You'll Think You're Dead, but You Sail Away on a Wave of Automation:

Reviews and Forecasts of Technological Displacement

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Introduction

The advent and improvement of big data analytics, artificial intelligence, and machine learning technology over the last half-century has vehicularized automated technologies. While various forms of automation have existed since 1900, this era of automation is marked by particular opportunity and angst, with forecasts predicting increased global GDPs as well as increased global unemployment.

The opinion among experts regarding the impacts of automation are widely varied, not only in terms of the number of jobs replaced, but also the limits of a machine's scope of work. Furthermore, the opinion between experts and the public also are varied: while experts in fact see human labor forces rising in value as more automated technology is integrated into businesses, the public perceives their own value to be decreasing. Moreover, there is uncertainty among the public as to how time normally spent working could be reallocated to other productive, personal ventures. Not only does a job loss scenario carry a potential, significant absence of daily structure, but it also removes important social and personal benefits that work naturally endows, and for which there are few suggested alternatives.

Business strategies for automation, however, seem more universally more aligned: companies are moving en masse to adopt automated technologies as they seek to sharpen their competitive edge, with 57% of organizations polled in a Mckinsey survey (2018) stating that their organizations are already in the process of at least piloting automated technologies in one or more business units or activities. This strategy is predicted to increase entrepreneurial spending in automated technologies from $12.4 billion USD in 2018 to $232 billion USD in 2024 (KPMG, 2018).

Among the dissent and concurrence of experts, businesses, and civilians is an opportunity for industrial-organizational (I-O) psychologists to shepherd these players through what will surely be a period of intense transition, by conducting research to better understand the challenges and effects of changing job descriptions, team and management structures, workplace human-machine interactions, and unemployment. The hopeful result is that these avenues of research can lead to actionable insights for businesses, workers, civilians, universities, and policymakers so that this transition untaps the utmost in human potential and enlightenment.

A Brief History of Big Data, AI, ML, and Automation

Big Data

Big data isn't just a big dataset; it's the idea that an absolute amount of data is used for statistical analysis, and is a concept which predates the advent of the technology commonly used today to analyze it. The first notable use of big data is reported to have occurred in 1842, when Matthew Fontaine Maury, a naval scientist, and his team sourced, tabulated, and analyzed stacks of logbooks filled with wind, ocean, and weather reports. The outcome of this pursuit were (then) new shipping lanes that drastically cut maritime transport times, many of which are currently still in use. It was an incredible feat for him and his team, one that continues to benefit society today.

More than a century after Maury's time, information became digitized at an ever-accelerating pace, and with that, big data gained new unique features, specifically: volume (the amount of accessible data), variety (the capacity to combine datasets for a wider scope of data), and velocity (the speed at which data is available). Two figures in particular capture the magnitude and rate of growth of digital information: first, in 2020, it is predicted that there will be 44 zettabytes (or one trillion gigabytes) of extant data, or tenfold the amount that existed in 2013 ("The Digital Universe of Opportunities," 2014); and second, 90% of the world's data was generated in the past two years (Marr, 2018). What this means is that a machine today, programmed with the intent of forging new shipping lanes, regresses many more predictors than wind, ocean, and weather indicators; it analyzes the data with many more mathematical models; and it takes much less time than it did Maury's team. In 2017, researchers from MIT tested the power of their automated big data analytics system with a prototype called the Data Science Machine; while it took the human data scientists months to decode their prediction algorithms, the Data Science Machine performed the same task in just few hours with 96% accuracy (Goyal, 2017). Big data can perhaps be seen as the lifeblood of many of the technological advances that followed in the wake of its maturation.

Artificial Intelligence

The term artificial intelligence (AI), was first coined in 1956 in Dartmouth College in the United States (Kaplan & Haenlein, 2018), and is defined as a device that can perceive its environment and undertake steps to maximize success in achieving programmed goals. However, AI had begun to sow its seeds a few years earlier thanks to recent discoveries in neurology: the realization that the brain contained an electrical network of neurons that communicated through pulses birthed the idea of an machine brain. Early analog circuits gave way to primitive neural networks, which in turn cleared a path for the first neural net machine to have synapses with a limited memory space (McCorduck, 2004). Meanwhile, Alan Turing was considering the ability of computers to have thoughts, and was imagining a future in which people could not tell if they were talking to another person or a machine, a concept called the Turing Test. In the two decades that followed the Dartmouth meeting, funding and hope was abound, with scientists predicting that the Turing Test could be passed before 1980 (McCorduck, 2004). By 1975, Intel co-founder Gordon Moore observed that transistors, the fundamental element of electronic devices, in integrated circuits were shrinking so quickly that every two years, twice as many transistors could fit onto a computer chip (Simonite, 2016). Nonetheless, machines still lacked a sufficient amount of computing power to process the immense amount of data it needed for fully functioning AI applications (Buchanan, 2005). Once enough computing power was achieved towards the end of the 20th century, however, AI began to significantly advance the areas of robotics, speech recognition, image recognition, natural language processing, and expert systems. Evidence of this progress is reflected through the growth rate of AI-centered start ups, the number of which today are fourteen times higher than they were in 2000 (Columbus, 2018).

Machine Learning

Machine learning (ML) is achieved through the combined force of computer algorithms and statistical models funneling large data sets, through which computers may achieve an objective without specific programmed instructions, relying instead on patterns and deduction. Like AI, ML was conceived far before it was realistic, and the term was coined in 1959 at IBM (Hurwitz & Kirsch, 2018). The timing of its origin story relates to the fact that ML began as a subset of AI: researchers wanted not only a machine capable of achieving goals, but also one that could learn from large pools of data (Singh, 2018). In a way, it is an analogous child of big data and AI. Early iterations of ML were based on the idea of knowledge as robust relational structures, and were overtime enhanced by pattern recognition and statistical approaches, and more current applications focus on reasoning, problem solving, and language understanding. By 2000, ML was accepted as a field of study independent from AI (Langley, 2011).

Automation

Automation, like big data, AI, and ML, is not a new phenomenon: it is the use of software or hardware that runs autonomously, with little need for oversight beyond maintenance and quality assurance purposes. In the early 20th century, technological advances in machinery most transformed the agricultural sector: more specifically, in 1900, 41% of the US workforce was employed in agriculture; by 2000, that figure shrunk to 2% (Autor, 2014). Manufacturing was later assisted by automated technology, starting in 1913 with the Ford Motor Company, where mechanical production lines replaced factory workers, reducing assembly time from 12 hours to nearly 1.5 hours per car (Autor, 2015). In 1967, the first automated teller machine (ATM) was invented, and by 2014 expanded its fleet to three million units worldwide (RBR, 2015).

But today's automation is different from that of yesteryear's: while in the last century automated technology was mechanical in nature and predominantly affected agricultural and manufacturing sectors, current automated technology begets advances in robotics and AI and, according to a McKinsey report, will predominantly improve data collection, data processing, and machine operating activities that span across a wide array of sectors (Manyika et al, 2017), beyond those of farming and manufacturing. A more extensive use of automated technologies is projected to increase global GDP by more than $1.1 trillion USD in the next ten to fifteen years (Martin, 2017), implying that there are heavy economic incentives for businesses to replace human labor with machine labor. In this regard, there is there is already movement by large corporations: Mcdonalds has begun to replace traditional cashiers with kiosks, and states that by 2020 all U.S. locations will have them in house (Rensi, 2018); Amazon has been increasing its army of warehouse robots by about 15,000 per year, which as of 2016 totaled at 45,000 (Shead, 2017); Uber is in the process of testing self-driving cars, with the objective of replacing all of its human drivers, despite one of them killing a pedestrian in May 2018 (Wakabayashi & Conger, 2018); most recently, in the wake of a 158% increase in annual profit, PepsiCo announced that they are looking to bolster their automated workforce and to that end allocated $2.5 billion USD majoritively for severance pay for an yet unknown, but speculatively significant, portion of PepsiCo's 263,000 current employees (Merchant, 2019). This undertaking by businesses promises impressive cost-benefits: when experts at McKinsey modeled automated scenarios across several industries, they found that the benefits of automation (including higher output, higher quality, improved reliability, among others) were on average between three and ten times the cost of investment (Chui, Manyika, & Miremadi, 2015).

Automation in the Workforce

Technological Displacement

At first blush, the nature of today's automated technology and the enthusiasm of businesses to implement it may seem to have severe consequences for human labor forces. Different agencies have produced wildly varying predictions concerning the replacement of employees by machines, a phenomenon called technological displacement, as shown in Figure 1 below.

Some of these assessments proposed that automation will replace entire occupations, while others say that it will replace specific tasks. Economists Carl Frey and Michael Osborne (2017, p. 261) seem to belong to the former camp, stating that "recent developments in ML and MR [mobile robotics], building upon big data, allow for pattern recognition, and thus enable computer capital to rapidly substitute for labour across a wide range of non-routine tasks. Yet some inhibiting engineering bottlenecks to computerization persist. Beyond these bottlenecks, however, we argue that it is largely already technologically possible to automate almost any task, provided that sufficient amounts of data are gathered for pattern recognition." David Autor, a professor of economics at MIT, subscribes to the latter ideology, with the caveat that as tasks are replaced by machines, human job descriptions will have to be redefined. Autor suggests that current technology can manage rather 45% of the activities performed in the market, work equating to $2 trillion USD in annual wages in the United States (Autor, 2015). By considering automated technologies as an activity- and

Figure 1: Predicted Jobs Automation will Create and Destroy. Reprinted from 'Every Study We Could Find On What Automation Will Do To Jobs, In One Chart'

Predicted Jobs Automation Will Create and Destroy

When	Where	Jobs Destroyed	Jobs Created	Predictor
2016	worldwide		900,000 to 1,500,000	Metra Martech
2018	US jobs	13,852,530*	3,078,340*	Forrester
2020	worldwide		1,000,000-2,000,000	Metra Martech
2020	worldwide	1,800,000	2,300,000	Gartner
2020	sampling of 15 countries	7,100,000	2,000,000	World Economic Forum (WEF)
2021	worldwide		1,900,000-3,500,000	The International Federation of Robotics
2021	US jobs	9,108,900*		Forrester
2022	worldwide	1,000,000,000		Thomas Frey
2025	US jobs	24,186,240*	13,604,760*	Forrester
2025	US jobs	3,400,000		ScienceAlert
2027	US jobs	24,700,000	14,900,000	Forrester
2030	worldwide	2,000,000,000		Thomas Frey
2030	worldwide	400,000,000-800,000,000	555,000,000-890,000,000	McKinsey
2030	US jobs	58,164,320*		PWC
2035	US jobs	80,000,000		Bank of England
2035	UK jobs	15,000,000		Bank of England
No Date	US jobs	13,594,320*		OECD
No Date	UK jobs	13,700,000		IPPR

not a occupational-replacement, the estimates of technological displacement in the United States drop to 9% from 38% (Arntz, Gregory, & Zierahn, 2017).

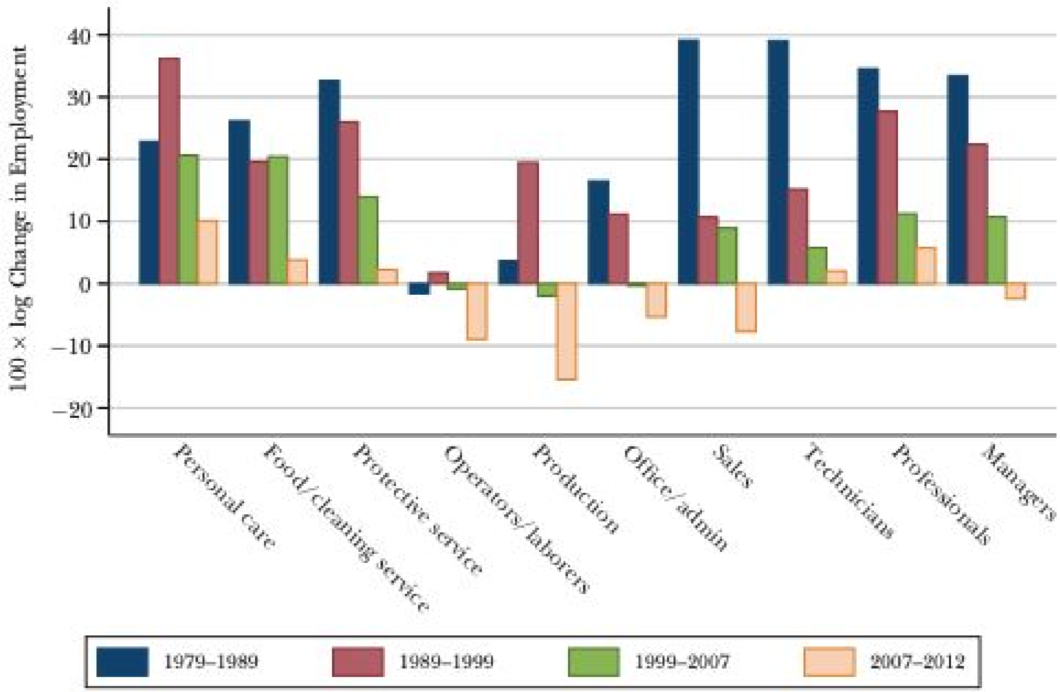
Autor's conclusion stems from the fact that despite the difference between skill levels, many jobs encompass both routine and non-routine tasks. It is the routine tasks that automation, past and present, is geared to address. However, non-routine tasks are more difficult to automate, because these tasks involve judgment, goal flexibility, common sense, situational adaptability, visual and linguistic recognition, and interpersonal relating (Autor, 2015). One of these non-routine skillsets falls under "abstract" tasks, which is addressed through problem-solving, creativity, intuition, and persuasion, primarily attracting those with higher educational levels, who are generally housed in technical and managerial domains. The other non-routine skillsets are called "manual" tasks, addressed through physical adeptness and language skills, primarily attracting those with lower educational levels, who are generally housed in food service, custodial, homecare, and security domains (Autor, Levy, & Murnane, 2003). And even though earlier predictions suggested that these low-skilled jobs comprised of manual tasks would be the first to be technologically displaced, the fact that these jobs encompass a degree of non-routine tasks in addition to the fact that they receive relatively lower wages may diminish business incentive to replace them with expensive technology (Doubek, 2017).

Job Polarization

The assumption that these high- and low-skill jobs cannot and will not be fully automated in turn assumes that there will be a reduced demand for middle-skill, middle-education workers. This concept of a shrinking middle-level working class is called "job polarization" (Goos & Manning, 2007), and has been reflected through technological advances in the last half-century. Figure 2 below shows the employment growth across different sectors over four decades, with the left three categories on the horizontal axis representing low-skilled work, the next four categories representing middle-skilled work, and the right three categories representing high-skilled work (Autor & Dorn, 2013). The figures portray a higher employment growth in both high- and low-skill jobs and a lower rate of growth, if not reduction of, employment in middle-skill jobs: notably, between 1979 and 2012, salespeople, office administrators, production workers, and operators went from accounting for 60% of employment to 46% of employment.

Figure 2: Change in Employment by Major Occupational Category, 1979-2012. Reprinted from 'Why Are There Still So Many Jobs? The History and Future of Workplace Automation.'

Change in Employment by Major Occupational Category, 1979–2012
(the y-axis plots 100 times log changes in employment, which is nearly equivalent to percentage points for small changes)

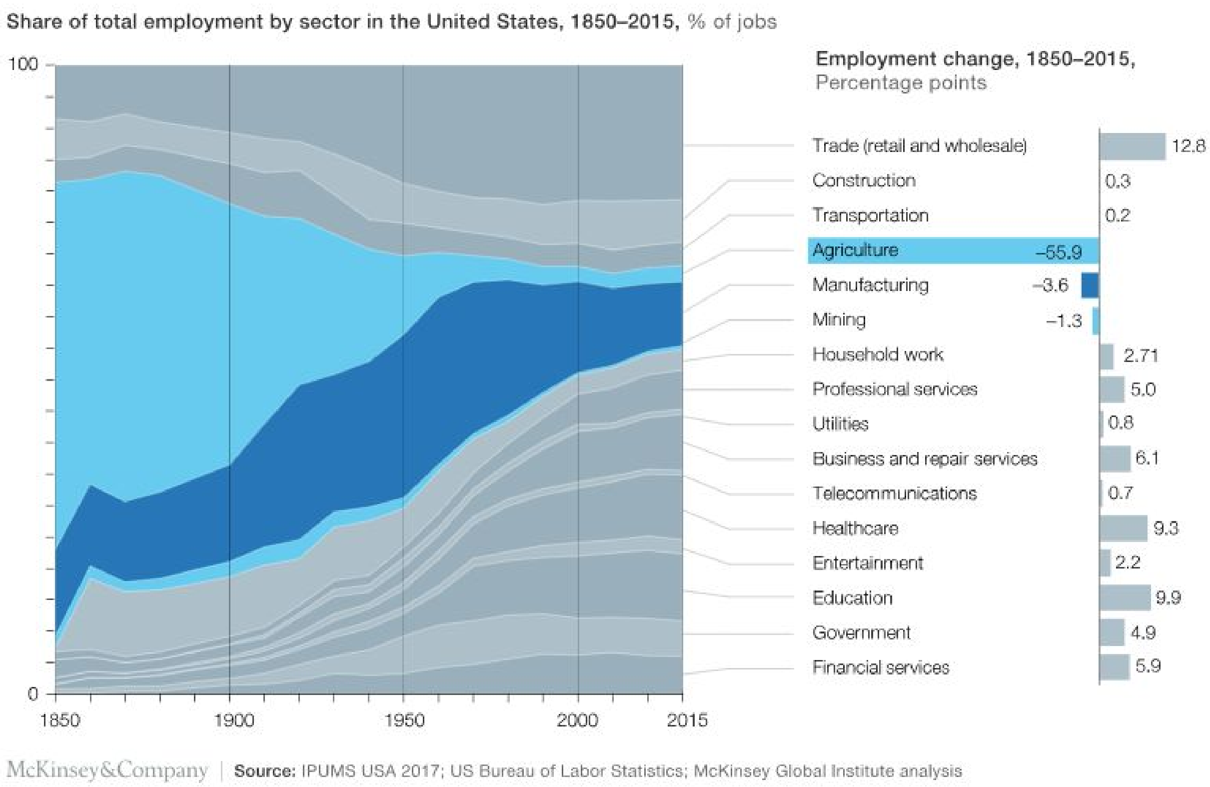


Sources: Author using data from the 1980, 1990, and 2000 Census IPUMS files, American Community Survey combined file 2006–2008, and American Community Survey 2012. The sample includes the working-age (16–64) civilian noninstitutionalized population. Employment is measured as full-time equivalent workers.
Notes: Figure 2 plots percentage point changes in employment (more precisely, the figure plots 100 times log changes in employment, which is close to equivalent to percentage points for small changes) by decade for the years 1979–2012 for ten major occupational groups encompassing all of US nonagricultural employment. Agricultural occupations comprise no more than 2.2 percent of employment in this time interval, so this omission has a negligible effect.

Employment Shifts

An idea is that this middle-skill class of workers will become the "new collar" workers of tomorrow, who comprehend technical skills with a higher educational background, and who implement activities that possess some degree of non-routineness (and therefore cannot be fully automated out). This adaptation is exemplified by the modern nurse practitioner, who, thanks to technological advances, is increasingly able to diagnose illnesses and prescribe medication, which has customarily been performed by physicians (Autor, 2015). This is reasonably supported by history, which has shown that automation is capable of creating new jobs in both highly-affected and lesser-affected sectors. For example, the economic gains resultant of the agricultural industrial revolution caused massive shifts in employment towards other sectors, generating new jobs primarily in trade, health, financial, and education sectors (Bughin, Hazan, Lund, Dahlström, Wiesinger, & Subramaniam, 2018). Figure 3 below exemplifies how employment has shifted between sectors since the first industrial revolution up until 2015. In addition to occupational shifts, it is encouraging that overall there is an average of .56% new job growth every year (Lin, 2011) which, if the trend continues, means that roughly 7% of jobs in 2030 will be jobs that do not exist today (Bughin et al, 2018).

Figure 3: Share of Total Employment by Sector in the United States, 1850-2015, % of Jobs. Reprinted from 'Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation.'



Beyond increased productivity, these employment shifts are also due to the fact that automated technologies, though they can be substitutionary, can also be complementarity to human work efforts, as is demonstrated in the case of the ATM: though the number of ATM installations steadily grew since the 1970s, so did the number of bank tellers (although this could speak more to the growth of the job market during those years, rather than the share of bank tellers in that job market); seemingly, therefore, in the midst of this automation, the demand for bank tellers increased. And although the number of tellers per banking branch fell by more 33% between 1988 and 2004, the demand for urban bank branches grew, and thus the overall number of tellers rose over 40% between the same time period. This helped redefine the roles of bank tellers, who moved away from being merely cash transactors and towards customer relations agents, ensuring the satisfaction of bank members and introducing them to other bank services (Bessen, 2016).

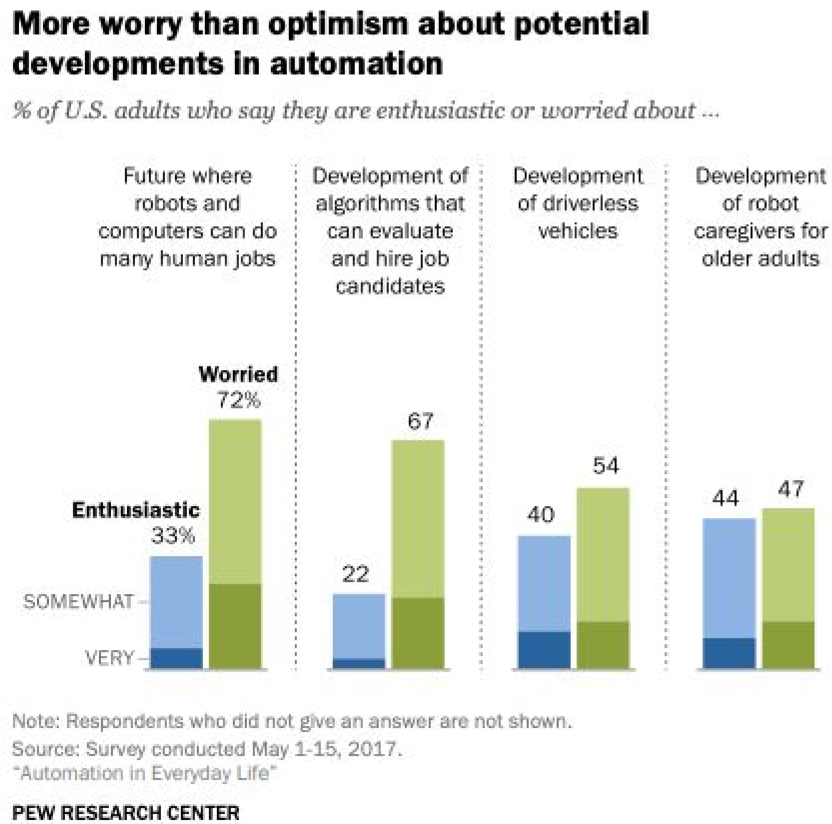
Despite the potential job gains and role changes, automation has been known to bring short-term increases in unemployment as the market adapts to the technological changes. For American workers in today's automated era, 2% report that they have at one point lost a job because of technological displacement, while 5% report a reduction in pay and/or hours due to automation. These results were more likely to be reported by respondents between the ages 18-24, by Latinos, by part-time workers, and by those with low household incomes (Smith & Anderson, 2017).

Automation in the Public Opinion

Public Anticipation

The current amount of actual displacement is not proportional to the fear of displacement among the public. Figure 4 displays the results of a 2017 Pew Research Center survey of over 4,000 American adults, who were asked to think about four scenarios involving automated technologies, specifically: technological displacement, automated personnel selection, driverless vehicles, and robotic caregivers. It was found that anticipation is seeded more by worry than enthusiasm (Smith & Anderson, 2017). This is supported by another piece of research that

Figure 4: More Worry than Optimism about Potential Developments in Automation. Reprinted from 'Automation in Everyday Life.'

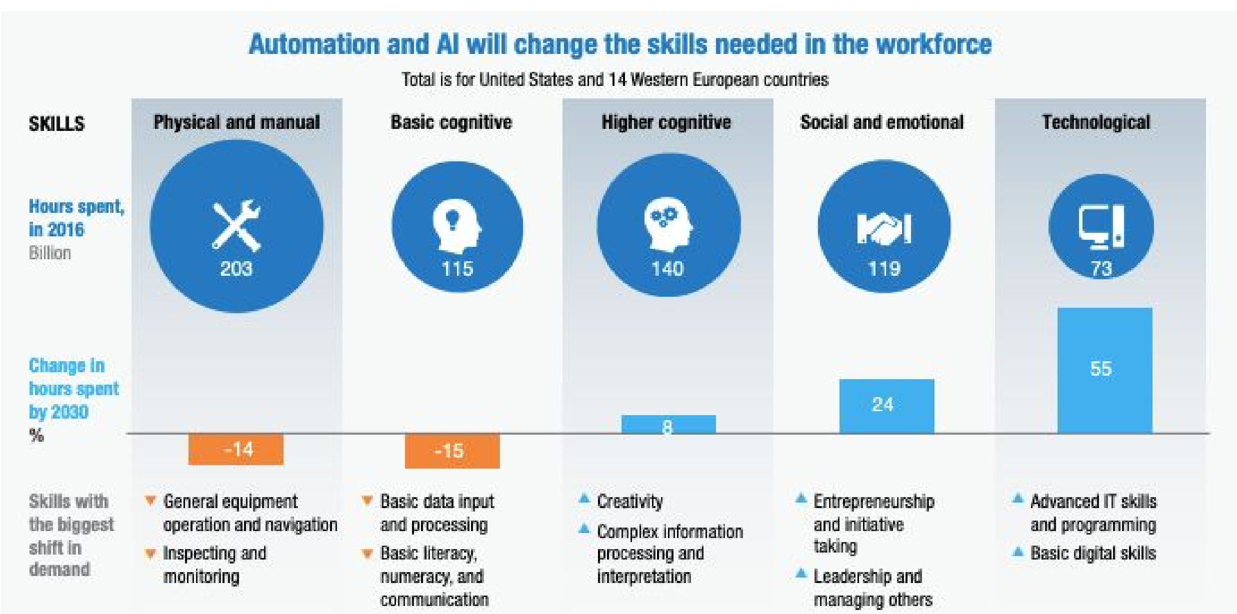


introduced an industrial robotic prototype to subjects in an experiment, to which the majorative response, despite the fact that the prototype was introduced as a cooperative agent, was a fear of being replaced (Weiss, Huber, Minichberger, & Ikeda, 2016).

This study also found that 75% of Americans expect that the economy will not create a significant number of new, higher-paying jobs for humans in automated contexts (Smith & Anderson, 2017), despite what experts say about automation's potential for job creation. This would imply that there is a gap of understanding and communication between experts and the public, and one would look to the media to bridge this divide. Unfortunately, there is little research about the attitude that journalists adopt when reporting on automation, and therefore it is unknown as to whether there is a significant correlation between journalistic tones and the public acceptance of automation. It can be inferred, however, that articles such as one referenced for this paper entitled "PepsiCo Is Relentlessly Automating' Its Workforce and It's Even More Dystopian Than It Sounds," intend to foment anxiety more so than to encourage optimism.

This finding also exposes the discrepancy between what Americans fear will take place, and what CEOs expect to happen as automated technology becomes more prevalent in business environments: 77% of senior-level executive expect no net change in their workforce size across the United States or Europe; in fact, more than 17% expect their domestic and international workforces to increase in size. From this same report, c-suite executives stated expecting a 19% lateral shift of employees into different or new roles, anticipating more cross-functionality between teams, a flatter organizational structure, continuous learning for employees, and a greater use of external contractors to provide timely and specific technical skills, looking to leverage the essential human skills that cannot yet be replicated by computers (Bughin et al, 2018). Relative to this prediction, 62% of American executives stated that they needed to retrain or replace more than 25% of their workforce in the next five years to prepare for increased automation (Cheng, 2018). Retraining efforts are expected to lift low-skilled workers into higher skill classes, freeing up high-skilled workers for more abstract tasks (Autor, 2015). Figure 5 below summarizes the change in skills that businesses are looking for as technology advances.

Figure 5: Automation and AI Will Change the Skills Needed in the Workforce. Reprinted from 'Skill Shift Automation and the Future of the Workforce.'



Industry leaders have already begun setting an example for retraining and continuous learning: in 2016, Google launched a "Learn with Google AI" program to help 18,000 employees worldwide transition from a desktop-first to a mobile-first and then to an AI-first business model; Rio Tinto, while applying autonomous vehicles in its mines, is retraining workers to learn vehicle repair, operation, and maintenance skills (Bughin, 2018); IBM has begun investment in new-collar workers by partnering with vocational schools to reformat academic curricula around future human workforce needs (Leaser, 2018).

Public Initiative for Higher Education

In the face of automation, retraining current employees is a business investment, but preparing future workers is a personal one. Historically, diminishing labor opportunities in sectors that have more quickly automated have caused educational shifts as workers seek to be relevant and employable, as was the case for American farmers in the wake of the agricultural revolution: decreased labor demands sparked a movement for universal high school education, which was indeed led by the farm states (Goldin & Katz, 2008).

Manual task learning requires less investment as these jobs generally require less education; however abstract tasks require a higher education, often in the form of college and graduate degrees. American men, as compared to women, have shown less initiative towards mastering the desired complementary skills for automation in the last 40 years: between 1975 and in 2005, the share of the hours worked by males with less than ten years' experience and who a college education remained stable at 40%; between 1982 and 2005, the number of hours worked by females with less than ten years' experience and who had a college degree rose from 42% to 53%. There was some uptick in both parties between 2005 and 2012, during which the hours worked by men and women with less than ten years' experience who held a college degree was 52% and 62% respectively (Autor, 2014). And even though the trend for young American men and women to go to college has risen in the last decade, the exorbitant costs of higher education in the United States can perhaps explain the relative lethargy of the movement: the average total cost to attend a four-year private college amounts to $104,480 USD as of 2016, which is double the amount of the same education in 1989, which totaled at $52,892 USD when adjusting for inflation. Meanwhile, wages did not increase at the same rate, with an average annual growth of 0.3%, amounting to a increase of median wages from $54,042 USD to $59,039 USD in 1989 and 2016 respectively. This means that, all in all, college tuition rose eight times faster than median incomes (Maldonado, 2018). No matter the reasons, experts and businesses remain unsure that labor demands will be met in the coming years. If this educational trend continues rising as slowly as it has, it may create a vacuum of available of high- and middle-skill workers with the onus on businesses to find workarounds, be it professional development opportunities for their employees or, as per IBM, working with vocational schools to reconceptualize curricula so that it reflects their labor needs.

Automation and IOP

Psychological Studies of Employed and Unemployed Workers

As is on theme, I-O psychologists must too ask themselves how their roles will change in the face of automation?

For one, while there have been plenty of theories about how workers may cope professionally and educationally with automation, there is a limited pool of research investigating how workers may cope psychologically. Some research has suggested that the introduction of technology in the workplace could cause a reduction of a sense of autonomy which consequently can produce stress, devaluation, demotivation, and counterproductive work behaviors (Cascio & Montealegre, 2016). Another study found that increasing demand for employee data relating to time allocation, activities, and results draw ethical concerns about personal data protection policies as well as to how this relates to an employee's feelings of oppression, dissatisfaction, and demotivation (Bonekamp & Sure, 2015). Despite these early findings, there is in general a salient need for more research in the form of longitudinal studies, both quantitative and qualitative, so as to provide a better understanding of the psychological consequences of workplace automation and in turn help optimize complementary human- and machine-led tasks, relationships, and performance (Ghislieri, Molino, & Cortese, 2018).

A job can contribute to an individual's financial security, social status, relationships, objectives, and moreover their personal identity and psychological health (Blustein, 2008). It is therefore of little surprise that Smith and Anderson's 2017 survey participants favor a national service program that would compensate humans to perform jobs even if machines could outperform them (58%), almost as equally as they favor having a guaranteed income (60%). Though the idea of a guaranteed basic income is gaining favor among Americans (and is in fact a scheme that is currently being piloted in Alaska), with 43% of 1,994 people surveyed either in strong or somewhat support ("Morning Consult National Tracking Poll," 2017), arguably a strong inhibitor of successful guaranteed basic income policies is the lack of public understanding and acceptance (Goldhill, 2016), especially among older generations. Among those surveyed in Morning Consult's 2017 poll, those who were over 65 had the lowest approval rating of any age demographic, with only 30% in support.

Moreover, with work accounting for nearly a third of the time spent per day (typically five days per week), 64% of people surveyed worry about how they would occupy themselves in the absence of a job (Smith and Anderson, 2017). This illuminates a certain potential existential crisis with job loss, which also threatens to destabilize an individual's mental health. This is shown through the fact that 18% of unemployed American adults have been treated for depression after being unemployed for 27 weeks or longer (Crabtree, 2014). A potential response by I-O psychologists to this alarming statistic could be an investigation of job alternatives that carry the benefits of work as well as stabilize mental health, and moreover advocate for policies which better support the wellbeing of displaced workers. This would be especially important if societal acceptance of automation remains low, which in turn may heighten the level of social value placed on gainful employment. And while, as aforementioned, experts surmise that there are opportunities for job creation in the wake of industrial revolutions, short-term personal consequences can be painful - this may be compounded if automation exacerbates the stigma of being unemployed.

Practical Studies of Changing Workplace Structures and Needs

Given that 19% of top executives claimed to lack an adequate understanding of technology to lead an organization's adoption of automated processes (Bughin et al, 2018), I-O psychologists have good reason to research necessary top management competencies and facilitate their appropriate role changes. Similarly, Human Resource (HR) departments will be sure to face systematic changes as well, with 88% of surveyed business leaders saying that their organization's HR functions will need to, at the very least, moderately adapt their methods (Bughin et al, 2018). Therefore, I-O psychologists have an opportunity to research and advise in not only the adoption of new performance analysis and management, team building, cross-functional personnel selection, continuous learning, and work-life balance indicators, but also later measure the actual efficacy of these changing work structures and strategies so as to develop suggestions for improvement.

Finally, the basic need of any business is a labor force and, as previously discussed, there will be a strong shift in the skills required to harmonize the human workforce with that of machines. Therefore, I-O psychologists may have a role to play in brokering relationships with businesses and universities to better cater the curricula around actual business needs, ensuring that the research on these abstract skills are reflected in the learning materials.

Conclusion

From a historical and macro-economic point of view, automation has and may well yet again prove to be extremely beneficial for the global economy, in terms of increased productivity and GDP. From a philosophical perspective, automation may help to greatly untap human potential by relieving people of rote tasks, which are sometimes stressful and dangerous, and elevating them to a position that allows for greater cognitive and interpersonal endeavours. This in turn would mean that the value of human labor will be maintained, or even increased as compared to current levels, even if the transition into more automated workplaces requires some role changes.

However, not everyone thinks in terms of macroeconomics or philosophy. Some individuals already, and potentially hundreds of millions more, will be technologically displaced. And with that carries a risk of mental and emotional decline, as jobs provide more than just a means of income but also significantly contribute to an individual's daily structure, identity, income, and perceived social value. It seems that the public is aware of these risks, as implied by survey results that show a greater focus on the potential losses instead of potential gains from automation. This is a rather troubling finding, as public opinion towards automation is perhaps one of the most important deciding factors of either a smooth or a turbulent transition into this new era of automation. Perhaps contributing to this angst is the tone of journalists when reporting on automation, however there is a dearth of this sort of research. Knowing how journalists present new workplace technological advancements could help inform advocacy efforts regarding the spread of positive messages about automation to wider public. However, research should also be tangentially conducted to study what if any replacements there are for work, which carries the same social, financial, and personal benefits. The findings from this latter domain of research may not be solved by just one thing, and may require coordinated actions between researchers, businesses, schools, and governments to create a holistic, sustainable alternatives to work. Nonetheless, it may prove to be critical in shaping automation as a phenomenon that liberates rather than oppresses.

Beyond this research, I-O psychologists have a great opportunity to help prepare academic institutions and businesses by studying, communicating, and teaching the complementary skills to automated technology. Moreover, as automation will only increase its presence in business, it will be important to understand what if any psychological effects arise from working with automated technologies, especially since there is a only small pool of extant research on the subject. And while automation promises certain changes for businesses, the application of these changes is uncertain - though top executives claim to be planning for more cross-functional teams and less middle-management, this may be a painful adjustment in practice. Therefore, I-O psychologists can also research and consult on optimal team dynamics and hiring practices.

What is clear is that an investment in human capital is crucial for automated business contexts to succeed regardless of the consequence in greater society. However, these potential consequences should not go unaddressed. Theoretically, the efforts of I-O psychologists could have an important role in facilitating a holistic and healthy human transition into (or out of) automated workspaces, and it should be the imperative of I-O psychologists working in this field to not just help business prosper, but also humanity.

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