CHAPTER 12

THE CHANGING NATURE OF KNOWLEDGE AND SERVICE WORK IN THE AGE OF INTELLIGENT MACHINES

CRISPIN COOMBS, DONALD HISLOP, STANIMIRA TANEVA, AND SARAH BARNARD

Introduction

One of the most significant recent technological developments concerns the application of intelligent, interactive, and highly networked machines to jobs that up to now have been considered safe from automation. These "intelligent machines" are characterized by autonomy, the ability to learn, and the ability to interact with other systems and with humans. They draw on new advances in technologies such as artificial intelligence (AI) and robotics, enabling them to undertake tasks that could previously only be completed by human workers. We define and describe intelligent machines in detail in the following section. Referring to what some have called the second machine age, analysts and commentators have forecast mass unemployment from the automation of a wide range of predictable, repetitive job roles (Brynjolfsson & McAfee, 2016). What sets this change apart from previous technological revolutions, such as the automation of factory work in the 19th century, is the potential of intelligent machines to affect dramatic changes to the demand for skill-intensive, knowledge-based workers (Loebbecke & Picot, 2015). However, there is considerable debate regarding the likely impacts of intelligent machines on work. For example, Frey and Osborne (2017) suggest that as much as 47% of jobs in the United States economy could be eliminated from widespread implementation of machine learning and mobile robotics over the next one to two decades. The Bank of England published a report in 2015 suggesting that almost half of United Kingdom jobs (about 15 million) could be lost to automation and AI technologies. By contrast, Arntz et al. (2016) found that only 9% of jobs were potentially automatable in Organization for Economic Co-operation and Development (OECD) economies.

A valuable source of guidance for understanding these developments is current academic knowledge. Indeed, there are a considerable number of AI and robotics related research contributions that consider the potential impacts of these new technologies. However, these contributions lie in a wide range of scholarly disciplines that draw on contrasting research paradigms, theories, methods, and perspectives. This presents business leaders, policymakers, and researchers with a messy environment that lacks a coherent overview of the current state of knowledge, key research gaps, and how researchers may proceed to fill these gaps. Therefore, the purpose of this chapter is to report the findings from a systematic review of the currently published academic literature around the key impacts of intelligent machines on work.

In order to explore the transformational effects of intelligent machines (such as AI and robotics), rather than capturing technological applications that are relatively mature (such as those of robots in manufacturing contexts (Dorf & Kusiak, 1994; Khouja & Offodile, 1994), the review is focused upon service and knowledge work. Several authors have noted that service and knowledge work has traditionally been safe from automation (for example, compared to manufacturing) but have identified that recent intelligent machine developments now threaten to erode many of these jobs (Brynjolfsson & McAfee, 2016; Davenport & Kirby, 2016). Unlike the manufacturing sector, the service sector produces intangible goods that may refer to a wide range of services in a variety of areas, including finance and commerce, government, transportation, health care and social assistance, tourism, arts, entertainment, and science. The growing size and importance of the service (and knowledge) sector, in comparison to agriculture and manufacturing, is a trend that has been occurring since the late 1970s in most developed economies. This idea links to and builds from Daniel Bell's vision of an information/knowledge society that was initially articulated in the early 1970s (Bell, 1973). Knowledge work is formally defined as work that is intellectual, creative, and non-routine and that involves the use and creation of knowledge (Hislop, Bosua, & Helms, 2018) and workers labelled as "symbolic analysts" (Reich, 1991). The knowledge sector (that partially overlaps with the service sector) is generally associated with work involving a great deal of research and development activities and the creation of innovative products. In a broader sense, the knowledge sector may refer to professional areas such as information and communication, consulting, pharmacology, and education (Kuusisto & Meyer, 2003). Thus, from an occupational perspective, this chapter considers all forms of non-manual work, including white-collar office and administrative work, service work and what can be labelled knowledge work.

The chapter is organized as follows. First the notion of intelligent machines and the different types of technologies that may be considered under this term are discussed. The approach and procedures adopted to undertake the literature review are then explained. The subsequent section presents the findings of the review. An overview of the nature of the literature sample is provided, followed by a discussion of the three main themes that emerged: human relations with intelligent machines; adoption and acceptance of intelligent machines; and ethical issues associated with machine-human collaboration. The chapter concludes with a review of the key gaps in the existing literature and suggestions for future research directions.

What Are Intelligent Machines (Artificial Intelligence and Robotics)?

Burkhard (2013) observed that it is difficult to define intelligent machines because there are no universal definitions of natural (animal, especially human) intelligence. Machines may be better at tasks that can be described as intelligent behavior, such as being able to apply a wide range of languages for translating text, but the quality of the translations is lower than that of human translations (so far). Further, machines do not understand the meaning of the words they translate; they use statistical calculations to determine the most likely suitable alternative word (Friend, 2018). However, recent advances in technologies have meant that these machines are more likely to be undertaking tasks that were previously performed by humans. Advances in two main types of technology have largely driven these developments: *artificial intelligence* (including machine learning and cognitive computing) and *robotics* (including service robots, robot assisted procedures, and robotic process automation). Thus, our review focuses on these two technologies.

Artificial Intelligence

Several authors have acknowledged that it is difficult to define AI (DeCanio, 2016). For example, it is possible to make a distinction between strong AI (or Artificial General Intelligence) and weak AI (or Artificial Narrow Intelligence; Bostrom & Yudkowsky, 2011). Strong AI implies a system that has superhuman intelligence and at present remains a fictional aspiration. Weak AI describes AI in terms of being able to complete specific tasks that require single human capabilities such as visual perception or probabilistic reasoning. In these tasks, AI can considerably outperform human capabilities. However, AI remains unable to make ethical decisions or manage social situations. In other words, weak AI refers to the ability to complete the specific tasks that humans do rather than replicating the way humans actually think (Hengstler, Enkel, & Duelli, 2016).

Despite these complexities, several authors have proposed definitions of AI. AI has been defined as the development of computers to engage in human-like thought processes such as learning, reasoning, and self-correction (Dilsizian & Siegel, 2014).

Building on the cognitive aspect, DeCanio (2016, p. 280) describes AI as a "broad suite of technologies that can match or surpass human capabilities, particularly those involving cognition." Niu et al. (2016, p. 2) add that AI "aims to understand the essence of intelligence and design intelligent machines that can act as human behavior." Others have emphasized the superiority of human intelligence over AI. For example, the computer scientist Larry Tesler described human intelligence as "whatever machines haven't done yet" (Friend, 2018). All these definitions highlight the role of AI in modelling human behavior and thought, but do not go as far as to talk about using AI technologies to build other smart technologies.

AI may be presented in various forms such as natural language processing, affective computing systems, virtual reality (avatars), or humanoid and non-humanoid robots (e.g., Luxton, 2014). Johnson (2014) introduces the term "artificial agent" (AA) that refers generally to computational devices performing tasks on behalf of humans autonomously (i.e., without immediate, direct human control or intervention from humans). Some AAs are software programs (e.g., bots undertaking Internet searches). A more advanced example of such a system is Robotic Process Automation (RPA), a software solution (essentially a software license) configured to do administrative work previously undertaken by humans. RPA is suited to automating a process in which a human takes in many electronic data inputs, processes these data using rules, adds data, and then enters this new information into another system, such as an enterprise or customer relationship management system (Willcocks, Lacity, & Craig, 2015).

Robots

A traditional view of robots that would be familiar to popular culture concerns service robots. Those are robots that provide assistance to a human to complete a physical task, such as scrubbing, cleaning, sorting, packaging instruments, and sending them for sterilization for dentists (Chen, 2013); helping an elderly person pour a liquid (Xu, Tu, He, Tan, & Fang, 2013); providing an intelligent interactive assistant for an office environment (Wang et al., 2013), or serving meals in a restaurant (Yu et al., 2012). The goal of these robots is to provide autonomous assistance to humans in undertaking these tasks but without the need for specific human guidance. By contrast, robot-assisted surgery concerns the use of a human controlled robot to perform surgical procedures that result in less invasive procedures than those undertaken by human surgeons alone. The robotic system (for example the Da Vinci robotic system) provides a three-dimensional view, hand-tremor filtering, fine dexterity, and motion scaling and are suitable for narrow, inaccessible operative areas (Zaghloul & Mahmoud, 2016).

Moreover, some robots involve a human-machine interaction that resembles the interaction between humans. These are robots that are no longer confined to factories but are specifically designed to interact with people in urban contexts. They are referred to as "social robots" (Torras, 2015). Social robots may replace receptionists or shop assistants in shopping malls, interact with elderly people or clinical patients, and even act as support teachers and nannies (e.g., Calo et al., 2011; Torras, 2015). Most recent developments in robotics are demonstrated by the appearance of humanoid robots. Thus, the notion of a "robot" is complex and heterogeneous, *physical robots* autonomously performing single or multiple tasks such as a robot waiter, *physical robotics* being used to extend human capabilities in terms of precision and micro-control (but not acting autonomously, such as robot assisted surgery), or *social robots* providing social, emotional, and informational support.

Literature Review Methods

We followed a rapid review approach outlined by Khangura et al. (2012), comprising a systematic literature search, screening and selection of studies, thematic synthesis of included studies, and production of a report. The four databases used to identify relevant academic studies included: *Scopus, Business Source Complete, Psychinfo*, and *Web of Science*. Two types of search terms were used in combination: those related to the types of technology/change we were interested in examining, and those related to the effects/impacts of these technologies/changes. The initial technology/change terms that were used included: *artificial intelligence, smart machines, cognitive computing, automation of knowledge work,* and *automation of service work*. The search was focused on these terms due to the focus of the review on the use of advance/contemporary developments in IT and computing in relation to the computerization and automation of knowledge and service work. These search terms were used in combination with other search terms related to the type of impact/effect that we were interested in examining. These impacts were in four broad areas: impacts on organizations, impacts on workers, impacts on society, and ethical implications. The search terms included *innovation, business value, quality of working life, productivity, employment, social impact, autonomy, collaboration, human computer interaction, service work, knowledge work, adoption,* and *implementation*. After exploratory searches and research, the search terms were extended to include robotic process automation, robot*/knowledge work, and robot*/service work. In all four databases all technology terms were combined individually with each impact term. The results from these searches were filtered to extract only peer reviewed articles or conference papers, published from January 2011 onwards, in English with full text available. These searches identified 1581 possible items for inclusion.

The titles and abstracts from all 1581 items were reviewed. Items were excluded if they were purely technical papers concerned with engineering and design issues related to the technologies examined, or they were not focused on the application of the selected technologies in the context of service and knowledge work (i.e., studies focused purely on manufacturing were excluded). While undertaking this reviewing of items identified via the primary searches, a number of secondary items were identified for inclusion in the study population. These were identified primarily via the abstracts and reference lists of the primary search items, where additional, widely cited sources were identified.

After these additional steps were completed, the total number of sources identified for review and in-depth coding was 219.

The thematic synthesis was undertaken by all of the project team, with each team member being allocated a roughly equal proportion of papers to read. The thematic synthesis of our review involved the creation of standardized summaries for each source that identified the year of publication, whether it was a journal article or conference paper, the context of the research, technology type, level of analysis (work practice, organizational or societal), research method, topic areas, and key findings. For the purposes of this chapter, we used the level of analysis categorization to extract items that focused on intelligent machines at the work practice level, resulting in a subsample of 84 publications. (Only those cited in this chapter are included in the References section; the Appendix lists all 84 references). During the in-depth coding, we identified several topic areas related to the impacts of intelligent machines on (service or knowledge) work. We discussed each of these topic areas and classified them into three broad categories: *human relations with intelligent machines, adoption and acceptance of intelligent machines*, and *ethical issues associated with machine-human collaboration*.

Before presenting the findings, it is useful to give an overview of the analyzed sample. Peer reviewed papers made up 79% of the sample, conference papers constituted 19%, and the remaining 2% of sources were working papers. Just over half (54%) of the sources were based on empirical studies, with the remainder either narrative discussions of selected literature and conceptual papers (31%) or thought-leading articles (13%). The embryonic nature of knowledge on the issues examined here is further reinforced by the method of data used in the empirical studies: the most common empirical methods (35%) were a "proof of concept" experiment, with case studies and survey research accounting for 25% and 23%, respectively. Much of the reviewed research was undertaken in the Sciences with Engineering and Technology (18%), Medicine, Dentistry, and Allied Health (15%), Computer Science (14%), and Behavioral Sciences (13%), contributing 60% of the sources. Social Sciences contributed a more modest 32% of the research literature, suggesting that current studies have been techno-centric in their focus and that a wider social-centric view is presently lacking. The following sections discuss the three main themes that emerged.

Changing Human Relations with Intelligent Machines

Human-Robot Interaction

Several studies have documented examples of humans using robots to complement and, in some cases, extend their abilities to complete specific social interaction tasks. The majority of these studies have been undertaken in health or social care settings.

For example, Huijnen, Lexis, Jansens, and de Witte (2016) discuss the use of humanoid robots to interact with children with autism spectrum disorders (ASD). Following a systematic review of the literature and focus groups with 53 ASD professionals, they report that a range of different humanoid robots had been found to be an effective aid for supporting health care professionals interviews with children with ASD, because the robot provides more predictable and clearly defined cues compared to human-to-human interaction. Huijnen et al. (2016) observe that the most common use of the robot was through remote-control in which an ASD professional operates the behavior of the robot, rather than a fully autonomous robot. Therefore, the ASD professional is needed to read the social situation with the child and control the robot accordingly. Interestingly, Huijnen et al. (2016) add that this approach also creates an additional increase in workload on the professional, and that often additional technical personnel are required to operate the robot.

Khosla et al. (2013) reported on three field trials of Matilda, a human-like affective communication (service and companion) robot in care homes for the elderly in Australia. The robot combines human communication tools (e.g., speech recognition) with artificial intelligence programs (e.g., emotionally intelligent, persuasive, diet suggestion dialog system). They found that the robot had the potential to increase the capacity of care homes to provide care and also improve the well-being of the elderly. For example, the elderly residents were keen for Matilda to participate in group activities and play games like Bingo and Hoy with them. Normally, a care worker would be required to be involved with calling the numbers for these games. However, Khosla et al. (2013) report that the residents did not miss the care giver that would normally have led the game. The researchers also refer to one of the residents performing a spontaneous clap and dance after winning the game, as evidence of improved well-being. However, although a care worker is no longer needed to perform the bingo calling task, the caregivers are free to complete additional care tasks, as well as deciding when to introduce and remove Matilda from the care environment and also monitoring the interaction between elderly residents and the robot.

A further example concerns the application of robotics to undertake particular surgical procedures. In this case, the robot assists the surgeon to complete manipulation and mobility tasks in a remote physical environment in correspondence to continuous control movements by the remote human (Sheridan, 2016). In a five year study of 116 children De Benedictis et al. (2017) found that robotic surgery (the application of the ROSA device, or Robotized Stereotactic Assistant) in pediatric neurosurgery improves safety and reduces intrusiveness of procedures. The ROSA system is composed of a compact robotic arm and a touch screen, mounted on a mobile trolley for surgical procedures involving the head of the patient. The surgeon can either supervise as the robot performs autonomously or directly control the surgical instrument during the procedure. The ROSA system combined human decision making with the accuracy of machine technology by improving ergonomics, visualization, and the haptic ability of the surgeon. However, again, the example illustrates that the surgeon works alongside the robot, either supervising or controlling the robot, rather than being replaced by the machine.

Human-Robot Hybrid Teams

An interesting vein of research is focusing on how workers collaborate with advanced robots in hybrid robot/worker teams. Schwartz, Krieger, and Zinnikus (2016) describe the conceptual organization of a hybrid team consisting of humans, robots, virtual characters, and softbots that combine artificial intelligence and robotics. They believe that a key challenge in establishing such hybrid teams is establishing intuitive interfaces between humans that typically usually use speech, gestures and facial expressions to transfer information, and intelligent machines that can use data streams to communicate with the system and other artificial team members. They add that the development of (robotic) team-competencies is also necessary to determine a suitable balance between autonomous behaviors of individual machines and coordinated teamwork. In experiments, Gombolay et al. (2015) found that when people work with robots they may actually allocate more work to themselves than to their robot co-worker because of their preferences for completing particular tasks, such as assembling compared to fetching. It was also found that people attribute greater value to human team members in comparison to robot team members. However, greater robot-autonomy positively affected the participants' desire to work with the robot again.

In an experimental study, Mubin et al. (2014) investigated the role of a robot assistant in office meetings. They constructed a hypothetical scenario of selecting a suitable job candidate with human subjects acting as members of a selection panel tasked with achieving agreement consensus regarding the most suitable candidate. The robot assistant was remotely controlled and was either dynamic and interactive (e.g., reminding the subjects that success would lie in sharing information), or passive (e.g., the robot would only interact when requested by the human subjects). Mubin et al. (2014) found that the human subjects preferred the more interactive robot as a partner in meetings compared to the passive robot, but also that the human subjects interacted with each other more than they did with the robot. They concluded that humans might be willing to engage and interact with, and even receive guidance from, a robot in the form of an active assistant, but not as a replacement for the human partner.

In sum, these studies provide several examples of AI and robots working in collaboration to enhance the working practices of knowledge and service workers. These intelligent machines appear to be assisting and augmenting existing work practices, in some cases replacing a small routine and repetitive task: for example, the ASD professional using a robot as an advanced form of ventriloquist dummy to interview child patients, the care worker no longer acting as bingo caller, and the surgeon being able to perform more precise surgical procedures. In these situations, the intelligent machine appears to be seen as a helpful additional aid to complete tasks in knowledge and service work. The intelligent machine is welcome in teams when the working circumstances allow people to take on a proportionate amount of work in line with their task preferences (Gombolay et al., 2015; Schwartz et al., 2016), and it does not add extra responsibility, such as monitoring the robot's work, to the human team members.

Adoption and Acceptance of Intelligent Machines

Following on from the exploration of human relations with robots, the adoption and acceptance of intelligent machines in practice has been researched most extensively in the health care and transport sectors. It has been suggested that the logistics of using robotic surgery, investment of time, and storage of bulky equipment may influence the adoption of the technologies, especially as it is deemed more expensive to run (Sananès et al., 2011). Sananes et al. (2011) argue that when there are operating theatres dedicated to robotic surgery, some of these logistical problems will no longer be an issue. In other cases, the technology requires less physical management. For example, Robotic Process Automation (RPA) is a software solution (essentially a software license) configured to do the work previously undertaken by humans, for example, structured tasks associated with validating the sale of insurance premiums, generating utility bills, creating news stories, paying health care insurance claims, and keeping employee records up to date (Willcocks et al., 2015). Other robots have rather more modest aspirations: Nielsen et al. (2016) found that robots being used to perform mundane tasks such as vacuuming were well received by managers in care home settings, mainly within the context of trying to modernize care of the elderly. The vacuum cleaners were viewed by managers as affordable and effective. However, clients held mixed views towards robot vacuum cleaning—some not happy with quality of cleaning or the reduction of contact with staff, whilst others enjoyed the "on-demand" nature of vacuuming.

Trust in AI and Robots

Over and above the practical issues of adoption, a clear factor for acceptance of AI and robots is trust. Trust in the technology was reported as important for air traffic controllers' willingness to accept increased levels of automation in two hypothetical scenarios (Bekier, Molesworth, & Williamson, 2011) and trust was also identified as important for the human acceptance of AI enabled autonomous cars (Hengstler et al., 2016). Findings of a study by Kolbjørnsrud et al. (2017) show that managers have mixed feelings about AI, and that top managers are more enthusiastic than mid/front-line managers. When asked if they are comfortable with AI monitoring and evaluating their work, participants' responses again became more negative lower in the management hierarchy. Kolbjørnsrud et al. (2017) hint that this may be due to apprehension about the threat of job losses as a result of AI implementation, although the study does not explicitly explore what underpins these differences. It is possible to make distinctions between fostering trust and enhancing confidence, as suggested by Pieters' (2011) study on cyber security and AI. There, system users' trust was fostered through explanations about the security and processes of the system (thus requiring an opening of the "black box"), and confidence was enhanced through explanations about the validity of the decisions themselves (here the "black box" can remain closed).

Cultural differences to AI were also noted, with managers in emerging economies (e.g. India, China and Brazil) more open to the technology (Kolbjørnsrud et al., 2017). Some suggest that, where appropriate, unions should be involved in consultations regarding the implementation of AI and robots. Further, the variability of the manual system and work practices should be fully understood by the integrator before the automated system is implemented (Charalambous, Fletcher, & Webb, 2015). It is also advised that in order to enhance trust in these new technologies, more support should be given to employees as their roles change from being workers to becoming supervisors of automated processes (Charalambous et al., 2015).

In sum, the findings of the literature in this area suggests that to facilitate the adoption and acceptance of intelligent machines it is necessary to create a suitable workplace environment, in terms of physical configuration and design. Top managers wishing to adopt intelligent machines may need to convince less senior managers that the implementation of AI or robotics will lead to positive change. In particular, less senior managers are likely to be concerned about worker fears regarding the loss of tasks and ultimately jobs, or about role changes. For example, service workers such as cleaners may see the introduction of robot vacuum cleaners as a threat to their long-term job security or may be apprehensive regarding new role expectations of having responsibility for checking and monitoring robot vacuum cleaner performance. There may also be a need for managers to provide support to knowledge workers to adjust to working with and following decision support provided by intelligent machines, such as supporting air traffic controllers' development of trust in AI decision making for choosing aircraft flight patterns. Again, changes in work roles and responsibilities may be a crucial area to be agreed regarding critical task outcomes. If the new AI system for aircraft flight control recommends an incorrect decision that the air traffic controller implements, where does the responsibility for this decision reside? These types of ethical issues are considered in the followings section.

Ethical Issues Associated with Machine-Human Collaboration

Intelligent machines are already present in many areas of our society (Friend, 2018) and will play an increasing role in our work and overall lives in the future. The more advanced intelligent machines become (e.g., more human-like androids), the more blurred the physical, psychological, and social boundaries between machines and humans will be. For example, robots will be "looking" after clinical patients, educating students, and making complex financial or security decisions (e.g., Luxton, 2014; Torras, 2015). While the experienced and anticipated benefits of these technologies for individuals, organizations and societies are apparent (e.g., Calo et al., 2011; Luxton, 2014), rapid technological developments in this area may also posit some serious risks. For example, using simulations for patients with delusional or psychotic psychopathologies in the absence of careful monitoring may put the health of these patients at a great risk (Luxton, 2014). Torras (2015) warns about potential negative impacts of robot nannies on children's psychological development. For instance, how could a robot achieve a balance between protecting a child from danger and restricting his/her freedom (hence, affecting the child's development to become mature and autonomous)? Such progressing interactions between machines and humans are psychologically complex and evoke some important ethical questions. Thus, a robust ethical strategy that will ensure the safe use of advanced technologies becomes an imperative (e.g., Luxton, 2014; Torras, 2015). The following paragraphs present two key emerging themes associated with intelligent machine-related ethical issues in a work context; safety and risks during human-machine relations, and responsibility and accountability for intelligent machines.

Safety and Risks during Human-Machine Relations

Luxton (2014) hypothesizes a number of ethical issues related to artificial intelligence care providers (AICPs) in mental health and in care professions (e.g., medicine, nursing, social work, education, and ministry) in general. Most of these refer to safety of a human-machine interaction. AICPs may exist in various forms and interact with users (e.g., patients) in different ways. For instance, AICPs may be avatars (virtual simulations), social robots (either humanoid or non-humanoid), as well as non-embodied systems (e.g., audio simulations). Many current "caring" machines are designed to "read" emotions and behavioral signals, and even simulate emotions and empathetic understanding. Thus, boundaries between humans and machines may become less obvious and in some extreme cases lead to "Turing Deceptions" (i.e., the inability of a human to determine if s(he) is interacting with a machine or not). This could be a significant ethical issue, especially in situations involving vulnerable people (such as children or clinical patients; Bryson, 2016). For example, Weizenbaum (Luxton, 2014) found that even when patients who interacted with an AI-simulated psychotherapist knew that it was just software, they still considered it a real therapist. A further illustration of such a situation is the case of Paro, a robotic baby seal used for therapeutic purposes with patients with mid- and advanced dementia (Calo et al., 2011). Paro is intended to be a replacement of social interaction with people or animals and is labelled as a Class 2 medical device by the U.S. Food and Drug Administration. Practically, Paro is considered a type of non-medication anti-depressant. Calo et al. (2011) argued that despite some hypothesized risks (e.g., of evoking empathetic response in patients, who are deceived by the robot's appearance), Paro can be highly beneficial for the patients' health, if used appropriately and competently. Hence, the related ethical issue here is not so much about whether, but how, to use intelligent machines.

"Healthy" machine-user interactions can also be secured through transparent information about a robot's characteristics, as well through limiting an intelligent machine's capabilities to a specific context (Bostrom & Yudkowsky, 2011; Bryson, 2016; Kinne & Stojanov, 2014). With regard to transparency of information, Bostrom and Yudkowsky (2011) suggest that "it will become increasingly important to develop AI algorithms that are not just powerful and scalable, but also transparent to inspection" (p. 1). More recent publications (e.g., Bryson, 2016) report the development of sets of guidelines for designers and users of intelligent machines. These guidelines (also known as "Principles of Robotics") emphasize the need of transparency, which Bryson explains as "…clear, generally comprehensible descriptions of their [robots] goals should be available to any owner, operator, or other concerned party" (Bryson, 2016, p. 205). Moreover, Kinne and Stojanov (2014) discuss the ethical issues associated with using Lethal Autonomous Weapon System (LAWS) and emphasize the importance of the specific context. For example, there might be situations in which an intelligent machine is superior in its ethical behavior to a human ethical judgement. Unlike humans, machines in a given context would not be susceptible to emotions, which can present a risk compromising ethical decisions. Notably, in order to be able to socially accept and properly utilize a human-machine interaction, humans should be aware of how (and within what boundaries) to interact/collaborate with intelligent systems.

Responsibility and Accountability for Intelligent Machines

Luxton (2014) emphasizes the importance of competency levels of the AICPs users for avoiding putting patients at risk. Competency refers to both the design and ethical use of intelligent machines. Increased complexity of AI systems causes greater difficulty in the prediction and interpretation of machine behaviors and, therefore, presents higher risks for the humans' safety (e.g., Friend, 2018). Also, with the evolution of intelligent machines the boundaries between the role of humans and machines may become less clear and, therefore, more difficult to manage (Bostrom & Yudkowsky, 2011; Johnson, 2014). In addition, when large numbers of people have been involved in the design and use of intelligent machines, it is not always obvious who the responsible individuals are. Examples in this area refer to a variety of sectors including scenarios about the use of robotic health care assistants, autonomous vehicles, AI in banking and commerce, etc. (e.g., Luxton, 2014; Torras, 2015). Both scientists and practitioners have vigorously argued about who should take responsibility, and at what point, for the (potential) negative consequences of the applications of intelligent machines (e.g., Johnson, 2014). One point upon which most authors agree is that the ultimate responsibility should lie with the human stakeholders (i.e., machine designers, manufacturers, implementers, and users (e.g., Luxton, 2014).

In sum, literature suggests that the transition of intelligent machines into the domain of knowledge and service work, a domain that had been solely the purview of humans, may present a number of ethical challenges, such as avoiding the creation of Turing

Deceptions at the work practice level. The studies provide examples of situations where such problems arise with human patients anthropomorphizing AI simulated psychotherapists or therapy robots such as Paro. Researchers argue that it will be important to focus on the transparency of information in intelligent machines and whether a human or machine is making the decisions. This transparency also has important implications for responsibility and accountability debates regarding knowledge and service work. As knowledge and service work becomes more augmented by intelligent machines and the boundaries of tasks and roles blur, decisions regarding responsibility and accountability will become even more complex.

The previous sections have described three key themes that emerged from the literature review regarding how intelligent machines may change knowledge and service work. In the following section we present an agenda for research in these areas.

Agenda for Future Research

The broad review of the literature related to recent developments in intelligent machines and their potential impact on service and knowledge work practices grounds the following agenda for future research. First, we discuss cross-cutting requirements for future multi-disciplinary, context-sensitive empirical research related to intelligent machines' impacts on knowledge and service work. Second, we consider the research priorities for each of the three themes that emerged from the literature review.

Cross-cutting Requirements

Multi-disciplinary research. First, the emerging notion of intelligent machines is multifaceted. It is associated with a variety of academic subjects and complex sociotechnical systems. For example, our review reveals that researchers have investigated the ethical issues associated with AI and robots from Computer Science (Bryson, 2016), Engineering (Johnson, 2014), Robotics and Industrial Informatics (Torras, 2015) and Philosophy perspectives (Michelfelder, 2011). Hence, it can be best studied through the adoption of a multi-disciplinary approach that is focused upon multiple stakeholders (e.g., the human designers, manufacturers, and users of machines, policymakers, regulators, and the intelligent machines themselves) and accounts for a wide range of person, social, technical, legal, and environmental factors.

Contextual focus. Although the importance of studying intelligent machines in specific contexts has been acknowledged, only a small number of recent studies have attempted to address organizational or work-specific topics (e.g., Dogan et al., 2016; Kinne & Stojanov, 2014; Luxton, 2014). Most of the existing published literature refers to general issues associated with intelligent machines and future-oriented scenarios. Future research should aim to capture work-specific themes along with key general issues and, thus, ensure a more in-depth knowledge of both the concept and the practical manifestations of intelligent machines. For example, linking back to the theme of changing human relations with intelligent machines, the speculative and experimental literature on human-robot dynamics in hybrid teams (e.g., Schwartz et al., 2016; Gombolay et al., 2015) raises questions about how humans team/co-work with intelligent machines, in relation to decision-making authority over scheduling decisions, for example. While there is an extensive body of literature of human-computer interaction, future research needs to examine in rich detail the nature of this dynamic, in ways which take account of ongoing technological developments in AI systems to communicate via increasingly human-like speech etc. The more human-like these systems become, the greater the implications for human-technology dynamics and interactions.

Empirical research. While this review has focused on empirically grounded analysis, the majority of the current academic literature on these issues proposes theoretical models or laboratory proof of concept experiments of intelligent machines rather than offering empirical evidence. In the future, research should move on to more empirical exploration of the context-specific issues. Given the complex nature of the topic, we recommend a mixed-method approach involving the use of both qualitative and quantitative research designs (e.g., experiments, real-time measurements, stakeholder surveys, focus groups, case studies, system-collected usage data). For example, the theme on the adoption and acceptance of these technologies highlighted the importance of human/user trust in technology for its implementation and use to be effective. Arguably, something like a longitudinal, mixed-methods, case study-based approach has the ability to capture data on how the attitudes and trust levels of different stakeholders (managers, IT staff, users etc.), dynamically evolve during the implementation and use of AI systems.

Research Priorities for the Three Themes

Investigating changing human relations with intelligent machines. It is clear from the literature that the nature of the relationship between humans and intelligent machines is changing. Studies suggest that the social aspect of human-machine interaction is an important mediating (and moderating) factor for the successful realization of the benefits from automation. For example, the literature on the use of robots in the provision of care for the elderly and those in care homes (e.g., Metzler, Lewis, & Pope, 2016; Nielsen et al., 2016) raises questions about how the success of such technologies will be shaped by factors such as user attitudes, and the extent to which it is perceived that robots and AI are able to provide the type of emotional support and care currently provided by human nurses and care staff. Thus, further research that examines mediating factors of human-machine relations, such as user perceptions of AI to provide emotional care and support, would provide a useful context to interpret how quickly we are likely to embrace these new technologies, how to foster more positive outcomes, and how to prevent or mitigate more negative ones.

We suggest that in-depth empirical studies drawing on ethnographic methods on real-life case studies (rather than in experimental settings) would offer crucial insights into the relationships between robots and humans in the workplace, which may discover interesting examples of how intelligent machines are assimilated and/or subverted in practice. Being sensitive to the idea of "subversion via practice" is important, as the way any technology is used and appropriated is often different from how it is designed, with user adaptation having significant implications for technology use (Beaudry & Pinsonneault, 2005). Thus, with the implementation and use of any form of AI, or advanced robotics, account needs to be taken of this, which can only be done via in-depth qualitative studies, which are sensitive to the micro-level subtleties of user behavior and intention. Aiming to include a range of case studies from different countries, sectors, and organization sizes would also enable research to begin unpacking some of the contextual factors that have only been hinted at so far.

Investigating the adoption and acceptance of intelligent machines. Much of the research in this review discusses intelligent machines in terms of complementing and extending human capabilities rather than removing humans from work processes. The concept of *augmentation* of humans and human work in a range of ways, rather than wholesale replacement from robotized job automation, flows through the literature across a range of domains (Davenport & Kirby, 2016). However, future research needs to better account for the "multi-layered" nature of the work that humans carry out and where automation fits. For example, the case of robot assisted surgery (e.g., De Benedictis et al., 2017; Sananès et al., 2011) represents an important and interesting context where AI and to robotics are augmenting the work of surgeons. Future research needs to examine, in a fine-grained way, the diverse ways in which surgical work is changed, where some aspects/roles/tasks may remain unchanged, and while others are radically transformed. To gain a more accurate understanding of these issues a large-scale cross-country survey study on experiences with implementation, trust issues, and feelings of confidence might be a suitable research strategy. The inclusion of participant employment information with regard to contract types, level, and job role would also help to find out more about how users' position in organizational hierarchies shapes their experiences with innovative technologies in the workplace.

Investigating intelligent machine-related ethical issues. The review highlights that some key ethical issues such as safety, accountability, and liability related to intelligent machines need further attention (e.g., Bryson, 2016; Johnson, 2014; Luxton, 2014; Yampolskiy & Fox, 2013). For instance, further research is needed on whether AI can or should be afforded moral agency or patience (Bryson, 2016); how the responsibility arrangements for intelligent machines will be negotiated and worded as the technology is being developed, tested, put into operation, and used (Johnson, 2014); who should be held responsible in a complex sociotechnical system with multiple human stakeholders (Luxton, 2014); and how, for the sake of humans' safety, the development and testing of advanced AI can be confined to a highly controlled environment (e.g. via a formalized confinement protocol) and thus directed by the human machine designers in accordance to the latest developments of machine ethics (Yampolskiy & Fox, 2013). Further, the current literature presents only a few examples of early attempts to create AI-related legal and policymaking frameworks (Bryson, 2016). Zeng (2015) highlights that current legislation refers mostly to low-tech technologies, leaving advanced AI systems unregulated. Consequently, the legal and policymaking approaches to AI ethics are reactionary (i.e., triggered sporadically by accidents that occur) rather than holistic (i.e., generally preventative; Ambrose, 2014). Further research that examines how legal and policy decisions are debated, agreed and implemented is needed to understand how different societies are responding to the challenges and opportunities intelligent machines present for knowledge and service work. Research that compares the emerging policy responses and regulatory systems proposed by different national governments may provide valuable insights regarding ethical concerns related to the adoption of intelligent machines.

Conclusion

The evidence so far, such as it is, suggests that intelligent machines (here, AI and robots) are augmenting what people are doing and enabling some degree of role expansion for employees. Key questions are still open and require further analysis based on evidence of how intelligent machines are being developed and implemented in practice, and how workers and humans interacting with these machines experience these changes. However, it is important to keep in mind that workers, organizations, governments, and society have the power to shape the future use of these new technologies. The future is malleable, but it is up to us to be pro-active in shaping it.

Acknowledgments

Funding Acknowledgement and Disclaimer: The Chartered Institute of Personnel and Development (CIPD) funded the initial data collection for this study. The views expressed are those of the authors and not necessarily those of the CIPD.

References

Ambrose, M. L. (2014). The law and the loop. In IEEE *international symposium on ethics in science, technology and engineering, ETHICS 2014*. Chicago. http://doi.org/10.1109/ETHICS.2014.6893374

Arntz, M., Gregory, T., & Zierahn, U. (2016). *The risk of automation for jobs in OECD countries: A comparative analysis* (No. 189). Retrieved from www.oecd.org/els/workingpapers

Beaudry, A., & Pinsonneault, A. (2005). Understanding user responses to information technology: A coping model of user adaptation. *MIS Quarterly*, *29*(3), 493–524.

Bekier, M., Molesworth, B. R., & Williamson, A. (2011). Defining the drivers for accepting decision making automation in air traffic management. *Ergonomics*, *54*(4), 347–356. http://doi.org/10.1080/00140139.2011.558635

Bell, D. (1973). *The coming of post-industrial society*. Harmondsworth: Penguin.
Bostrom, N., & Yudkowsky, E. (2011). The ethics of artificial intelligence. In K. Frankish & W. Ramsey (Eds.), *Cambridge handbook of artificial intelligence* (pp. 1–20). New York: Cambridge University Press. http://doi.org/10.1016/j.mpmed.2010.10.008
Brynjolfsson, E., & McAfee, A. (2016). *The second machine age—work, progress, and prosperity in a time of brilliant technologies*. New York and London: WW Norton & Co.
Bryson, J. J. (2016). Patiency is not a virtue : Intelligent artefacts and the design of ethical systems. In *Association for the Advancement of Artificial Intelligence* (pp. 1–18). Phoenix. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.299.5725
Burkhard, H.-D. (2013). Let the machines do. How intelligent is artificial intelligence? In *36th international convention on information and communication technology, electronics and microelectronics (MIPRO)* (pp. 947–952). Opatija.
Calo, C. J., Hunt-Bull, N., Lewis, L., & Metzler, T. (2011). Ethical implications of using the Paro robot with a focus on dementia patient care. In *Association for the Advancement of Artificial Intelligence workshop* (Vol. WS-11–12, pp. 20–24). San Francisco, CA. Retrieved from http://www.scopus.com/inward/record.url?eid=2-s2.0-80,054,913,481&partnerID=40&md5=cf9ad1b74f81299aa3f48be4f8e9700f
Charalambous, G., Fletcher, S., & Webb, P. (2015). Identifying the key organisational human factors for introducing human-robot collaboration in industry: An exploratory study. *International Journal of Advanced Manufacturing Technology*, *81*(9–12), 2143–2155. http://doi.org/10.1007/s00170-015-7335-4
Chen, L. (2013). The application of robots and eye tracking devices in a general dentist's clinic. In *IEEE third international conference on consumer electronics* (pp. 5–7). Berlin.
Davenport, T. H., & Kirby, J. (2016). *Only humans need apply: Winners and losers in the age of smart machines*. New York: Harper Business.
De Benedictis, A., Trezza, A., Carai, A., Genovese, E., Procaccini, E., Messina, R., . . . Marras, C. E. (2017). Robot-assisted procedures in pediatric neurosurgery. *Neurosurgical Focus*, *42*(5), 1–12. http://doi.org/10.3171/2017.2.FOCUS16579
DeCanio, S. J. (2016). Robots and humans—complements or substitutes? *Journal of Macroeconomics*, *49*, 280–291. http://doi.org/10.1016/j.jmacro.2016.08.003
Dilsizian, S. E., & Siegel, E. L. (2014). Artificial intelligence in medicine and cardiac imaging: Harnessing big data and advanced computing to provide personalized medical diagnosis and treatment. *Current Cardiology Reports*, *16*(441), 1–8. http://doi.org/10.1007/s11886-013-0441-8
Dogan, E., Chatila, R., Chauvier, S., & Evans, K. (2016). Ethics in the design of automated vehicles: The AVEthics project. In *1st workshop on ethics in the design of intelligent agents* (pp. 1–6). The Hague.
Dorf, R. C., & Kusiak, A. (1994). *Handbook of design, manufacturing, and automation*. London and New York: Wiley.
Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. http://doi.org/10.1016/J.TECHFORE.2016.08.019
Friend, T. (2018, May). How frightened should we be of A.I.? *The New Yorker*, 1–19. Retrieved from https://www.newyorker.com/magazine/2018/05/14/how-frightened-should-we-be-of-ai
Gombolay, M. C., Huang, C., & Shah, J. A. (2015). Coordination of human-robot teaming with human task preferences. In *AAAI Fall symposium series on AI-HRI*. Arlington.

Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust: The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change*, *105*, 105–120. http://doi.org/10.1016/j.techfore.2015.12.014

Hislop, D., Bosua, R., & Helms, R. (2018). *Knowledge management in organisations: A critical introduction* (4th ed.). Oxford: Oxford University Press.

Huijnen, C. A G. J., Lexis, M. A S., Jansens, R., & de Witte, L. P. (2016). Mapping robots to therapy and educational objectives for children with autism spectrum disorder. *Journal of Autism and Developmental Disorders*, *46*(6), 2100–2114. http://doi.org/10.1007/s10803-016-2740-6

Johnson, D. G. (2014). Technology with no human responsibility? *Journal of Business Ethics*, *127*, 707–715. http://doi.org/10.1007/s10551-014-2180-1

Khangura, S., Konnyu, K., Cushman, R., Grimshaw, J., & Moher, D. (2012). Evidence summaries: The evolution of a rapid review approach. *Systematic Reviews*, *1*(1), 10. http://doi.org/10.1186/2046-4053-1-10

Khosla, R., Chu, M. T., & Nguyen, K. (2013). Affective robot enabled capacity and quality improvement of nursing home aged care services in Australia. In *IEEE 37th annual computer software and applications conference workshops* (pp. 409–414). Kyoto. http://doi.org/10.1109/COMPSACW.2013.89

Khouja, M., & Offodile, o Felix. (1994). The industrial robots selection problem: Literature review and directions for future research. *IIE Transactions*, *26*(4), 50–61. http://doi.org/10.1080/07408179408966618

Kinne, E., & Stojanov, G. (2014). Grounding drones' ethical use reasoning. In *Association for the Advancement of Artificial Intelligence* (pp. 231–235). Québec City.

Kolbjørnsrud, V., Amico, R., & Thomas, R. J. (2017). Partnering with AI: How organizations can win over skeptical managers. *Strategy & Leadership*, *45*(1), 37–43. http://doi.org/10.1108/SL-12-2016-0085

Kuusisto, J., & Meyer, M. (2003). *Insights into services and innovation in the knowledge intensive economy*. *Technology Review, 134*. Helsinki: Tekes. Retrieved from https://www.tekes.fi/globalassets/julkaisut/insights.pdf

Loebbecke, C., & Picot, A. (2015). Reflections on societal and business model transformation arising from digitization and big data analytics: A research agenda. *Journal of Strategic Information Systems*, *24*, 149–157. http://doi.org/10.1016/j.jsis.2015.08.002

Luxton, D. D. (2014). Recommendations for the ethical use and design of artificial intelligent care providers. *Artificial Intelligence in Medicine*, *62*(1), 1–10. http://doi.org/10.1016/j.artmed.2014.06.004

Metzler, T. A., Lewis, L. M., & Pope, L. C. (2016). Could robots become authentic companions in nursing care? *Nursing Philosophy*, *17*(1), 36–48. http://doi.org/10.1111/nup.12101

Michelfelder, D. P. (2011). Dirty hands, speculative minds, and smart machines. *Philosophy and Technology*, *24*(1), 55–68. http://doi.org/10.1007/s13347-010-0009-0

Mubin, O., D'Arcy, T., Murtaza, G., Simoff, S., Stanton, C., & Stevens, C. (2014). Active or passive? Investigating the impact of robot role in meetings. In *IEEE international workshop on robot and human interactive communication* (pp. 580–585). Edinburgh. http://doi.org/10.1109/ROMAN.2014.6926315

Nielsen, J. A., Andersen, K. N., & Sigh, A. (2016). Robots conquering local government services: A case study of eldercare in Denmark. *Information Polity*, *21*(2), 139–151. http://doi.org/10.3233/IP-160381

Niu, J., Tang, W., Xu, F., Zhou, X., & Song, Y. (2016). Global research on artificial intelligence from 1990–2014: Spatially-explicit bibliometric analysis. *International Journal of Geo-Information*, *5*(66), 1–19. http://doi.org/10.3390/ijgi5050066

Pieters, W. (2011). Explanation and trust: What to tell the user in security and AI? *Ethics and Information Technology*, *13*(1), 53–64. http://doi.org/10.1007/s10676-010-9253-3
Reich, R. (1991). *The work of nations: Preparing ourselves for 21st-century capitalism*. London: Simon & Schuster.
Sananès, N., Garbin, O., Hummel, M., Youssef, C., Vizitiu, R., Lemaho, D., ... Wattiez, A. (2011). Setting up robotic surgery in gynaecology: The experience of the Strasbourg teaching hospital. *Journal of Robotic Surgery*, *5*(2), 133–136. http://doi.org/10.1007/s11701-010-0231-x
Schwartz, T., Krieger, H., & Zinnikus, I. (2016). Hybrid teams : Flexible collaboration between humans, robots and virtual agents. In *Proceedings of the 14th German conference on multiagent system technologies* (pp. 131–146). Klagenfurt.
Sheridan, T. B. (2016). Human-robot interaction: Status and challenges. *Human Factors*, *58*(4), 525–532. http://doi.org/10.1177/0018720816644364
Torras, C. (2015). Social robots: A meeting point between science and fiction. *MÈTODE Science Studies Journal*, *5*, 111–115. http://doi.org/10.7203/metode.82.3546
Wang, C.-M., Tseng, S.-H., Wul, P.-W., Xu, Y.-H., Liao, C.-K., Lin, Y.-C., ... Fu, L.-C. (2013). Human-oriented recognition for intelligent interactive office robot. In *13th International conference on control, automation and systems* (pp. 960–965). Gwangju. http://doi.org/10.1093/gbe/evv015
Willcocks, L., Lacity, M. C., & Craig, A. (2015). *The IT function and robotic process automation*. The Outsourcing Unit Working Research Paper Series. London. http://eprints.lse.ac.uk/64519/1/OUWRPS_15_05_published.pdf
Xu, S., Tu, D., He, Y., Tan, S., & Fang, M. (2013). ACT-R-typed human–robot collaboration mechanism for elderly and disabled assistance. *Robotica*, *32*(November 2013), 1–11. http://doi.org/10.1017/S0263574713001094
Yampolskiy, R., & Fox, J. (2013). Safety engineering for artificial general intelligence. *Topoi*, *32*(2), 217–226. http://doi.org/10.1007/s11245-012-9128-9
Yu, Q., Yuan, C., Fu, Z., & Zhao, Y. (2012). An autonomous restaurant service robot with high positioning accuracy. *The Industrial Robot*, *39*(3), 271–281. http://doi.org/10.1108/01439911211217107
Zaghloul, A. S., & Mahmoud, A. M. (2016). Preliminary results of robotic colorectal surgery at the National Cancer Institute, Cairo University. *Journal of the Egyptian National Cancer Institute*, *28*(3), 169–174. http://doi.org/10.1016/j.jnci.2016.05.003
Zeng, D. (2015). AI Ethics: Science fiction meets technological reality. *IEEE Intelligent Systems*, *3*, 2–5.

Appendix: Publications Analyzed

Abdel Raheem, A., Song, H. J., Chang, K. D., Choi, Y. D., & Rha, K. H. (2017). Robotic nurse duties in the urology operative room: 11 years of experience. *Asian Journal of Urology*, *4*(2), 116–123. http://doi.org/10.1016/j.ajur.2016.09.012
Albu, A., & Stanciu, L. (2015). Benefits of using artificial intelligence in medical predictions. In *2015 e-health and bioengineering conference (EHB)* (pp. 1–4). Iasi. http://doi.org/10.1109/EHB.2015.7391610
Alizadehsani, R., Zangooei, M. H., Hosseini, M. J., Habibi, J., Khosravi, A., Roshanzamir, M., ... Nahavandi, S. (2016). Coronary artery disease detection using computational intelligence methods. *Knowledge-Based Systems*, *109*, 187–197. http://doi.org/10.1016/j.knosys.2016.07.004

Amershi, S., Fogarty, J., Kapoor, A., & Tan, D. (2011). Effective end-user interaction with machine learning. In *Proceedings of the twenty-fifth AAAI conference on artificial intelligence* (pp. 1529–1532). San Francisco. http://doi.org/10.1145/2046396.2046416

Amrit, C., Paauw, T., Aly, R., & Lavric, M. (2017). Identifying child abuse through text mining and machine learning. *Expert Systems with Applications*, *88*, 402–418. http://doi.org/10.1016/j.eswa.2017.06.035

Aron, R., Dutta, S., Janakiraman, R., & Pathak, P. A. (2011). The impact of automation of systems on medical errors : Evidence from field research. *Information Systems Research*, *22*(3), 429–446.

Autor, D. H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives*, *29*(3), 3–30. http://doi.org/10.1257/jep.29.3.3

Balfe, N., Sharples, S., & Wilson, J. R. (2015). Impact of automation: Measurement of performance, workload and behaviour in a complex control environment. *Applied Ergonomics*, *47*, 52–64. http://doi.org/10.1016/j.apergo.2014.08.002

Balkin, T. J., Horrey, W. J., Graeber, R. C., Czeisler, C. a., & Dinges, D. F. (2011). The challenges and opportunities of technological approaches to fatigue management. *Accident Analysis and Prevention*, *43*(2), 565–572. http://doi.org/10.1016/j.aap.2009.12.006

Balram, N., Tošić, I., & Binnamangalam, H. (2016). Digital health in the age of the infinite network. In *APSIPA Transactions on Signal and Information Processing* (Vol. 5, pp. 1–13). Cambridge. http://doi.org/10.1017/ATSIP.2016.6

Baril, C., Gascon, V., & Brouillette, C. (2014). Impact of technological innovation on a nursing home performance and on the medication-use process safety. *Journal of Medical Systems*, *38*(3), 1–12. http://doi.org/10.1007/s10916-014-0022-4

Bekier, M., Molesworth, B. R., & Williamson, A. (2011). Defining the drivers for accepting decision making automation in air traffic management. *Ergonomics*, *54*(4), 347–356. http://doi.org/10.1080/00140139.2011.558635

Bennett, C. C., & Hauser, K. (2013). Artificial intelligence framework for simulating clinical decision-making: A Markov decision process approach. *Artificial Intelligence in Medicine*, *57*(1), 9–19. http://doi.org/10.1016/j.artmed.2012.12.003

Bocci, T., Moretto, C., Tognazzi, S., Briscese, L., Naraci, M., Leocani, L., … Sartucci, F. (2013). How does a surgeon's brain buzz? An EEG coherence study on the interaction between humans and robot. *Behavioral and Brain Functions : BBF*, *9*(1), 1–12. http://doi.org/10.1186/1744-9081-9-14

Bogue, R. (2011). Robots in the nuclear industry: A review of technologies and applications. *Industrial Robot: An International Journal*, *38*(2), 113–118. http://doi.org/10.1108/01439911111106327

Broussard, M. (2015). Artificial intelligence for investigative reporting. *Digital Journalism*, *3*(6), 814–831. http://doi.org/10.1080/21670811.2014.985497

Byun, S., & Buyn, S.-E. (2011). Exploring perceptions toward biometric technology in service encounters: a comparison of current users and potential adopters. *Behaviour & Information Technology*, *32*(3), 217–230. http://doi.org/10.1080/0144929X.2011.553741

Calo, C. J., Hunt-Bull, N., Lewis, L., & Metzler, T. (2011). Ethical implications of using the Paro robot with a focus on dementia patient care. In *Association for the Advancement of Artificial Intelligence workshop* (Vol. WS-11-12, pp. 20–24). San Francisco. Retrieved from http://www.scopus.com/inward/record.url?eid=2-s2.0–80,054,913,481&partnerID=40&md5=cf9ad1b74f81299aa3f48be4f8e970of

Chang, A. C. (2012). Primary prevention of sudden cardiac death of the young athlete: The controversy about the screening electrocardiogram and its innovative artificial intelligence solution. *Pediatric Cardiology*, *33*(3), 428–433. http://doi.org/10.1007/s00246-012-0244-5

Charalambous, G., Fletcher, S., & Webb, P. (2015). Identifying the key organisational human factors for introducing human-robot collaboration in industry: an exploratory study. *International Journal of Advanced Manufacturing Technology*, *81*(9–12), 2143–2155. http://doi.org/10.1007/s00170-015-7335-4

Charchat-Fichman, H., Uehara, E., & Santos, C. F. (2014). New technologies in assessment and neuropsychological rehabilitation. *Trends in Psychology*, *22*(3), 539–553. http://doi.org/10.9788/TP2014.3-01

Collins, J. W., Patel, H., Adding, C., Annerstedt, M., Dasgupta, P., Khan, S. M., . . . Wiklund, P. N. (2016). Enhanced recovery after robot-assisted radical cystectomy: EAU robotic urology section scientific working group consensus view. *European Urology*, *70*, 649–660. http://doi.org/10.1016/j.eururo.2016.05.020

Danilchenko, A., Balachandran, R., Toennies, J. L., Baron, S., Munske, B., Fitzpatrick, J. M., . . . Labadie, R. F. (2011). Robotic mastoidectomy. *Otology and Neurotology*, *32*(1), 11–16. http://doi.org/10.1097/MAO.0b013e3181fcee9e.Robotic

De Benedictis, A., Trezza, A., Carai, A., Genovese, E., Procaccini, E., Messina, R., . . . Marras, C. E. (2017). Robot-assisted procedures in pediatric neurosurgery. *Neurosurgical Focus*, *42*(5), E7. http://doi.org/10.3171/2017.2.FOCUS16579

Decker, M., Fischer, M., & Ott, I. (2017). Service robotics and human labor: A first technology assessment of substitution and cooperation. *Robotics and Autonomous Systems*, *87*, 348–354. http://doi.org/10.1016/j.robot.2016.09.017

Dilsizian, S. E., & Siegel, E. L. (2014). Artificial intelligence in medicine and cardiac imaging: Harnessing big data and advanced computing to provide personalized medical diagnosis and treatment. *Current Cardiology Reports*, *16*(441), 1–8. http://doi.org/10.1007/s11886-013-0441-8

Doryab, A., Min, J. K., Wiese, J., Zimmerman, J., & Hong, J. I. (2014). Detection of behavior change in people with depression. In *Twenty-eighth AAAI Conference on Artificial Intelligence workshop* (pp. 12–16). Québec.

Drew, J. (2017). Real talk about artificial intelligence and blockchain. *Journal of Accountancy*, *224*(1), 22–26,28. Retrieved from https://ucd.idm.oclc.org/login?url=https://search.proquest.com/docview/1917636631?accountid=14,507 %0Ahttp://jq6am9xs3s.search.serialssolution.com?ctx_ver=Z39.88-2004&ctx_enc=info:ofi/enc:UTF-8&rfr_id=info:sid/ProQ%3Aabiglobal&rft_val_fmt=info:ofi/fmt:kev:m

Drigas, A. S., & Ioannidou, R.-E. (2012). Artificial intelligence in special education: A decade review. *International Journal of Engineering Education*, *28*(6), 1366–1372.

Edwards, P., & Ramirez, P. (2016). When should workers embrace or resist new technology? *New Technology, Work and Employment*, *31*(2), 99–113. http://doi.org/10.1111/ntwe.12067

Fischer, M. (2012). Interdisciplinary technology assessment of service robots: the psychological/work science perspective. *Poiesis & Praxis: International Journal of Ethics of Science and Technology Assessment*, *9*(3–4), 231–248. http://doi.org/10.1007/s10202-012-0113-6

Gilbert, B. J., Goodman, E., Chadda, A., Hatfield, D., Forman, D. E., & Panch, T. (2015). The Role of Mobile Health in Elderly Populations. *Current Geriatrics Reports*, *4*(4), 347–352. http://doi.org/10.1007/s13670-015-0145-6

Gombolay, M. C., Huang, C., & Shah, J. A. (2015). Coordination of human-robot teaming with human task preferences. In *AAAI Fall symposium series on AI-HRI*. Arlington.

Hengstler, M., Enkel, E., & Duelli, S. (2016). Applied artificial intelligence and trust: The case of autonomous vehicles and medical assistance devices. *Technological Forecasting and Social Change*, *105*, 105–120. http://doi.org/10.1016/j.techfore.2015.12.014

Hirsch, P. B. (2017). The robot in the window seat. *Journal of Business Strategy*, *38*(4), 47–51. http://doi.org/10.1108/JBS-04-2017-0050

Holloway, B. B., Deitz, G. D., & Hansen, J. D. (2013). The benefits of sales force automation (SFA): An empirical examination of SFA usage on relationship quality and performance. *Journal of Relationship Marketing*, *12*(4), 223–242. http://doi.org/10.1080/15332667.2013.846735

Huijnen, C. a G. J., Lexis, M. a S., Jansens, R., & de Witte, L. P. (2016). Mapping robots to therapy and educational objectives for children with autism spectrum disorder. *Journal of Autism and Developmental Disorders*, *46*(6), 2100–2114. http://doi.org/10.1007/s10803-016-2740-6

James, K. L., Barlow, D., Bithell, A., Hiom, S., Lord, S., Oakley, P., . . . Whittlesea, C. (2013). The impact of automation on pharmacy staff experience of workplace stressors. *International Journal of Pharmacy Practice*, *21*(2), 105–116. http://doi.org/10.1111/j.2042-7174.2012.00231.x

Jeong, G. M., Park, C. W., You, S., & Ji, S. H. (2014). A study on the education assistant system using smartphones and service robots for children regular paper. *International Journal of Advanced Robotic Systems*, *11*(1), 1–9. http://doi.org/10.5772/58389

Jeske, D., & Santuzzi, A. M. (2015). Monitoring what and how: Psychological implications of electronic performance monitoring. *New Technology, Work and Employment*, *30*(1), 62–78. http://doi.org/10.1111/ntwe.12039

Junejo, F., Amin, I., Hassan, M., Ahmed, A., Hameed, S., & Author, C. (2017). The application of artificial intelligence in grinding operation using sensor fusion. *International Journal of GEOMATE*, *12*(30), 11–18.

Jung, J., Song, H., Kim, Y., Im, H., & Oh, S. (2017). Intrusion of software robots into journalism: The public's and journalists' perceptions of news written by algorithms and human journalists. *Computers in Human Behavior*, *71*, 291–298. http://doi.org/10.1016/j.chb.2017.02.022

Kaivo-Oja, J., Roth, S., & Westerlund, L. (2017). Futures of robotics. Human work in digital transformation. *International Journal of Technology Management*, *73*(4), 176–205. http://doi.org/10.1504/IJTM.2017.083074

Khosla, R., Chu, M. T., & Nguyen, K. (2013). Affective robot enabled capacity and quality improvement of nursing home aged care services in Australia. In *IEEE 37th annual computer software and applications conference workshops* (pp. 409–414). Kyoto. http://doi.org/10.1109/COMPSACW.2013.89

Kim, C., Kim, D., Yuan, J., Hill, R. B., Doshi, P., & Thai, C. N. (2015). Robotics to promote elementary education pre-service teachers' STEM engagement, learning, and teaching. *Computers and Education*, *91*, 14–31. http://doi.org/10.1016/j.compedu.2015.08.005

Klintong, N., Vadhanasindhu, P., & Thawesaengskulthai, N. (2012). Artificial intelligence and successful factors for selecting product innovation development. In *3rd International Conference on Intelligent Systems Modelling and Simulation* (pp. 397–402). Kota Kinabalu. http://doi.org/10.1109/ISMS.2012.86

Kokina, J., & Davenport, T. H. (2017). The emergence of artificial intelligence: How automation is changing auditing. *Journal of Emerging Technologies in Accounting*, *14*(1), 115–122. http://doi.org/10.2308/jeta-51,730

Kolbjørnsrud, V., Amico, R., & Thomas, R. J. (2017). Partnering with AI: how organizations can win over skeptical managers. *Strategy & Leadership*, *45*(1), 37–43. http://doi.org/10.1108/SL-12-2016-0085

Kraan, K. O., Dhondt, S., Houtman, I. L. D., Batenburg, R. S., Kompier, M. A. J., & Taris, T. W. (2014). Computers and types of control in relation to work stress and learning. *Behaviour & Information Technology*, *33*(10), 1013–1026. http://doi.org/10.1080/0144929X.2014.916351

Kumar, S., Pragatheeswarane, M., Sharma, A. P., Bishnoi, K., Sharma, M. K., Panwar, V. K., & Sethi, S. (2017). Expanding the horizon of robotic surgery to large pelvic paraganglioma. *Journal of Robotic Surgery*, *11*(2), 247–250. http://doi.org/10.1007/s11701-016-0648-y

Lacity, M. C., & Willcocks, L. P. (2016). Robotic process automation at telefónica O2. *MIS Quarterly Executive*, *15*(1), 21–35.

Lee, H., Troschel, F. M., Tajmir, S., Fuchs, G., Mario, J., Fintelmann, F. J., & Do, S. (2017). Pixel-level deep segmentation: Artificial intelligence quantifies muscle on computed tomography for body morphometric analysis. *Journal of Digital Imaging*, *30*(4), 487–498. http://doi.org/10.1007/s10278-017-9988-z

Lund, H. H. (2011). Anybody, anywhere, anytime—Robotics with a social impact through a building block approach. In *Proceedings of IEEE workshop on advanced robotics and its social impacts* (pp. 2–7). Menlo Park. http://doi.org/10.1109/ARSO.2011.6301970

Luxton, D. D. (2014). Artificial intelligence in psychological practice: Current and future applications and implications. *Professional Psychology: Research and Practice*, *45*(5), 332. http://doi.org/10.1037/a0034559

Mathers, N., Goktogen, A., Rankin, J., & Anderson, M. (2012). Robotic mission to Mars: Hands-on, minds-on, web-based learning. *Acta Astronautica*, *80*, 124–131. http://doi.org/10.1016/j.actaastro.2012.06.003

Mubin, O., D'Arcy, T., Murtaza, G., Simoff, S., Stanton, C., & Stevens, C. (2014). Active or passive? Investigating the impact of robot role in meetings. In *IEEE International Workshop on Robot and Human Interactive Communication* (pp. 580–585). Edinburgh. http://doi.org/10.1109/ROMAN.2014.6926315

Naik, G., & Bhide, S. S. (2014). Will the future of knowledge work automation transform personalized medicine? *Applied and Translational Genomics*, *3*(3), 50–53. http://doi.org/10.1016/j.atg.2014.05.003

Nezhad, H. R. M. (2015). Cognitive assistance at work. In *AAAI 2015 Fall symposium* (pp. 37–40). Arlington.

Nielsen, J. A., Andersen, K. N., & Sigh, A. (2016). Robots conquering local government services: A case study of eldercare in Denmark. *Information Polity*, *21*(2), 139–151. http://doi.org/10.3233/IP-160381

Noor, A. (2011). Intelligent adaptive cyber-physical ecosystem for aerospace engineering education, training, and accelerated workforce development. *Journal of Aerospace Engineering*, *24*(October), 403–408. http://doi.org/10.1061/(ASCE)AS.1943-5525.0000128.

Ohlsson, S. (2016). Constraint-based modeling: From cognitive theory to computer tutoring—and back again. *International Journal of Artificial Intelligence in Education*, *26*(1), 457–473. http://doi.org/10.1007/s40593-015-0075-7

Peña, P., Del Hoyo, R., Vea-murguía, J., Rodrigálvarez, V., Calvo, J. I., & Martín, J. M. (2016). Moriarty: Improving "time to market" in big data and artificial intelligence applications. *International Journal of Design & Nature and Ecodynamics*, *11*(3), 230–238. http://doi.org/10.2495/DNE-V11-N3-230-238

Piccoli, M., Mullineris, B., Santi, D., & Gozzo, D. (2017). Advances in robotic transaxillary thyroidectomy in Europe. *Current Surgery Reports*, *5*(8), 1–7. http://doi.org/10.1007/s40137-017-0180-7

Pieters, W. (2011). Explanation and trust: What to tell the user in security and AI? *Ethics and Information Technology*, *13*(1), 53–64. http://doi.org/10.1007/s10676-010-9253-3

Samani, H. (2016). The evaluation of affection in human-robot interaction. *Kybernetes*, *45*(8), 1257–1272. http://doi.org/10.1108/K-09-2015-0232

Samarakou, M., Fylladitakis, E. D., Prentakis, P., & Athineos, S. (2014). Implementation of artificial intelligence assessment in engineering laboratory education. In *International conference e-learning* (pp. 299–303). Lisbon: International Association for Development of the Information Society.

Sananès, N., Garbin, O., Hummel, M., Youssef, C., Vizitiu, R., Lemaho, D., . . . Wattiez, A. (2011). Setting up robotic surgery in gynaecology: The experience of the Strasbourg teaching hospital. *Journal of Robotic Surgery*, *5*(2), 133–136. http://doi.org/10.1007/s11701-010-0231-x

Schwartz, T., Krieger, H., & Zinnikus, I. (2016). Hybrid teams : Flexible collaboration between humans, robots and virtual agents. In *Proceedings of the 14th German conference on multiagent system technologies* (pp. 131–146). Klagenfurt.

Semerjian, A., & Pavlovich, C. P. (2017). Extraperitoneal robot-assisted radical prostatectomy: Indications, technique and outcomes. *Current Urology Reports*, *18*(42), 1–7. http://doi.org/10.1007/s11934-017-0689-4

Sheridan, T. B. (2016). Human-robot interaction: Status and challenges. *Human Factors*, *58*(4), 525–532. http://doi.org/10.1177/0018720816644364

Skulimowski, A. M. J. (2014). Future prospects of human interaction. In *International conference on adaptive and intelligent systems* (pp. 131–141). Bournemouth.

Stalidis, G., Karapistolis, D., & Vafeiadis, A. (2015). Marketing decision support using artificial intelligence and knowledge modeling: Application to tourist destination management. *Procedia—Social and Behavioral Sciences*, *175*, 106–113. http://doi.org/10.1016/j.sbspro.2015.01.1180

Sundararajan, S. C., & Nitta, S. V. (2015). Designing engaging intelligent tutoring systems in an age of cognitive computing. *IBM Journal of Research and Development*, *59*(6), 10:1–10:9. http://doi.org/10.1147/JRD.2015.2464085

Sutton, S. G., Holt, M., & Arnold, V. (2016). "The reports of my death are greatly exaggerated"—Artificial intelligence research in accounting. *International Journal of Accounting Information Systems*, *22*, 60–73. http://doi.org/10.1016/j.accinf.2016.07.005

Szalma, J. L., & Taylor, G. S. (2011). Individual differences in response to automation: the five factor model of personality. *Journal of Experimental Psychology. Applied*, *17*(2), 71–96. http://doi.org/10.1037/a0024170

Taylor, A. K., & Cotter, T. S. (2014). Human-machine intelligence interaction in aviation. In *Proceedings of the American Society for Engineering Management* (pp. 210–217). Virginia Beach.

van de Merwe, K., Oprins, E., Eriksson, F., & van der Plaat, A. (2012). The influence of automation support on performance, workload, and situation awareness of air traffic controllers. *The International Journal of Aviation Psychology*, *22*(2), 120–143. http://doi.org/10.1080/10508414.2012.663241

van Doorn, J., Mende, M., Noble, S. M., Hulland, J., Ostrom, A. L., Grewal, D., & Petersen, J. A. (2017). Domo arigato Mr. Roboto: Emergence of automated social presence in organizational frontlines and customers' service experiences. *Journal of Service Research*, *20*(1), 43–58. http://doi.org/10.1177/1094670516679272

Willcocks, L., Lacity, M. C., & Craig, A. (2015a). *Robotic process automation at Xchanging* (The Outsourcing Unit Working Research Paper Series). London.

Willcocks, L., Lacity, M. C., & Craig, A. (2015b). *The IT function and robotic process automation*. (The Outsourcing Unit Working Research Paper Series). London.

Xu, J., Le, K., Deitermann, A., & Montague, E. (2014). How different types of users develop trust in technology: A qualitative analysis of the antecedents of active and passive user trust in a shared technology. *Applied Ergonomics*, *45*(6), 1495–1503. http://doi.org/10.1016/j.apergo.2014.04.012

Yang, S., Wei, R., Guo, J., & Xu, L. (2017). Semantic inference on clinical documents: Combining machine learning algorithms with an inference engine for effective clinical diagnosis and treatment. *IEEE Access*, *5*, 3529–3546. http://doi.org/10.1109/ACCESS.2017.2672975

Ye, J. J. (2015). Artificial intelligence for pathologists is not near-it is here: Description of a prototype that can transform how we practice pathology tomorrow. *Archives of Pathology and Laboratory Medicine*, *139*(7), 929–935. http://doi.org/10.5858/arpa.2014-0478-OA

Zaghloul, A. S., & Mahmoud, A. M. (2016). Preliminary results of robotic colorectal surgery at the National Cancer Institute, Cairo University. *Journal of the Egyptian National Cancer Institute*, *28*(3), 169–174. http://doi.org/10.1016/j.jnci.2016.05.003