Nokelainen, P., Nevalainen, T., & Niemi, K. (2017). Mind or Machine? Opportunities and limits of automation. To appear in C. Harteis (Ed.), *The impact of digitization in the workplace - An educational view*. Dordrecht: Springer.

Mind or machine? Opportunities and limits of automation

Petri Nokelainen*

Industrial and Information Management laboratory, Tampere University of Technology, Finland

petri.nokelainen@tut.fi

Timo Nevalainen

Proakatemia, Tampere University of Applied Sciences, Finland

timo.nevalainen@tamk.fi

Kreeta Niemi

Faculty of Education, University of Tampere, Finland

kreeta.niemi@uta.fi

* Corresponding author

Abstract: Automation of work is not a new phenomenon. For businesses, technological development has an impact how enterprises organize work and production processes. Mechanical power has replaced some human workforces to eliminate unsafe work processes. New information and communication technologies have thus raised important questions as to what types of work can be replaced by technology and which require human decision making and social and creative intelligence. This chapter discusses general developments in the automation of work and reflects on forecasts that have been made regarding changes in the labor market.

Keywords: world of work, automation, skills, education, ethics

1. Introduction

It is common to see headlines with menacing titles, such as "Will YOUR job be stolen by a robot?", or interactive calculators that estimate when technology will make certain jobs redundant. This information is based on a study by the University of Oxford (Frey & Osborne, 2013), which categorized 70 occupations based on risk for automation to provide training data for probabilistic classification and to predict the probability of automation for 702 occupations.

This calculator even indicates that the current researchers are at small risk of losing their jobs to technology; the closest job profile (Education—College Professors) produced a 3.2% chance of automation in the next 20 years. Although this is a small number compared to production (e.g., baker: 88.8%) and legal (e.g., legal assistant: 94.5%) occupations, we expected teaching jobs to be less replaceable by machines.

Why is this? The answer lies in statistical procedures by Frey and Osborne (2013), who analyzed US Department of Labor data. First, they selected the following nine variables as predictors of job automation: 1) assisting and caring for others, 2) persuasion, 3) negotiation, 4) social perceptiveness, 5) fine arts, 6) originality, 7) manual dexterity, 8) finger dexterity, and 9) cramped work space. These variables fit into three categories: social intelligence (I; variables 1–4), creative intelligence (II; variables 5 and 6), and perception and manipulation (III; variables 7–9), which revealed that occupations demanding social or creative intelligence (categories I and II) are quite safe from automation. Thus, academics are at low risk of losing their jobs to automation, although the machine-learning approach that Frey and Osborne used found that student essays (Rudner, 2009) and written research (Kersting, Sherin, & Stigler, 2014) scoring systems have been developed.

Automation of work is not a new phenomenon and has advanced in waves during the past two-hundred years (Autor, 2015). Mechanization has influenced occupations that involve both cognitive (analytic/interactive) and manual routine tasks (Autor, Levy, & Murnane, 2003), such as those found in knitting and automotive factories. As a result, requirements for workforce skill level and flexibility were lowered as work tasks were simplified. The second wave of automation occurred during the early twentieth century and was introduced by electrification, which automated low-skill level production processes but increased demand for skilled workers to operate machinery (Goldin & Katz, 1998.) Currently, automation has eliminated (switchboard operators or door-to-door sales workers) or affected (agricultural workers and cashiers) a number of occupations.

The current wave of automation has made it difficult to predict which occupations will remain manual. According to Frey and Osborne (2013), advancements in machine learning and mobile robotics challenge Autor et al. (2003) prediction that non-routine manual tasks, such as truck driving, are safe from automation. Thus, many occupations that contain non-routine tasks (e.g., legal writing) might change in future.

In this chapter, we discuss the general development of automation and reflect on forecasts of how automation will change the labor market. We begin by investigating different skills that are desirable in future working life. Then, automated, assistance, and augmenting technologies related to education will be discussed. Finally, ethical challenges of workplace automation and a discussion of topics presented earlier will be related to the wider context of technological advancement based on the seminal 2 x 2 model of cognitive/manual and routine/non-routine tasks proposed by Autor et al. (2003).

2. Skills and Automation

The consequences of new technology include increasing automation of low-skill tasks, potential elimination of current work practices, and the new significance of highly cognitive skills in the workforce, all of which may lead to labor market polarization. This polarization will lead to a growing demand for employment in highly cognitive-based jobs and manual low-income jobs, hollowing out of middle income jobs requiring routine manual and cognitive skills (Frey & Osborne, 2013; Goos & Manning, 2007).

Highly cognitive skills that are in demand include sophisticated ICT skills as well as more generic skills requiring creativity and social intelligence. Maintaining a high skill level can be challenging for both new employees and senior workers, who must continuously update their skills. To remain valuable, people must have the skills to use novel innovations and the ability to make decisions in self-organizing learning environments (Brynjolfsson & McAfee, 2014). Highly cognitive skills include creative thinking, problem solving, entrepreneurship, negotiation, and learning (World Economic Forum, 2016), which are generic and transverse multiple industries, providing lifelong learning opportunities and requiring adaption to new transformative working environments (Frey & Osborne, 2013).

New technologies also require collaboration and a set of soft skills from human operators, such as emotional intelligence, empathy, altruism, and reciprocity. These skills are built into the mechanics of everyday interpersonal exchanges. Workers need to communicate, network, and make collaborative decisions to distribute and maintain collective knowledge. At the same time, they need to understand the perspectives of others, and the fastest growing cognitive occupations, such as physicians, lawyers, teachers, and therapists, include a remarkable amount of social interactions and sustained intersubjectivity (Frey, Osborne, & Holmes, 2016).

The features of social interaction are difficult to automate (Deming, 2015). A person's ability to read and react to others' needs, intentions, and emotions is primarily based on tacit knowledge and hidden social orders. Thus far, computers are very poor substitutes for tasks that require an underlying set of rules unknown to programmers (Autor, 2015). Computers are unable to do anything outside a frame of programming, and human interaction can be based on creating novel ideas and building rapport (i.e., thinking outside the box; Brynjolfsson & McAfee, 2014). The labor market increasingly rewards workers who have high cognitive and social skills.

The growing demand for these skills creates an educational challenge for preparing individuals. Increasing opportunities to develop high-level cognitive and social skills narrows the gap between experienced and inexperienced workers and reduces inequality, aligning societal and labor market needs. Success in education has been based on measuring achievement of cognitive skills, using tests such as PISA and OECD, and the results are utilized in policy making. Although these scientific analyses provide important information, many other skills taught and learned in school have been ignored. For institutions to be able to respond to future educational challenges, research is needed on how these skills evolve over time and what motivates people to acquire and develop these skills.

The Future of Jobs report published by the World Economic Forum (2016) contains an analysis of the top 10 skills required for a successful working life in 2020. Many of the skills listed are the same as those included in the report for 2015 and are indicative of the increasing complexity of global and digital working life. At the top of the list are skills such as complex problem solving (1), critical thinking (2), and creativity (3).

The complexity of work tasks in global and digital working contexts, coupled with rapid development and increasing availability of digital technologies that assist or augment human problem-solving, is radically improving the productivity of cognitive labor distributed between humans and algorithms (Frey & Osborne, 2013). Development and wider availability of learning algorithms and robotics is threatening to diminish the value of human manual labor and make certain types of workers redundant. Skills needed in complex working tasks are followed by those needed for collaborating with others in increasingly flexible work contexts, such as people management (4) and coordinating with others (5). The ranking of creativity changed from a rank of 10 in 2015 to 3 in 2020, because creativity plays a crucial role in how workers benefit from new products, technologies, and ways of working. The role of strategic decision making became slightly less prominent due to the development of machines that are able to make strategic decisions based on very large sets of data and deep-learning algorithms (World Economic Forum, 2016).

3. Education and Automation

Any teacher that can be replaced by a machine should be! - Arthur C Clarke

The role of education is more important as skill demand increases (Goldin & Katz, 2007). More than ten years ago, Rintala and Suolanen (2005) noticed that the effects of automation on job descriptions were evident in three ways: 1) the transfer of tasks, 2) the fusion of job descriptions, and 3) the adding of tasks. Tasks for professional groups were transferred to the job descriptions for fused jobs that were previously performed by two or more separate professional groups. The new tasks were primarily related to the emergence of new media and were created and added to existing job descriptions.

Vocational education is an example of a profession in which automation can both present a challenge to existing working practices and create opportunities for new ones. When examining the current and possible future effects of automation on teaching profession, for example, it is easy to be pessimistic because of increasing use of technology to reduce the need for human contact in teaching and learning. A more optimistic outlook would be to consider the possibilities of educational technology to facilitate new pedagogical practices, such as flipped classrooms (Strayer, 2012), e-learning, informal learning, project-based learning, or other inductive teaching and learning methods (Prince & Felder, 2006). These practices develop academic, but also non-academic skills, such as social-emotional skills (Liu & Huang, 2017) that are needed in working life. Thus, developing technology can give rise to new skills.

To examine the actual impact rather than possible future challenges of machine learning and automation on education, we need to dig deeper and examine this phenomenon on a granular level, to determine the different tasks involved in teaching and learning (Figure 1).

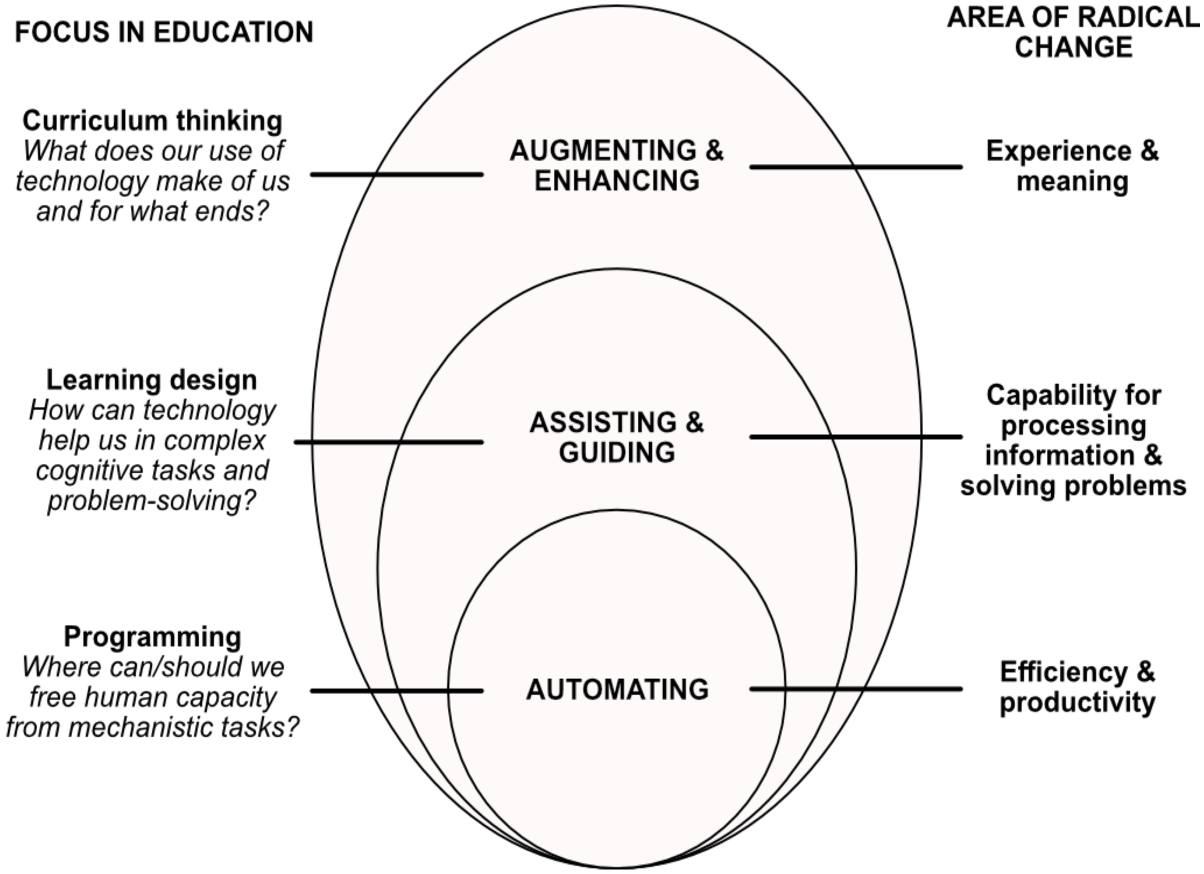

Figure 1. Automating, assisting, and augmenting education

First, even in vocational teaching, there are simple and mechanistic coordination and information sharing tasks that ensure that students are in the right place at the right time or that correct information in a suitable format. For example, mechanistic tasks related to monitoring and control of coursework and student achievement require grades to be input into a school information system or a spreadsheet file. Technology that automates these relatively simple, instrumental tasks already exists, and in the near future, the time and resources needed to complete these tasks manually will be reduced. Automation of these tasks will have a radical effect on efficiency and productivity in education.

Second, there are more complex but still instrumental and relatively repetitive tasks related to information retrieval, filtering and sharing, and moderately complex problem solving in many work processes. For these tasks, technology can be an intelligent agent that assists and guides teachers and students during information gathering and processing (Nenkov, Dimitrov, Dyachenko, & Koeva, 2016). Use of intelligent agents, such as IBM Watson (IBM, 2016), will have a radical effect on human capability for information processing and problem-solving.

Third, there are tasks in education that are deeply connected to human meaning and the meaningful *ends* of education (in contrast to instrumental *means*). Especially in the educational contexts, meaning-related tasks often involve cognitively demanding decision making in an environment where social and psychological, even existential factors, introduce uncertainty and complexity. Technological capacity required for full automation or even meaningful assistance by artificial intelligence agents for these tasks is still quite far from being realized; however, technologies, such as augmented and virtual reality appliances, and wearable devices connected to the internet can be used to augment and enhance human perception and experience of meaningful things in new ways. The question to consider about enhancing technologies for these tasks is not how we can use innovation to work more efficiently but how will using such technology change us and to what (or whose) end are such changes beneficial?

Encouraging entrepreneurship has been identified as a key policy to effectively offset the risks of automation for the labor market and distribution of wealth (Frey, Osborne, & Holmes, 2016). Creating new business when existing businesses are being automated and require less human labor seems like an intuitively viable option. However, human labor plays different roles in different industries. While startup companies leverage effective use of digital platforms, they rarely employ a significant number of people, which may still enable people to create new forms of employment based on the use of a platform for offering products or services to other users of a platform. This employment often takes the form of part-time freelancing for extra income, which results in little stability or the job security associated with more traditional forms of employment.

Relevant to vocational education is the push towards entrepreneurship education. This push, is often motivated by ideological reasons connected to neoliberalism (Komulainen et al., 2011) or the perceived need to grow a private sector through creation of new enterprises. Alongside this ideologically or economically motivated push for entrepreneurship education, there is a perceived need to train more entrepreneurially minded specialist workers and managers for existing companies. This entrepreneurial mindset consists of the ability to spot opportunities for creating value and willingness to take a measured degree of personal risk to realize these opportunities (Hagel, 2016).

4. Ethics and Automation

Rapid automation of labor poses different challenges for societies with different economic conditions. In economies based mainly on industrial production without the support structures of a welfare state, the platform economy may help people find paid work in flexible services when the need for industrial labor becomes scarce due to automation. In Nordic countries, where the state economy is based on taxation of regular and relatively high monthly wages, this very same flexibility threatens the social support structures of the welfare state.

Automation and development of extremely efficient social media communication tools will enable emergent forms of organization to flourish, where hierarchical structures were previously required to maintain effective communication. Now everyone has access to communication that was previously available only to leaders of states and large corporations. Social networking has given knowledge-power to the majority, who have become active information seekers and producers (Spencer-Scarr, 2014).

In societies where automation challenges the established structures of the labor market, there is an increasing need to educate citizens who are able to take responsibility for their own economic well-being, as well as that of others. One possible answer to this need is entrepreneurship education that focuses on increasing students' abilities to find opportunities to create value and to withstand the risk required to take these opportunities. The success of this approach depends on the capabilities of individuals and organizations to use and expand both individual and cultural strengths to their fullest, including the ability to use and work together with new technologies.

Entrepreneurship education should go beyond teaching students about the financial management of the current forms of corporations. Even if these corporations play a central role in the current economy, the platform economy or whatever comes after may challenge this role. In fact, the role of traditional companies is already being challenged by emerging platforms that cooperate economically. Entrepreneurship as the creation of a living for oneself or one's community, as the ability to find opportunities to create value, and as the willingness to take risks to take advantage of these opportunities goes beyond the current forms of corporation and financial management.

Economic forecasts and reports have identified relevant competencies and skill requirements for workers, such as being able to tolerate instability and adapt to new ways of working and working environments. This requires an open and flexible mindset from the employee to constantly update their skills and change professions more frequently throughout their careers. No matter how qualified a person is, he or she must be able to adjust and upgrade their career paths and update skills through sophisticated learning tools, both formally and especially informally, shaped by ICT. Open mindsets also require the ability to think and act globally, which can mean accepting situations that one would not normally experience.

An ethical challenge of automation is how to redefine the human meaning of work and what to do about the human need to feel that their work is needed by their communities when robots and algorithms are equally able to perform the same tasks. Another aspect of the human meaning of work is that human beings have certain capabilities (Nussbaum, 2011) that are, alongside the capability for learning, required to live a fulfilling life within a society. These central capabilities include, according to Nussbaum (2011), life, bodily health, bodily integrity, senses, imagination and thought, emotions, practical reason, affiliation, other species, play, and political and material control over one's environment. For many people, these capabilities are actualized and developed in the context of daily work or based on being employed and earning sufficient wages. If we take the expectation of employment out of the equation, there must be alternative structures in place to ensure that people feel needed by their communities and that they still have the ability to actualize and develop the capabilities that are critical to living a human life with dignity.

5. Discussion

In the past, working people competed with each other in the labor market. Nowadays, people compete against machines, and professional careers have become more flexible for all workers, no matter how highly qualified they are. In this sense, people must take charge of the development of their skills and qualifications and accept the role of technology that allows learning to happen anywhere and anytime, in multiple learning environments.

According to the mindset theory (Dweck, Chiu, & Hong, 1995), people may be more or less fixed to certain traits (entity) or open for change (incremental). Empirical studies (Yeager et al., 2011) have shown associations between the entity and incremental mindsets and the desire to behave in certain ways. However, workers with an entity mindset might be in greater danger of losing their jobs to automation compared to workers with an incremental mindset Current research on the development of expertise (Hytönen, Palonen, Lehtinen, & Hakkarainen, 2016) supports this assumption and stresses the importance of workers actively expanding their skills and competencies to dynamically adapt to changing professional environments (i.e., adaptive expertise).

In public discourse, both in traditional press and in blogosphere digitalization, the automation of work is usually discussed based on its effect on jobs and the job market. We suggest that it would be fruitful to discuss the impact of digital technologies on the more granular levels of tasks. Any meaningful occupation consists of professional or work ethics, different social, cultural, and physical contexts, and relationships between different people and organizations. The effects of automation on work ethics and situational and relational aspects of work are beyond the scope of this short introduction.

It has been suggested that routine tasks with a lower level of cognitive complexity are more likely to be automated than cognitively more complex tasks that involve a higher degree of uncertainty (Autor et al., 2003; Frey & Osborne, 2013). Goos, Manning, and Salomons (2014) agreed with this view and proposed that skill-biased technological change hypothesis only partially explains job polarization.

While tasks that require fine mechanical accuracy and skill, such as medical surgery or electronic repair, have previously been difficult for robots, recent developments in soft robotics has created technology that equals the skills of human specialists. Artificial structures and materials that emulate soft tissue in animals enables robots to receive more detailed feedback from physical interactions to fine-tune reactions (Laschi, Mazzolai, & Cianchetti, 2016.) Recent developments in deep machine learning indicate that predicting future automation of work tasks on the basis of simplicity or complexity is no longer enough. Computers based on deep-machine-learning algorithms are increasingly capable of strategic decision making; for example, the AlphaGo algorithm developed by DeepMind Technologies (a subsidiary of Alphabet, formerly Google) beat the top Go player in the world, Lee Sedol, four out of five games in March 2016 (Liu & Huang, 2017). Go had previously been thought to require such a level of strategic creativity that it would take artificial intelligence at least 50 years to win over professional human players. What makes AlphaGo especially interesting is that it is based on a general deep-learning algorithm, not one that was built for the sole purpose of playing Go like earlier artificial intelligence applications that won over grandmasters in chess (Chen, 2016). Currently, similar algorithms are being developed for different strategic decision-making contexts in both business and medicine. What is common to these contexts is that there is a fairly limited number of known variables for which value is optimized through strategic action.

We suggest human *meaningfulness* as another factor that could play a role in determining how likely a task is to be automated and the nature of automation. Tasks that are meaningful add meaning either in or through the process of being completed. Meaning can be added to tasks through social relationships and specific social, cognitive, and embodied human practices. We contrast this meaningfulness with the *instrumentality* of tasks. Here, an instrumental task is one for which purpose is optimized to a limited number of known variables, often to accomplish something that may or may not be a meaningful task. An instrumental task is a means to an end that does not add to the meaningfulness of the process or its outcomes, while the specifically human way a person completes a meaningful task adds to the meaningfulness of the process or its outcomes. If we compare routine–complex and instrumental–meaningful distinctions, most tasks in any profession can be categorized relatively easily (Figure 2).

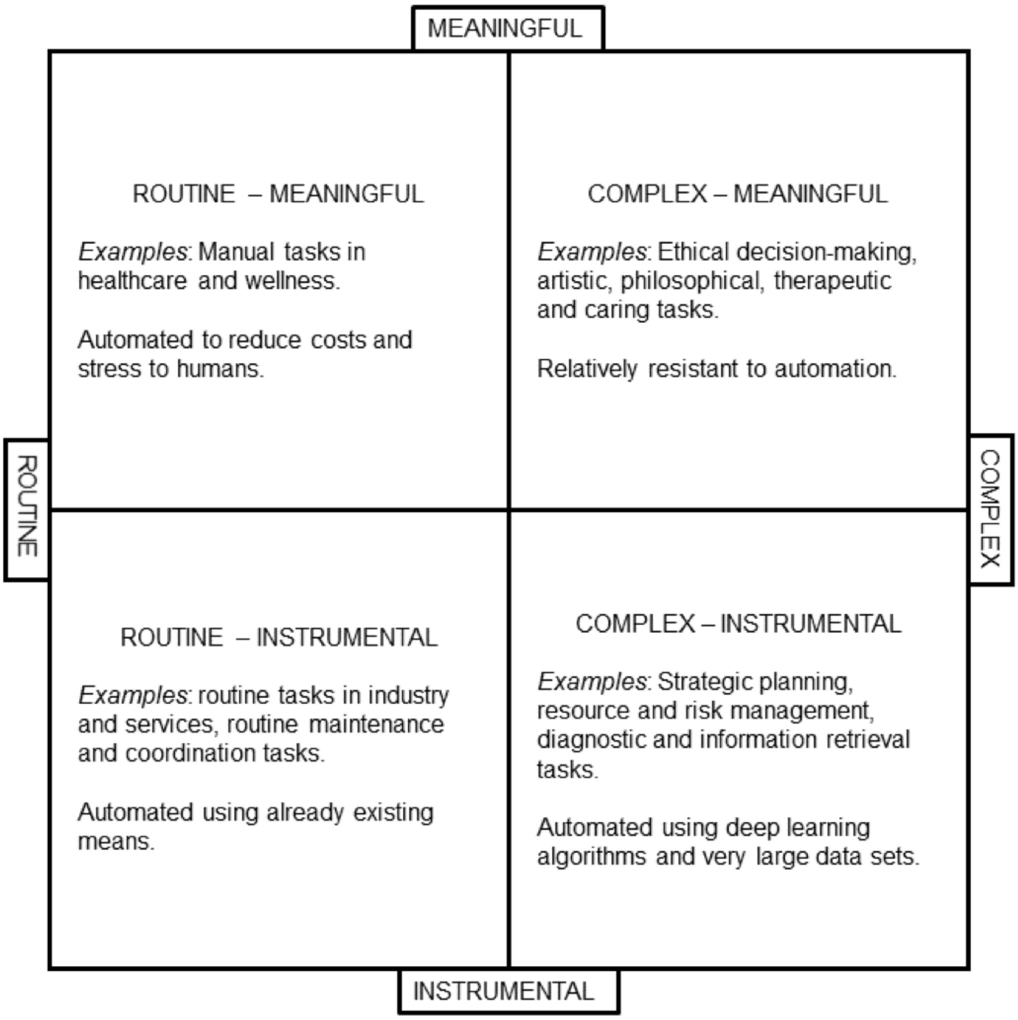

Figure 2. Framework to predict automation of work tasks (adapted from Autor, Levy, & Murnane, 2003, p. 1286)

When starting from the bottom-left quadrant (routine–instrumental) of Figure 2, many of the tasks falling into this category have already been automated or are in the process of being automated. This is the category in which human work adds little value and where tasks are often relatively easy to automate. Moving to the top-left quadrant (routine–meaningful), we find tasks for which human work adds meaning to the process or outcomes but for which algorithms and machines are gradually being introduced to reduce labor or other costs or physical or psychological stress to human workers. Tasks falling into this category include manual tasks in healthcare, such as lifting patients, and many tasks in service industry, such as working at the counter in a supermarket or hotel reception. Human interaction in these tasks often adds value to the process but can also be costly or stressful. This category is especially important to monitor to assess the ethical effects automation; for example, professional human care should be available to all elderly individuals regardless of their ability to pay a premium for human care.

In lower-right quadrant (complex–instrumental) are tasks that were previously too complex for automation but for which human work does not add intrinsic value to the process or its results. This includes most strategic and tactical coordination and management tasks for which immediate personal human contact does not add meaningfulness. Automating complex decision making requires learning algorithms that are capable of learning from the results of their previous actions and interactions with other actors and of estimating probable outcomes based on all information available. Examples of this include algorithms that use very large databases to assist doctors in medical diagnostic tasks and deep-learning algorithms used to assist decision making by corporate boards.

Future applications could include any strategic decision making that optimizes a limited number of variables, such as minimizing casualties in warfare. The ethical implications of having an algorithm make decisions over military forces would be as complicated as choosing a human general, and it would risk the loss of human life due to inefficient decision making. This same problem applies, less drastically, to corporate financial decision making.

Where human work is relatively resistant to being replaced by learning algorithms or robotics is in the top-right quadrant (complex–meaningful). This category includes complex tasks for which a human specialist adds meaning of the process or the outcome. Examples include ethical decision making, for which decisions are not simply a means to optimize for a limited number of variables, such as minimizing casualties or maximizing profit, but contributes to the meaningful end of the activity. Other such tasks include artistic, philosophical, therapeutic, and care tasks that are deeply intertwined with the human experience of meaningfulness.

The categorizations in Figure 2 provide an overly simplistic view but expands on the previous ways of assessing the probable impact of automation by taking into account the value of experienced meaning of work activities and outcomes. When thinking about the possibilities of increasing work efficiency through automation, it must be noted that many people experience work as one of the most meaningful aspects of their lives (Csikszentmihalyi, 1997).

Advances in automation have surprised us in many ways over the last two centuries. According to Goldin and Katz (2007), technological change as the engine of economic growth creates winners and losers as new technologies increase the relative demand for more skilled workers. As a solution to this, they suggest that workers have flexible skills and access to expansive educational infrastructure: “Growth and the premium to skill will be balanced and the race between technology and education will not be won by either side and prosperity will be widely shared” (p. 26). As technology races ahead, it is only a matter of time before current limitations or bottlenecks related to originality, creativity, and social skills are solved. To prepare the workforce for the next wave of automation, vocational education should identify and acknowledge competencies that are least susceptible to automation in both generalist (knowledge of human heuristics) and specialist (development of novel ideas and artifacts) occupations and modify curricula accordingly.

References

Autor, D. (2015). Why are there still so many jobs? The history and future of workplace automation. *The Journal of Economic Perspectives, 29*(3), 3–30.

Autor, D., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333.

Bloch-Budzier, S. (2016). *NHS using Google technology to treat patients*. BBC News. Retrieved from http://www.bbc.com/news/health-38055509

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. New York: WW Norton & Company.

Chen, J. X. (2016). The Evolution of Computing: AlphaGo. *Computing in Science & Engineering*, *18*(4), 4-7.

Csikszentmihalyi, M. (1997). *Finding Flow: The Psychology of Engagement with Everyday Life*. New York, NY: Basic Books.

Deming, D. J. (2015). *The Growing Importance of Social Skills in the Labor Market.* The National Bureau of Economic Research Working Paper No. 21473. Cambridge, MA: NBER. Retrieved from: https://scholar.harvard.edu/files/ddeming/files/deming_socialskills_august2015.pdf

Dweck, C. S., Chiu, C., & Hong, Y. (1995). Implicit theories and their role in judgments and reactions: A world from two perspectives. *Psychological Inquiry*, *6*, 267–285.

Frey, C. B., & Osborne, M. A. (2013). *The future of employment: How susceptible are jobs to computerisation.* Retrieved from http://www.oxfordmartin.ox.ac.uk/downloads/academic/future-of-employment.pdf

Frey, C. B., Osborne, M. A., & Holmes, G. (2016). *Citi GPS: Global Perspectives & Solutions*. Retrieved from https://www.citivelocity.com/citigps/ReportSeries.action?recordId=49.

Goldin, C., & Katz, L. F. (1998). The origins of technology-skill complementarity. *The Quarterly Journal of Economics*, *113*(3), 693–732.

Goldin, C., & Katz, L. F. (2007). *The race between education and technology: The evolution of U.S. educational wage differentials, 1890 to 2005* (NBER working paper series) Cambridge, MA: National Bureau of Economic Research. Retrieved from: http://www.nber.org/papers/w12984.pdf.

Goos, M., & Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in Britain. *The Review of Economics and Statistics*, *89*(1), 118–133.

Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, *104*(8), 2509–2526.

Gray, A. (2016). *The 10 skills you need to thrive in the Fourth Industrial Revolution*. Retrieved from https://www.weforum.org/agenda/2016/01/the-10-skills-you-need-to-thrive-in-the-fourth-industrial-revolution/

Hagel, J. (2016). *We need to expand our definition of entrepreneurship*. Retrieved from https://hbr.org/2016/09/we-need-to-expand-our-definition-of-entrepreneurship

Hytönen, K., Palonen, T., Lehtinen, E., & Hakkarainen, K. (2016). Between two Advisors: Interconnecting Academic and Workplace Settings in an Emerging Field. *Vocations and Learning*, *9*(3), 333–359.

IBM. (2016). *Watson Health*. Retrieved from https://www.ibm.com/watson/health/

Laschi, C., Mazzolai, B., & Cianchetti, M. (2016). Soft robotics: Technologies and systems pushing the boundaries of robot abilities. *Science Robotics*, *1*(1), 1-11. Retrieved from http://robotics.sciencemag.org/content/1/1/eaah3690/tab-pdf.

Kersting, N. B., Sherin, B. L., & Stigler, J. W. (2014). Automated scoring of teachers' open-ended responses to video prompts: Bringing the classroom-video-analysis assessment to scale. *Educational and Psychological Measurement*, *74*(6), 950–974.

Komulainen, K., Naskali, P., Korhonen, M., & Keskitalo–Foley, S. (2011). Internal entrepreneurship: A Trojan horse of the neoliberal governance of education? Finnish pre- and in-service teachers' implementation of and resistance towards entrepreneurship education. *Journal for Critical Education Policy Studies*, *9*(1), 342–374.

Liu, M-C., & Huang, Y-M. (2017). The use of data science for education: The case of social-emotional learning. *Smart Learning Environments*, *4*(1), 1-13.

Nenkov, N., Dimitrov, G., Dyachenko, Y., & Koeva, K. (2016). Artificial intelligence technologies for personnel learning management systems. In R. Yager, V. Sgurev, M. Hadjiski, & V. Jotsov (Eds.), *2016 IEEE 8th International Conference on Intelligent Systems* (pp. 189-195). New York, NY: IEEE. DOI: 10.1109/IS.2016.7737420.

Nussbaum, M. C. (2011). *Creating capabilities: The human development approach*. Cambridge, MA: Belknap Press of Harvard University Press.

Prince, M. J., & Felder, R. M. (2006). Inductive teaching and learning methods: Definitions, comparisons, and research bases. *Journal of Engineering Education*, *95*(2), 123–138.

Rintala, N., & Suolanen, S. (2005). The implications of digitalization for job descriptions, competencies and the quality of working life. *Nordicom Review*, *26*(2), 53–67.

Rudner, L. M. (2009). Scoring and classifying examinees using measurement decision theory. *Practical Assessment, Research & Evaluation*, *14*(8). Retrieved from http://pareonline.net/getvn.asp?v=14&n=8.

Spencer-Scarr, D. (2014). Long Tail Leadership: Understanding Soft Power Affecting Organizations. In H. Rahman & R. D. de Sousa (Eds.), *Information Systems and Technology for Organizational Agility, Intelligence, and Resilience* (pp. 1-24). Hershey, PA: Business Science Reference.

Strayer, J. F. (2012). How learning in an inverted classroom influences cooperation, innovation and task orientation. *Learning Environment Research*, *15*(2), 171–193.

World Economic Forum. (2016). *The future of jobs: Employment, skills and workforce strategy for the Fourth Industrial Revolution*. Retrieved from http://www3.weforum.org/docs/WEF_Future_of_Jobs.pdf.

Yeager, D. S., Trzesniewski, K. H., Tirri, K., Nokelainen, P., & Dweck, C. S. (2011). Adolescents' implicit theories predict desire for vengeance after peer conflicts: Correlational and experimental evidence. *Developmental Psychology*, *47*(4), 1090–1107.