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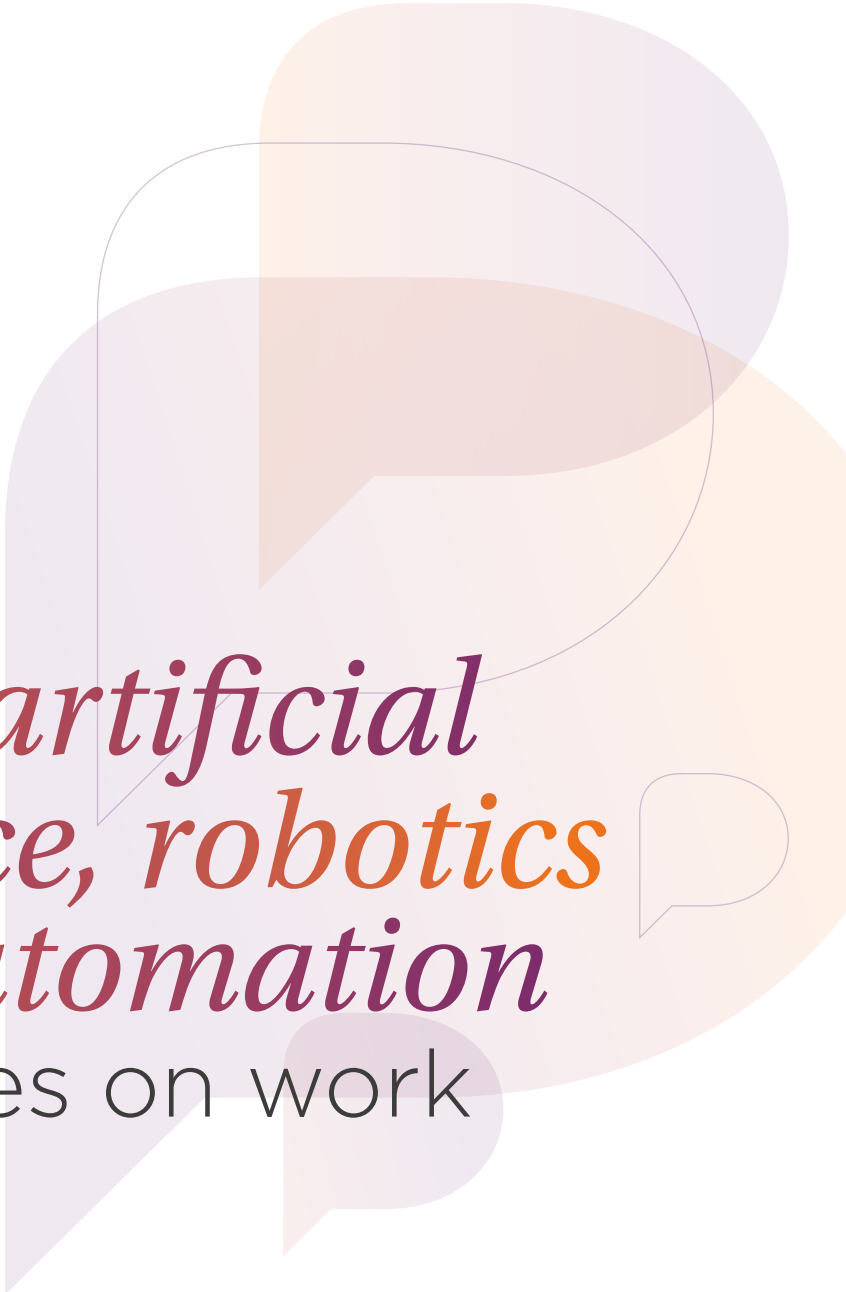
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Impact of *artificial intelligence, robotics* and *automation* technologies on work

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Impact of artificial intelligence, robotics and automation technologies on work

Rapid evidence review

Contents

Acknowledgements

Loughborough University

Introduction

This report summarises the findings of a rapid evidence review that was conducted between October and December 2016 into the impact of various emerging technologies (artificial intelligence, robotics, and automation technologies) on knowledge and service work, relevant professions, and society. The review focuses on academic literature (peer-reviewed journal papers and conference papers) that had been published since 2011. The aim is to evaluate the state of contemporary academic knowledge on this topic. The specific focus of the review is on the following questions:

1   What should the technological and occupational focus of the review be?
2   What are the factors driving contemporary developments in AI, robotics and automation technologies?
3   What are the work-related outcomes and mediators from the utilisation of AI, robotics and automation technologies (considering both the impact for workers and organisations)?
4   What are the impacts of AI, robotics and automation technologies on professions and society more generally?
5   What are the ethical issues related to the contemporary utilisation of AI, robotics and automation technologies?

The search undertaken produced a population of 182 separate sources for analysis. When the source material was analysed, there was very little material that addressed question 2. Consequently this question is not used in this report and the analysis focuses on the remaining four questions. The report begins by outlining the literature search method that was utilised, before presenting the textual summary of our findings in relation to each question.

Method

Our review followed the rapid review protocol outlined by Khangura et al (2012). This protocol has eight specific steps:

- Step 1: needs assessment
- Step 2: question development and refinement
- Step 3: proposal development and approval
- Step 4: systematic literature search
- Step 5: screening and selection of studies
- Step 6: thematic synthesis of included studies (including assignment of evidence level)
- Step 7: report production
- Step 8: ongoing follow-up and dialogue with knowledge users.

Steps 1–3: needs assessment to proposal development and approval

The first three steps were negotiated between the CIPD and the Loughborough research team following the award of the work to the Loughborough team. The conclusion of stages 1–3 was to focus the review on the impact of various emerging technologies (artificial intelligence, robotics, and automation technologies) on knowledge and service work, relevant professions, and society. The production of this report constitutes step 7 in the review protocol. This method section focuses on describing how steps 4–6 were undertaken.

Step 4: systematic literature search

The four databases used to identify relevant academic studies were: *Scopus, EBSCO: Business Source Complete, EBSCO: 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 technology/change terms that were used were: *artificial intelligence, smart machines, cognitive computing, automation of knowledge work,* and *automation of service work.* The search was focused on these terms because of the focus of the review on the use of advanced/contemporary developments in IT and computing in relation to the computerisation and automation of knowledge and service work. It was decided not to examine the automation and computerisation of manufacturing work, because of the likely maturity of research in this area, and because it was anticipated that developments in the computerisation and automation of knowledge and service work represented some of the most significant contemporary technological developments in the work context.

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 organisations, impacts on workers, impacts on society, and ethical implications. The specific search terms used were: *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 search databases, all technology terms were combined individually with each impact term.

Consequently, these searches were filtered using the following, identical filtering criterion:

- peer-reviewed articles or conference papers
- published from January 2011 to December 2016
- published in English
- full text available
- search by title/abstract.[1]

Dr Taneva undertook these searches. The full results of these searches are summarised in Appendix A[2]. These searches identified 1,896 possible items for inclusion. How this population was screened and narrowed down is explained in step 5.

Step 5: screening and selection of studies

The screening and filtering of the identified items to produce the final population of sources to be used in the review was carried out in a number of systematic steps. First, Dr Taneva, utilising title and abstract only, considered each source. Items were excluded for the following reasons: if they were purely technical papers concerned with engineering and design issues related to the technologies examined; they were not focused on the application of the selected

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[1] With Web of Science there isn't an option to search by abstract. For these searches, searches were done by title (Ti) and topic (To).
[2] Appendices A, B and C available at https://www.cipd.co.uk/knowledge/work/technology/artificial-intelligence-workplace-impact

technologies in the context of service and knowledge work (thus studies focused purely on manufacturing were excluded). When this process of filtering was undertaken, and when all duplicate sources were identified, a final population of 134 sources was identified (see Appendix B[3]).

Finally, while undertaking this reviewing of sources 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. This produced another 79 items for inclusion in the study population (see Appendix B). Thus, the total number of sources identified for full review and inclusion was 213 (134 from the primary search plus 79 from the secondary search).

Other members of the research team reviewed a sample of Dr Taneva's inclusion and exclusion decisions to validate the filtering process. To do this, samples of included and excluded sources were identified, and two members of the research team independently checked the inclusion/exclusion decisions that had been made. The results of this independent checking process were combined to evaluate the validity of the filtering process.

The final filtering process occurred during the full reading and analysis of all sources, which is described fully in step 6. This process of reading papers, which was divided between the research team, resulted in 31 further papers being excluded from the study. Thus, the final population of sources included in this rapid review was 182. Mendeley referencing software was used in the project to categorise and store the population of sources examined.

Step 6: thematic synthesis of included studies (including assignment of evidence level)

This step was undertaken by all of the project team, with each team member being allocated a roughly equal proportion of papers to read. As outlined above, one outcome of this process was the exclusion of a small number of studies that were identified as not being relevant to our focus. The thematic synthesis of our review was undertaken in two separate stages. First, standardised summaries were written for each source, with this information listed in Appendix C. Further, each source was coded in Mendeley with tags identifying key themes. These summaries included details on the type of source, the research methods used in empirical studies, relevant findings, any limitations, and categorisation regarding the extent to which original empirical evidence was presented and analysed.

The second stage of the thematic synthesis involved utilising the tagged library of project sources in Mendeley, combined with the summary of the papers (Appendix C), to produce a textual analysis of the data in relation to the focal questions. This analysis is presented in the Findings section.

Before presenting the findings, it is useful to give an overview of the population of sources utilised, both in terms of the type of papers included in the review, and in terms of the extent to which original empirical evidence is presented and analysed. In terms of the type of sources examined, peer-reviewed journal papers and conference papers represent the predominant sources, with peer-reviewed papers making up 62% of the sample, conference papers constituting 25% of the sample, and the remaining 13% of sources being working papers, or professional association journal articles (Table 1 and Appendix C). Thus, the high proportion of peer-reviewed academic journal papers in the sample population gives some degree of confidence regarding the quality of the sources examined.

Table 1: Type of publication in review population

Type of publication	Percentage of reviewed population
Peer-reviewed journal paper	62
Conference paper	25
Other (working paper, report)	13

In considering the extent to which original empirical data is presented in the sources examined, we were interested in identifying the extent to which the issues examined were supported by good-quality empirical evidence, whether they involved the use of brief anecdotes, or whether they involved speculation unsupported by empirical evidence (see Table 2). Our categorisation of the sources found that 41% presented detailed empirical evidence, with a further 37% being literature reviews where second-hand evidence was reviewed and evaluated. Of the remaining sources, 11% used either detailed or brief anecdotes, and 12% were opinion pieces without a clearly specified empirical base. As well as documenting this information in Table 2, whenever we utilise a source to make a claim in the report, we will make reference to our classification of its empirical basis (for example Collins et al 2016 – category 1). This suggests that, at this point in time, with just over 40% of papers presenting detailed original empirical evidence, extensive and robust academic knowledge on the topics examined is somewhat embryonic. Thus, more than 50% of the material reviewed consists of literature reviews, which typically end by making predictions regarding possible future scenarios, analysis based on brief anecdotes of unknown quality, or pure speculation and reflection. Overall, this means that despite the amount of interest in these issues, and the quantity of writing on them, robust empirical evidence regarding the use of these technologies in workplace contexts is lacking.

This is a finding supported by the Council for Science and Technology, which advises the UK prime minister on science policy, which said that it was '*struck by the lack of robust evidence about the social and economic impacts of these technologies, including on the labour market*' (RP 2016).

The embryonic nature of knowledge on the issues examined here is further reinforced when the data collection methods used on the 41% of empirical studies is analysed (see Table 3). This shows that the most common empirical methods used is a 'proof of concept' experiment, and that over 50% of the empirical studies identified are trials or experiments of some sort.

Table 2: Extent/quality of empirical data in review population

Extent/quality of empirical data in source	Percentage of reviewed population (%)	Category of evidence in Appendix C
Detailed empirical studies with information on research method	41	1
Secondary research/literature reviews	37	2
Detailed anecdotal examples, but no information on research methods	6	3
Brief anecdotes, but no information on research methods	5	4
Opinion piece with an unclear empirical base	12	5

Table 3: Type of data collected and analysed by sources presenting detailed/systematic empirical evidence

Type of empirical data analysed	Percentage of empirical studies
Proof of concept test/experiment	33
Survey-based study	25
Trial/experiment/simulation	18
Interview-based study	16
Documentary-based analysis	11
Mixed methods	8
Historical analysis	2
Delphi study	2
Ethnographic study	2

Findings

'All these definitions highlight the role of AI in modelling human behaviour and thought, but do not go as far as to talk about using AI technologies to build other smart technologies.'

As outlined in the Introduction, our analysis of the literature found very little material on the topic of what the drivers of the technological developments being considered are. Consequently, this question was dropped from our analysis. Following are the findings in relation to the four remaining questions.

1 Definition of technologies examined and occupational focus

Three main types of emerging technology featured in the research were identified from the search strategy: artificial intelligence (AI) (including machine learning and cognitive computing); robots (including service robots, robot-assisted procedures, and robotic process automation (RPA)); and automation technologies.

Artificial intelligence

Several authors have acknowledged that it is difficult to define artificial intelligence (AI) (DeCanio 2016). Burkhard (2013) observes that it is difficult to define intelligent machines because there are no universal definitions of natural intelligence. Machines may be better at tasks that can be described as intelligent behaviour, 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. Further, machines do not understand the meaning of the words they translate; they use statistical calculations to determine the most likely suitable alternative word. Thus, a distinction may be made between strong AI and weak AI.

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 et al 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 and Siegel 2014). Building on the cognitive aspect, DeCanio (2016) describes AI as a *'broad suite of technologies that can match or surpass human capabilities, particularly those involving cognition'* (DeCanio 2016). Niu et al (2016) add that AI *'aims to understand the essence of intelligence and design intelligent machines that can act as human behavior'.* All these definitions highlight the role of AI in modelling human behaviour and thought, but do not go as far as to talk about using AI technologies to build other smart technologies.

Robots

Service robots refer to robots that provide assistance to a human to complete a physical task, such

as scrubbing, cleaning, sorting, packaging instruments and sending them for sterilisation for dentists (Chen 2013), helping an elderly person pour a liquid (Xu et al 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 is suitable for narrow, inaccessible operative areas (Zaghloul and Mahmoud 2016).

Rather than a physical robot, robotic process automation (RPA) is a software solution (essentially a software licence) configured to do the work previously undertaken by humans. RPA is suited to automating a process where 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 et al 2015a).

Automation technologies
In much of the recent debate concerning automation, the term has been equated to *'the substitutability of humans by machines'* (Arntz et al 2016). However, this simplifies the notion of automation and masks whether automation is of entire job roles – such as the study presented by Frey and Osborne

(2013) – or specific job tasks – such as the study presented by Arntz et al (2016). A more detailed definition is offered by Balfe et al (2015), who define automation as *'the performance of tasks by machines (often computers) rather than human operators often to increase efficiency and reduce variability'*. Drawing on work by Parasuraman et al (2000), Balfe et al (2015) explain that automation can occur at different levels and for different purposes, such as information acquisition, information analysis, decision and action selection, and action implementation. In each category the level of automation may be low or high. Thus, it is important to recognise the different types of automation that may be present within particular systems and that applying a blanket 'automation' label may imply higher levels of automation than have actually been implemented.

Occupational focus
The occupational focus of this report is on all forms of non-manual work, including white-collar office and administrative work, service work, and what can be labelled knowledge work. This focus (and exclusion of manufacturing work) is for a number of reasons. First, the focus of this report is on how contemporary developments in AI and robotics are affecting work. The use of robots and automation is relatively mature in manufacturing contexts, and the aim of this report is not to consider such developments. Anecdotally it appears that potentially some of the most significant developments associated with the work-related use of AI and robotics is in the domain of occupations that had previously made little use of them. The aim of this report is thus to focus on and investigate such developments.

2 Work-related outcomes and mediators (on organisations and employees) from the utilisation of AI, robotics and automation technologies

The majority of research that considers the work-related outcomes of emerging technologies has been conducted in the healthcare and transport sectors. Non-sector-specific technological developments are considered at the end of this section. Where the research on specific technological developments indicates employment-related impacts, this is also discussed. However, the societal-level impact on employment levels from the widespread adoption of these technologies is an issue considered in relation to question 3.

Emerging technologies in the healthcare sector
In the healthcare sector, there has been considerable interest in the usage of robot-assisted surgical procedures. Robot-assisted surgery is less invasive and patient recovery times appear to be shorter (Collins et al 2016 – category 1; Zaghloul and Mahmoud 2016 – category 1). It has been suggested that robotic surgery may be easier for a surgeon to learn without the need for long cognitive training; however, these hypotheses have not been tested (Bocci et al 2013 – category 1). Researchers are also exploring the potential of fully autonomous robotic surgery tools. For example, an autonomous robot for mastoidectomy (where the bone is drilled away, exposing but not damaging vital anatomy) was able to remove 96% of the targeted bone without damage to critical structures. However, a human supervisor for the robot is required because of the potential for clinical error if the wrong starting point is chosen (Munske 2011). Robot-based therapy interventions are also being

'Making the financial case for investments in AI may be challenging for some healthcare organisations when competing with alternative financial pressures. This challenge may be exacerbated because of medico-legal and regulatory concerns regarding liability for misdiagnosis or incorrect treatment recommendations.'

explored, such as using paro-robots to mimic pet behaviour for supporting elderly patients with dementia (Calo et al 2011 – category 2), introducing assistive robots to play games with elderly patients (for example bingo) (Khosla et al 2013 – category 1), or the use of humanoid robots to interact with children with autism spectrum disorders (ASD) (Bekele et al 2013 – category 1).

Medical robots are reported as the main growth area for service robot sales in the USA, totalling $1,495 million, which accounts for 44% of the total sales value of professional service robots (Moniz and Krings 2014 – category 2). However, the uptake of robots in healthcare remains slow in some countries. For example, robotic surgery in France is reported as still being in its infancy, largely because of the difficulties in organising suitable processes and timetabling operating slots. Sananès et al (2011 – category 1) explain that arranging robotic surgery operating slots required 18 days' lead time and that at least 20 operations needed to be conducted before procedures and setup time reduced. They argue that because robotic surgery involves bulky technical equipment, it requires a dedicated surgery to store the equipment and facilitate scheduling. From their study of robotic surgery in Egypt, Zaghloul and Mahmoud (2016 – category 1) add that the high cost of robotic surgery and the length of time needed to learn new techniques are also reasons for the slow uptake of this technology.

A small number of applications of artificial intelligence are also evident in the healthcare sector, although the majority are still in the experimental stage of research. Bennett and Hauser (2013 – category 1) propose a framework that uses AI to study

existing clinical data and develop complex care plans by simulating numerous, alternative sequential decision paths. By adopting this AI framework, a more refined care plan can be proposed based on a far wider consideration of existing clinical data than a human consultant could read and retain. Bennett and Hauser (2013 – category 1) suggest that, compared with human decision-making, this approach could deliver better outcomes at lower costs. AI prototypes have also been developed as a method of reducing the administrative work of pathologists, reducing the time pathologists take to compile their reports (Ye 2015 – category 2). However, both these examples have still to be empirically tested in healthcare environments.

Dilsizian and Siegel (2014 – category 2) identify a number of challenges for the widespread uptake of AI in healthcare environments. Making the financial case for investments in AI may be challenging for some healthcare organisations when competing with alternative financial pressures. This challenge may be exacerbated because of medico-legal and regulatory concerns regarding liability for misdiagnosis or incorrect treatment recommendations. Further, the development of AI software may be inhibited by privacy and security concerns of providers that hold the electronic health records of patients. If healthcare organisations are unwilling to share patient data with AI vendors, it will be difficult for the vendors to create a fully integrated software solution. Thus, it is likely that in the near future, AI developments will be based on localised organisational arrangements between vendors and specific healthcare organisations, targeting specific medical conditions. An example of this

is IBM's relationship with the University of Texas MD Anderson Cancer Centre for cancer treatment using IBM's Watson supercomputer.

Emerging technologies in the transport sector

In the context of the transport sector, research has focused on human–computer or human–machine interactions.

In a study of rail signalling automation that compared a realistic automation model and experienced human rail signal operators, it was found that as automation levels increased, perceived workload of human operators (physical and mental) decreased and consistency of performance increased (Balfe et al 2015 – category 1). Similarly, the provision of automated decision support for air traffic controllers that provides advice on optimal solutions in a real-time trial was found to increase the performance accuracy of controllers without increasing workload (van de Merwe et al 2012 – category 1). These studies take into account an important aspect of human–computer relationships: the response from humans when they experience a loss of control of the machine or computer, which is explored below.

A study of smart cars found that human drivers' experiences of assisted technology were generally positive, and there were not significant levels of malfunction (Weyer et al 2015 – category 1). However, research (Dehais et al 2012 – category 1) has shown that when conflict occurs during human–computer interaction, such as over which action to pursue, it may result in degradation of performance due to the human persevering with resolving the conflict and not considering alternative forms of action. In an

experiment where French military staff use a robot to identify a target, when the human operator encountered a conflict with the robot – for example the robot reporting it was low on battery and needed to return to base during the critical targeting part of the operation – the human operator would overrule the robot and prevent it from returning to base. The human operator remained focused on completing the task and ignored the low battery warning messages (Dehais et al 2012 – category 1). Understanding the mechanisms of such 'conflicts' are also important in situations where human operators' actions may jeopardise safety and need to be overridden, such as during aircraft flights. However, if the human operator does not understand the automation behaviour, they are likely to ignore warnings and attempt to retake control from the automated system. Thus, human–computer conflicts may be moderated by the level of trust and understanding that the human has in the automated system. Trust in the technology was reported as important for air traffic controllers' willingness to accept increased levels of automation in two hypothetical scenarios (Bekier et al 2011 – category 1) and trust was also identified as important for the human acceptance of AI-enabled autonomous cars (Hengstler et al 2016 – category 1).

Applications of emerging technologies in relation to non-sector-specific, routine administrative work

The majority of research studies that examine applications of AI have done so with the aim of improving performance, efficiency, and decision-making outcomes. For example, in the telecom industry AI has been used to reduce the work of customer service employees in tracking the reason for contract

cancellations and more effective management of customer service calls (Kon et al 2016 – category 3). AI has been used to help develop an automated system for software security specialists to sort and identify relevant artefacts regarding cybercrime (Fahdi 2013 – category 2), help support system administrators to monitor and diagnose Linux-based software systems (Haen et al 2012 – category 1), help guide logistics managers to improve warehouse productivity through work-log data analysis (Kudo et al 2015 – category 1), provide a work assistant to help office workers track work items over interactions in various communication channels (email, social media, chat, messaging and calendar applications) (Nezhad 2015 – category 2), and to support public affairs reporters to sort through data to identify investigative storytelling opportunities (Broussard 2015 – category 2). In all these examples, the use of AI is to help humans extend their work capacity and capability, but they provide little evidence of human workers being replaced by the new technology.

Applications of robotic process automation have also been reported as providing significant returns on investment, with O2 reporting that the automation of 15 processes using 160 robots resulted in 600–800% return on investment. No internal jobs were threatened at O2, although the automation did impact on outsourced job levels (Lacity and Willcocks 2016a – category 1). Some suggest that, where appropriate, unions are involved in consultations regarding the implementation of robots and AI, and that the variability of the manual system is fully understood by the integrator before the automated system is implemented (Charalambous et al 2015 – category 1). It is also advised that support is given to employees as

their roles change from worker to supervisors of automated processes (Charalambous et al 2015 – category 1).

Automation technologies were generally reported in the literature as removing mundane or repetitive tasks but not substituting for human workers. Automated assessment tools have been proposed for reducing the workload of humans in engineering laboratories (Samarakou et al 2014 – category 4), automated decision support has been trialled and data suggest that air traffic controllers' performance accuracy can be increased without increased workload (van de Merwe et al 2012 – category 1), the automation of error prevention in a medical context has been reported to reduce interpretive medical errors (Aron et al 2011 – category 1), automated medical distribution technology had operational benefits for a pharmacy and care home in Quebec (Baril et al 2014 – category 1), and monitoring of driver fatigue levels can be improved via the automated real-time evaluation of transportation workers (Balkin et al 2011 – category 2). Holloway et al (2013 – category 1) investigated how sales force automation technology affected sales staff performance and found that performance was moderated by learning, customer orientation and the quality of the relationship with the customer.

3 The impact of AI, robotics and automation technologies on professions and society

Current and potential societal impacts

The implications for society and contemporary professions of the widespread work-related adoption of the technologies examined are both profound and diverse. Within the space of this report it is only possible to briefly highlight a few issues. The focus here is on the issues and topics that were most widely discussed in the literature.

Employment levels
One of the most significant potential social impacts of the widespread implementation of the technologies examined here is on employment levels. However, opinion is divided on this topic, ranging from those who predict large-scale job losses through the automation of non-routine work, through to those who suggest that large-scale job losses are unlikely.

Fears of large-scale 'technological unemployment' are nothing new, and in fact typically accompany every wave of radical technological development, dating back to the machine-breaking Luddites in eighteenth-century England, who attempted to sabotage the implementation of automated production technologies because of fears that they would eliminate the need for factory workers. For the technologies considered here, there are many who suggest large-scale unemployment in the near future is likely (see for example Ford 2016 – category 1; Brynjolfsson and McAfee 2016 – category 1). Most prominent among this perspective is the work of Frey and Osborne (2013 – category 1). Their analysis, which focused on the implementation of what they referred to as 'machine learning' and 'mobile robotics' technologies, suggested that as much as 47% of jobs in the US economy could be eliminated. Their analysis takes a 'job focused' approach, considering the likelihood of complete jobs being eliminated by automation. This influential work has been highly cited, and has inspired similar analyses in other economies. For example, Frey and Osborne, in partnership with Deloitte (Deloitte 2016 – category 1), have suggested that as many as 850,000 UK public sector jobs (predominantly in administrative and repetitive roles) could be automated by 2030, with this analysis being reported in the media (Inman 2016). Analysis undertaken by the Bank of England suggested that up to 15 million jobs in the UK could be lost through the utilisation of advanced robotics and automation technologies, with those most likely to be affected undertaking administrative, clerical and production work (Elliott 2015).

However, such predictions have been challenged by a number of other analysts, with it being argued that overall levels of unemployment resulting from the implementation of these technologies may be more modest. Such analyses are based on two separate arguments. First, Arntz et al (2016 – category 1) adopt a task-based rather than a job-based analysis. This analysis assumes that all jobs are made of heterogeneous tasks, and that while some tasks undertaken may be automated, other, more complex, non-routine tasks may not. When their analytical method was applied to data on the OECD economies, they found that 9% of jobs were potentially automatable. A second type of analysis, based more on the use of history, examining the impact of previous technological developments on employment levels, comes to similar conclusions. Autor (2015 – category 2) represents an example of such work, arguing that the extent to which technological developments substitute for labour, resulting in unemployment, is counterbalanced by the way in which such developments complement and augment labour, creating increased demand for labour in new ways. Such a perspective is articulated and reinforced by a number of writers (Badke 2015 – category 4; Fourie 2016 – category 5).

Ultimately, the extent to which the widespread implementation and use of AI, robotics and automation technologies in work impacts on employment levels is uncertain, with opinion on the topic being significantly divided. The analysis of the contrasting perspectives is made by established academics underpinned by robust, if different, methodologies (job-focused versus task-focused analyses versus historical analysis). Edwards and Ramirez (2016 – category 4) suggest we are at too early a stage in the implementation of these technologies to be able to predict such outcomes with any degree of certainty.

The changing nature of the human–IT/technology relationship and increased need for IT competence

A social impact resulting from the increased work-related use of AI, cognitive computing and the use of robots for administrative and service work is the increased need for people, as both workers and consumers, to communicate and interact with these technologies. Examples of some of the diverse ways in which this occurs is via people interacting with voice recognition systems (Reeves 2016 – category 2), workers collaborating with advanced robots in hybrid robot/worker teams (Schwartz et al 2016 – category 2), the use of robot assistants in the delivery and consumption of healthcare (Khosla et al 2013 – category 1; Goeldner et al 2015 – category 2), virtual friends/assistants (Del Pino et al 2012 – category 3), and the application of these technologies within the context of 'smart homes' (Du et al 2013 – category 1; Shahriar and Rahman 2015 – category 1).

Several research studies have considered people's attitudes towards and feelings about interacting with advanced computer systems (Charalambous et al 2015 – category 1; Samani 2016 – category 1; Skulimowski 2014 – category 5; Nomura et al 2011 – category 1). For example, Dang and Tapus (2015 – category 1) report on an experiment into young people's attitudes towards the use of robot assistants and the extent to whether this affected people's performance and stress levels. While they found that people preferred working with robotic support, the use of robotic support did not improve their performance. Also, when the robot acted in a way that was sensitive to people's personalities, this did not improve their performance. Further, Nomura et al's (2011 – category 1) experiment into people's anxiety levels towards robots found that anxiety levels increased for those who had pre-existing high levels of anxiety when robots behaved in certain ways.

In this context, as discussed in the preceding section, workers' attitudes to and behaviour in relation to these technologies is a key mediator of the way in which, and the extent to which, they are used. For example, the extent to which workers trust the technological systems they are required to use can impact significantly on the effectiveness with which they are used (Hengstler et al 2016 – category 1). Workers' trust and relationship with the technologies they use is likely to evolve over time, thus a full understanding of how user trust mediates the way technologies are used requires the application of longitudinal research methods. Finally, Reeves (2016 – category 2), whose focus is on the 'automation of communicative labour' – such as via the use of voice recognition software/robots – suggests that how workers and consumers will be affected by such developments is not yet fully understood.

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'In relation to the social benefits of using these technologies in a healthcare context, it has been argued that the data mining and analysis capabilities of advanced computers in particular have the potential to contribute to the improvement of healthcare planning.'

Developments in the consumption of healthcare

As outlined earlier, one sector where AI, robotics and automation technologies are being applied is healthcare. This sector will also be returned to later when discussing the changing nature of professional work. Here the focus is more on the social impact, considering both the potential social benefits from the use of these technologies in a healthcare context, as well as the impact the use of such technologies has on patients and how healthcare is consumed. With regard to patients, the particular focus is on the provision of care to the elderly via the use of robots and electronic care assistants.

In relation to the social benefits of using these technologies in a healthcare context, it has been argued that the data mining and analysis capabilities of advanced computers in particular have the potential to contribute to the improvement of healthcare planning (Durairaj and Ranjani 2013 – category 2). For example, Bennett and Hauser (2013 – category 1) report on the findings of an exploratory study into the application of an electronic health records system which used the health records of 500 patients in a single hospital. Analysis of data held on electronic records systems provides the opportunity to more effectively plan the often complex healthcare options available to patients, thus supporting organisational decision-making processes.

In relation to the impact on patients, the focus in the literature is on eldercare (Khosla et al 2013 – category 1; Metzler et al 2016 – category 2; Goeldner et al 2015 – category 1) in the context of increasing numbers in the population of many nations who are living longer. Research in this area is primarily focused on the use of 'care robots' to improve the care given to elderly patients. Goeldner et al (2015 – category 2) suggests that the most advanced development in this area has been done in Japan and Asia. Khosla et al (2013 – category 1) report on a field experiment regarding the use of robots in care homes for the elderly in Australia. These experiments were focused on using the robot to play games and manage the diet of patients. The conclusions of the field study suggested that the robot had the potential to both increase the capacity of care homes to provide care, and also improve the well-being of the elderly. The use of robots in this context is intended to augment rather than replace care workers.

Finally, a more critical perspective is put forward by Metzler et al (2016 – category 2), who raise a number of philosophical questions regarding the use of robots in the provision of care, which has implications for the type of care activities they should provide. Metzler et al argue that the provision of emotional labour can only be effectively provided by humans, as any emotional care provided by robots involves utilising 'fake' emotions that have been programmed, as robots are not able to feel and express 'real' emotions in the same way as people. As a consequence, they argue that robots in this context should not be used for any 'emotion work'.

Current and potential impact on professions

In the space available here it is only possible to scrape the surface regarding the potential impact of the utilisation of AI, robotics and automation technologies on contemporary professions. This is a topic that Susskind and Susskind (2015 – category 1) devote a whole book to. However, a number of general observations can be made. First, these technologies

have the potential to impact on a wide range of traditional and contemporary professions, including medicine, education (Pinkwart 2016 – category 2; Drigas and Ioannidou 2012 – category 2; Kim et al 2015 – category 1), accounting (Sutton et al 2016), journalism (Broussard 2015 – category 2), information science (Badke 2015 – category 2) and air traffic management (van de Merwe et al 2012 – category 1). In the domain of medicine these technologies are applicable in a wide range of areas, including surgery (Collins et al 2016 – category 1; Bocci et al 2013 – category 1), mental health provision (Huijnen et al 2016 – category 2; Luxton 2014 – category 2), the care of the elderly (Calo et al 2011 – category 2; Metzler et al 2016 – category 1), pharmacy (James et al 2013 – category 1), pathology (Ye 2015 – category 2), and forensics (Fahdi 2013 – category 2; Baggili and Breitinger 2015 – category 2). Empirical evidence from these studies suggests that the most significant way in which the utilisation of these technologies is changing the nature of professional work is, first, via the automation/computerisation of routine tasks and, second, through involving a greater interaction with, and utilisation of, robots and AI systems, which increasingly facilitate various aspects of people's work activities. These developments can best be illustrated through a few brief vignettes.

James et al's (2013 – category 1) qualitative study into the implementation of an automated dispensing system (ADS) in a single UK hospital provides insights into how this change affected the work of pharmacists. The implementation had broadly positive effects for the pharmacists, reducing their stress levels (in coping with busy workloads), creating a generally calmer working environment, and also allowed some degree of role expansion. For example, the ADS reduced the amount of time pharmacists had to stay in the dispensary, and allowed them to become more active on patient wards. On the negative side, when working in the dispensary and utilising the ADS, they felt similar to 'production like' workers, and malfunctions with the ADS could be a source of stress, as pharmacy staff were typically unable to fix them themselves. The implementation of the ADS had no impact on overall staffing levels. Thus, the ADS did significantly affect the work of pharmacists, but in a largely positive way, through reducing stress levels during busy times and allowing for some degree of role expansion. Something not addressed in the article was the extent to which the ADS had implications for the skills required of pharmacists, and whether the use of such technologies has significant training implications.

The use of two quite different AI applications provides some insights into the way the work of healthcare professionals is being transformed. One application is a robotic pet (a seal called Paro), for use with elderly dementia patients (Calo et al 2011 – category 2). This robot mimics the behaviour of a real animal and responds when people interact with it (via talk or touch). The second application is a smartphone/tablet app for the chronic disease Crohn's, which allows sufferers to record important daily information on their health (such as pain levels, weight, medication changes, sleep patterns) (Kreps and Neuhauser 2013 – category 1). Both of these applications are argued to have positive benefits for patient health and well-being, with the Paro robot helping calm and comfort many patients, and with the Crohn's app providing patients with access to a systematic body of data on their ongoing health that allows them to more effectively monitor how their health evolves and changes.

Both of these applications also have significant implications for the work of healthcare professionals through changing the way healthcare is provided. First, there are implications for the skills and knowledge required of healthcare professionals, who need to understand how these applications work and their potential impact on patient health. Thus they are required to develop technical skills and knowledge of AI systems and technologies, and also develop medical knowledge through monitoring the impact of their use on patients. Second, these examples both have implications for the practitioners' relationship with the patient. For example, with the Crohn's app, the role of the patient, and the relationship between patient and practitioner, were transformed. The information provided by the app made patients more knowledgeable about their health, and practitioners reported that the use of the app changed the nature of patient consultations as it helped patients more clearly explain their evolving symptoms and problems.

In the domain of forensics, both Baggili and Breitinger (2015 – category 2) and Fahdi (2013 – category 2) suggest that AI systems have the potential to change and improve digital/cyber forensic investigations into digital evidence. Both articles are speculative, outlining proposed changes and developments, rather than evaluating the use of AI applications in contemporary work contexts. While Fahdi (2013 – category 2) considers the use of social media as a potentially valuable tool for cyber forensics, Baggili and Breitinger (2015 – category 2) examine a potential application for helping to sort and manage digital evidence.

Both articles imply that forensic examinations increasingly require the analysis of digital sources, and that forensic professionals are now required to develop the necessary skills and competencies for this kind of work. This suggests that the use of these applications is likely to broaden and enhance the skills base of these workers.

4 Ethical issues related to the contemporary utilisation of AI, robotics and automation technologies

AI-enabled technologies are already used in a variety of professional contexts and sectors such as labour, healthcare, transport, education, research, commerce, military and security, and so on (Luxton 2014 – category 2; Lutz and Tamò 2015 – category 3). According to the US scientist Mosche Verdi, *'by 2045 machines will be able to do if not any work that humans do, then a very significant fraction of the work that humans do'* (Reeves 2016, p151 – category 2). However, these rapid technological developments may also present risks and have negative impacts on individuals, organisations and societies (Belloni et al 2015 – category 5; Zeng 2015 – category 5; Reeves 2016 – category 2). Recently both scientists and practitioners have pointed out the need for a robust ethical strategy that will ensure the safe use of advanced technologies.

AI-related ethics has been approached from a multidisciplinary perspective. Current discussions incorporate themes from philosophy, psychology, anthropology, politics, law, economics, computer science, different branches of advanced technology, and even science fiction (Dodig-Crnkovic and Çürüklü 2012 – category 2; Zeng 2015 – category 5; Belloni et al 2015 – category 5; Torras 2015 – category 4; Frank 2016 – category 2). New disciplines and terminology such as *AI ethics,*

roboethics, machine ethics, cyberethics, artificial moral agents, robotic privacy, robot rights, and so on, have emerged (Luxton 2014 – category 2; Lutz and Tamò 2015 – category 4; Ashrafian 2015 – category 5; Reeves 2016 – category 2; Bryson 2016 – category 2). Yet, most examples describe situations of anticipated impacts of future technologies and, thus, are rather visionary and speculative, rather than being derived from real-life situations (Michelfelder 2011 – category 2; Torras 2015 – category 4; Zeng, 2015 – category 5). Potential ethical conflicts may refer broadly to machine–user relations, accountability, privacy and human/robot rights, technological singularity, and design of ethical machines (see below for details).

Machine–user relations

Luxton (2014 – category 2) hypothesises a number of ethical issues related to artificial intelligence care providers (AICPs) in mental health and in care professions (for example medicine, nursing, social work, education, and ministry) in general. AICPs may exist in various forms and interact with users (for example 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 (for example audio simulations). Many current AICPs/'caring' machines are designed to 'read' emotions and behavioural 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' (that is, the inability of a human to determine if they are interacting with a machine or not). This could be a significant ethical issue, especially in situations involving vulnerable people (for example children, patients). For

instance, Wisenbaum (Luxton 2014 – category 2) found that even when patients who interacted with an AI-simulated psychotherapist knew that that was just software, they still considered it a real therapist. Similar concerns have been raised in relation to the increased use of robotic nannies and companion machines in general (Torras 2015 – category 4; Frude and Jandrić 2015 – category 3; Reeves 2016 – category 2). One subconscious way of humans to protect themselves from the potential negative impacts of advanced social robots on their mental health is the tendency to base their emotional responses to an AI system on its anthropomorphism (that is, resemblance to a human). This is explained through the *'uncanny valley'* effect (that is, the more human-like a robot is, the less likely it is to evoke positive reactions in humans) (Torras 2015 – category 4).

Privacy and human/robot rights

Generally, AI systems collect a lot of information from human users. This presents a potential risk of breaking (personal) data protection rules and, ultimately, human privacy and trust (Luxton 2014 – category 2; Zeng 2015 – category 5). For instance, some technologies that are designed for healthcare (such as a psychological signal detection system with applicability to mental health) could be used for multiple purposes other than that originally intended (for example prisoner interrogation). There is also a possibility that the data collected with intelligent systems is used by organisations and governments in unintended ways. For example, some current AI technologies are used to track phone calls. The risks described go beyond the context of the caring professions into spheres such as banking and commerce. Therefore,

a key ethical consideration is the possible harvesting of large amounts of data about the public without consent.

Another dimension of the ethical issues associated with human rights is the idea that using AI technologies may threaten the rights of large groups of people by drastically transforming labour markets and reducing job opportunities. Consequently, rates of unemployment and inequality may increase (Zeng 2015 – category 5). In some scenarios humans are to be replaced by machines. In this context, Metzler et al (2016 – category 1) argue that creating human-like companion machines is neither desirable nor cost-effective. They further raise the question that if the intended role of AI systems is to perform just certain tasks and allow nurses to dedicate more time to caring and companionship, is it necessary to design companion machines that take on the caring role performed by humans?

At present, the emerging theme of robot rights is covered more by the media than academic publications. The core argument is that, like animals, robots should be considered as having rights (Zeng 2015 – category 5). However, this depends on whether robots are treated as conscious beings or not. According to Bryson (2016 – category 2), considering whether a machine should be a moral subject depends on the potential benefits and costs for both humans and machines. Bostrom and Yudkowsky (2011 – category 3) specify two criteria associated with high intelligence and linked to moral status: sentience (the capacity to feel and suffer) and sapience (self-awareness and self-responsibility). It is believed in general that animals are sentient, but only humans have sapience. In

a similar fashion, an AI system will be considered having some moral status if, for instance, it can feel pain. If it is not acceptable to cause pain to an animal, it should also not be acceptable to hurt an intelligent machine. Moreover, following this argument, if an AI system also has conscience, it would have moral status like humans do. However, Zeng (2015 – category 5) argues that although current intelligent machines do not have moral status, it is still important to protect their 'rights', and suggests that people who abuse robots would be likely to be abusive towards animals and even other humans.

Technological singularity
There is much speculation regarding the (potential) future situation where AI systems will become more intelligent, perhaps even able to understand their own design and create more intelligent successor systems. Eventually, machines may become 'super intelligent', that is, more intelligent than humans (Bostrom and Yudkowsky 2011 – category 3; Excell and Earnshaw 2015 – category 2). For instance, AI could publish outstanding academic papers, patents, or make money on the stock market. Furthermore, super-intelligent machines would be able to self-modify their goal systems, meaning they would acquire a level of autonomy. While current AI technologies are not intelligent enough to overshadow humans, some scientists warn of the danger of losing control over machines (for example highly intelligent drones/lethal autonomous weapon machines) in the future (Russell et al 2015 – category 5; Kinne and Stojanov 2014 – category 3).

Design of ethical machines
Most available AI ethics-related literature discusses the design of machines with moral status. Roboethics is an emerging field of

'There is much speculation regarding the (potential) future situation where AI systems will become more intelligent, perhaps even able to understand their own design and create more intelligent successor systems.'

'Furthermore, with the evolution of autonomous machines' responsibility, boundaries between the role of humans and machines may become less clear and even impossible to manage.'

AI ethics that is focused upon the behaviours of AI systems. More specifically, the term 'artificial intelligent agents' describes AI systems that demonstrate ethical behaviours towards humans and other machines (Luxton 2014 – category 2). The complexity of this issue is evidenced by the variety of attempts to suggest models and frameworks for designing ethical machines. For instance, Belloni et al (2015 – category 5) point out the need for the implementation of ethical machine behaviours that vary across contexts and proposed a conflict management framework for dealing with ethical conflicts in autonomous agents. They illustrate potential ethical conflicts using four scenarios associated with an autonomous car, a military robot, a 'lying' AI personal assistant, and a patient-monitoring AI system. Dogan et al (2016 – category 2) discuss the potential testing of automated vehicle ethics principles in simulated dilemma situations. Lutz and Tamò (2015 – category 4) comment on the emerging field of robotic privacy and the role of code as a central governing element of robots. Overall, most arguments are around developing AI algorithms as well as more general approaches towards predicting potential risks and designing moral/more human-like machines. There are questions about whether (machine) morality is just an extension of human motivation/morality or more than that (Bryson 2016 – category 2). This and other questions remain open to investigation.

Accountability
Luxton (2014 – category 2) emphasises the importance of competency levels of the AICPs' users for avoiding putting patients at risk. This refers to both the ethical use and design of intelligent machines. Increased complexity of AI systems causes greater difficulty in the prediction and interpretation of machine behaviours and, therefore, represents higher risks for the patients' security. Furthermore, with the evolution of autonomous machines' responsibility, boundaries between the role of humans and machines may become less clear and even impossible to manage (Bostrom and Yudkowsky 2011 – category 3; Luxton 2014 – category 2; Zeng 2015 – category 5). 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 extend beyond the context of helping professions, incorporating scenarios about the use of autonomous vehicles, banking and commerce, and even autonomous weapon systems (AWS) (Zeng 2015 – category 5; Dogan et al 2016 – category 5). Recently, both scientists and practitioners have argued vigorously about who, and at what point, should take responsibility for the negative consequences of the applications of intelligent machines. Johnson (2015 – category 5) discusses the 'responsibility gap' – whether persons and/or machines should be considered responsible – and raises the question about the fairness of attributions of responsibility. Again, this is a question of who is in control – the human user or the machine itself? For instance, should a human be held responsible for actions of a machine that is significantly more intelligent than them? Bryson (2016 – category 2) answers this question, stating that since humans have the control over the design of the robots, they also have a responsibility for them. She goes further, suggesting that *'making AI agents or patients is an intentional action ... avoidance would be most ethical choice'* (Bryson 2016, p206 – category 2).

Principles, policy and legislation

Several researchers have developed rules and principles to address these ethical considerations (Luxton 2014 – category 2; Belloni et al 2015 – category 5; Zeng 2015 – category 5; Bryson 2016 – category 2). These rules and principles are guided by considerations of both human and machine safety. Some examples are reminiscent of the three laws of robotics suggested by twentieth-century science fiction literature (that is, Isaac Asimov). For instance, in 2011, British scientists (funded by the Engineering and Physical Research Council and the Arts and Humanities Research Council) proposed an extended set of ethical rules for building robots (Luxton 2014 – category 2; Ashrafian 2015 – category 5; Zeng 2015 – category 5; Bryson 2016 – category 2). Five principles of robotics are formulated:

1 'Robots are multi-use tools. Robots should not be designed solely or primarily to kill or harm humans, except in the interests of national security.'

2 'Humans, not robots, are responsible agents. Robots should be designed and operated as far as is practicable to comply with existing laws and fundamental rights and freedoms, including privacy.'

3 'Robots are products. They should be designed using processes which assure their safety and security.'

4 'Robots are manufactured artefacts. They should not be designed in a deceptive way to exploit vulnerable users; instead their machine nature should be transparent.'

5 'The person with legal responsibility for a robot should be attributed' (Bryson 2016, p207 – category 2).

Early attempts to define and regulate AI-related ethics may indicate the future development of this emerging discipline (Zeng 2015 – category 5). Recent research (Ashrafian 2015 – category 5) emphasises that most studies in this field are focused only on human–robot interactions and do not consider potential ethical issues associated with robot(s)–robot(s) interactions. Ashrafian proposes a new robotic law – 'artificial intelligence to artificial intelligence' (AIonAI).

From guidelines to policy-making

Current literature presents only a few examples of early attempts to create AI-related legal and policy-making frameworks. Zeng (2015 – category 5) points out that current legislation refers mostly to low-tech technologies, leaving advanced AI systems unregulated. According to Ambrose (2014 – category 2), the legal and policy-making approaches to AI ethics are reactionary (that is, triggered sporadically by accidents that occur) rather than holistic (that is, generally preventative). Legal and policy decisions refer to automated systems across a small range of legal situations and are most likely to address the machine's design. Ambrose (2014) argues the issues associated with safety, dignity, accountability and privacy have been handled without recognition of the socio-technical nature of automation.

Indicative of the importance of the need for revised legislation regarding robots is the EU's work on this topic, initiated in early 2017. The proposed legislation has the aim of allowing the EU '*to fully exploit the economic potential of robotics and artificial intelligence*' while simultaneously guaranteeing a '*standard level of safety and security*' (EU 2017). This legislation is intended to be wide-ranging, covering issues such as liability, safety and changes in labour markets. Also under discussion are proposals for an EU-wide agency for robotics and AI, and the development of a voluntary code of ethics.

'Indicative of the importance of the need for revised legislation regarding robots is the EU's work on this topic, initiated in early 2017.'

Conclusion

This rapid review has synthesised key themes and emerging debates in the literature on some key emerging technologies in the context of knowledge and service work, also taking into account impacts on professions and society, to provide an up-to-date review of this field of study. This review provides a foundation for contextualising broader discourses in society around this issue.

The three main types of emerging technology that feature in the research are artificial intelligence (AI), robots and automation technologies. What is interesting in these cases are what is new and what the recurring issues are – for example, studies on the medical application of 'robots' where similar technologies have been implemented in other sectors, such as in manufacturing. New contexts for these technologies highlight the need for more nuanced ethical and moral considerations of current developments.

The majority of research that considers the work-related outcomes of emerging technologies has been conducted in the healthcare, and transport sectors. Studies of emerging technologies in the transportation context suggest that these technologies will complement and extend human capabilities rather than remove humans from the process. An example of this is the automated

decision support for air traffic controllers that increases the performance accuracy of controllers. The concept of augmentation of humans and human work in a range of ways, rather than wholesale replacement, flows through the literature across a range of domains and also those studies taking a more historical perspective of technological progress. However, the possibility for the segmentation of computer-optimal tasks from more 'human tasks', such as emotion work, is not fully debated. A key stumbling block may be the 'multi-layered' nature of much of the work that humans carry out – when a nurse takes the temperature of an elderly patient and does 'emotion work' simultaneously, will a patient miss contact with the nurse if this task is performed by a robot? Will this free up time for the nurse to enhance the 'emotion work' further? Will the emotion work be successfully taken on by the robot as technology develops? Some of the studies analysed for this review do touch upon these issues.

The most interesting themes identified in the literature centre on the relationships between humans and computers. Some studies suggest that the social aspect of machine interaction is an important mediating factor for the successful realisation of the benefits from automation. There are potentially significant social impacts related to the increasing work-related use of

these technologies which require everyone in society to develop some level of IT competency, and which transform the way products and services are delivered by workers and consumed by people. Studies highlight the ethical implications of emerging technology use, and suggest how we as humans should develop legal and policy frameworks for human–computer interaction and take responsibility for their development and treatment. It is important that legal and policy approaches focus on the human values they are trying to protect rather than on the range of possibilities that technological development represents.

As less than half of the papers are based on empirical evidence, this review highlights the need for much more extensive and robust development of knowledge around these topics in line with recommendations from the Council for Science and Technology (RP 2016). Key questions are still open and require further analysis based on evidence of how emerging technologies are being developed and implemented in practice, and how workers and humans interacting with the technology experience this. Speculative discourses, whether from the positive techno-centric or the pessimistic naysayer, are merely that – without evidence we cannot be sure of where we are now, let alone where we are headed.

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