Some consumers did not give up on shopping in person due to switching costs, as they could not accept the behavioral adjustments needed. The recent COVID-19 pandemic has brought down many of these barriers, including the psychological (Corkery and Gelles, 2020). By necessity, large parts of commerce in many countries had to be conducted via online delivery services. The necessity of these alternative means of commerce inculcates new behaviors in consumers that may be hard to switch back from. Given how routine job types never recovered from economic shocks in the past (Jaimovich and Siu, 2020), the COVID-19 downturn may also induce businesses to readjust permanently, reducing or replacing jobs with technology forever, at the very least, to avoid carrying high employee costs (Ovide, 2020).

Sources of Augmented Firms' Economies of Scope and Scale

Part of what we term 'digitally transformed' enterprises has also been recently referred to as "AI factories" (Iansiti and Lakhani, 2020). The term describes scalable business models with a basis in algorithms and analytics, from which emanate economies of scale and scope. Our argument is that digitally transformed firms also have these same economic features, but rather than having the advantage resting on a specific analytics function within the firm, we have been describing a broader complex of AI-augmented automation that integrates and streamlines many work activities, and especially on the operations side of firms. The economies of scale and scope in our model come from treating work modularly, reusing the modules where possible, and if necessary (to the firm), replacing the "modules" of work with automation. Since business model changes are implemented in software, this allows digital services to be added with relative ease, and facilitates rapid scaling and changes. Digital platforms also provide an experimental ability that can be scaled quickly and that allows for rapid adjustments.

This has the ability to move quickly from exploring to exploiting, i.e., that allows rapid scaled-up rollouts. The platforms can automate many business activities, including even the automation process itself! Amazon's automation of its intelligent machine implementation is a case in point: "*RoboMaker, the company's cloud robotics service (is) designed to expedite developing, testing, and deploying intelligent machines at scale*" (Wiggers, 2019).

Digitally transformed firms have inherent economies of scope, in part because digital goods and content can be massively personalized to consumers as their online behaviors are captured. Amazon's recommender system alone has been described as helping Amazon in *"building a store for every customer*" (Smith and Linden, 2017) - a phrase reflecting the economies of scope. Huge data flows result from IoT technology acquiring data from sensors, remote cameras and drones, as well as customer interactions on the Web. AI can be applied to these in order to develop characterizations of user behaviors and preferences with great granularity, as well as the devisement of and rolling out of services to address these.

To reiterate, the software-based modularity at the heart of digitally transformed firms promotes reuse and interchangeability (for ease of recombination) of processes and services. This allows additional products and services to be added at lower marginal costs, garnering further economies of scale and scope. To Amazon, it is less material whether it is selling a book or a can of food, since its operations are organized as information. Many decisions are traditionally the purview of hierarchically-organized chains of command – such as pricing, logistics (e.g. instructions to suppliers), and planning. Automation or even partial automation in digital environments can cause these to become more efficiently conveyed and allow ease of updating.

Employment Implications of the Ongoing Dynamics of Digital Transformation

To understand the changes to employment in digitally transformed firms, we look at the changing character of work, focusing on the development (of product and business) activities as a case in point. Organizational work is traditionally classified as exploratory or exploitative, but exploitative work tends to be routinized, raising its risk of being automated. When organizations digitally transform, they may revisit how they innovate. They may explore more, and engage in a mode of exploring tied to a strong experimental mindset. Typical exploitation forms of development may include the refinement of existing product lines, while exploration activities include the design and launch of new products. However, the experimental nature of digitally transformed organizations involving digital products and services blurs the line between exploration and exploitation. The embedding of key processes in software and in the cloud allows exploration by experiments. These may be followed up by the rapid scaling up in an "exploitation" phase, but with less costly or irretrievable commitments. While potential replacement effects (on employment) are commonly discussed for operational activities (e.g. the displacement of drivers by self-driving cars), product and business development work can be presumed to require more profound and multivariegated types of thinking - ones requiring human contextualization of action. The amount of 'multivariegated' work remaining may depend on how much firms and technology augment the work, and how automatable and scalable the work becomes. The workforce for development activities in digitally transformed firms consists of highly-skilled employees like programmers, analysts and data scientists. However, such development teams may also be smaller in size, with one estimate noting that with current advances in software, development teams for creating new models and platforms could be as small as a few engineers and scientists (Seibel, 2019).[28]

Another factor that dictates whether development work is replaced is that large parts of it still fundamentally involves human forms of interaction and knowledge creation. The degree

[28] Seibel notes that with a model-driven (modularized) architecture, "*small teams of between three and five software engineers and data scientists… can develop production AI and IoT applications in as little as 10 weeks*" (Seibel, 2019, pp 49-50).

to which this exploratory work can be replaced depends on the circumstances of the work in question. Tasks such as business or market development involve a search for business opportunities, partly achieved through human interaction with customers and vendors on rich contexts (e.g. customer-specific contexts). While human sensemaking is not replaceable by digital means, digitally transformed firms may *substitute* the *function* of a more unstructured search with digital forms of search grounded in data (e.g. e-commerce firms' use of digital channels and analytics). In the future, it is also possible for automated searches to occur with software agents acting as intermediaries between the firms. In a traditional firm, many activities in product development and marketing also involve inter-departmental interactions. Interactions and task handoffs can be imprecise, requiring communication to reconcile different perspectives. However, these different perspectives or 'thought worlds' can also be enriching if they shed different kinds of light on ill-formulated or unsolved problems. The question is whether the digital replacements are as effective as these traditional ways of working, or are augmentative (and hence, replacing of some of the work). In a similar way, for customer-facing work, it is well-known that the human touch may still be valued by customers in areas where personal services and neighborhood stores are involved, but as we have seen, e-commerce and digital interfaces are steadily eroding these organizational forms. Finally, on the most creative end, development activities such as design benefits from human senses and abilities. Creativity, synthesis and sensemaking are still needed to create new products and experiences. Employees may be required to have superior capabilities at synthesizing new knowledge, depth of knowledge, and the ability to explore interstitial areas. The trouble is, even if these human qualities are prized, they are also challenging for many employees to acquire. They are also increasingly possible to augment and scale.

5. Conclusion

Our goal was to better inform the replacement and augmentation debate by examining it from the broader perspective of AI's augmentation of automation. While in prior eras of automation, the loss of employment to automation was offset by the growth of new sectors and jobs, this also involved a loss of routinized, middle-skilled work, and a polarization of jobs into high and low skilled ones. In an era of AI-augmented automation, we suggest that this imbalance may be further aggravated. We examined digitally transformed firms and developments in AI to help articulate an argument for the further replacement of work. Essentially, AI helps automation to become self-governing, even while a broader automation of firms' work processes occurs. Firms can more easily replace modularized work, and the modularizing of nonroutine work makes them more tractable (and solvable) as new AI problems. Furthermore, given that the remaining manual work essentially involves basic cognitive functions such as pattern recognition, and/or manual dexterity, this eliminates any wage premium accruable from training, and might be considered as a form of deskilling. These trends may bode poorly for employment. At one extreme, this has led to onerous closed-loop systems that automate the monitoring, assessment and even firing, of human resources. Ford (2015) further notes that the structure of employment could be very distorted, with very few at "the top" gaining the remaining (most intellectual of) work. Furthermore, the combination of AI with analytics and technologies such as cloud computing and IoT, in conjunction with the basis of these digitally transformed organizations in software, platforms and models, provide digitally transformed firms with economies of scale and scope over traditional non-AI using firms, putting further pressure on these other firms to transform themselves. We have noted certain conditions under which cognitive human work is preservable, these being ones where the richness of knowledge context and complex human interactions remains important to firms. Replacement will thus have a ceiling until critical technical advances are made.

The societal implications of this scenario are profound. If AI-induced automation replaces more and more work, and much of the remaining work is concentrated into a smaller, highly technical workforce, there will be a need for policy to ensure jobs for sustainable livelihoods. Governments, firms and scholars should to come together to engage firms in thinking of new models of socially-minded production, and to consider social protections. This also raises implications for business school education. We still largely teach computable forms of analysis as a holdover from the training of workforces for corporations organized for mass production. We need to think about how business models affect work, and we do not educate enough on how to use new technologies to promote sustainable forms of work, and livelihoods.

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