Debates and Perspectives

JIT

Journal of Information Technology
2020, Vol. 35(4) 286–302

DOI: 10.1177/0268396220925830
Journals.sagepub.com/jinf
SAGE

Robo-Apocalypse cancelled? Reframing the automation and future of work debate

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Abstract

Robotics and the automation of knowledge work, often referred to as AI (artificial intelligence), are presented in the media as likely to have massive impacts, for better or worse, on jobs skills, organizations and society. The article deconstructs the dominant hype-and-fear narrative. Claims on net job loss emerge as exaggerated, but there will be considerable skills disruption and change in the major global economies over the next 12 years. The term AI has been hijacked, in order to suggest much more going on technologically than can be the case. The article reviews critically the research evidence so far, including the author's own, pointing to eight major qualifiers to the dominant discourse of major net job loss from a seamless, overwhelming AI wave sweeping fast through the major economies. The article questions many assumptions: that automation creates few jobs short or long term; that whole jobs can be automated; that the technology is perfectible; that organizations can seamlessly and quickly deploy AI; that humans are machines that can be replicated; and that it is politically, socially and economically feasible to apply these technologies. A major omission in all studies is factoring in dramatic increases in the amount of work to be done. Adding in ageing populations, productivity gaps and skills shortages predicted across many G20 countries, the danger might be too little, rather than too much labour. The article concludes that, if there is going to be a Robo-Apocalypse, this will be from a collective failure to adjust to skills change over the next 12 years. But the debate needs to be widened to the impact of eight other technologies that AI insufficiently represents in the popular imagination and that, in combination, could cause a techno-apocalypse.

Keywords

AI, automation, cognitive automation, robotic process automation, future of work, information technology, jobs, skills

Introduction: the AI hijack

Artificial intelligence (AI) is an academic term that has been seized upon by the media, marketing departments and commentators as shorthand, and to add narrative spice. The hijack is that it is regularly applied to technologies and uses that are not strictly definable as AI. You will be familiar with the now-dominant AI storyline: physical and software robots are becoming enhanced by the collection of tools being called – amongst many other things – 'robotic process automation', 'cognitive automation' and 'artificial intelligence', to infiltrate all aspects of our lives. By 2020 one can find Amazon promising to deliver our purchases by drone; Uber pressing ahead with driverless cabs despite some embarrassing failures to date; China developing a social credit system based on surveillance and other technologies; and a hotel in Japan with android receptionists, plus porter, cloakroom, service and cleaning robots. Meanwhile, a company in California was attempting to automate the world's oldest profession, which will enable robots capable of the most intimate of services.

So, are humans and human workers rapidly heading for history's work scrap heap? The accumulated evidence gathered here, including our own extensive research into the actual and likely effects of automation presents a much more complex and nuanced narrative than emerges from all too many commentaries, media stories, reports and the avalanche of publications on automation and the future of work.

The AI story hijacking begins with the very words 'artificial' and 'intelligence'. As Boden (2016) says, 'Artificial

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Intelligence (AI) seeks to make computers do the sorts of things minds can do'. Today the term AI is often used when a machine mimics 'cognitive' and other functions that humans associate with human minds, for example, learning, problem solving, visioning, prediction and association. In contrast, in a more reserved view on AI, both Margaret Boden and leading AI researcher Igor Aleksander point out that AI (and AI-powered robots) can be neither conscious nor mindful. For Aleksander, 'intelligence' here addresses an algorithmic category of processes needing a human designer and cannot be equated to intelligence in human beings. Polson and Scott (2018), commenting on contemporary AI, suggest that 'if you chain lots of algorithms together in a clever way, you can produce "AI" defined more accurately and limitedly as "a domain-specific illusion of intelligent behaviour"'. Even by 2020, a lot of so-called AI would seem to me to be statistics on data steroids. Aleksander (2017) regrets the descriptor AI – 'smart computing would have done'. For him, after 60 years of intense scientific effort, intelligent robots that vie with the intelligence human beings exhibit is proving much more elusive than most contemporary accounts and predictions suggest.

The over-the-top, hijacked AI story has become too good to be false. The rhetoric runs way ahead of the reality and during the 2017–2019 period, unfortunately, an academic research term, AI, had become permanently hijacked not only to often misrepresent, certainly to add glamour to, product offerings, events and stories, but also to become a narrative wherein what is aspired to, or worried about, is conflated with actually existing capabilities – an example of a category error if ever there was one.

This is not to say that the existing AI technologies are not impressive. Moreover, the capabilities are increasing, and at a fast pace. Our own work manifestly demonstrates this (Lacity and Willcocks, 2018; Willcocks et al., 2019).[1] But, looking at hundreds of deployments and accumulating evidence, one can see, beyond the verbiage and claims, three main technologies: physical robots, robotic process automation (RPA) and cognitive automation (CA). Physical robots, driven by software, cover industrial work, for example, manufacturing, service work, for example, healthcare robots and such developments as driverless vehicles and delivery drones. RPA uses software to automate tasks previously performed by humans that use rules to process structured data to produce deterministic outcomes. It automates the repetitive, largely physical, clerical tasks typical of much office work. CA sees more sophisticated tools using software to automate or augment tasks that use inference-based algorithms to process structured and unstructured data to produce probabilistic outcomes (Lacity and Willcocks, 2018). This is the realm of machine and deep learning algorithms, visual processing and natural language processing, driven by the increasing availability of very large data sets, immense computing power and notable, continuing advances in memory and storage capacity.

Two points are to be noted in regard to the hijacking of the term AI and the over-inflated expectations of AI. First, the above three technologies are commonly called AI though neither add up to 'strong' or 'general intelligence', AI nor do they regularly meet the definitions Boden and Aleksander offered above. Second, while the market potential of AI is generally reported as huge, the estimates for actual size are not. The highest estimate for the RPA, CA and AI markets has been US$4.1 billion in 2018, rising to US$46.5 billion in 2024 (Lacity and Willcocks, 2018; Statista, 2019). Compared with the overall global information technology spend, reckoned by IDC (2019) to be US$5 trillion in 2019, rising to US$6 trillion in 2022, these figures do not gel well with, and raise warning signs about, a storyline of fast, massive, unstoppable impacts of these AI branded technologies, including impacts on job numbers and work contents.[2] What is going on here?

'Hype or fear' – deciphering the AI narrative

Looking at the bigger picture, it is not easy to pick your way through the media representations of the debate around AI, automation, robots and the future of work. Relevant sources and often-cited studies are, in fact, very variable in quality, evidence and rigour. But they seem to polarize around two storylines – hype or fear. These are repeated over and over in both public discourse and information systems studies. We have met these two storylines before in information systems studies as typical early stage responses to technology adoption (for example, O'Leary, 2008).

In the case of AI, the 'hype' storyline tells us that it is largely going to be fine and most of us are going to live in a well-run technologized world – let us call it 'Automotopia' – with more than enough goods, services and leisure. Technology will create jobs and provide solutions to multiple problems. There are many symbols for this but a typical one is a service robot deployed in service or care settings.[3] The assumptions embedded in this narrative are that technology will be a panacea, there will be massive benefits, the technology is perfectible, there will be few barriers and adoption will be quick and pervasive (see, for example, Kelly, 2016).

In contrast, the 'fear' vision is essentially dystopian, with sample headlines or article titles being *Who Owns The Robots Rules The World; How The Robots Will Take Your Job and Kill The Economy; and Robots could displace 10 million British workers.*[4] This polarized narrative – let's call it Robo-Apocalypse – also assumes quick and pervasive adoption of the technology, but sees it as displacing a huge number of physical and cognitive-based jobs across industries, and geographies, and at most levels in the organization. Here the assumptions are that automation means job displacement; that there will be little job creation; that societies, organizations and individuals will be ill-placed to respond to the rapid deployment of automation; and that human capabilities will have little role to play in the future of work.

Interestingly, the 'Automotopia' view is not well represented by detailed studies of, as opposed to speculations about, this optimistic scenario.[5] The 'Robo-Apocalypse' view does find more underpinning in thorough studies such as Richard and Daniel Susskind's *The Future of the Professions* and Martin Ford's *The Rise of the Robots*.[6] But other accumulating evidence and our own work over 4 years suggest to information systems scholars, policy makers and the wider audience, a much more nuanced and complex narrative than the headlines shout at us on a daily basis, and less pessimistic conclusions than Ford and the Susskind's arrive at.

The studies since early 2016 have tended to be richer in data, and more fine-tuned in their analysis than the polarized debates in the media. Nevertheless, media reportage of AI tends to follow the hype or fear views, downplaying qualifications and counter-evidence actually often in the studies themselves to favour a dominant, simpler, certainly more seductive, storyline.[7]

We should exercise caution about the numbers used to support the above views. We have to become sceptical about the more macro studies on the technology and future job numbers. The problem with all too many is that they are projections going forward, with not necessarily good data sets, often carrying questionable, even tacit assumptions and few make their methodology transparent. Moreover, technology is a highly dynamic space, where trajectories are notoriously difficult to predict. Even if you take the best of the studies under purview, the limitations start to become clear quite quickly. For example, the still most quoted study in the media, and one of the most rigorous and admirable of its time, is by Frey and Osborne (2013). Looking at 2010 data for 702 occupations in the United States, they found that 47% of occupations were under high risk of being computerized. However, the researchers do not try to specify the speed of technology development, nor a time period for the loss of jobs – 'some unspecified number of years, perhaps a decade or two' – they say (p. 38). Nor do they attempt to predict the share and number of actual jobs lost (as opposed to, for example, jobs only being reconfigured in their task composition, but not lost).

There are several further limitations of the Frey and Osborne (2013) study that I would point to. First, the study, like many others in this area, does no analysis of jobs likely to be created by changes in work and technology. Second, it focuses on job and occupations, not on activities and tasks, nor the amount of work that needs to be done, which seems to be increasing exponentially (see below). Third, the study largely factors out the key bottleneck of how commercially feasible, viable and organizationally adoptable the emerging technologies are, that is, the long road to diffusion of innovation dilemma is ignored. The researchers do, however, point to three engineering barriers to computerization, that is, tasks that humans do that are not easily automatable. These are 'complex perception and manipulation tasks' (manual, finger, cramped workspace); 'creative intelligence' (involving novelty and value, originality, fine arts production) and 'social intelligence', including social perceptiveness and recognition of human emotion, for example, negotiation, persuasion and care. But the three concepts are not adequate for fully describing the multiple valuable human qualities that will continue to apply at work (see below; also, Colvin, 2015; Davenport and Kirby, 2016a, 2016b).

The research method employed in Frey and Osborne (2013, 2017) also reveals limitations. They labelled 70 jobs as automatable or not – a binary distinction, yet some of the jobs classified undoubtedly fell in between. They then used this training data to develop a machine learning programme to classify the other 632 occupations. Walsh (2017, 2018) found that 7% of the 70 jobs in the training set were classified differently, and wrongly, by their automated classifier. Small differences in the skills needed for a job can lead to large differences in the estimated probability. Walsh suggests that the machine learning methods used are somewhat unstable.[8] Walsh (2017, 2018) looks at 26 occupations covered by the study and questions the automated results for many of them. Is the probability of bicycle repair automation and watch repair really 94% and 97%, respectively? Walsh thinks it is unlikely these jobs will be automated at all. For an electrician and a hairdresser, the figures are 15% and 11%, respectively – Walsh thinks it should be lower. We dwell here on the minutiae of research methods because little tweaks in assumptions and methodology can make huge differences in the resultant findings.

We will move on to demonstrate that these are important, in some cases fundamental, omissions, if you want to arrive at a balanced view of what job losses are likely to be as a result of automation. However, media everywhere continue to quote the headline figure of 47% job loss as a result of automation without often stating any, certainly always downplaying most, of these critical qualifications to the storyline. Unfortunately, this 47% figure has become what Kahneman (2011) calls an 'anchor figure' from which media find it all too difficult to move. Another media case, perhaps, of too good to be false.

Recall that Frey and Osborne (2013, 2017) remains one of the more transparent and rigorous of the studies so far available.[9] It becomes highly necessary, therefore, to examine the studies, reports and research that have been produced more recently to find a way through them. We first look at job numbers.

The strange case of the disappearing net job loss

The first key point: there is little agreement on the overall figures for job losses as a result of automation. The studies are best seen as a starting point rather than definitive statements. All have some flawed assumptions and data weaknesses, hidden often by seemingly precise figures. Across the 2013–early 2019 period we reviewed the major published reports quoting statistics on automation and jobs. We can only draw upon them selectively here, but collectively, they provide a complex picture rather than a straightforward one of job displacement.

As we have seen, Frey and Osborne suggested that on an unstated time horizon 47% of current US occupations were under high threat from automation.[10] In 2016, Forrester Research estimated 16% of US jobs lost by 2025 (23 million – about 11% of the extant US workforce), but also job gains of some 9% leaving a net loss of 7%. Their revised figures in Forrester Research (2017) suggested that robots will take 24.7 million jobs, but create 14.9 million new jobs by 2027, leading to a net loss of 9.8 million jobs, again about 7% of the US workforce.[11]

A study by Arntz et al. (2016) for the Organisation for Economic Co-operation and Development (OECD) came to different figures. Re-running the US data using a task-based rather than an occupation-based approach (see below), they found that only 9% of US individuals (not 47%) face high job automatability (i.e. in excess of 70% automatability). Using different, European data from 2012, it analysed the tasks within jobs (see below) and suggested that an average of 9% of OECD jobs would become highly automated within a decade.[12]

Assessing the methodologies used in the Frey and Osborne and Arntz et al. studies, Price Waterhouse Coopers (2017)[13] attempted to reconcile these figures and concluded that up to 30% of UK jobs could potentially be at high risk of early automation by the early 2030s (comparisons are the United States 38%, Germany 35% and Japan 21%). However, the report suggests that not all such jobs may actually be automated due to a variety of economic, legal and regulatory reasons, and also makes the point that these studies do not factor in job creation.

By 2019, however, the picture of high job loss had changed dramatically, though not necessarily in the headlines. To get a global perspective, five major reports are worth highlighting. First, the World Economic Forum (2018a) surveyed 313 companies representing 15 million workers in 20 economies for the period 2018–2022 and found automation replacing 0.98 million jobs while creating 1.74 million new ones. The Asia Development Bank (2018) was positive on net job creation from automation, pointing out that new technologies in the 2005–2015 period in 12 Asian economies had created 134 million jobs compared with the 101 million jobs lost through technology. Price Waterhouse Coopers (2018) estimated that the net job effect of automation in the United Kingdom from 2017 to 2037 would be a slight gain of 168,000 jobs (7.176 million created, 7.008 million displaced). McKinsey Global Institute (MGI) produced two reports based on scenario modelling for more than 800 occupations and their 2000 activities in 46 countries. MGI (2017) suggests that on a midpoint scenario some 15% or 400 million workers could be displaced by adoption of automation from 2016 to 2030. However, this could be offset by seven major trends – rising incomes, more healthcare, investment in technology, infrastructure and buildings, energy transitions – improving energy efficiency, meeting climate challenges and more marketization of unpaid work. These trends could create anything between 390 million and 590 million jobs.

Meanwhile MGI (2018b, 2018c) examined the effect of five broad sets of AI technologies[14] and draws upon a 3000-corporation survey, a proprietary database of 400 potential use cases, and the MGI jobs database updated from MGI (2017). The report suggests that, 'overall, the adoption of AI may not have a significant impact on net employment in the long term. . . Our average global scenario suggests that total full time equivalent employment may remain flat at best compared with today' *(*pp. 44 and 45).[15]

What is startling here is that as time has gone by, the estimates for net job loss from automation have been disappearing to the point of being negligible – though of course, as we shall see, the net figures mask considerable disruption and skills shifts. There have to be serious qualifications to the Robo-Apocalypse narrative. We see eight major qualifiers, which individually undermine the usefulness of many job loss estimates, and collectively produce quite a compelling alternative, complex picture.

Qualifier 1 – job numbers versus tasks and activities

Are whole jobs lost as a result of automation? Of key interest is the percentage of the job or activity that is automatable. MGI's Chui et al. (2015) picked up this point early. Some illustrations from their study include 80%–100% of a file clerk's work is automatable in the near future, 25% of landscaping and grounds-keeping work and more than 20% of a CEO's work. Chui et al. (2015) suggest about 73% of work preparing and serving food in restaurants (3 million staff in the United States) could be done by robots – but ask, will 73% of those people really be replaced? Research by MGI (2017, 2018a, 2018b, 2018c) consistently shows that roughly half of the time spent on various tasks could theoretically be automated, but that on average, automation is likely to substitute no more than 15%–17% of existing time worked globally by 2030.

Studies that look at work activities as a better unit of analysis than whole jobs suggest that job restructuring will be the more normal pattern. Manyika et al. (2017) estimated that only 5% of jobs could be completely displaced by automation tools currently available. They suggest that in the United States 60% of workers could have 30% or more of their jobs automated, while 30% of US workers are in jobs where 50% or more of the work could be automated. MGI

(2018) suggests that less than 10% of jobs can be 90% automated by 2030. In their view, the consequences will be considerable role redefinition for many, and it is not just low wage, low skill jobs being impacted by automation. MGI (2017) gives additional detail on how this is likely to pan out between 2018 and 2030, suggesting that between 3% and 14% of workers will have to switch job categories.

Supporting this view, OECD (2016) data posit that while on average 9% of jobs are highly automatable, anything between 10% and 35% of jobs (depending on country) face a medium risk (50%–70%) of changes in task as a result of automation. Certainly, our own organizational-level research suggests that every person's job is likely to be changed by at least 25% on a 10-year time horizon, as technology increasingly permeates task performance (Lacity and Willcocks, 2018). The World Economic Forum (2018a, 2018b) and Price Waterhouse Coopers (2018) see the most likely scenario for most jobs is partial automation and work restructuring rather than the wholesale replacement of jobs.

Qualifier 2 – job creation from automation

What impact will job creation have? With a few notable exceptions such as Forrester Research (2017) and Stewart et al. (2015), until 2018 very few studies focused on job creation from new technology, though job creation has invariably happened in the past. One pattern has been that process innovation enabled by technology has seen jobs lost, while product innovation has seen job gains. For example, one UK study estimated that around 6% of all UK (10% in London) jobs in 2013 did not exist in 1990. The new jobs related mostly to digital technologies. Price Waterhouse Coopers (2017) suggest that by the 2030s, 5% or more of UK jobs may be in areas related to new robotics and AI of a kind not existing now. In addition, the report sees the productivity and income generated from these innovations being recycled into additional spending, so generating demand that will generate extra jobs in less automatable sectors, for example, healthcare and personal services. MGI (2017) endorses this, suggesting that, as a result of automation, 8%–9% of workers in 2030 will be in occupations not existing before 2018.

New jobs, historically, also come from new services and business models and innovations that are made possible by changed technologies.[16] For the United Kingdom, Deloitte (2016) estimated that over the previous 15 years, technology contributed to 800,000 job losses but also helped to create 3.3 million new, higher skilled jobs. Reviewing the recent history of jobs and technology, Stewart et al. (2015) argued that the present debate is skewed towards job destruction. In practice, technology has substituted for labour as a source of energy, jobs have been created for the drivers of technological change, technology has created jobs in knowledge-intensive industries, and technological change has lowered expenditure on essentials, creating new demand and jobs. Machines replacing humans has resulted paradoxically in faster growth and, in time, rising employment. Is this time different? Stewart and colleagues believe not. Those who argue otherwise, for example, Brynjolfsson and McAfee (2015), tend to focus on the technological possibilities, rather than the many other more shaping non-technological factors that have affected the speed and pervasiveness of technology adoption and job creation/destruction in the past, and will continue to do so in the future. However, Manyika et al. (2017), Price Waterhouse Coopers (2017) and Forrester Research (2017) tend to support our own research (Lacity and Willcocks, 2018) that this prior pattern, if not the exact figures, is likely to repeat in the future as new work and new products and services are enabled by the technologies.

Arntz et al. (2016) put more focus on the possibilities for job creation. Using OECD data, they point out that labour-saving technologies have to be produced and this has already created a demand for labour in new sectors and occupations, along with jobs complementary to the new technologies. New technologies can boost a firm's competitiveness and so customer demand, creating new demand for labour.[17] In past waves of technological innovations, this is supported, with qualifications, by Mokyr et al. (2015). Reviewing many studies, they suggests that workers, at least in the long run, benefitted in terms of higher wages and income, although there is also evidence that there was at least a temporary increase in income inequality related to some technological innovations. At the same time, as in the past, automation and digitization are likely to be associated with large shifts within occupations and industries, pressuring workers to adjust to changing economic and working environments and skill needs.

Looking across the studies and at our own projections within organizations we have researched, it seems that across the next 10 years at least, for every 20 jobs lost another 13 could be created, before taking into account the further six qualifiers we discuss below (Lacity and Willcocks, 2018). In our own studies we are seeing new jobs developing around the technologies and their delivery within major business organizations. There are new, more technical jobs, but there are also a range of managerial and administrative jobs around maintenance and keeping the new technologies going. In business operations, automation also frees up people to focus on what people do well, and on work they could not previously have the time to do. A lot of recombination of tasks is already taking place, while technology can be, and is most frequently being used to complement and augment human strengths rather than substitute for them. Newly configured jobs emerge from this process of transition through work redesign. Automation also needs oversight. As yet we have not come across an automated system at work that does not need human attending and intervention. New jobs are also emerging from doing what machines are just not able to do and that require human attributes (see below). During 2016–2019, we also saw new work arising from new products and services enabled by automation deployment in banking, insurance, education, utilities and manufacturing (Lacity and Willcocks, 2018; Willcocks et al., 2019). These may be 'early days' phenomena, but the patterns are familiar to us in our studies of other digital technologies (Willcocks et al., 2001, 2014).

To summarize, while earlier reports downplayed job creation from automation, later studies estimate a 20% increase for the United Kingdom between 2017 and 2037 (Price Waterhouse Coopers, 2018); an increase of 1.74 million workers in 313 companies from 2018 to 2022 (World Economic Forum, 2018a); a 21% increase in jobs from demand growth to 2030 (but not just from automation – MGI, 2017); and a 17% gain in employment to 2030 (MGI, 2018b, 2018c). These figures do not make the prospect of a Robo-Apocalypse go away but are a major corrective to the one-sided view that automation means predominantly job losses. But there are six further qualifiers that need to be highlighted, before we can reconsider whether the Robo-Apocalypse is likely, cancelled or merely postponed.

Qualifier 3 – is technology (ever) a fire-and-forget missile?

How fast will automation technologies be deployed pervasively in work organizations? In studies of e-business and cloud computing technologies, we found key antecedents that affect technology diffusion (Willcocks et al., 2001, 2014). Two seem significant in the context of automation technologies (Willcocks et al., 2019).

The first is *attributes of the technology itself*. Does it give relative advantage? Is it compatible with existing ways of operating? What is the risk level? Is it too complex or not administratively feasible? Is it easily trialable with tangible outcomes? Is technical support given? Is there potential for reinvention? While e-business and cloud computing technologies had many positive attributes, we still found widespread diffusion of innovation in specific major organizations was slow, taking often 4–5 years. Our own research suggests a similar pattern for robotic process and CA (Lacity and Willcocks, 2018).

The second factor is *the innovation implementation process*. This includes a range of practical factors that support or slow an innovation's progress from design to adoption, diffusion and usage, through to exploitation and further innovation. Key issues here are as follows:

- The sectoral structure, absorptive capacity for new knowledge and sectoral receptiveness to change;
- Adopter attributes;
- Organizational readiness for innovation;
- How easy is the innovation to assimilate – an easy and straightforward change, or a complex, non-linear process with many 'soft' elements;
- The quality of the organization's implementation processes.

Our own research suggests that implementation challenges are very real in the context of automation, especially for large organizations with a legacy of information technology (IT) investments, infrastructure and outsourcing contracts. There are also cultural, structural and political legacies that will shape the speed of implementation, exploitation and reinvention. In particular, we found in the 2017–2019 period organizations running up against 'silo challenges' – in respect of technologies, data, processes, skill bases, culture, managerial mindsets and organizational structures – that slow adoption considerably. We also observed in several organizations a slowing down in their ability to absorb further technological change (Lacity and Willcocks, 2017, 2018; Willcocks et al., 2019). In practice, we have found getting a digital technology to a workable, safe, commercial level and then engineering the technology for specific use cases can take several years (Willcocks et al., 2014). The same is likely to happen to cognitive tools ranging from digital personal assistants to driverless cars.[18]

Modelling CA tools, Manyika et al. (2017) found solutions development taking 1–9 years, depending on human capabilities being automated, with social and emotional capabilities having the longest time frames. CA is costly to develop.[19] Deploying service automation tools also incurs expenditure often three to six times the cost of the actual software. For example, we found one cognitive solution in organizations costing US$1.5 million to get to proof-of-concept, and US$12 million to fully implement across less than four processes. These figures are not typical of every solution. However, case studies show that data have to be collected and proven, software adapted to organizational processes, people have to be trained, stakeholder buy-in achieved, governance structures established, projects undertaken, and technical and organizational change managed (Willcocks et al., 2019).[20]

Labour market dynamics can be complex. Because a task can be automated, it does not follow that it is cheaper or better to replace a human in that role. Humans also possess degrees of flexibility and composite skills application that CA tools will not exhibit any time soon, and on some estimates, not for 35 years (see below). There is quite a lot of evidence that humans prefer human interaction and presence in many situations, for example, on airplanes, in service contexts, and when being judged in legal cases, even where machines may seem safer, faster and/or more objective. Economic organizational benefits from automation may be very promising, but much depends on not just attributes of the technology, but also of the innovation implementation process, as already described. It is also early days for considering regulatory and social acceptance. As automation becomes more pervasive the regulatory burden and social concerns are likely to mount, even if, as with all previous technologies, operating in catch-up mode.[21]

To bring this together, Manyika et al. (2017) reviewed the historical rate of adoption of 25 previous technologies. Once commercially available, technologies still took between 8 and 28 years to achieve 90% adoption (the range for 50% adoption was between 5 and 16 years).[22] These figures are consistent with our own findings on the adoption of customer relationships management systems, enterprise resource planning (ERP) systems, and e-business and cloud computing technologies (Finnegan and Willcocks, 2007; Seddon et al., 2003; Willcocks et al., 2001, 2014). Manyika et al. (2017) suggest that hardware-based automation technologies like driverless cars/lorries and physical service robots could see the time for adoption lengthen, as they need capital and physical production. Meanwhile the researchers still expect software/cloud-based automation technologies to fall within the range of 8 to 28 years for 90% adoption. But they, together with all commentators, see speed of adoption varying, sometimes dramatically, across occupations, sectors and countries.[23]

All this suggests that the technology set of RPA, physical robots, CA and AI can hardly be presented as a 'fire-and-forget missile'. This would be immediately recognized by information systems researchers. However, too many other commentators seriously misrepresent the likely speed of deployment, and this derives from misunderstanding the technologies, and underestimating the long, often troubled route from concept through implementation, institutionalization, to individual, business and societal impacts.

Qualifier 4 – technology: born perfect? perfectible?

How perfectible is the technology? Historically, the IT industry has done a good job of convincing their customers that the story is one of continuous technology innovation and improvement, often conflating this with the reality of endless upgrades, and new versions frequently needed due to early releases of limited and/or imperfect technology and software. This trend continues into the design and development of automation tools. We are now regularly presented with the narrative that automation technologies, quite quickly, will match and supersede human capabilities by huge margins. Brennen et al. (2019) point to one source of this narrative, finding that nearly 60% of the 760 news articles they looked at across outlets in 2018 were linked to industry products, initiatives or announcements. These typically portrayed AI as a relevant and competent solution to a range of public problems: 'outlets regularly assert the influence it will have across areas of public life, often with little acknowledgement of ongoing debates concerning AI's potential effects'.

But from our own research, and considering the small market size (see above), by late-2019 applications were discrete, small in impact and the overall market still quite immature (Willcocks et al., 2019). One must also post reservations about conflating exponential growth of AI market *revenues* from a very low base, with exponential *impacts* (Willcocks et al., 2019). Informed sources also point to the fact that the kind of AI we have today is narrow or weak AI, able to perform a specific kind of problem or task. Nearly all refer to the reality of the Moravec Paradox, that is, the easy things for a 5-year-old human are the hard things for a machine, and vice versa (see, for example, Burgess, 2018; Polson and Scott, 2018; Reese, 2018; Walsh, 2017).

In sum, we are already seeing rapid growth of automation across sectors in the areas of repeatable, physical activities, data collection and data processing. The more automatable capabilities at work include information retrieval, recognizing known patterns, optimization, planning, natural language generation, sensory perception and gross motor skills. However, many other capabilities are much less automatable, as are tasks that require composite skills such as managing people, applying expertise in decision-making, planning, creativity, interfacing with stakeholders and performing unpredictable physical activities. This may help to frame the uneven adoption rate.[24] All this leads us to the conclusion that assumptions about the perfectibility of automation tools any time soon need to be heavily qualified. Attributes of the technology are frequently less than as represented, even by quite well-informed technical sources.

Qualifier 5 – distinctive human strengths at work

Will human qualities have any future role in work? Above, we looked at this issue from the point of view of the perfectibility (i.e. ability and applicability) of technology and found the technology both impressive and wanting. In practice, however, the argument is all too often cast in the frame that human qualities are all replaceable by machines, eventually. But is this so?

To assess the perfectibility of current and future automation tools, Manyika et al. (2017) developed a highly useful (though not exhaustive) framework of 18 human capabilities needed at work, and likely to be needed in the future. These divide into sensory perception, cognitive capabilities, natural language processing, social and emotional capabilities and physical capabilities. They found that automation could perform 7 capabilities at medium to high performance, but their modelling suggests that automation tools are nowhere near able to perform the other 11 capabilities (e.g. creativity, socio-emotional capabilities) to an above human level, and that it would be anything between 15 and 50 years before many tools could. Furthermore, humans tend to use a number of capabilities in specific workplace contexts, and machines are not, and will not be good any time soon, at combining capabilities, let alone being integrated to deal with complex real-life problems (Aleksander, 2017; Davenport and Kirby, 2016a, 2016b).

While multiple studies give examples where human capability is being, or will be eroded by automation, certain human capabilities remain vital at work. Adding to Manyika et al. (2017), and consistent with their schema, consider, for example, leadership, empathy, creativity, sense-making, intuition, judgement, tacit knowing, influencing, insight, imagination, humour, social interaction, peer judgement, motivation, teaming, taste, worry/anxiety/concern, happiness, consciousness and 'knowingness', defined by Aleksander (2001) as 'a happy resonance between imagination and perception'.[25] This list is indicative rather than exhaustive and is derived from our own casework supported by Colvin (2015), Davenport and Kirby (2016) and Madsbjerg (2017). These human capabilities are not easy to replicate in specific contexts, and humans also have a facility to combine any or all of these in ways that machines are unlikely to master.

'Polanyi's paradox' also raises important qualifications about the codifiability and automatability of human skill, experience and tacit knowing (Polanyi, 2009; Walsh, 2017). Polanyi suggested that 'we can know more than we can tell' – we might add 'and more than we can automate'.[26] Autor (2014) argues that the 'Polanyi paradox' could be reduced by simplifying the environment (for example, structuring systems and highways to make driverless vehicles more tenable), or improving machine learning algorithms, but records the limitations of each approach when comparing likely technologies and human capabilities. I think he makes strong points, though predicting how technologies will develop will always be a difficult guessing game.

In our own empirical work, looking at over 450 deployments so far, we are rarely seeing human work being totally eliminated from work processes. The ideal conditions for high automation remain a highly structured environment, closed system, rules-based processes, clean data and relatively simple decision-making (Lacity and Willcocks, 2018; Willcocks et al., 2019). This may be an 'early days' phenomenon, but the work of Gray and Suri (2019) suggest that there are large and intractable automation limitations and challenges, and there will invariably be a 'last mile' where human work is needed to close the gap between what technology and humans can do. Using multiple examples they argue that technological advancement has always depended on expandable, temporary labour pools, and with contemporary automation, humans are the 'ghost workers' in the machine, carrying out tasks like data creation and cleansing, supporting web search, censoring unacceptable social media material, dealing with complex non-routine requests, analysis, security checks and decision-making to name but a few. On their evidence, this automation 'last mile' workforce could already be several million workers and expanding annually.[27]

2020	Skills Gap →	2030
Repetitive	To	Non-Repetitive
Physical	To	Digital
Non-technical	To	Technical (STEM)
Non-cognitive	To	Cognitive
Basic human	To	Distinctive human
Low skills	To	Medium/high skills

Figure 1. The skills demand shift 2020–2030.
Source: author.

While ghost work involves retaining distinctive human capabilities that machines cannot replicate well or cheaply enough, most of these capabilities are relatively low-skilled, in human terms. The bigger picture we are formulating in our research on technology deployment is a radical shift already underway and accelerating over the next 10 years (Lacity and Willcocks, 2018; Willcocks et al., 2019). Taking a 10-year horizon to allow technological impacts to play out, we see in Figure 1 a significant decline, but not elimination, of skills on the left side, not least because these are the easier automation targets. We anticipate emerging supply–demand gap and skills shortages developing at varying rates across sectors. Meanwhile, it is difficult to predict the speed or penetration levels, but we also see evidence for automation technologies also moving into the skills on the right side of Figure 1. The immediate point is that, though regularly underrated and even discounted, distinctive human strengths and capabilities will be still needed at work, but that the *kinds* of skills and combinations will shift. I elaborate on this point further below when discussing skills shortages.

On the positive side, in practice, automation may well free up humans to bring their distinctive qualities much more into play, with positive impacts on productivity. There is evidence for machines augmenting rather than straightforwardly displacing human work, for redesign of new forms of processes and human–machine interaction in the workplace, and the development of, indeed the necessity for, what Broussard (2018) calls 'human-in-the-loop' systems.[28] In our own studies of automation, we have found multiple cases where this was already happening – healthcare, insurance, utilities, banking, manufacturing, service providers and legal services are just some examples (Lacity and Willcocks, 2018; Willcocks and Lacity, 2016).

In sum, too little consideration is given to distinctive human qualities that are not easily codifiable or replaceable, especially in combination, and are likely to remain vital at work. Perhaps the direction of travel should be not for replicating human strengths but for automation to be focused on what humans cannot do, or do not want to do.

Qualifier 6 – ageing populations, demographics and automation

Many recent studies reassess the role of automation in the light of changing demographics across many countries (Dobbs et al., 2015; Forrester Research, 2017; Manyika et al., 2017; Price Waterhouse Coopers, 2017). Having said that, several major reports into IT, AI, automation and the US economy/workforce choose to ignore altogether the issue of ageing populations (for example, Executive Office of the President of the United States of America, 2016a, 2016b; National Academies of Science, Engineering and Medicine, 2017). Is this wise? Ageing populations in the G20 (countries producing between them some 80% of the world's gross domestic product (GDP)) may well lead to significant global shortfalls in labour and skills over the next 30 years. Against the dominant narrative, further automation may be one way of coping with such shortfalls.

Some details around this proposition. Declining birth rates and ageing populations across the G20 may well see workforce growth decline to 0.3% a year, leaving a workforce too small to maintain current economic growth, let alone meet espoused aspirational targets. Manyika et al. (2017) estimated that the G20 gap in economic output needs to be filled by the productivity equivalent of 130 million full-time equivalents (FTEs) to maintain current GDP per capita for the following 35 years. However, to meet projected targets, this figure rises to 6.7 billion FTEs by 2065.

The Manyika et al. study projects 11 ageing developed and emerging economies having labour pool shortfalls of between 2% (e.g. China and South Korea) and 9% (Germany) by 2030. Some 14 of the G20 economies will have shortfalls of between 2% (e.g. Turkey) and 16% (e.g. Canada) by 2065. MGI (2017) suggests that the Japanese workforce will shrink by 4 million between 2016 and 2030. By 2026, without productivity improvements, China may well be short of some 600 million FTEs to meet its projected economic growth targets. The United States has already faced a shortfall of about 15 million workers by 2020 just to maintain its current GDP per capita figure (Lacity and Willcocks, 2018). Clearly, there are strong demographic pressures inhibiting economic growth in countries with high shares of ageing populations such as Germany, Japan and South Korea. These could benefit quite quickly from any productivity boost automation could give, while other countries with shrinking populations – the United States, United Kingdom, Australia, Canada, France, Italy – will need significant productivity gains by 2030 to offset labour shortfalls.

Not all countries will see declining work populations. India's labour force is expected to grow by 138 million, Mexico by 15 million and the United States by 15 million people by 2030 (Manyika et al., 2017). The demographics from birth rate and ageing population changes will vary by country. However, the inclusion of all such demographic changes is important, as a corrective to the studies of job loss that either downplay these factors, for example, Ford (2015) and World Economic Forum (2016, 2018a, 2018b), or choose not to look at demographic changes at all, for example, Frey and Osborne (2013, 2017) and Bowles (2014). To put it clearly, automation may take jobs and carry out work that could not be fulfilled by humans anyway, as work increases (see below) and skills demand rises, in the face of shrinking workforces.

Qualifier 7 – automation, skills and productivity shortfalls

Are there skills and productivity shortfalls that inhibit organizations and countries from reaching their economic targets? Most recent studies recognize skills shortages and mismatches now and into the future, with increasing automation. At a macro-level, across the G20 countries, by 2020, there is likely to be a surplus of 95 million low-skilled workers.[29] But there is also likely to be a shortage of some 45 million medium-skilled and 40 million high-skilled workers (Dobbs et al., 2015). Skills security is eroding across sectors and geographies. Clearly, major issues are reskilling, continuous education and redeployment of labour forces, with the automation effects mainly (certainly over the next 12 years) in the low-skill areas, concerning repetitive physical activities, data collection and data processing, and on the other more automatable capabilities (see above).

There is an irony here in that, while many studies are predicting large job losses as a result of automation, we are also seeing skills shortages reported across many sectors of the G20 countries. These shortages are not necessarily just in areas relating to designing, developing, supporting or working with emerging digital, robotic and automation technologies. Demographic changes, plus skills mismatches and shortages, feed into productivity issues at macro and organizational levels. Therefore, it is increasingly likely that despite the lack of attention given to the issue by most studies, major economies over the next 20 years are going to experience large productivity shortfalls even to maintain their present economic growth rates, let alone achieve their espoused growth targets. Automation and its productivity contribution may turn out to be a coping, rather than a massively displacing phenomenon.[30]

Thus Manyika et al. (2017) estimated that 'by 2065 the productivity enabled by automation could potentially increase economic growth by 0.8 percent to 1.4 percent annually, the equivalent of 1.1 billion to 2.3 billion FTEs'. Different countries will need different levels of productivity boost, but the McKinsey modelling suggests that, assuming the earliest adoption scenario, 15 out of the 20 countries – 8 ageing developed economies, 3 ageing emerging economies, together with Nigeria, South Africa, Saudi

Arabia and Turkey – would close the gap between growth targets and actual economic output by 2030. But on the late adoption scenario, nearly all will be in economic deficit by 2030.[31]

There are historical precedents for such productivity boosts as a result of technological development. Looking at robots at work in IT and manufacturing, Graetz and Michaels (2015) estimated that these accounted for annual productivity increases of 0.4% in manufacturing and 0.6% in IT between 1993 and 2007. Crafts (2004) estimated that the steam engine led to annual productivity growth of 0.3% per annum between 1850 and 1910. As the McKinsey researchers suggest, there are also precedents for large-scale structural shifts of the sort that automation could bring about if fully adopted, for example, the shift from agriculture in the US from 40% to 2% total employment from 1900 to 2000, and in US manufacturing from 25% to 10% between 1950 and 2010.

One important point emerging from the studies is that, with automation, it is increasingly looking as though, if there is to be a Robo-Apocalypse, it may well be due to an incapacity to deal not with job loss, but with massive skills disruption. As one example, the World Economic Forum (2018a) reports 313 companies saying they would need to reskill 54% of their workforces by 2022, with training for each worker taking between 6 months and 1 year. A mix of studies suggest that by 2030, up to 14% of workers globally will need to change occupations, and 9% of jobs will be new, not existing today, and will require new skill combinations (MGI, 2018a, 2018b, 2018c; Willcocks et al., 2019; World Economic Forum, 2018a, 2018b). As discussed above, jobs with low technical, cognitive, digital skills involving repetitive activity may decline from 43% to 32% of jobs in the global economy, while workers engaged in non-repetitive tasks with medium to high technical, digital and cognitive skills could move from 42% to 53% in the same period. But the demand for social and emotional skills (as described above) will likely grow as fast as the demand for more advanced technical skills. Meanwhile, automation will spur the demand for higher cognitive skills (for example, critical thinking, complex information processing, creativity) as it also reduces the requirement for physical and manual skills, though these may still remain the single biggest category of workforce skills in many countries (Asian Development Bank, 2018; Lacity and Willcocks, 2018; MGI, 2018a, 2018b, 2018c; Price Waterhouse Coopers, 2018; World Economic Forum, 2018a, 2018b).

In sum, many studies have underrated the impact of skills and productivity shortfalls across multiple sectors and economies over the medium and long term to 2065. But automation will undoubtedly add considerable disruption to the existing skills shortages and require new skills profiles. Meanwhile, on automation and its productivity contributions, these may create considerable transitional disruption, depending on the speed of deployment, but may well be more of a coping, than a massively displacing phenomenon.

Qualifier 8 – exponential increases in work to be done

Will the amount of work to be done remain stable? Most studies of automation and the future of work tend to have a black hole in their analysis when it comes to not allowing for several major work developments that have massive implications for the future amount of work to be done. As background, work intensification would seem to have been increasing for over a decade, but especially since the financial crisis of 2008. Organizations have sought to increase productivity and the amount of work done by ‘sweating the assets’ and attempting to do more with less using the same labour base and partly through applying digital technologies. This phenomenon is very under-researched – people seem so used to work increase and work intensification, it is as though it is part of the everyday work climate and not worth remarking upon. However, some studies are indicative.

Thus, Willcocks et al. (2009) record the ‘sweat the assets’ strategy being adopted in many organizations they researched following the financial crisis. Felstead et al. (2013) found that the percentage of UK jobs needing hard work moved from 31.5% in 1992 to 45.3% in 2012. Since 2006, both the speed of work has quickened and the pressures of working to tight deadlines have also risen to record highs. Korunka and Kubicek (2017) collect a range of research papers recording work intensification over the past 10 years across several economies.

In our own research we very frequently found that, apart from the many other benefits, a major reason for automation was a range of stakeholders experiencing a rising tide of work to be done (Lacity and Willcocks, 2018; Lacity et al., 2021). The limits to working smarter and of high-performance practices were being tested and the practices often found wanting.[32] But where is this dramatic increase in the amount of work coming from? Willcocks (2019) identified, through a close reading of the automation and future of work studies to date, that almost all routinely leave out three factors that are already and will be increasing sources of considerable work growth over the next 12 years.[33]

The first is the exponential data explosion. ServiceNow (2017) found, for example, that nearly 80% of respondents reported that data from mobile devices and the Internet of Things were accelerating the pace of work. Some estimates suggest that 90% of the world’s digital data that we try to process was created in the past 2 years, and that the amount of digital data grows by 50% a year. Ganz et al. (2017) estimated that by 2025 there will be 10 times the data generated in 2016. Even if these are only ball park figures, they still raise the fundamental question of how we are going to collect, store, process, analyse and use data arriving in such colossal volumes. It implies a massive explosion of work, especially as data seem to create more data. Maybe we really do need more automation just to cope.

In the automation and future of work studies, the other largely unheralded source of work growth is the cross-sectoral explosion of audit, regulation and bureaucracy, amplified by the data explosion and the application of modern information and communication technologies. We have been creating, we would argue, a veritable witches brew of data, technology and bureaucracy. Graeber (2015, 2018) is one of the few to pinpoint the importance of this development for the future of both work and the capitalist system itself. But even he probably understates the degree to which audit and regulation inevitably accompany high levels of distrust, the likelihood of market failure and increased demands for transparency. Such work may not be seen as particularly productive, but it is dramatically increasing across government agencies, business sectors and economies almost everywhere.

A third source of more work is technology's double-edged capacity to provide solutions that also create additional problems.[34] If you create more data, that then raises the problem of how to process, store, analyse and then use it. What about unanticipated work making consequences? For example, the Internet has created cybersecurity issues. The cost of cyberattacks was estimated at US$445 billion in 2013 and continued to rise dramatically to beyond US$600 billion into 2018. This has led to further technology solutions, of course – with the cybersecurity market being US$75 billion in 2015 and also growing much faster since then to reach potentially US$170 billion by 2020.[35] As another example, concerns about fake news through social media had, by 2019, led to Facebook employing fact checkers in 20 countries. Meanwhile, in China social media companies Sina Weibo, Baidu and Tencent have vied with one another to create more censors, while Toutaio, the world's most successful news app., had some 6000 news moderators by 2017.

There is also increasing evidence for the addictive properties of mobile devices, games, the Internet, email and related technologies and applications (see, for example, Aiken, 2016; Alter, 2017). Much has been made of the productivity enhancing potential of these and AI technologies. But such technologies are often deliberately designed to support multi-tasking and constant interruption at considerable cost to real productivity at work. The emerging evidence is that task switching, being constantly interrupted and multi-tasking result in substantial performance costs. For peak performance, the goal should be sustained, focused and require singular attention. But the modern worker is all too easily distracted from task performance by irrelevant information and suffers interruption by attempting to pursue simultaneous multiple goals, aided and abetted by technologies such as email, social media, the Internet and mobile devices (Aiken, 2016; Gazzaley and Rosen, 2016). These distractions and interruptions can come from outside or be self-generated. Modern technologies also allow a worker to easily elide work and non-work, while ostensibly at work.

Some indicative examples are as follows. A 2015 CareerBuilder survey found the smartphone, Internet, social media and email among the five most cited workplace disrupters and productivity killers.[36] A 2018 Udemy survey found a third of Generation Z employees admitting to using their smartphones for personal activities for up to 2 h in the work day.[37] Alter (2017) cites studies showing that 70% of office emails are read within 6 s of arriving. This is hugely disruptive; on one estimate it can take up to 25 min to become re-immersed in an interrupted task. Gazzaley and Rosen (2016)[38] found that multi-tasking and task switching incur notable performance costs in disengaging from a task, focusing on the new task, then disengaging and re-entering the original work. A pre-smartphone study they cite found that when office workers are interrupted as often as 11 times an hour, it cost the United States US$558 billion a year in lost productivity. Wajcman and Rose (2011)[39] found workers spending only half their day on actual 'work episodes' with two-thirds of interruptions self-generated and most involving a mediated communication through a technological device. Meanwhile most workers have access to email and other communications networks, and about 45% of the world's population owns a mobile phone (Gazzaley and Rosen, 2016).

In these ways more technology is undoubtedly having complex, even contradictory effects, including a significant, if largely unresearched, adverse impact on productivity and on the time required to accomplish work tasks. While more technology is the frequently touted answer to personal, social and business problems, we can find ourselves on an endless treadmill of technological solutions and the new problems they also generate.

In sum, the dramatic increase in the amount of work to be done is one of the least weighed factors in the automation and future of work debate. In our view, it may well be one of the more impactful. Consider how many organizations are self-reportedly at breaking point despite work intensification, working smarter and the application of digital technologies to date. Then reflect on how the exponential data explosion, the rise in audit, regulation and bureaucracy and the complex, unanticipated impacts of new technologies are already interacting, and increasing the amount of work to be done, and the time it takes to get around to doing productive work. I would propose a new Willcocks Law to capture some of what is happening, namely 'work expands to fill the digital capacity available'. Far from the headlines, a huge if under-analysed work creation scheme may well be underway, to which automation will only be a part solution.

Conclusion: likely, cancelled, or postponed?

This article provides major qualifiers to the argument that robotic process and CA will create massive net job loss in the next phase of what the World Economic Forum (2018), among others, has called the Fourth Industrial Revolution. Automation and work, like technology itself, is a story told by interested parties. Furthermore, in studying the future, there are no guarantees on predictive power. Like machine learning algorithms, much depends on assumptions, factors considered and how they are weighted, range and quality of data utilized, how probabilities are calculated and the interpretation of outcomes. Despite these limitations, we have seen a dominant, dualistic, hype-fear discourse arising, underpinned by a common belief in the rapid, application of AI with massive impacts, for better or worse, depending on the levels of optimism, pessimism or realism held by the narrator. We deconstruct these several narratives and offer a more complex, nuanced analysis of the future than has been emerging from the headlines and many earlier studies of automation and the future of work.

The major, recent studies and our own work suggest that the later the study, the lower the job loss estimates. When job creation is added in, several reports even suggest that the net job loss over the next 12 years, at least, is going to be negligible. A number of assumptions imbedded in the debate are questioned: in particular, that the number of people at work stays stable or goes up, that automation creates few jobs short or long term, that humans are machines that can be replicated, that it is economically, politically and socially feasible to build these and that the amount of work to be done remains stable. My eight qualifiers suggest instead that the focus on jobs, rather than tasks and activities leads to serious misunderstanding of the likely effects of automation; that historically and into the future, particularly over a 12-year period, advanced technologies are likely to create a considerable number of new jobs, as well as restructure most existing ones. Rooted in ignoring history, contexts and process, faith in the perfectibility of AI technologies, and the speed of their deployment, is belied by what detailed studies are already telling us, and also by what has happened in previous technological rounds. Macro-factors – ageing populations, changing demographics, productivity and skills shortfalls – will act dynamically, pulling in diverse ways both to promote, and in some ways hold back automation. Meanwhile the article identifies the dramatic increase in the amount of work to be done as the seriously neglected factor across all the studies so far.

Robo-Apocalypse from net job loss emerges as unlikely. The much bigger storyline is of skills disruption and change from automation over the next 12 and possibly 20 years. Globally, hundreds of millions of workers will need to change occupations, and/or need new mixes of skills, including new skills, to operate in future workplaces. Whether this is a likely, cancelled or postponed Robo-Apocalypse will depend on choices – on training, financial support, education, speed of automation, what the tools are designed for, for example. Moreover, these choices will be made by governments, non-government agencies, corporates and individuals in the face of multiple factors and dynamic business, social, political and economic contexts. The reports suggest also that AI deployment and impacts will also vary considerably across countries, sectors, individual organizations and occupations. At country level, the impact on workforces will depend not least on the mix of economic sectors and occupations, demographics, wage levels and demand growth. MGI (2018b) also suggests that automation readiness and early adoption may lead to front-runner countries and companies getting stronger, and irreversibly ahead, over the next 12 years. This may lead to a form of more or less adulterated workforce Robo-Apocalypse for the many ‘followers’ and ‘laggard’ countries and corporates, but not for the few.

All this has important policy, work design and social responsibility implications that are not addressed in this article. My primary objective is to provide a more convincing base from which such discussions could be better pursued. However, it is clear that the dramatic skills shifts I anticipate in Figure 1 need to be addressed at individual, corporate, educational institution and governmental levels. Individuals need to adopt a continuous learning ethos and think through the skills that are going to be in demand at various points in their work careers. Corporates cannot be in denial about likely skills shortages and about anticipating training requirements. Educational institutions need to update much more quickly than historically both what they teach and how they teach. There is evidence that a lot of subsequent skills disadvantage occurs due to inequities in primary education. This needs to be addressed. Governments need to intervene to shape and structure educational and commercial possibilities, but also to ensure that automation proceeds in socially responsible ways.

Beyond skills, there are many issues this article has only touched on, including the likely radical changes to the way work is organized and accomplished, the impact of the rise of technology and born digital organizations with very different employment patterns, changing notions of the value and meaning of work in society and how broader trends such as economic power shifts and urbanization in different parts of the world will affect the future of work. I certainly see these as very important issues, and hope the article has given a better grounding to pursue the debate and challenges further.

There are two twists in the tale. First, it may well be that robotics and the automation of knowledge of work is not actually the big story at all. On one reading ‘robots’ and ‘automation’ have, going back to ancient times, always been a psychological repository for some of our deepest anxieties, about future uncertainties and loss of control, including over our own creations. Such concerns have, historically, resurrected themselves in periods of social disruption, global flux and slow economic growth such as the present one.

The second, bigger point is that robotics and automation are only part of much bigger SMAC/BRAIDA technological developments, that is, social media, mobile, analytics cloud, blockchain, robotics, automation of knowledge work, Internet of things, digital fabrication and augmented reality. We see these 10 technologies, in combination, likely to have growing, then massive impacts on work, organizations and society (Lacity and Willcocks, 2018). If so, then the automation hype-fear storyline may well be largely filling in for the underlying anxieties about advanced communications technologies in general, and a Robo-Apocalypse is neither likely, cancelled or postponed, but a misdirected narrative framing.

Declaration of conflicting interests

The author declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The author received no financial support for the research, authorship and/or publication of this article.

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Notes

1. Our research database draws upon detailed investigation into 85 published robotic process automation (RPA) client adoption case studies throughout 2015–2019, with detailed research into a further 234 cases. We also published 12 cognitive automation cases and researched 25 cases. During 2019, we assembled a new database of 98 automation deployment and innovation case studies from Europe, the United States, Canada and Australia. In all, at the time of writing, we draw upon more than 459 case histories, running to August 2019, but also 6 surveys of automation practice between 2015 and 2019. The conduct of the research is described in Lacity et al. (2021).
2. Some additional figures. The biggest market is for global industrial robotics technology, which is expected to reach US$71.72 billion by 2023 and growing at a compound annual growth rate (CAGR) of 9.60% during the forecast period (Markets and Markets, 2018). Within this, the global service robotics market was valued at US$10.36 billion in 2017 and is expected to reach a value of US$28.65 billion by 2023, at a CAGR of 17.9% (Mordor Intelligence, 2019).
3. A frequently cited example is Japan to solve elderly care problems and labour shortages – a country also sporting the fully robotized Henn na Hotel.
4. See Freeman (2015), Futurist Forum (2015) and *The Guardian* (2017).
5. But one example is Nowak (2015).
6. We are not suggesting that these authors subscribe to the polarized media version of Robo-Apocalypse. These are distinctive studies but, in their tone, and conclusions lean towards more pessimistic scenarios.
7. As one example, the 24th March 2017 *Guardian* headline 'Robots could displace ten million British workers' is followed by a sub-title 'Almost a third of UK jobs at risk, says report by PwC'. But reading what the study actually says in the body of the article reveals that the PwC position is much more qualified, suggesting, for example, that automation would boost productivity and create job opportunities. Also that replacement would depend on economic feasibility, and there were a series of legal, regulatory, organizational, legacy hurdles that would slow down the shift towards automation and artificial intelligence (AI). Reading the actual study suggests that the authors are much more circumspect than even this suggests. Subsequently, indeed, in their UK Economic Outlook of July 2018, PwC suggest that these inhibiting factors reduce their estimate of job loss for the 2017–2037 period to 20% (not almost 33%) and that job creation will be around 20%, thus suggesting for the United Kingdom at least virtually no net job loss. I searched for major headlines reporting this but could not find any.
8. For example, the training set labelled waiter/waitress as not susceptible to automation, while the machine gave a 95% probability. Zoologist is given a nil probability of automation in the training set, but the automated classifier gives a 30% probability.
9. Frey (2019) does not address these criticisms, but does acknowledge that the original paper was widely misunderstood and had limited objectives, and actually made limited claims.
10. In a follow-up study the researchers found 25% of UK occupations (21% US) having a creativity component too high to be automated (Bakhshi et al., 2015)
11. The report updates, and includes details of, an earlier September 2016 report.
12. This work is interestingly critiqued by Frey and Osborne (2018).
13. Reviewing these methodologies makes one realize how small changes in assumptions or adjustments in formulae can make very big differences in the figures produced.
14. MGI (2018a, 2018b, 2018c) takes a broad, pragmatic view of AI technologies in play as computer vision, natural language, virtual assistants, RPA and advanced machine learning – basically our categories of robotic process and cognitive automation.
15. In fact the report estimates a net loss of 1% in total full-time equivalents (FTEs) by 2030 as a result of automation. If AI displaces 18% of labour, then AI also leads to labour gains from augmentation (5%), innovation and redeployment (10%), reinvestment (1%) and increased global flows (1%).
16. It is difficult to calculate what the impact might be but a McKinsey and Company (2011) study of the impact of the Internet in France between 1996 and 2011 found that for every job lost 2.4 were gained. Automated teller machines (ATMs) introduced in the United States in the 1970s to replace bank tellers actually increased their job numbers by the 1990s. Lower cost branches were opened needing more tellers, and tellers moved to customer interaction tasks beyond ATM capabilities (Lacity and Willcocks, 2018).

17. They cite a study by Graetz and Michaels (2015), of industrial robots in 17 countries having no negative impact on the total working hours at the sector level. They also cite the Gregory et al. (2016) finding that computerization generated 11.6 million net jobs across 27 European countries between 1999 and 2010.
18. Manyika et al. (2017) also raise this point. They point to five factors affecting the pace and extent of automation: technical feasibility, cost of developing and deploying, labour market dynamics – will labour continue to be cheaper or comparable; economic benefits – does the technology deliver notably superior outcomes, and regulatory and social acceptance.
19. Market revenues, as indicated earlier, are low, but in terms of investment in research and development, the area saw at least US$45 billion invested during 2016–2017, with much more since.
20. To support this, McKinsey Global Institute (MGI; 2018a) looked at some 400 AI use cases and provided a detailed list of major real-world challenges to delivering step change performance. These included data labelling, obtaining massive comprehensive data sets, explaining results, generalizing learning, security concerns, the state of legacy data, states of work process and work flow, and skills shortages.
21. A 2017 report by the International Bar Association warned that legal frameworks regulating employment and safety were becoming rapidly outdated. It suggested that 'AI' will test employment law safety and insurance, and that human quotas could be needed for certain jobs (Bowcott, 2017). From 2015 to 2019 we were seeing mounting regulation, and rising concerns on privacy, safety, security (Baldwin, 2019; Willcocks and Lacity, 2016), dangers of excessive control by big providers (Zuboff, 2015, 2019) and exacerbation of social divisions through differential access to work, education and the benefits flowing from automation (MGI, 2019; World Economic Forum, 2018a).
22. Fast adoption included airbags, TVs and online airline booking; relatively slow adoption included dishwashers, pacemakers, cell phones and personal computers.
23. Healthcare, transportation, accommodation and food services, and administration and financial services feature as early adopting sectors, along with jobs focusing on repetitive physical activities, data collection and processing. On the other hand, jobs requiring higher education qualifications and non-automatable skills will attract pay premiums. Japan, the United States, France, Germany, Italy, Spain and the United Kingdom will see faster adoption than emerging economies, while cost and relatively lower wage levels in India and China will likely slow adoption (MGI, 2018a, 2018b; Price Waterhouse Coopers, 2017, 2018; Willcocks and Lacity, 2016; World Economic Forum, 2018a).
24. For example, a 2018 McKinsey survey found nearly half of companies had embedded at least one, and 21% more than one AI capability in their business processes, 30% were piloting and only 3% of large firms had integrated AI across their full enterprise workflows (MGI, 2018c). Even these figures must come with a caveat, because of how broadly AI was defined in the study.
25. As one of the major AI researchers, Aleksander (2001) in *How to Build a Mind* still points to the fundamental mindlessness and 'unknowingness' of computers and AI.
26. Polanyi (2009) suggested that nearly all tasks we perform rely on tacit, intuitive knowledge, which is difficult to codify and automate. In practice, this acts as a constraint on what is automatable, and is not fundamentally a paradox. The Polanyi paradox was named in Autor (2014).
27. Gray and Suri (2019) suggest a rising new world of work in which software manages people doing jobs that computers and automation technologies cannot do. While the boundary will continually move, there will always be the 'paradox of automation's last mile', that is, to accomplish tasks and processes not easily automatable, human strength – such as creativity, insight, social and emotional capabilities, understanding context and linguistic nuances – will be needed. All this suggests that managers will have new 'people' areas to focus on, and will need to think through, very carefully, the work redesign and skills implications when designing and deploying RPA and more advanced, complementary technologies.
28. See Colvin (2015), Davenport and Kirby (2016a, 2016b) and MGI (2018a).
29. A total of 58 million in India, China and young developing economies.
30. Looking across the 20 biggest global economies, the projections of Manyika et al. (2017) point inexorably in this direction. On this analysis, workforce size will be too small to maintain even current per capita gross domestic product (GDP) growth over the next 50 years. Over the past 50 years productivity growth has been 1.8% per annum. If this rate is maintained, then the rate of GDP growth over 2015–2065 will fall by some 40%. To achieve required aggregate GDP per capita growth of 2.9%, acceleration is needed to some 2.8% compound annual productivity growth between 2015 and 2065.
31. Interestingly, on either early or late adoption scenarios, South Korea, China and India as well as Indonesia and Mexico will, despite automation, have economic output deficits by 2030.
32. In the context of automation, our findings are supported by a 2017 multi-country survey of some 1874 corporate respondents (ServiceNow, 2017). Of these executives, 70% said that the pace of work grew by at least 10% in 2016, and nearly half said it grew by 20% or more. Only 15% said that the pace of work had decreased or stayed the same. It found that by 2018, 46% of companies were going to need greater automation to handle the volume of tasks being generated. By 2020, without more automation, 86% of organizations believed they would reach their breakpoint when dealing with the volume of work would no longer be sustainable.
33. An earlier version of the following argument and section appears in Willcocks (2019).
34. On the 'solutions' side, one reviewer also pointed to 'tech entrepreneurship' – largely unforeseeable new business models creating jobs based on new information technology (IT) in the future. Again the impacts of climate change through pollution may be reaching an irreversible point where we will need to invent new technologies, around which new jobs and even industries will develop. My thanks to the reviewer for these examples. Both see additional work and jobs that did not exist before.
35. Bank of America Merrill Lynch report detailed in Cybersecurity Investing News 9 September 2015. Other figures from composite news sources. As another example,

concerns about fake news through social media have led to Facebook employing fact checkers in 20 countries.

36. Chad Brooks in Business News Daily, 16 April 2015.
37. David Shimkus in HR Technologist.com downloaded 6 April 2018.

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