Journal of Strategic Information Systems 29 (2020) 101600

Contents lists available at ScienceDirect

Journal of Strategic Information Systems

journal homepage: www.elsevier.com/locate/jsis

The strategic impacts of Intelligent Automation for knowledge and service work: An interdisciplinary review

Crispin Coombs[a,*], Donald Hislop[b], Stanimira K. Taneva[c], Sarah Barnard[a]

[a] School of Business and Economics, Loughborough University, Ashby Road, Loughborough LE11 3TU, UK
[b] Business School, University of Aberdeen, Aberdeen AB24 5UA, UK
[c] Faculty of Social Sciences, University of Nottingham, University Park, Nottingham NG7 2RD, UK

ARTICLE INFO

Keywords:
Artificial intelligence
Automation
Business value
Computerisation
Machine learning
Mobile robotics

ABSTRACT

A significant recent technological development concerns the automation of knowledge and service work as a result of advances in Artificial Intelligence (AI) and its sub-fields. We use the term Intelligent Automation to describe this phenomenon. This development presents organisations with a new strategic opportunity to increase business value. However, academic research contributions that examine these developments are spread across a wide range of scholarly disciplines resulting in a lack of consensus regarding key findings and implications. We conduct the first interdisciplinary literature review that systematically characterises the intellectual state and development of Intelligent Automation technologies in the knowledge and service sectors. Based on this review, we provide three significant contributions. First, we conceptualise Intelligent Automation and its associated technologies. Second, we provide a business value-based model of Intelligent Automation for knowledge and service work and identify twelve research gaps that hinder a complete understanding of the business value realisation process. Third, we provide a research agenda to address these gaps.

Introduction

Analysts and commentators have forecast mass unemployment from the automation of a wide range of job roles that involve predictable, repetitive work (Grace et al., 2018; Makridakis, 2017). The McKinsey Global Institute has claimed that 60% of jobs could become 30% automated by the early 2020s (Chui et al., 2016), while Frey and Osborne (2017) argue that automation could eliminate 47% of jobs in the United States economy by 2033. Researchers also predict that Artificial Intelligence (AI) will outperform humans in many activities in the next ten years (Grace et al., 2018), thereby becoming a practical alternative to human labour (Makridakis, 2017). These claims are based on a recent step change in the technological advance of AI. AI is the broad suite of technologies that can match or surpass human capabilities, particularly those involving cognition such as learning and problem solving (DeCanio, 2016). Applications of AI are wide-ranging and include knowledge reasoning, machine learning, natural language processing, computer vision, and robotics. For clarity, we use the term AI to refer to all these technologies.

Advances in AI and its sub-fields have enabled the development of a new form of automation that we describe as Intelligent Automation[1] (the application of AI in ways that can learn, adapt and improve over time to automate tasks that were formally

* Corresponding author.
E-mail addresses: c.r.coombs@lboro.ac.uk (C. Coombs), donald.hislop@abdn.ac.uk (D. Hislop), Stanimira.Taneva@nottingham.ac.uk (S.K. Taneva), s.h.barnard@lboro.ac.uk (S. Barnard).

[1] We use the term Intelligent Automation throughout this paper, rather than the abbreviation IA, to avoid confusion with AI.

https://doi.org/10.1016/j.jsis.2020.101600
Received 1 July 2017; Received in revised form 29 January 2020; Accepted 3 February 2020
Available online 09 March 2020

undertaken by a human). Frey and Osborne (2017) observe that algorithms are being developed that would allow cognitive tasks to be automated. They also state that the application of AI in mobile robotics has extended the opportunity for automation of manual tasks. Cognitive and manual tasks are commonly found in knowledge and service work (Davenport and Kirby, 2016a). Knowledge work is defined as work which is intellectual, creative, and non-routine, and which involves the utilisation and creation of knowledge (Hislop et al., 2018). Knowledge work includes work in a wide range of professional areas, such as information and communication, consulting, pharmacology, and education (Kuusisto and Meyer, 2003). Service work can be defined as the process of using one's resources (e.g., knowledge) for someone's (self or other) benefit (Barrett et al., 2015). It includes jobs as diverse as working in retail, security, office cleaning, and more knowledge-intensive work such as consulting. Our definition of service work thus includes (white-collar) office and administrative work.

Until recently, knowledge and service work tasks have been considered too difficult to automate because they require a high degree of cognitive flexibility and physical adaptability (Lacity and Willcocks, 2016b). However, the scope and capability of AI has recently expanded and is likely to continue to grow (Brynjolfsson and McAfee, 2016). For example, applications of AI are predicted to significantly reduce the need for humans to translate languages (by 2024), drive a truck (by 2027), work in retail (by 2031), and work as surgeons (by 2053) (Grace et al., 2018). Frey and Osborne (2017) predict that most office and administrative support work, as well as a substantial proportion of service work in the US, is likely to be automated. In which case, the advance of AI will create dramatic changes to the supply of knowledge and service work (Loebbecke and Picot, 2015). It is this impact on knowledge and service work that sets this change apart from previous technological revolutions, such as the industrialisation of factory work in the 19th century, or the adoption of transactional computers for administrative and service work in the late 20th century (Davenport and Kirby, 2016b). This review focuses on knowledge and service work to examine the transformational effects of Intelligent Automation in sectors that have previously been relatively untouched by automation compared to other industries, such as manufacturing (Brynjolfsson and McAfee, 2011).

The transformation of knowledge and service work presents organisations with a new strategic opportunity to increase business value. Recent advances in AI could enable organisations to create new business value opportunities through the application of Intelligent Automation to middle-income cognitive jobs (Manyika et al., 2017). Alternatively, organisations may opt to substitute new AI capital for high-skilled labour or choose to reassign high-skilled workers to focus more exclusively on the most complex, non-routine cognitive tasks (Davenport and Kirby, 2016a). However, there is considerable disagreement regarding the possible impacts of AI on knowledge and service work. Makridakis (2017) identified four contrasting perspectives: optimists that predict a utopian future of AI (e.g., Kurzweil, 2005); pessimists that predict a dystopian future where AI reduces humans to a second rate status (e.g., Bostrom, 2014); pragmatists that predict AI will augment human skills (e.g., Markoff, 2016); and doubters that predict that AI will never be able to replicate human intelligence (e.g., Jankel, 2015). This lack of consensus means that there is little coherent guidance regarding the new strategies that need to be developed to realise business value from Intelligent Automation. Thus, there is a pressing need for research that examines the latest advances in AI and considers their impact on the application of Intelligent Automation for business value.

A valuable source of guidance for strategic perspectives on Intelligent Automation is current academic knowledge. Numerous studies, many employing sound rigorous methods, consider the potential impacts of AI on work. However, these contributions are situated in a wide range of scholarly disciplines that draw on contrasting research paradigms, theories, methods, and perspectives, resulting in a lack of consensus regarding critical findings and implications. Operating at the intersection of many scholarly disciplines, considering both social and technical aspects, IS researchers are well placed to assemble a cohesive understanding of this emerging research challenge. Thus, this paper aims to inform researchers of the current state (state of the art) of research relating to the application of Intelligent Automation for knowledge and service work.

To assist the IS research community in navigating this complex domain, this paper provides a scoping review of existing academic literature (Paré et al., 2015). Scoping reviews focus on breadth rather than depth of coverage in the literature. They describe and summarise the size and nature of the literature on a particular topic and allow researchers to identify research gaps in the extant literature (see, for example, Smith et al., 2011). The advantage of this approach is to offer a comprehensive view of the research landscape. This review explores the potential impacts of Intelligent Automation through the classification of AI research related to knowledge and service work published between January 2011 and December 2017. We focused our review on knowledge and service work for two reasons. First, the most significant developments associated with the work-related use of AI have been in occupations that have hitherto made little use of them, such as the knowledge and service industries (Brynjolfsson and McAfee, 2011; Loebbecke and Picot, 2015). Second, the late 20th century and the start of this century has witnessed a significant growth of employment in knowledge and service work, and a decline in jobs in manufacturing sectors in advanced economies (Castells, 1998; Hislop et al., 2018). To provide a business value perspective, we utilised the strategic IS business value literature to guide our review (Schryen, 2013). We address the salient features of the Intelligent Automation field regarding the generation of business value from knowledge and service work that will serve as a roadmap for future research.

Our review provides three important contributions to the literature. First, we conceptualise Intelligent Automation and review the technologies that enable it. This conceptualisation is essential because academic and media articles are characterised by inconsistent use of terminology regarding the automation of knowledge and service work. Second, based on our review of the literature, we present a business value-based model of Intelligent Automation for knowledge and service work and identify twelve crucial research gaps that hinder a complete understanding of the business value process. Third, we provide a research agenda to address these research gaps. These contributions respond to calls to synthesise the current state of academic knowledge across multiple disciplines regarding automation of knowledge and service work (Loebbecke and Picot, 2015; Newell and Marabelli, 2015).

The remainder of this paper is structured as follows. In the next section, we define Intelligent Automation and discuss the technologies that enable it. We then briefly discuss the IS business value literature that guided our review framework and analysis. After explaining the method for our interdisciplinary scoping review, we adopt a business value perspective to present our findings. Based on our analysis, we then offer a business value-based model of Intelligent Automation for knowledge and service work, critically discuss key research gaps, and provide an agenda for future research.

Conceptualising Intelligent Automation for knowledge and service work

In this section, we discuss our definition of Intelligent Automation and the technologies that enable it.

Scholars have proposed a variety of terms to describe the application of computer technologies to automate work tasks. Some of the most commonly applied terms include computerisation, virtualisation, and automation. Computerisation has been used by economists to describe the substitution of human labour by computers to complete tasks since the computer revolution of the 20th century (Autor et al., 2003). Frey and Osborne (2017: p254) extend the definition to include the latest technological advances in AI describing computerisation as the "automation of jobs by means of computer-controlled equipment such as machine learning and mobile robotics". By contrast, McAfee and Brynjolfsson (2017) use 'virtualisation' to describe transactions and interactions that used to take place between people in the physical world that are now completed via digital interfaces. For example, the Eatsa restaurant allows a customer to order and receive a meal without having to speak or interact with a human. Thus, this transaction may be considered to have become 'virtualised' (McAfee and Brynjolfsson, 2017). Automation is an established term from Ergonomics and Human Computer Interaction research. Automation has been defined as "the execution by a machine agent (usually a computer) of a function that was previously carried out by a human" (Parasuraman, 1997: p231). Davenport and Kirby (2016b) have chosen 'automation' as the term to describe the use of AI as a substitute for knowledge and service workers. They argue that it is the application of AI to automate knowledge and service tasks that set the current transformation apart from 'traditional' automation of repetitive, manual tasks in sectors such as manufacturing.

However, all these terms struggle to fully encompass the recent step change in intelligent technology advancements and the new opportunities for replacing human labour in knowledge and service work. Computerisation has the merit of being an established term in the economics literature, but it fails to capture, in our view, the transformational aspect of recent advances in AI. Virtualisation presents a more future-focused image of computing, but it is a term widely used in the Computer Science literature for a different phenomenon, about virtual (rather than actual) versions of computer resources (Ali and Meghanathan, 2011). Thus, the use of 'virtualisation' to describe the substitution of human work by AI is likely to confuse with established research terminology. Finally, although automation is an established concept and reflects the replacement of humans by machines, referring to computers automating work does not encapsulate the radical transformation of work that AI may enable. What differentiates automation in the 21st century with automation in the 20th century is the use of computer technologies that may be described as 'intelligent' (Davenport and Kirby, 2015). The latest advances in AI are demonstrating striking abilities to learn and improve, adapting and increasing performance over time through exposure to greater amounts of data or increasing experience of attempting to complete a task (Brynjolfsson and McAfee, 2016). While these advances do not equate to human levels of intelligence (Aleksander, 2017), they are demonstrating new cognitive capabilities that can substitute for humans in some knowledge and service work tasks (Davenport and Kirby, 2015). Thus, we define Intelligent Automation as the use of technologies, (e.g., AI and its sub-fields), to replace human capabilities, particularly those involving cognition such as learning and problem solving, for the execution of work tasks that were previously carried out by a human. Intelligent Automation differs from previous forms of automation in that AI machines can learn, adapt and improve over time. In the following section, we define the technologies that enable the Intelligent Automation of knowledge and service work.

Technologies for Intelligent Automation

Research in AI has been undertaken since the 1970s with early developments in decision support systems (DSS) and expert systems (ES) (El-Najdawi and Stylianou, 1993). However, in recent years, game-changing progress has been made in addressing some of the fundamental challenges of the AI discipline. Advances have been made in Natural Language Processing, Machine Learning, and Computer Vision (Brynjolfsson and McAfee, 2016). The rapid growth in the availability and accessibility of big data combined with vast computing power, readily available through the cloud, have aided these developments (Davenport and Kirby, 2016b). These recent advances in AI are creating a new generation of systems that are distinct from the early DSS and knowledge-based systems in three respects.

- First, the old systems could not automatically learn and improve their methods and results and were reliant on human programmers to make adjustments.
- Second, the old systems functioned as assistants or advisors to human professionals providing recommendations or advice, but they required a human worker to apply the decision.
- Third, while these systems were designed to help managers with repetitive decisions and complex unstructured problems, they were not designed to remove cognitive tasks from the workload of the human.

Thus, although the recent advances in AI may be considered a further evolution and extension of the original AI field, their widespread adoption in organisations presents a fundamentally different landscape to what came before. Table 1 summarises these early AI applications and their limitations.

To investigate the application of Intelligent Automation for knowledge and service work we were guided by the highly cited work

Table 1
Early applications of AI and associated limitations.

Application	Description	Limitations
Decision Support System (DSS)	A set of tools utilising models and or analytic techniques to assist managers in their decision-making (El-Najdawi and Stylianou, 1993).	It contains the knowledge of human experts in solving particular problems but is not able to automatically enhance that knowledge based on the experience of results without human intervention. System designed to support, and not replace, humans (Mallach, 2000).
Expert Systems (ES)	Systems designed to capture the knowledge of human experts in a narrow problem domain, and help solve problems (El-Najdawi and Stylianou, 1993).	Aimed to achieve the flexibility to remove experts from repetitive decisions but not to replace human counterparts (El-Najdawi and Stylianou, 1993; Ye and Johnson, 1995).
Knowledge Management Systems (KMS)	Support the creation, transfer, and application of knowledge in an organisation (Alavi and Leidner, 2001).	Provides professionals with a support tool to find organisational knowledge to solve business problems or locate the relevant internal expertise, but do not implement decisions (Alavi and Leidner, 2001).
Recommendation Agent (RA)	Software agents that capture the preferences of customers and make recommendations based on these preferences (Xiao and Benbasat, 2007).	A human is still required to review the recommendations presented by an RA and decide which recommendation to apply (Alavi and Leidner, 2001; Xiao and Benbasat, 2007).

of Frey and Osborne (2017).[2] In their study of how susceptible jobs in the US labour market were to computerisation Frey and Osborne (2017) focused on Machine Learning (ML) and related fields including data mining and machine vision, as well as sub-fields of AI that were related to cognitive task automation. They also focused on the application of ML in mobile robotics to consider the automation of manual tasks. ML refers to the ability of a computer to automatically refine its methods and improve results as it receives more data (Brynjolfsson and McAfee, 2016). Frey and Osborne's (2017) study indicates that the recent developments in ML are likely to have significant impacts on knowledge and service work. Consequently, we focused our literature review on the same technologies that Frey and Osborne (2017) used in their study. We discuss some of the potential impacts on knowledge and service work below.

Advances in ML are enabling the development of algorithms that allow cognitive tasks found in knowledge and service work, to be automated (Frey and Osborne, 2017). Frey and Osborne (2017) emphasise the importance of advances in ML that develop algorithms that mimic human cognitive functioning. Therefore, ML advances are critical, as once progress has been made regarding machines' ability to build on their knowledge for decision making, real-world applications of automated decision making are likely to follow (Davenport and Kirby, 2016a). For example, ML algorithms are enabling the automation of cognitive tasks such as medical imaging analysis (Lee et al., 2017), or auditing tasks such as identifying accounting anomalies in unusually high sales figures (Kokina and Davenport, 2017).

Combining ML technologies with mobile robotics enables the automation of manual tasks (Frey and Osborne, 2017). There are many definitions of robotics, and the term is not clearly defined (Dautenhahn, 2013). You and Robert (2018) observe that there is agreement among scholars that embodiment and the representation of embodied behaviours are characteristics that differentiate robots from other technologies. Thus, we decided to adopt the definition of robots proposed by You and Robert (2018: p 377) as "technologies with both virtual and physical embodied actions". Mobile robots are being used in various ways in the knowledge and service sectors. For example, mobile service robots can complete a physical task, such as scrubbing, cleaning, sorting and packaging instruments (Chen, 2013), pouring a liquid for a human (Xu et al., 2013), or serving meals in a restaurant (Yu et al., 2012). These robots may operate autonomously without the need for specific human guidance or intervention. Mobile robots may also enable humans to complete physical tasks more efficiently, achieving higher levels of accuracy and performance than would have been possible relying on human physical capabilities alone, such as robot-assisted surgery (Zaghloul and Mahmoud, 2016).

Moreover, some robots achieve human–machine interactions that resemble communication between humans and are referred to as "social robots" (Torras, 2015). Social robots may interact with older adults or clinical patients and even act as support teachers and nannies (e.g., Torras, 2015; Calo et al., 2011). In this paper, we included studies of any robot type (as well as applications of AI or ML) if they were associated with some aspect of knowledge or service work.

IS business value

The delivery of value from IS investments remains a critical strategic issue for organisations. IS business value is defined as "the impact of investments, in particular, IS assets on the multidimensional performance and capabilities of economic entities at various levels, complemented by the ultimate meaning of performance in the economic environment" (Schryen, 2013: p. 141). The importance of business value has led to considerable research interest with much of it presenting empirical evidence supporting the operational and strategic relevance of IS (Schryen, 2013).

[2] Frey and Osborne originally published their study as an Oxford Martin Programme on Technology and Employment working paper in 2013 https://www.oxfordmartin.ox.ac.uk/publications/the-future-of-employment/. The study was published in Technological Forecasting and Social Change in 2017.

One outcome of this research has been the creation of several IS business value models. Four models that have been particularly prominent in the IS literature are, 1) IT and Economic Performance Framework (Dedrick et al., 2003); 2) Benefits of IT Investments Framework (Dehning and Richardson, 2002); 3) IT Business Value Model (Melville et al., 2004); and 4) Process Model of IT Business Value (Soh and Markus, 1995). Schryen (2013) reviewed these models and demonstrated that they shared common insights. These insights included the recognition that IS investment impacts could be assessed across several performance measures (e.g., business process performance, firm market performance, firm accounting performance); that improvements in business processes and firm performance are influenced by contextual factors (e.g., firm, industry or country factors); that IS investments and assets can be classified in different forms (e.g., hardware/software, human IS resources, or IS management capabilities); and that lag effects need to be accounted for when assessing the impact of IS investments.

Drawing on these common insights, Schryen (2013) combined these models to produce a new synthesised model of IS business value. This synthesised model provides a hybrid perspective combining their most useful qualities. Consequently, we decided to use Schryen's (2013) synthesised model of IS business value as a framework to structure our literature analysis, which means that the review foregrounds an IS business value perspective in its assessment of the literature.

Literature review

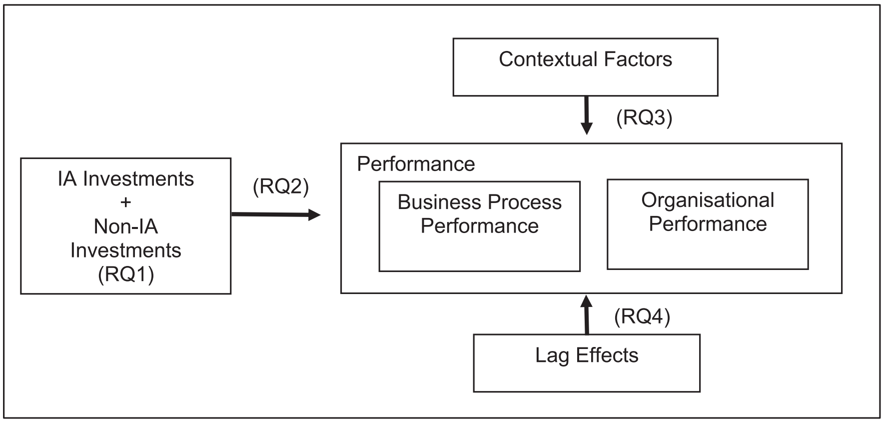
To understand the size and nature of the literature regarding the strategic impacts of Intelligent Automation for knowledge and service work, we undertook a scoping review of the literature (Paré et al., 2015). Responding to several calls for research that goes beyond the boundaries of individual academic disciplines (Loebbecke and Picot, 2015; Newell and Marabelli, 2015), we aimed to focus on breadth rather than depth of literature coverage and in so doing identify research gaps in the extant literature. Schryen's (2013) synthesised model of IS business value indicates that to understand the process of realising business value, four broad elements need to be investigated:

(1) IS investment types (e.g., infrastructure and business applications) and complementary non-IS investments (e.g., organisational structure, policies and rules, workplace practices);
(2) Business process performance (e.g., measures of customer service, flexibility, information sharing) and organisational performance (e.g., measures of productivity, efficiency, profitability);
(3) Context/environmental factors (e.g., industry competitiveness, level of development, population growth rate);
(4) Lag effects (e.g., the delay of IS investment effects by years).

Schryen (2013) does not provide detailed definitions for all the terms in his synthesised model. Consequently, we referred to one of the four underpinning IS business value models (IT Business Value Model, Melville et al., 2004) to define the key terms for our review framework. These key terms and their definitions are summarised in Table 2.

Table 2
Definition of key terms used in literature review framework (adapted from Melville et al., 2004; Schryen, 2013).

Research Question	Key terms	Definition
1) What Intelligent Automation investments and non-Intelligent Automation investments have been studied?	Intelligent automation investments	Technologies such as AI and its sub-fields that can replace human capabilities, particularly those involving cognition, for the execution of work tasks that were previously carried out by a human.
	Non-Intelligent Automation investments	Organisational investments complementary to Intelligent Automation, e.g. non-IA physical resources, non-IA human resources, organisational structure, policies and rules, workplace practices.
2) How have Intelligent Automation investments influenced business process performance or organisational performance?	Business processes	Activities that underly value-generating processes (transforming inputs to outputs), e.g., inbound logistics, manufacturing, sales, distribution, customer service.
	Business process performance	Operational efficiency of specific business processes, measures of which include customer service, flexibility, information sharing, and inventory management.
	Firm/ organisational performance	Overall firm performance, including productivity, efficiency, profitability, market value, competitive advantage.
3) How have contextual factors influenced Intelligent Automation enabled business process performance or organisational performance?	Contextual factors	Factors shaping the way in which Intelligent Automation is applied within the focal firm to generate business value, including competitiveness, regulation, and/or industry or country factors shaping Intelligent Automation application and Intelligent Automation enabled business value generation, including the level of development, basic infrastructure, education, research and development investment, population growth rate, culture, etc.
4) How have lag effects influenced Intelligent Automation enabled business process performance or organisational performance?	Lag effects	Period that may be several years.



Note: IA = Intelligent Automation

Fig. 1. Framework for Intelligent Automation Literature Analysis (based on Schryen, 2013).

When reviewing our sample literature, we used four research questions to structure our review framework: 1) What Intelligent Automation investments and non-Intelligent Automation investments have been studied? 2) How have Intelligent Automation investments influenced business process performance or organisational performance? 3) How have contextual factors influenced Intelligent Automation enabled business process performance or organisational performance? 4) How have lag effects influenced Intelligent Automation enabled business process performance or organisational performance? Fig. 1 presents the research framework we adopted with the associated research questions.

We followed the three-stage approach for undertaking the literature review advocated by Webster and Watson (2002). First, we selected four bibliographical databases (Scopus; Business Source Complete, PsycINFO and Web of Science) that between them encompass the academic literature in the fields of science, technology, medicine, social sciences, and arts and humanities, all disciplines of business, and interdisciplinary research in the behavioural and social sciences. These databases also index the AIS basket of eight journals. We developed two categories of search terms for interrogating the databases. The first category concerned terms related to Intelligent Automation and associated technologies such as “automation”, “artificial intelligence”, “machine learning”, “cognitive computing”, “smart machines”, “mobile robots” and “robot”. The second category included search terms that were related to the effects or impacts of these technologies and included “innovation”, “business value”, “productivity”, “employment”, “ethics”, “social impact” as well as “knowledge work” and “service work”. Within the four databases, search combinations were performed where each search combined a technology search term with an impact term using truncation and wildcards.

Paré et al. (2015) state that for scoping reviews, inclusion and exclusion criteria must be established to help researchers eliminate studies that do not address the initial research questions. The initial inclusion criteria for our review were peer-reviewed articles and conference papers published in English from January 2011 – December 2017 that had full text available. We chose to focus our attention on published research in the last six years for one primary reason. The significant growth in awareness regarding the impact of Intelligent Automation on knowledge and service work can be arguably traced back to significant contributions in 2011 from Brynjolfsson and McAfee (2011) and Acemoglu and Autor (2011). This year range is also the norm for this type of scoping study (Zheng and Lee, 2016).

These searches identified a total of 1581 articles and conference papers from all disciplines. The titles and abstracts were reviewed for each source to see whether they should be included. Items were excluded if they were purely technical papers concerned with engineering and design issues related to the technologies examined, or they were not focussed on the application of the selected technologies in the context of knowledge and service work. Duplicate sources were also identified and removed. This filtering process produced 136 sources for review and coding. Second, a backward search was conducted via the reference lists of these 136 sources. Third, we used Web of Science to perform a forward search to identify sources that cited key articles identified from the initial search. These two steps produced a further 83 sources for inclusion. Thus, the total number of sources identified for review and in-depth coding was 219.

The sources were coded according to the four research questions, plus immediate context,[3] level of analysis, and reference discipline. The main research finding of the paper was used as the primary basis for research question coding. Papers that provided substantive findings related to more than one research question were coded to all relevant research questions. After completing the coding and review, an additional 35 sources were removed from the sample. These sources included working papers, trade professional or newspaper articles (15 sources), sources that referred to technologies that were not of direct interest to this study, for example, crowdsourcing and virtual reality (16 sources) or sources whose origin was unclear, not peer-reviewed or only comprised of

[3] For this study, we only consider the immediate context where the study is conducted, i.e. the organisation, industry or sector. For studies that were proof of concept or experiments, we recorded the context for where the Intelligent Automation was intended to be applied, e.g., an ML experiment to identify genes associated with Alzheimer's disease was classified as the healthcare context.

an abstract (4 sources). The resulting sample of 184 coded journal and conference papers are listed in Appendices A and B.

Findings

In this section, we discuss the findings of our analysis of the literature concerning our four research questions.

What Intelligent Automation investments and Non-Intelligent Automation investments have been studied?

Research on Intelligent Automation for knowledge and service work tends to present new artefacts or technological solutions that are designed to improve on human limitations in information processing for completing cognitive or manual tasks. Information processing comprises four stages (a) information acquisition, (b) information analysis, (c) decision making, and (d) action (Parasuraman et al., 2000). Two interconnected streams of research have driven these improvements: advances in AI and developments in mobile robotics.

Much of the literature in our sample focused on using AI in the first two information-processing stages (a and b). For example, scholars have developed AI systems to automate clinical report writing (Ye, 2015) and a non-disease-specific AI system for the development of complex care plans (Bennett and Hauser, 2013). Anomaly intrusion detection systems have been developed to improve cyber security (Enache et al., 2015) as well as an automated forensic examiner that can be used to sort and identify relevant artefacts of cybercrime (Fahdi, 2013). Broussard (2015) describes the development of intelligence-based software system prototypes for data sorting and identification of investigative storytelling opportunities for public affairs reporting. These research findings show that Intelligent Automation can provide new information processing capabilities to organisations, managing large volumes of data that are overwhelming to humans. They are also capable of adjusting and adapting internal models as new data becomes available to provide results that are increasingly consistent with past data (Tarafdar et al., 2017).

Although less prevalent, scholars have also made progress in developing Intelligent Automation technologies to optimise decision-making and action. For example, scholars have developed new AI-enabled applications to predict the likelihood of outcomes, such as bankruptcy (Chaudhuri and De, 2011), flooding (Sayers et al., 2014), or improving stock market timing and portfolio creation (Hilovská and Koncz, 2012). ML-enabled mobile robots are capable of making sorting decisions and packaging objects (Chen, 2013); navigating a restaurant and picking up plates (Yu et al., 2012) or giving directions in a shopping mall (Brscic et al., 2017). These studies show how some tasks that formerly required human intervention are being automated. However, it was notable in these studies that robots were positioned as supporting rather than substituting for the worker. For example, a mobile robot can pick up plates in a restaurant, but a human is still required to clean and reset the table (Yu et al., 2012). Similarly, new mandatory auditing procedures might be automated, but a human is still needed to check and sign off the audit (Sutton et al., 2016; Kokina and Davenport, 2017). Thus, it is essential to consider Intelligent Automation at the level of *tasks*, rather than *jobs* per se when attempting to predict the implications for technologically driven unemployment/underemployment.

The level of Intelligent Automation may also vary for different tasks. For example, fully autonomous mobile robots have been equipped with environmental sensors to collect environmental data in warehouse environments (Russo et al., 2016), complete cleaning tasks in elderly care environments (Nielsen et al., 2016) or adapted to be able to navigate their way around an environment without collisions with objects or other robots (Dewi et al., 2014). In each case, these mobile robots can complete their assigned tasks without the need for any human supervision. By contrast, Calo et al. (2011) describe the use of the Paro animalistic robot that mimics the behaviour of a seal to help with care for elderly dementia patients. Paro responds when people interact with it via talk or touch. Although Paro can react to humans automatically, a health or social care professional is still needed to decide when to give the robot to the patient, the duration of the patient's interaction with the robot, and to supervise the interaction. Thus, while the robot operates autonomously, a human is necessary for robot deployment and supervision. The humanoid child robot Kaspar illustrates a further level of automation. Kaspar has been designed for interactions with children with Autism Spectrum Disorders (ASD). Wood et al. (2013) report that during interviews, children with ASD found it easier to interact with Kaspar, compared to a human interviewer, because the robot was more predictable and offered fewer complex cues to interpret. Kaspar was operated remotely by a healthcare professional using a ‘Wizard of Oz’ style of control, so the robot appeared to behave autonomously. In this example, the robot required healthcare workers to operate the robot and also monitor and supervise the interaction between the child and the robot (Bekele et al., 2013; Wood et al., 2013). Therefore, it appears that the level of Intelligent Automation may vary for different tasks, ranging from no automation, the worker does everything, to full automation where the worker is no longer needed (Sheridan and Parasuraman, 2005).

These studies also indicate that for the successful deployment of Intelligent Automation, human work roles may need to be redesigned or created. Human workers may be required to perform new tasks such as supervising, collaborating, controlling, or rectifying malfunctions in AI applications. These new or re-designed roles may result in role expansion or job deskilling. For example, the implementation of an automated dispensing system enabled the expansion of the pharmacy technicians’ role to ward-based dispensing and discharge services, but also made the technicians feel like production-line workers rather than skilled dispensers (James et al., 2013). Further, when redesigning the task, developers need to consider whether the work task is solely to perform the required function (e.g., serving food to a handicapped person) or requires a more holistic perspective that connects to other ‘work’ (e.g., that the service employee ‘notices’ that the person with a disability is experiencing acute health problems). A care robot may be able to perform both functions but must be designed to be able to undertake these tasks (Fischer, 2012). Thus, the redesign or creation of Intelligent Automation work tasks should consider two perspectives: the tasks to be processed and the functions the Intelligent Automation should perform (task-orientated perspective), and whether this is a desirable organisation of work to deliver the required performance results, for example, in relation to service quality and profitability (organisation of societal work perspective) (Fischer, 2012).

A small number of studies highlighted some of the related technical skills needed by human workers for the application of Intelligent Automation. For example, surgeons initially undergo a steep learning curve to perform robot-assisted surgery (Sananès et al., 2011). However, it has been found that once surgeons have experience of using robot surgery and conducting particular types of operation, they can extend their skills to related surgical procedures relatively easily (Semerjian and Pavlovich, 2017). One study also reviewed the role of nurses as part of the robot-assisted surgical team, reporting that these nurses were required to obtain a high level of professional knowledge alongside expertise in robotic technology to manage robotic malfunctions (Raheem et al., 2017). These studies highlight the need for human workers to have complementary technical skills for the Intelligent Automation of some work activities.

How have Intelligent Automation investments influenced business process performance or organisational performance?

The literature reviewed suggests that the application of Intelligent Automation can deliver improvements in business process performance. Bogue (2011) reports that the use of robots in science labs can reduce labour, provide greater precision, reduce risks to human operators, eliminate sample contamination, and complete tasks more quickly compared to human manual processes. Ye (2015) reports on the development of a secretary-mimicking AI system claiming that pathologists can save time via automating routine secretarial work. Similar claims have been made for the Intelligent Automation of sales work (Holloway et al., 2013), forensic work, where AI-enabled data mining technologies can be used to analyse social media (Baggili and Breitinger, 2015), and public affairs reporting (Broussard, 2015). These studies suggest that Intelligent Automation can have a positive influence on business process performance.

Improvements in business process performance can be achieved either through full automation of processes or augmenting human capabilities. For example, Robotic Process Automation (RPA) automates routine administrative tasks. It eliminates the need for people to undertake routine data entry work, which has widespread business relevance, e.g., validating the sale of insurance premiums, generating utility bills, creating news stories, paying healthcare insurance claims, and keeping employee records up to date (Lacity and Willcocks, 2016b). Lacity and Willcocks (2016a) report a case study of the RPA implementation experiences of Telefónica O2. The company automated 15 processes using 160 RPA robots[4] Providing a 600–800% return on investment over three years and reported labour reductions or re-deployments of full-time employees (FTE) in the 'hundreds'. The duration of some processes were described as being reduced from days to minutes and follow up calls to customers had fallen by 80% compared to previous levels. In another case study of Xchanging, a London-based business process and technology services provider, it was reported that the application of RPA to validate the sale of 500 insurance policies reduced the process from several days to about 30 min (Lacity and Willcocks, 2016b). By 2016, Xchanging had automated 14 processes using 27 RPA robots, saving an average of 30% on each process. In both cases, it was implied that the business process performance improvements had contributed to overall organisational performance improvement, but this link was not studied directly. The studies suggest that organisations that are keen to adopt full Intelligent Automation for work tasks are likely to prioritise internal cost-saving and productivity improvements, thereby following an efficiency strategy to deliver business value (Melville et al., 2004).

Process performance improvements have also been reported when Intelligent Automation and human capabilities have been combined to perform complex tasks such as robot-assisted surgery. The use of a surgical robot enables the human surgeon to complete surgical operation procedures to higher levels of precision using less invasive methods than would have been possible without the robot's assistance leading to better patient recovery times. For example, when compared to open surgery, robot-assisted radical cystectomy combined with an enhanced recovery process reduced surgical morbidity and length of stay (Collins et al., 2016). Similarly, a study of robotic colorectal surgery found that a length of bowel around the tumour could be removed more safely with reduced blood loss (Zaghloul and Mahmoud, 2016). A study reporting the development of autonomous robot-assisted mastoidectomy (a surgical procedure that removes diseased mastoid air cells located in the skull) found that 96% of the targeted bone could be removed without damage to critical structures (Danilchenko et al., 2011). These studies of Intelligent Automation suggest that organisations that augment human capabilities, rather than fully automate tasks, thereby prioritising service quality improvements, are more likely to adopt an effectiveness strategy to deliver business value (Melville et al., 2004).

Many of the performance improvements reported in the literature are achieved by combining the technical capabilities of Intelligent Automation with the social skills of human workers in hybrid worker teams (Schwartz et al., 2016). Thus, where the human worker continues to contribute to the work task, the performance of the human, as well as the Intelligent Automation technology, may influence business process performance. Several studies have explored the role of humans working alongside automated business processes and the impact on the performance of the human and report mixed results. For example, in the transport sector, Balfe et al. (2015) report on an experiment to compare increasing levels of Intelligent Automation in rail signalling. They found that human rail signalling performance was most consistent during the highest level of automation and that human operators perceived their workload to have reduced. Reporting on an air traffic control experiment and trial, van de Merwe et al. (2012) found that automation enabled air traffic controllers to achieve more accurate air traffic delivery. They also found that some air traffic controllers reported reduced levels of physical workload but no reduction of mental workload. By contrast, Dang and Tapus (2015)

[4] An RPA 'robot' is a software solution and not a physical robot. An RPA robot is the equivalent of one software license (Lacity and Willcocks, 2016a).

report on an experiment into young people's attitudes towards the use of robot assistants and the extent to which this affected people's performance and stress levels. While they found that people preferred working with robotic support, the use of robotic assistance did not improve their performance. Kraan et al.'s (2014) secondary analysis of European survey data suggests that a combination of technological pacing of tasks and lack of autonomy of workers can increase stress levels.

Further, Nomura et al.'s (2011) experimental study found that human anxiety levels increased when robots behaved in specific ways for those who had pre-existing high levels of anxiety and Gombolay et al. (2015) found that when people work with robots, they allocate more work to themselves than their robot co-worker. These studies provide evidence to show that worker performance may improve or deteriorate when working with Intelligent Automation. Scholars recommend that Intelligent Automation needs to be designed to prevent the creation of additional work for the human worker, such as data entry or the monitoring of the robot's work, if reductions in human worker performance is to be avoided (Dang and Tapus, 2015; Gombolay et al., 2015).

How have contextual factors influenced Intelligent Automation enabled business process performance or organisational performance?

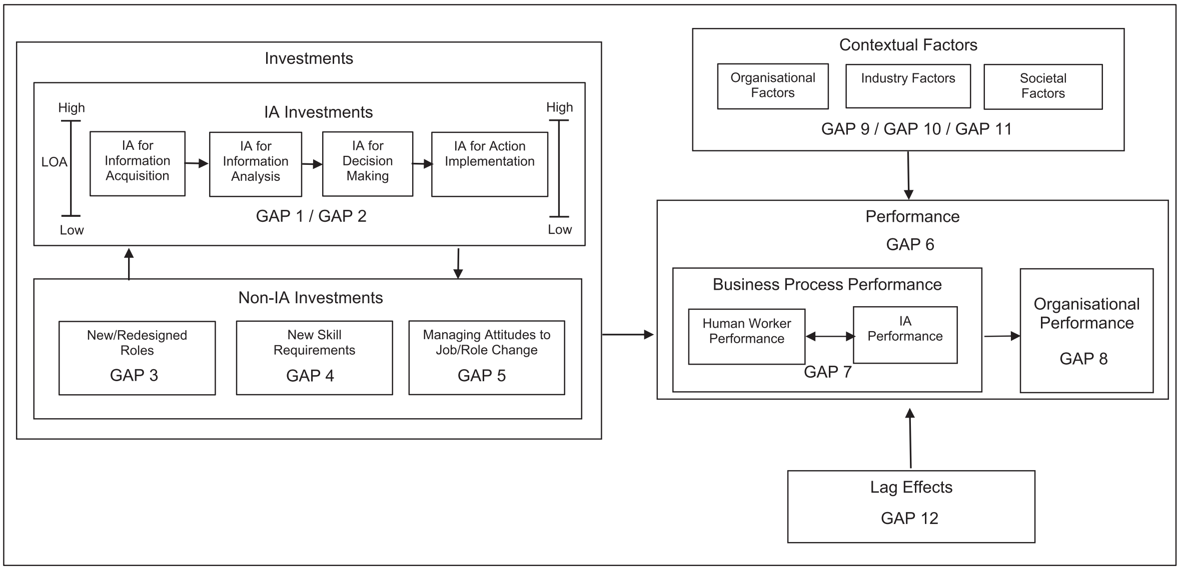
The literature suggested several factors could influence whether investments in Intelligent Automation for knowledge and service work processes could deliver business value in organisational, industry and societal contexts.

In organisational contexts, human worker's trust in Intelligent Automation was identified by several scholars as necessary for workplace acceptance (Davenport et al., 2012; Gilbert et al., 2015; Nielsen et al., 2016). For example, trust in the decisions made by Intelligent Automation was reported as necessary for air traffic controllers' willingness to accept increased levels of automation in two hypothetical scenarios (Bekier et al., 2011). Trust in Intelligent Automation technologies was particularly crucial for situations of conflict between the human worker and Intelligent Automation. If conflict occurs, for example in deciding which action to pursue, degradation of business process performance may result due to the human concentrating on resolving the conflict, rather than considering alternative forms of action (Dehais et al., 2012). In an experiment where French military staff used 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 returning to base. The human operator remained focused on completing the task and ignored the low battery warning messages (Dehais et al., 2012). Understanding the mechanisms of such 'conflicts' are important to inform protocols to determine the level of autonomy that should be assigned to the Intelligent Automation, and the level of control that should be retained by the human worker. These protocols would be essential for safety-critical situations but also business process performance in organisations. For example, an insurance company implementing automated claims assessment needs to be confident that the error rate for identifying fraudulent claims is sufficiently low, in order to minimise the risk of losses and reputational damage from incorrect automated decisions.

In industry contexts, highly regulated sectors such as healthcare may encounter challenges in the uptake and application of Intelligent Automation. For example, there may be privacy and security concerns regarding the integration of health related big data from individuals' wearable devices and sensors (Balram et al., 2016). The financial costs of robot-assisted surgery remain high, and there is a shortage of suitably trained healthcare professionals (Sananès et al., 2011) which may prevent some healthcare organisations from investing in these areas. Technical errors are also more unacceptable in health contexts with the result that technology vendors have avoided developing software systems that enact medical diagnoses or treatment recommendations because of fears of legal liability (Dilsizian and Siegel, 2014). However, in other sectors, these factors may not have the same level of significance. For example, technical errors may be more tolerable in lower-risk environments such as education or finance. However, at present, the literature does not provide a comprehensive picture of different sector requirements.

In societal contexts, the literature discusses the ethical and moral aspects of Intelligent Automation applications and responsible and accountable decision-making. For example, the development of 'caring' machines designed to read emotions and behavioural signals, may mean the boundaries between humans and machines become less visible and lead to 'Turing Deceptions' (i.e. the inability of a human to determine whether or not s(he) is interacting with a machine). This confusion could present a significant ethical issue, especially in situations involving vulnerable people (such as children, or clinical patients) which may limit the application of these technologies (Bryson, 2016). There may also be situations where the Intelligent Automation is more 'ethical' than humans because it is not swayed by emotions (Kinne and Stojanov, 2014) or prejudices. It has been argued that one way to achieve 'healthy' machine-user interactions may be through the development of Intelligent Automation technologies that are transparent in terms of their decision-making processes (Bostrom and Yudkowsky, 2011; Bryson, 2016; Kinne and Stojanov, 2014).

Further, when large numbers of people have been involved in the design and use of Intelligent Automation technologies, it may not be obvious where responsibility for Intelligent Automation and its actions lie. Scientists and practitioners have argued vigorously about who should take responsibility for the (potential) negative consequences of Intelligent Automation technologies (Johnson, 2014). One point upon which most scholars agree is that the ultimate responsibility should lie with the human stakeholders, i.e., machine designers, manufacturers, implementers, and users (Bryson and Winfield, 2017). Social attitudes to these ethical and moral issues are likely to be manifested through government policies and regulations that may promote or limit the use of Intelligent Automation technologies in different national contexts. Organisations will need to be sensitive to these societal issues to ensure that applying Intelligent Automation to knowledge and service work is not at the expense of demonstrating high levels of corporate social responsibility.



Notes: IA = Intelligent Automation; LOA = Level of automation

Fig. 2. A Business Value Model of Intelligent Automation for Knowledge and Service Work.

How have lag effects influenced Intelligent Automation enabled business process performance or organisational performance?

A small number of studies considered the speed of advances in Intelligent Automation technologies in general terms, with several scholars observing the exponential increase in the rate of technological innovations being translated to widespread practical use (e.g., Autor, 2015; Makridakis, 2017). For example, Danilchenko et al. (2011) observe that it took 10–15 years for robot-assisted surgery to move from the design and development lab to the operating theatre. This lag was due to the time it took to overcome challenges that had to be resolved, such as maintenance of sterility, logistics regarding transportation and set-up of the robot, and safety constraints. It has been suggested that AI will perform 30% of corporate audits by 2025 (Kokina and Davenport, 2017) and Frey and Osborne (2017) indicate that jobs most at risk of Intelligent Automation could be lost within the next decade. These studies suggest that there may be a lag of between eight to ten years before Intelligent Automation starts to change knowledge and service work jobs significantly.

A further dimension to lag effects is the length of time it takes for the initial investment in Intelligent Automation to be translated into improvements in business value. This lag may be dependent on the technical infrastructure and complementary workforce skills needed to exploit the technology. For example, RPA operates on existing technology platforms and does not require developers to have special abilities for it to be deployed (Lacity and Willcocks, 2016b). By contrast, robot-assisted surgery requires dedicated operating theatres to be created and specialist training of clinicians (Sananès et al., 2011). Thus, the lag between initial investment and business value returns may be longer for applications of Intelligent Automation that have more complex resource requirements. In general, research in this area is limited, with significant gaps in knowledge, and few studies being conducted on these topics.

Critical review of the literature and future research agenda

We mapped the knowledge areas the reviewed literature covers and the ones that still deserve more investigation in Fig. 2. In this model, we put forth a business value-based perspective of Intelligent Automation for knowledge and service work. In the following paragraphs, we critically evaluate the literature related to our four research questions and highlight critical gaps in knowledge. We develop an agenda of broad research questions that build from the identified gaps. How the research agenda is linked to the four core research questions, and gaps identified, is summarised in Table 3, and described below.

Our first research question investigated the Intelligent Automation investments and complementary non-Intelligent Automation investments that have been studied in the literature. Research findings reveal that recent advances in Intelligent Automation technologies have enabled new capabilities in managing and deriving insights from big data (Tarafdar et al., 2017). These new capabilities are mainly situated at the job task level, and the level of Intelligent Automation may vary for different tasks (e.g., Russo et al., 2016; Wood et al., 2013; Calo et al., 2011). Organisations need to consider the precise functionality that is required to complete the task, ideally through combining task-orientated and organisation of work perspectives (Fischer, 2012) to ensure desired outcomes are achieved from the application of Intelligent Automation. In some situations, tasks may be fully automated and require no human intervention (e.g. Nielsen et al., 2016). However, in many cases, Intelligent Automation involves some level of human worker contribution (e.g., Bekele et al., 2013; Wood et al., 2013). This involvement is likely to mean that the job tasks and roles are likely to change, the human worker no longer being solely responsible for the completion of the work task but working in collaboration with

Table 3
Research questions, gaps, and agenda for intelligent automation research.

Research questions	Gaps in literature	Future research agenda
What Intelligent Automation and non-Intelligent Automation investments have been studied?	GAP 1: Range and type of tasks targeted for Intelligent Automation	• How do organisations determine which tasks are appropriate for Intelligent Automation, and what factors shape this decision-making process? • How can socially acceptable values be designed into Intelligent Automation to enable ethical decision-making, and how should this be tested?
	GAP 2: Level of Intelligent Automation implemented	• How do organisations determine an appropriate level of Intelligent Automation for tasks, what factors shape this decision-making process, and how does micro-level variation of Intelligent Automation within tasks influence task performance?
	GAP 3: Impact of Intelligent Automation on jobs/work	• How do new configurations of human-Intelligent Automation interactions emerge, and what are their impacts on working and organising? • What are the positive/negative consequences of these new ways of working in organisations? • How can organisations ensure Intelligent Automation is an enabler of meaningful work?
	GAP 4: Impact of Intelligent Automation on worker's skills	• How are new forms of expertise, skill requirements, and training emerging to meet the demands of using Intelligent Automation? • Does the use of Intelligent Automation cause degradation or enhancement of human worker skills over time?
	GAP 5: Workers attitudes and behaviours in response to the implementation of Intelligent Automation	• How do new configurations of human-Intelligent Automation interactions influence attitudes and actions towards Intelligent Automation? • What are the psychological, emotional, and social aspects of human-Intelligent Automation collaboration? • What are the design implications for Intelligent Automation technologies for effective human-Intelligent Automation collaboration in the workplace?
How have Intelligent Automation investments influenced business process performance or organisational performance?	GAP 6: Linkage of Intelligent Automation to organisational strategy	• How do organisations make strategic decisions regarding Intelligent Automation, why do they make these decisions, and what are the consequences of these decisions over time?
	GAP 7: Impact of Intelligent Automation on worker performance	• How and why do new configurations of human-Intelligent Automation interactions influence human worker performance?
	GAP 8: Impact of Intelligent Automation on organisational performance	• How and why do investments in Intelligent Automation impact on organisational performance?
How have contextual factors influenced Intelligent Automation-enabled business process performance or organisational performance?	GAP 9: Influence of contextual factors on Intelligent Automation decision-making	• How do organisations in different contexts devise policies and procedures for combining human judgement with Intelligent Automation decision-making? • How do organisations decide where the balance of control lies in situations of human-Intelligent Automation conflict, and how do contextual factors influence this decision? • How do organisations decide whether the human should be retained in the decision-making loop, and how do contextual factors influence this decision?
	GAP 10: Role of contextual factors on design and implementation of Intelligent Automation	• How do contextual factors such as organisation size, industry type, or regulatory context shape the way Intelligent Automation technologies are developed and implemented?
	GAP 11: Stakeholders responsible for consequences of Intelligent Automation use	• How do organisations decide who is responsible for the consequences of Intelligent Automation investments, and why? • What constitutes a responsible Intelligent Automation system? • How can an organisation identify bias in emerging decision-making capabilities of Intelligent Automation?
How have lag effects influenced Intelligent Automation-enabled business process performance or organisational performance?	GAP 12: Length of time between investment in Intelligent Automation, and positive return on investment	• What is the return on investment from investments in Intelligent Automation, how should such returns be measured, and over what timescale should such investments be evaluated?

the Intelligent Automation to complete the work task. These new work roles may require workers to learn new technical and professional skills (e.g., Raheem et al., 2017).

As indicated, the literature contains several significant gaps, which point towards a future research agenda. First, it provides limited guidance regarding how organisations determine which jobs or tasks are appropriate for Intelligent Automation and the factors that shape this decision-making process (GAP 1). The literature indicates that Intelligent Automation can be applied to the information processing stages required for a range of knowledge and service work tasks. For example, Intelligent Automation can be used for information acquisition, information analysis, decision-making or action implementation (e.g., Bennett and Hauser, 2013; Chaudhuri and De, 2011; Fahdi, 2013; Kokina and Davenport, 2017). However, much of the literature has focused on developing Intelligent Automation systems for individual information processing stages, under laboratory conditions (e.g., Enache et al., 2015; Ye, 2015). Thus, while this literature confirms that such functionality is possible (proof of principle), future research is required to examine how organisations select the jobs or tasks for Intelligent Automation and implement these new technical capabilities (design application). Further, it will be crucial that socially acceptable values and norms are designed into the decision-making capabilities of new applications of Intelligent Automation. Thus, research is needed to investigate how engineers, management, and society consider and incorporate social values into new Intelligent Automation applications and the associated dynamic test protocols necessary to verify whether the Intelligent Automation continues to make ethically acceptable decisions over time.

Second, there are significant limitations in our understanding of how organisations decide the level of Intelligent Automation that is implemented (GAP 2). The literature shows that the level of Intelligent Automation applied for each information processing stage of a task may vary (Russo et al., 2016; Wood et al., 2013; Calo et al., 2011). How is the level decided on? A single task may also bring together high, medium and low levels of Intelligent Automation. For example, high levels of Intelligent Automation for information acquisition and analysis, medium levels of Intelligent Automation for decision-making and low levels of Intelligent Automation for action implementation (Balfe et al., 2015). Consequently, organisations and researchers must consider this potential micro-level variation of Intelligent Automation within tasks. Merely describing a task along one continuum (e.g., having high, medium or low Intelligent Automation) does not give an appreciation of the different levels of automation that may be present within tasks and would not allow an analysis of the impact of automation at various stages of decision-making (Balfe et al., 2015). It would be valuable to investigate how organisations determine an appropriate level of Intelligent Automation for tasks, the factors that shape these decisions, and how micro-level variation of Intelligent Automation within tasks may influence task performance. It would also be essential to explore the positive and negative consequences of these new ways of working in organisations, such as whether they increase or reduce the level of meaningful work undertaken by human workers.

Third, there are several gaps concerning how workers are affected by and respond to Intelligent Automation. We know little about how human work tasks are redesigned to accommodate Intelligent Automation (GAP 3), how the skill requirements of jobs change because of this (GAP 4), and how human workers respond to new and redesigned job changes (GAP 5). Implementing Intelligent Automation in organisations is likely to involve significant changes to existing jobs and the creation of new posts from new configurations of human-Intelligent Automation interactions. Human workers may find their job roles expanded or deskilled (James et al., 2013). Further, the implementation of Intelligent Automation requires organisations to consider all possible elements of the selected task to ensure a holistic view of the work activity is captured to reduce the risk of Intelligent Automation delivering undesirable work outcomes (Fischer, 2012). For example, does the use of Intelligent Automation over time cause degradation or enhancement of human worker skills? This gap calls for further research that investigates how new configurations of human-Intelligent Automation interactions emerge and what their impacts are on working and organising.

Further research is also needed to investigate the new skills that workers need to develop to perform these jobs. The literature indicates that human workers may require new skills in supervising Intelligent Automation, collaborating with Intelligent Automation, controlling Intelligent Automation, or rectifying Intelligent Automation malfunctions (e.g., Raheem et al., 2017; Sananès et al., 2011; Semerjian and Pavlovich, 2017). Thus, it would be valuable to have further research that examines how new requirements for expertise, skill, and training emerge to meet the demands of using Intelligent Automation. Finally, further research is necessary to explore workers' attitudes and behaviours in response to the implementation of Intelligent Automation. The literature on human-robot dynamics in hybrid teams (e.g., Gombolay et al., 2015; Schwartz et al., 2016) highlights the importance of the interface between workers and robots. The more human-like these systems become, the more significant the implications for psychological, emotional and social impacts from human-Intelligent Automation interactions. Future research needs to examine the nature of this dynamic to understand how Intelligent Automation technologies should be designed in terms of physical form and function and how new configurations of human-Intelligent Automation interactions influence attitudes and behaviours toward Intelligent Automation. It is encouraging to note that IS researchers are beginning to address this critical research challenge (e.g., You and Robert, 2018).

The second research question examined how Intelligent Automation has influenced the business process or organisational performance. The literature provides evidence to suggest that applications of Intelligent Automation can deliver improvements in business process performance, although the impact on overall organisational performance is less clear. Organisations can adopt different levels of automation to provide performance improvements from efficiency gains, such as using RPA to remove the need for a human worker to perform a routine or mundane task (Lacity and Willcocks, 2016a, 2016b). Alternatively, organisations can employ automation for effectiveness gains by enabling work tasks to be completed to a higher level of performance than could be achieved by the human worker, such as a surgeon using robot-assisted surgery to perform a medical procedure (Collins et al., 2016; Zaghloul and Mahmoud, 2016), or providing a new capability, such as mining big social media data (Baggili and Breitinger, 2015). In many studies, Intelligent Automation is used to augment existing human capabilities rather than substitute the human (Schwartz et al., 2016). In these situations, the human is a vital contributor to the successful completion of work tasks. Studies reveal that when collaborating with Intelligent Automation, worker performance may vary, improving in some situations and declining in others (Balfe et al., 2015;

Gombolay et al., 2015; van de Merwe et al., 2012).

However, several significant gaps in the literature remain. First is the link between business strategy and Intelligent Automation investment. Intelligent automation can enable organisations to follow a range of strategies to deliver business value. For example, organisations could use Intelligent Automation for efficiency or productivity-enhancement strategies, supporting changes/improvements in service quality, innovation-enhancement policy, or strategy linked to the provision of new products or services (Melville et al., 2004). However, it is unclear which strategies organisations find most beneficial for delivering business value from Intelligent Automation (GAP 6). Davenport and Kirby (2016b) argue that organisations should focus on an augmentation path to realise business value from Intelligent Automation. McAfee and Brynjolfsson, (2017) agree that this business value strategy is likely to be evident in the short term, but argue that over longer time, as advances in Intelligent Automation continue, organisations will shift from an augmentation strategy to a full Intelligent Automation strategy. This debate highlights the need for further research to gather empirical evidence about organisations' actual strategic decisions regarding Intelligent Automation, how and why organisations make these decisions and their consequences over time (Markus, 2017).

Second, there is limited evidence regarding how the implementation of Intelligent Automation may impact on human worker performance (GAP 7). A small number of studies indicate that some humans are happy to collaborate and work with robots (Gombolay et al., 2015) whereas others experience high levels of anxiety (Nomura et al., 2011) degrading human performance (Dang and Tapus, 2015). However, the majority of technically focused studies lack human involvement, which presents a significant limitation on their findings. Further, there were no studies in our sample that discussed the effects of Intelligent Automation on organisational performance such as changes in stock market value, productivity, profitability or competitive advantage. While the connection between business process improvements and organisational performance has been established for traditional technologies (Schryen, 2013), it not clear whether the relationship is the same for Intelligent Automation (GAP 8). This gap calls for further research that investigates how and why new configurations of human-Intelligent Automation interactions may influence human worker performance, and how and why investments in Intelligent Automation may impact on organisational performance.

The third research question examined the contextual factors that may influence Intelligent Automation enabled business process performance or organisational performance. The review revealed a range of factors might influence the uptake and application of Intelligent Automation in organisational, industry and societal contexts. For example, the relative importance of mediating factors such as trust, for the acceptance of Intelligent Automation, varied by organisational context (Davenport et al., 2012; Gilbert et al., 2015; Nielsen et al., 2016). Also, the significance of the consequences of human-Intelligent Automation decision-making conflicts is likely to change in different settings (Dehais et al., 2012). Many of these factors, such as trust in technology, are not new and have been associated with traditional IT. However, the significance of these factors is magnified for applications of Intelligent Automation because of the potential shift in decision-making control, from the human to the technology. This transformation presents three new research gaps.

First, there is limited research that examines how organisations design governance arrangements and structures associated with Intelligent Automation decision-making in different contexts (GAP 9). In safety-critical environments, such as air traffic control, stakeholders are more cautious in the level of autonomy they give to the Intelligent Automation system (Bekier et al., 2011). However, researchers have not yet investigated whether stakeholders follow the same degree of caution in business and management environments. Similarly, for service delivery for vulnerable people, decision-making may be particularly important. To ensure the interests of these people can be protected, clear lines of governance are recommended for automated decision making with human stakeholders taking responsibility and being accountable for the decisions made on their behalf by Intelligent Automation (Bryson, 2016). However, further research is needed in different contexts to understand how organisations devise suitable policies and procedures for combining human judgement and Intelligent Automation for decision-making. Also, studies that investigate how organisations decide where the balance of control lies in situations of human-Intelligent Automation conflict, whether the human should be retained in the decision-making loop, and how contextual factors may influence these decision-making processes, would be valuable.

Second, given that the benefit-risk calculus is likely to vary by Intelligent Automation technology and situation (Markus, 2017) it was notable that the literature had not examined many common organisation-related factors such as size, infrastructure, training, or industry factors such as regulatory constraints or intensity of competition and their influence on Intelligent Automation (GAP 10). The gap in knowledge in this topic is extensive, with little work in this area. Thus, further research is needed to investigate how contextual factors (such as industry type, government policy, or organisation size) may shape the ways that Intelligent Automation technologies are developed and implemented.

Third, although the literature points to the role of human stakeholders in taking ultimate responsibility (Bryson and Winfield, 2017), there is a broad group of different stakeholders operating in multiple organisations so it is unclear how accountability would be realised in practice (GAP 11). Knowledge is limited regarding how organisations manage the legal liability associated with Intelligent Automation applications. There appears to be agreement in the literature that it will be the human stakeholders that are most likely to be held accountable and responsible for AI decision-making. What impact does this have for innovation and applications of these technologies? As has been discussed, machine designers, manufacturers, implementers, and users may all be potentially liable for damages (e.g., Johnson, 2014). Many technology firms already stress that their products are designed to support decisions, but the choice of whether to follow any recommendations made by the AI system is ultimately the responsibility of the human operator (e.g., IBM, 2017; Ross and Swetlitz, 2017). This gap calls for future research that investigates how organisations decide who is responsible for the consequences of Intelligent Automation investments, why and what impacts this has on technological developments. Also, research that explores the characteristics that constitute 'responsible' Intelligent Automation systems would be valuable, as well as methods for organisations to identify bias in the emerging decision-making capabilities of Intelligent

Automation.

The fourth research question addressed the influence of lag effects on Intelligent Automation enabled business process performance or organisational performance. Research findings suggest that lag effects will vary by technology, process and context, and in terms of investment for business value return (e.g., Lacity and Willcocks, 2016b; Sananès et al., 2011). The findings indicate that we are still a decade away from Intelligent Automation having wide-scale impacts on organisations and levels of employment, although the expectation is that these impacts will be dramatic (Frey and Osborne, 2017; Kokina and Davenport, 2017). When lag effects were discussed, they tended to be considered at a high level with general statements about the increasing speed of technological innovation, and past experiences of previous technological innovations (e.g., Autor, 2015). It appears too early for research to provide a clear and nuanced picture of how lag effects may occur for Intelligent Automation. This limitation is compounded by the lack of empirical studies of Intelligent Automation implementations. Thus, there is little guidance on how long organisations may have to wait before they see a return on their Intelligent Automation investments (GAP 12), nor on the level of value returned. As with the gap in knowledge concerning contextual factors, the lack of research in this topic is significant. Thus, further studies are needed to investigate the extent to which investments in Intelligent Automation provide a return on investment, how such returns should be measured, and the timescale over which such investments should be evaluated.

To investigate the research gaps highlighted above, we propose three broad recommendations for research design. First, we recommend that future empirical research should be guided by theories that reflect the complex and dynamic impacts of Intelligent Automation, such as complex adaptive system theory (e.g., Marjanovic and Cecez-Kecmanovic, 2017). Second, given the complex nature of the topic, we recommend a mixed-method approach, combining qualitative and quantitative research designs (e.g., experiments, real-time measurements, observations, stakeholder surveys, focus groups, ethnographic case studies). For example, a longitudinal, mixed-methods, case study-based approach could capture data on how the attitudes and trust levels of different stakeholders (e.g., managers, IT staff, users) dynamically evolve during the implementation and use of Intelligent Automation within organisations. Third, Intelligent Automation of knowledge and service work is multifaceted and associated with a variety of academic disciplines. Hence, it can be best studied through the adoption of a multi-disciplinary approach (Markus, 2017). For example, IS researchers could work with computer scientists and philosophers to inform the ethical design of transparent Intelligent Automation decision-making processes and the factors that influence their organisational adoption and acceptance.

Concluding remarks

The Intelligent Automation of knowledge and service work is likely to be a highly significant global economic development, and this paper provides a foundation to advance IS research by synthesising existing literature, identifying research gaps and presenting an agenda for future research. Based on a comprehensive multi-disciplinary literature review and analysis guided by IS business value theory, we make three significant contributions to knowledge. First, we present a new conceptualisation and definition of Intelligent Automation. Second, we provide a business value-based model of Intelligent Automation for knowledge and service work and identify twelve research gaps that hinder a complete understanding of the business value realisation process. Third, we provide a research agenda to address these gaps and further our understanding of the strategic impacts of Intelligent Automation for knowledge and service work.

Funding acknowledgement and disclaimer

This study was funded by the Chartered Institute of Professional Development (CIPD). The views expressed are those of the authors and not necessarily those of the CIPD.

Acknowledgements

We would like to thank Professor Jarvenpaa and the review team for all the constructive comments and suggestions that were most helpful in revising the paper and in offering a stronger contribution. We would also like to thank Professor Guy Fitzgerald for his constructive comments on earlier versions of the paper.

Appendix A

Table A1
Coded articles: sources, levels of analysis and immediate context.

Author	Source		Level of analysis			Immediate context				
	Peer-reviewed Journal	Conference Proceedings	Work practice	Organizational	Supra-organizational (societal)	General Business (inc Finance, HR, Sales, Marketing)	Education	Healthcare and Social Care (including elderly)	Transport	Other
(Abdel Raheem et al., 2017)	*		*					*		
(Adelson, 2011)	*		–	–	–	–	–	–	–	–
(Albu and Stanciu, 2015)		*		*	*			*		
(Alizadehsani et al., 2016)	*		–	–	–			*		
(Ambrose, 2014)		*	–	–	–	–	–	–	–	–
(Amershi et al., 2011)		*	–	–	–	–	–	–	–	–
(Amrit et al., 2017)	*		*					*		
(Ardiansyah, 2016)		*			*			*		
(Aron et al., 2011)	*		–	–	–			*		
(Ashrafian, 2014)	*		–	–	–	–	–	–	–	–
(Ashrafian, 2015)	*		*			–	–	–	–	–
(Autor, 2015)	*				*	–	–	–	–	–
(Baggili and Breitinger, 2015)		*	–	–	–					*
(Balfe et al., 2015)	*				*				*	
(Balkin et al., 2011)	*		*	*	*				*	
(Balram et al., 2016)	*		–	–	–			*		
(Baril et al., 2014)	*				*			*		
(Barua and Barua, 2012)	*		–	–	–	–	–	–	–	–
(Bekele et al., 2013)	*		*	*				*		
(Bekier et al., 2011)	*			*					*	
(Bennett and Hauser, 2013)	*		–	–	–			*		
(Bibel, 2014)	*				*	–	–	–	–	–
(Bilal et al., 2012)		*	*							*
(Blanson et al., 2017)	*		*				*	*		
(Bocci et al., 2013)	*		*					*		
(Bogue, 2011)	*		–	–	–					*
(Boman and Gillblad, 2015)		*	–	–	–			*		
(Bostrom and Yudkowsky, 2011)			*	*		–	–	–	–	–
(Broussard, 2015)	*		–	–	–					*
(Brscic et al., 2017)	*				*					*
(Bryson, 2016)		*	–	–	–	–	–	–	–	–
(Burkhard, 2013)		*	*			–	–	–	–	–
(Byun and Buyn, 2011)	*		–	–	–	*				
(Calo et al., 2011)		*			*			*		
(Carneiro et al., 2017)	*		*	*	*	*				

(continued on next page)

Table A1 (*continued*)

Author	Source		Level of analysis			Immediate context				
	Peer-reviewed Journal	Conference Proceedings	Work practice	Organizational	Supra-organizational (societal)	General Business (inc Finance, HR, Sales, Marketing)	Education	Healthcare and Social Care (including elderly)	Transport	Other
(Cavalcante et al., 2016)	*		–	–	–	*				
(Chang, 2012)	*		*	*				*		
(Charalambous et al., 2015)	*		–	–	–					*
(Charchat-Fichman et al., 2014)	*		–	–	–			*		
(Chaudhuri and De, 2011)	*		–	–	–	*				
(Chelliah, 2017)	*		–	–	–	*				
(Chen, 2013)		*	*	*				*		
(Chibani et al., 2013)	*				*	–	–	–	–	–
(Coenen, 2011)	*		*	*		–	–	–	–	–
(Collins et al., 2016)	*		*	*				*		
(Conrad and Zeleznikow, 2015)		*	–	–	–					*
(Cronin et al., 2017)	*		*					*		
(Dang and Tapus, 2015)	*		–	–	–	–	–	–	–	–
(Davenport et al., 2012)	*		*	*				*		
(De Benedictis et al., 2017)	*		–	–	–			*		
(de la Paz-Marín et al., 2012)	*		*							*
(de León et al., 2017)	*		*	*						*
(DeCanio, 2016)	*			*	*	–	–	–	–	–
(Decker et al., 2017)	*		*			*				
(Dehais et al., 2012)	*		*	*	*					*
(Del Pino et al., 2012)	*			*		–	–	–	–	–
(Dewi et al., 2014)	*		*	*	*	–	–	–	–	–
(Dilsizian and Siegel, 2014)	*		*					*		
(Dirican, 2015)		*			*	*				
(Dodig Crnkovic and Çürüklü, 2012)	*		*			–	–	–	–	–
(Dogan et al., 2016)		*			*				*	
(Doryab et al., 2014)		*			*			*		
(Drew, 2017)	*		*			*				
(Drigas and Ioannidou, 2012)	*		–	–	–		*			
(Du et al., 2013)	*		*							*
(Durairaj and Ranjani, 2013)	*		*	*				*		
(Edwards and Ramirez, 2016)	*		–	–	–	*				
(Enache et al., 2015)		*	*							*
(Excell and Earnshaw, 2015)		*	–	–	–	–	–	–	–	–
(Fahdi, 2013)		*		*						*
(Fischer, 2012)	*		*			–	–	–	–	–
(Frank and Klincewicz, 2016)		*	*	*		–	–	–	–	–
(Frey and Osborne, 2017)	*			*	*					*
(Frude and Jandrić, 2015)	*			*	*			*		
(Gilbert et al., 2015)	*		*					*		
(Goeldner et al., 2015)	*			*	*			*		

(*continued on next page*)

Table A1 (*continued*)

Author	Source		Level of analysis			Immediate context				
	Peer-reviewed Journal	Conference Proceedings	Work practice	Organizational	Supra-organizational (societal)	General Business (inc Finance, HR, Sales, Marketing)	Education	Healthcare and Social Care (including elderly)	Transport	Other
(Gombolay et al., 2015)		*		*		–	–	–	–	–
(Haen et al., 2012)	*				*	–	–	–	–	–
(Hamet and Tremblay, 2017)	*		*	*				*		
(Hanson et al., 2011)		*	*l	*	*			*		
(He et al., 2014)	*		–	–	–				*	
(Hengstler et al., 2016)	*		–	–	–					*
(Hilovská and Koncz, 2012)	*		–	–	–	*				
(Hirsch, 2017)	*		–	–	–	*				
(Holloway et al., 2013)	*		*			*				
(Howley and Rosé, 2011)		*	*			–	–	–	–	–
(Huijnen et al., 2016)	*				*			*		
(Iliadis, 2014)	*				*					*
(James et al., 2013)	*		–	–	–			*		
(Jang and Kim, 2015)		*		*	*	–	–	–	–	–
(Jeong et al., 2014)	*			*			*			
(Jeske and Santuzzi, 2015)	*		–	–	–	*				
(Johnson, 2014)	*		*			–	–	–	–	–
(Junejo et al., 2017)	*		*							*
(Jung et al., 2017)	*		*							*
(Kaivo-oja et al., 2015)		*	*			*				
(Kaivo-oja et al., 2017)	*		*	*		*				
(Khosla et al., 2013)		*	–	–	–			*		
(Kile, 2013)	*		–	–	–	–	–	–	–	–
(Kim et al., 2015)	*		*	*			*			
(Kinne and Stojanov, 2014)		*	*							*
(Kinshuk et al., 2016)	*		*				*			
(Klintong et al., 2012)		*	*			*				
(Ko et al., 2017)	*		*							*
(Kokina and Davenport, 2017)	*				*	*				
(Kolbjørnsrud et al., 2017)	*			*		*				
(Kowalski et al., 2017)	*			*	*					*
(Kraan et al., 2014)	*		–	–	–	–	–	–	–	–
(Kreps and Neuhauser, 2013)	*		–	–	–			*		
(Kudo et al., 2015)		*	–	–	–					*
(Kumar et al., 2017)	*		*	*	*			*		
(Lacity and Willcocks, 2016a)	*		*							*
(Lacity and Willcocks, 2016b)	*		*	*		*				
(Lee et al., 2017)	*				*			*		
(Tsang et al., 2017)	*		*	*				*		
(Litwin, 2011)	*		*					*		
(Loi, 2015)	*		–	–	–	*				

(*continued on next page*)

Table A1 (*continued*)

Author	Source		Level of analysis			Immediate context				
	Peer-reviewed Journal	Conference Proceedings	Work practice	Organizational	Supra-organizational (societal)	General Business (inc Finance, HR, Sales, Marketing)	Education	Healthcare and Social Care (including elderly)	Transport	Other
(Lund, 2011)		*	–	–	–		*	*		
(Luxton, 2014)	*		*	*	*			*		
(Macas et al., 2017)		*	*							*
(Major et al., 2014)	*		*	*			*			
(Martínez-Ballesteros et al., 2017)	*		*					*		
(Martínez-López and Casillas, 2013)	*		*			*				
(Mathers et al., 2012)	*		*				*			
(Menager et al., 2011)	*		*	*				*		
(Metzler et al., 2016)	*			*				*		
(Michelfelder, 2011)	*				*	–	–	–	–	–
(Mohaghegh, 2011)	*		*							*
(Mokyr et al., 2015)	*		*	*	*	*				
(Moniz and Krings, 2014)		*		*	*					*
(Morris et al., 2017)	*		–	–	–					*
(Mubin et al., 2014)		*	–	–	–	*				
(Danilchenko et al., 2011)	*		–	–	–			*		
(Naik and Bhide, 2014)	*		*	*						*
(Nezhad, 2015)		*	*	*		*				
(Nielsen et al., 2016)	*			*				*		
(Niu et al., 2016)	*				*					*
(Nomura et al., 2011)		*	–	–	–	–	–	–	–	–
(Noor, 2011)	*		–	–	–				*	
(Ohlsson, 2016)	*		*				*			
(Peña et al., 2016)	*				*	–	–	–	–	–
(Piccoli et al., 2017)	*		*					*		
(Pieters, 2011)	*		*	*						*
(Pinkwart, 2016)	*		–	–	–		*			
(Queenan et al., 2016)	*		*					*		
(Reeves, 2016)	*		–	–	–	*				
(Richert et al., 2016)		*	–	–	–	–	–	–	–	–
(Russell et al., 2015)	*		–	–	–	–	–	–	–	–
(Russo et al., 2016)	*		*							*
(Samani, 2016)	*		–	–	–	–	–	–	–	–
(Samarakou et al., 2014)		*		*	*		*			
(Sananès et al., 2011)	*		–	–	–			*		
(Sayers et al., 2014)		*	–	–	–					*
(Schwartz et al., 2016)		*	–	–	–	*				
(Semerjian and Pavlovich, 2017)	*		*					*		
(Sendra et al., 2018)	*				*			*		
(Shahriar and Rahman, 2015)	*		–	–	–					*
(Sheridan, 2016)	*		–	–	–		*	*		

(*continued on next page*)

Table A1 (*continued*)

Author	Source		Level of analysis			Immediate context				
	Peer-reviewed Journal	Conference Proceedings	Work practice	Organizational	Supra-organizational (societal)	General Business (inc Finance, HR, Sales, Marketing)	Education	Healthcare and Social Care (including elderly)	Transport	Other
(Skulimowski, 2014)		*	–	–	–	–	–	–	–	–
(Stalidis et al., 2015)		*	*			*				
(Sundararajan and Nitta, 2015)	*				*		*			
(Sutton et al., 2016)	*		–	–	–	*				
(Szalma and Taylor, 2011)	*				*	–	–	–	–	–
(Taylor and Cotter, 2014)		*	*	*	*				*	
(Tepeš et al., 2015)	*		–	–	–					*
(Torras, 2015)	*				*	–	–	–	–	–
(van de Merwe et al., 2012)	*		–	–	–				*	
(van Doorn et al., 2017)	*		*	*		–	–	–	–	–
(Verne and Bratteteig, 2016)	*			*						*
(Vollmer et al., 2014)	*		–	–	–	–	–	–	–	–
(Wang et al., 2013)		*			*	*				
(Weyer et al., 2015)	*		*						*	
(Wolbring, 2016)	*		–	–	–	*				
(Wood et al., 2013)	*		*	*				*		
(Xu et al., 2013)	*		–	–	–			*		
(Xu et al., 2014)	*				*	–	–	–	–	–
(Yampolskiy and Fox, 2013)	*		–	–	–	–	–	–	–	–
(Yang et al., 2017)	*		*					*		
(Ye, 2015)	*		–	–	–			*		
(Yu et al., 2012)	*				*					*
(Zaghloul and Mahmoud, 2016)	*		*	*	*			*		
(Zheng et al., 2016)	*		–	–	–			*		
(Ziuziański et al., 2014)	*		*	*				*		
(Zurek et al., 2013)		*	–	–	–					*

Note: - not specified/not known.

Appendix B

Table B1
Coded articles: reference discipline.

Author	Reference Discipline						
	Engineering and Technology	Computer Science	Economics, Finance, Business and Industry	Information Systems and Management	Medicine, Dentistry, Nursing and Allied Health	Behavioural Sciences	Other
(Abdel Raheem et al., 2017)					*		
(Adelson, 2011)	*						
(Albu and Stanciu, 2015)	*						
(Alizadehsani et al., 2016)				*			
(Ambrose, 2014)	*						
(Amershi et al., 2011)		*					
(Amrit et al., 2017)				*			
(Ardiansyah, 2016)		*					
(Aron et al., 2011)				*			
(Ashrafian, 2014)		*					
		*					
(Autor, 2015)			*				
(Baggili and Breitinger, 2015)		*					
(Balfe et al., 2015)						*	
(Balkin et al., 2011)	*						
(Balram et al., 2016)		*					
(Baril et al., 2014)		*					
(Barua and Barua, 2012)		*					
(Bekele et al., 2013)	*						
(Bekier et al., 2011)						*	
(Bennett and Hauser, 2013)		*					
(Bibel, 2014)		*					
(Bilal et al., 2012)	*						
(Blanson et al., 2017)		*					
(Bocci et al., 2013)						*	
(Bogue, 2011)	*						
(Boman and Gillblad, 2015)	*						
(Bostrom and Yudkowsky, 2011)		*					
(Broussard, 2015)							*
(Brscic et al., 2017)	*						
(Bryson, 2016)		*					
(Burkhard, 2013)		*					
(Byun and Buyn, 2011)				*			
(Calo et al., 2011)		*					
(Carneiro et al., 2017)				*			

(continued on next page)

Table B1 (*continued*)

Author	Reference Discipline						
	Engineering and Technology	Computer Science	Economics, Finance, Business and Industry	Information Systems and Management	Medicine, Dentistry, Nursing and Allied Health	Behavioural Sciences	Other
(Cavalcante et al., 2016)				*			
(Chang, 2012)					*		
(Charalambous et al., 2015)	*						
(Charchat-Fichman et al., 2014)						*	
(Chaudhuri and De, 2011)		*					
(Chelliah, 2017)			*				
(Chen, 2013)	*						
(Chibani et al., 2013)	*						
(Coenen, 2011)		*					
(Collins et al., 2016)					*		
(Conrad and Zeleznikow, 2015)		*					
(Cronin et al., 2017)				*			
(Dang and Tapus, 2015)	*						
(Davenport et al., 2012)					*		
(De Benedictis et al., 2017)					*		
(de la Paz-Marín et al., 2012)				*			
(de León et al., 2017)				*			
(DeCanio, 2016)			*				
(Decker et al., 2017)	*						
(Dehais et al., 2012)						*	
(Del Pino et al., 2012)							*
(Dewi et al., 2014)	*						
(Dilsizian and Siegel, 2014)					*		
(Dirican, 2015)						*	
(Dodig Crnkovic and Çürüklü, 2012)				*			
(Dogan et al., 2016)		*					
(Doryab et al., 2014)		*					
(Drew, 2017)			*				
(Drigas and Ioannidou, 2012)	*						
(Du et al., 2013)							*
(Durairaj and Ranjani, 2013)		*					
(Edwards and Ramirez, 2016)			*				
(Enache et al., 2015)		*					
(Excell and Earnshaw, 2015)	*						
(Fahdi, 2013)	*						
(Fischer, 2012)						*	

(continued on next page)

Table B1 (*continued*)

Author	Reference Discipline						
	Engineering and Technology	Computer Science	Economics, Finance, Business and Industry	Information Systems and Management	Medicine, Dentistry, Nursing and Allied Health	Behavioural Sciences	Other
(Frank and Klincewicz, 2016)		*					
(Frey and Osborne, 2017)							*
(Frude and Jandrić, 2015)							*
(Gilbert et al., 2015)							*
(Goeldner et al., 2015)							*
(Gombolay et al., 2015)		*					
(Haen et al., 2012)							*
(Hamet and Tremblay, 2017)							*
(Hanson et al., 2011)	*						
(He et al., 2014)				*			
(Hengstler et al., 2016)							*
(Hilovská and Koncz, 2012)			*				
(Hirsch, 2017)			*				
(Holloway et al., 2013)			*				
(Howley and Rosé, 2011)		*					
(Huijnen et al., 2016)							*
(Iliadis, 2014)		*					
(James et al., 2013)					*		
(Jang and Kim, 2015)		*					
(Jeong et al., 2014)	*						
(Jeske and Santuzzi, 2015)			*				
(Johnson, 2014)			*				
(Junejo et al., 2017)	*						
(Jung et al., 2017)		*					
(Kaivo-oja et al., 2015)			*				
(Kaivo-oja et al., 2017)				*			
(Khosla et al., 2013)							*
(Kile, 2013)		*					
(Kim et al., 2015)							*
(Kinne and Stojanov, 2014)		*					
(Kinshuk et al., 2016)							*
(Klintong et al., 2012)			*				
(Ko et al., 2017)				*			
(Kokina and Davenport, 2017)			*				
(Kolbjørnsrud et al., 2017)			*				
(Kowalski et al., 2017)	*						
(Kraan et al., 2014)				*			
(Kreps and Neuhauser, 2013)							*
(Kudo et al., 2015)			*				
(Kumar et al., 2017)		*					

(continued on next page)

Table B1 (*continued*)

Author	Reference Discipline						
	Engineering and Technology	Computer Science	Economics, Finance, Business and Industry	Information Systems and Management	Medicine, Dentistry, Nursing and Allied Health	Behavioural Sciences	Other
(Lacity and Willcocks, 2016a)			*				
(Lacity and Willcocks, 2016b)				*			
(Lee et al., 2017)				*			
(Tsang et al., 2017)							*
(Litwin, 2011)			*				
(Loi, 2015)							*
(Lund, 2011)	*						
(Luxton, 2014)						*	
(Macas et al., 2017)		*					
(Major et al., 2014)		*					
(Martínez-Ballesteros et al., 2017)		*					
(Martínez-López and Casillas, 2013)			*				
(Mathers et al., 2012)	*						
(Menager et al., 2011)					*		
(Metzler et al., 2016)					*		
(Michelfelder, 2011)							*
(Mohaghegh, 2011)	*						
(Mokyr et al., 2015)			*				
(Moniz and Krings, 2014)		*					
(Morris et al., 2017)	*						
(Mubin et al., 2014)	*						
(Danilchenko et al., 2011)					*		
(Naik and Bhide, 2014)							*
(Nezhad, 2015)		*					
(Nielsen et al., 2016)							*
(Niu et al., 2016)							*
(Nomura et al., 2011)	*						
(Noor, 2011)	*						
(Ohlsson, 2016)		*					
(Peña et al., 2016)							*
(Piccoli et al., 2017)					*		
(Pieters, 2011)							*
(Pinkwart, 2016)							*
(Queenan et al., 2016)			*				
(Reeves, 2016)							*
(Richert et al., 2016)							*
(Russell et al., 2015)							*
(Russo et al., 2016)	*						
(Samani, 2016)	*						
(Samarakou et al., 2014)							*
(Sananès et al., 2011)					*		

(*continued on next page*)

Table B1 (*continued*)

Author	Reference Discipline						
	Engineering and Technology	Computer Science	Economics, Finance, Business and Industry	Information Systems and Management	Medicine, Dentistry, Nursing and Allied Health	Behavioural Sciences	Other
(Sayers et al., 2014)	*						
(Schwartz et al., 2016)	*						
(Semerjian and Pavlovich, 2017)					*		
(Sendra et al., 2018)		*					
(Shahriar and Rahman, 2015)		*					
(Sheridan, 2016)						*	
(Skulimowski, 2014)		*					
(Stalidis et al., 2015)						*	
(Sundararajan and Nitta, 2015)				*			
(Sutton et al., 2016)				*			
(Szalma and Taylor, 2011)						*	
(Taylor and Cotter, 2014)	*						
(Tepeš et al., 2015)	*						
(Torras, 2015)	*						
(van de Merwe et al., 2012)						*	
(van Doorn et al., 2017)			*				
(Verne and Bratteteig, 2016)		*					
(Vollmer et al., 2014)	*						
(Wang et al., 2013)	*						
(Weyer et al., 2015)	*						
(Wolbring, 2016)							*
(Wood et al., 2013)	*						
(Xu et al., 2013)	*						
(Xu et al., 2014)						*	
(Yampolskiy and Fox, 2013)	*						
(Yang et al., 2017)							*
(Ye, 2015)					*		
(Yu et al., 2012)	*						
(Zaghloul and Mahmoud, 2016)					*		
(Zheng et al., 2016)	*						
(Ziuziański et al., 2014)							*
(Zurek et al., 2013)	*						

Note: - not specified/not known.

References

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 J. Urol. 4, 116–123. https://doi.org/10.1016/j.ajur.2016.09.012.

Acemoglu, D., Autor, D., 2011. Skills, tasks and technologies: implications for employment and earnings. Handbook of Labor Economics. https://doi.org/10.1016/S0169-7218(11)02410-5.

Adelson, B., 2011. Task analysis, calculation and approximation: the work of stuart K. Card, 2007 bower laureate in computer & cognitive science for human-centered computing. J. Franklin Inst. 348, 439–445. https://doi.org/10.1016/j.jfranklin.2007.12.004.

Alavi, M., Leidner, D.E., 2001. Knowledge management and knowledge management systems: conceptual foundations and research issues. Manag. Inf. Syst. Q. 25, 107–136. https://doi.org/10.2307/3250961.

Albu, A., Stanciu, L., 2015. Benefits of using artificial intelligence in medical predictions. In: 2015 E-Health Bioeng Conf. pp. 1–4. https://doi.org/10.1109/EHB.2015.7391610.

Aleksander, I., 2017. Partners of humans: a realistic assessment of the role of robots in the foreseeable future. J. Inf. Technol. 32, 1–9. https://doi.org/10.1057/s41265-016-0032-4.

Ali, I., Meghanathan, N., 2011. Virtual machines and networks – installation, performance, study, advantages and virtualization options. Int. J. Netw. Secur. Its Appl. 11, 1–15. https://doi.org/10.5121/ijnsa.2011.3101.

Alizadehsani, R., Zangooei, M.H., Hosseini, M.J., Habibi, J., Khosravi, A., Roshanzamir, M., Khozeimeh, F., Sarrafzadegan, N., Nahavandi, S., 2016. Coronary artery disease detection using computational intelligence methods. Knowledge-Based Syst. 109, 187–197. https://doi.org/10.1016/j.knosys.2016.07.004.

Ambrose, M.L., 2014. The law and the loop. In: 2014 IEEE Int Symp. Ethics Sci. Technol. Eng. ETHICS 2014, https://doi.org/10.1109/ETHICS.2014.6893374.

Amershi, S., Fogarty, J., Kapoor, A., Tan, D., 2011. Effective end-user interaction with machine learning. Proc. Twenty-Fifth AAAI Conf. Artif. Intell. 1529–1532. https://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 Syst. Appl. 88, 402–418. https://doi.org/10.1016/j.eswa.2017.06.035.

Ardiansyah, R.A., 2016. Design of an electronic narrator on assistant robot for blind people. MATEC Web of Conf. 1–5.

Aron, R., Dutta, S., Janakiraman, R., Pathak, P.a., 2011. The impact of automation of systems on medical errors: evidence from field research. Inf. Syst. Res. 22, 429–446.

Ashrafian, H., 2014. Artificial Intelligence and Robot Responsibilities: innovating Beyond Rights. Sci. Eng. Ethics 317–326. https://doi.org/10.1007/s11948-014-9541-0.

Ashrafian, H., 2015. AIonAI: A Humanitarian Law of Artificial Intelligence and Robotics. Sci. Eng. Ethics 21, 29–40. https://doi.org/10.1007/s11948-013-9513-9.

Autor, D.H., 2015. Why are there still so many jobs? The history and future of workplace automation. J. Econ. Perspect. 29, 3–30. https://doi.org/10.1257/jep.29.3.3.

Autor, D.H., Levy, F., Murnane, R.J., 2003. The skill content of recent technological change: an empirical exploration. Q. J. Econ. 118, 1279–1333. https://doi.org/10.1162/003355303322552801.

Baggili, I., Breitinger, F., 2015. Data sources for advancing cyber forensics: what the social world has to offer. AAAI Spring Symp. 2009–2012.

Balfe, N., Sharples, S., Wilson, J.R., 2015. Impact of automation: measurement of performance, workload and behaviour in a complex control environment. Appl. Ergon. 47, 52–64. https://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. Accid. Anal. Prev. 43, 565–572. https://doi.org/10.1016/j.aap.2009.12.006.

Balram, Nikhil, Tošić, Ivana, Binnamangalam, Harsha, 2016. Digital health in the age of The Infinite Network. APSIPA Trans. Signal Inf. Process. 5. https://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. J. Med. Syst. 38, 1–12. https://doi.org/10.1007/s10916-014-0022-4.

Barrett, M., Davidson, E., Prabhu, J., Vargo, S.L., 2015. Service innovation in the digital age: key contributions and future directions. MIS Q. 39, 135–154. https://doi.org/10.25300/MISQ/2015/39:1.03.

Barua, A., Barua, A., 2012. Gendering the digital body: women and computers. AI Soc. 27, 465–477. https://doi.org/10.1007/s00146-012-0371-9.

Bekele, E.T., Lahiri, U., Swanson, A.R., Crittendon, J.A., Warren, Z.E., Sarkar, N., 2013. A step towards developing adaptive robot-mediated intervention architecture (ARIA) for children with autism. IEEE Trans. Neural Syst. Rehabil. Eng. 21, 289–299. https://doi.org/10.1109/TNSRE.2012.2230188.

Bekier, M., Molesworth, B.R., Williamson, A., 2011. Defining the drivers for accepting decision making automation in air traffic management. Ergonomics 54, 347–356. https://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. Artif. Intell. Med. 57, 9–19. https://doi.org/10.1016/j.artmed.2012.12.003.

Bibel, W., 2014. Artificial Intelligence in a historical perspective. AI Commun. 27, 87–102. https://doi.org/10.3233/AIC-130576.

Bilal, M., Persson, C., Ramparany, F., Picard, G., Boissier, O., 2012. Multi-agent based governance model for machine-to-machine networks in a smart parking management system. IEEE Int. Conf. Commun. 6468–6472. https://doi.org/10.1109/ICC.2012.6364789.

Blanson, O.A., Bierman, B.P.B., Janssen, J., Looije, R., Neerincx, M.A., Dooren, M.M.M. Van, Vries, J.L.E. De, Jan, G., Burg, V. Der, Huisman, S.D., 2017. Design and evaluation of a personal robot playing a self-management education game with children with diabetes type 1. Int. J. Hum. – Comput. Stud. 106, 63–76. https://doi.org/10.1016/j.ijhcs.2017.06.001.

Bocci, T., Moretto, C., Tognazzi, S., Briscese, L., Naraci, M., Leocani, L., Mosca, F., Ferrari, M., Sartucci, F., 2013. How does a surgeon's brain buzz? An EEG coherence study on the interaction between humans and robot. Behav. Brain Funct. 9, 1–12. https://doi.org/10.1186/1744-9081-9-14.

Bogue, R., 2011. Robots in the nuclear industry: a review of technologies and applications. Ind. Robot An Int. J. 38, 113–118. https://doi.org/10.1108/01439911111106327.

Boman, M., Gillblad, D., 2015. Learning machines for computational epidemiology. Proc. – 2014 IEEE Int. Conf. Big Data, IEEE Big Data 2014, 1–5. https://doi.org/10.1109/BigData. 2014.7004419.

Bostrom, N., 2014. Superintelligence: Paths, Dangers, Strategies. Oxford University Press, Oxford.

Bostrom, N., Yudkowsky, E., 2011. The ethics of artificial intelligence. In: Frankish, K., Ramsey, W. (Eds.), Cambridge Handbook of Artificial Intelligence. Cambridge University Press, New York, pp. 1–20. https://doi.org/10.1016/j.mpmed.2010.10.008.

Broussard, M., 2015. Artificial intelligence for investigative reporting. Digit. Journal. 3, 814–831. https://doi.org/10.1080/21670811.2014.985497.

Brscic, D., Ikeda, T., Kanda, T., 2017. Do you need help? A robot providing information to people who behave atypically. IEEE Trans. Robot. 33, 500–506. https://doi.org/10.1109/TRO.2016.2645206.

Brynjolfsson, E., McAfee, A., 2011. Race Against The Machine: How The Digital Revolution Is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and The Economy. Digital Frontier Press Lexington, MA.

Brynjolfsson, E., McAfee, A., 2016. The Second Machine Age – Work, Progress, and Prosperity in a Time of Brilliant Technologies. WW Norton & Co., New York and London.

Bryson, J., Winfield, A., 2017. Standardizing ethical design for artificial intelligence and autonomous systems. Computer (Long. Beach. Calif) 50, 116–119. https://doi.org/10.1109/MC.2017.154.

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. Phoenix, pp. 1–18.

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.

Byun, S., Buyn, S.-E., 2011. Exploring perceptions toward biometric technology in service encounters: a comparison of current users and potential adopters. Behav. Inf.

Technol. 3001, 1–14. https://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. San Francisco, pp. 20–24.
Carneiro, N., Figueira, G., Costa, M., 2017. A data mining based system for credit-card fraud detection in e-tail. Decis. Support Syst. 95, 91–101. https://doi.org/10.1016/j.dss.2017.01.002.
Castells, M., 1998. The Rise of the Network Society. Basil Blackwell, Oxford.
Cavalcante, R.C., Brasileiro, R.C., Souza, V.L.F., Nobrega, J.P., Oliveira, A.L.I., 2016. Computational intelligence and financial markets: a survey and future directions. Expert Syst. Appl. 55, 194–211. https://doi.org/10.1016/j.eswa.2016.02.006.
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. Pediatr. Cardiol. 33, 428–433. https://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. Int. J. Adv. Manuf. Technol. 81, 2143–2155. https://doi.org/10.1007/s00170-015-7335-4.
Charchat-Fichman, H., Uehara, E., Santos, C.F., 2014. New technologies in assessment and neuropsychological rehabilitation. Temas em Psicol. 22, 539–553. https://doi.org/10.9788/TP2014.3-01.
Chaudhuri, A., De, K., 2011. Fuzzy Support Vector Machine for bankruptcy prediction. Appl. Soft Comput. J. 11, 2472–2486. https://doi.org/10.1016/j.asoc.2010.10.003.
Chelliah, J., 2017. Will artificial intelligence usurp white collar jobs? Hum. Resour. Manag. Int. Dig. 25, 1–3. https://doi.org/10.1108/HRMID-11-2016-0152.
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.
Chibani, A., Amirat, Y., Mohammed, S., Matson, E., Hagita, N., Barreto, M., 2013. Ubiquitous robotics: recent challenges and future trends. Rob. Auton. Syst. 61, 1162–1172. https://doi.org/10.1016/j.robot.2013.04.003.
Chui, M., Manyika, J., Miremadi, M., 2016. Where machines could replace humans and where they can't (yet). McKinsey Q. 3, 58–69.
Coenen, F., 2011. Data mining: past, present and future. Knowl. Eng. Rev. 26, 25–29. https://doi.org/10.1017/S0269888910000378.
Collins, J.W., Patel, H., Adding, C., Annerstedt, M., Dasgupta, P., Khan, S.M., Artibani, W., Gaston, R., Piechaud, T., Catto, J.W., Koupparis, A., Rowe, E., Perry, M., Issa, R., McGrath, J., Kelly, J., Schumacher, M., Wijburg, C., Canda, A.E., Balbay, M.D., Decaestecker, K., Schwentner, C., Stenzl, A., Edeling, S., Pokupić, S., Stockle, M., Siemer, S., Sanchez-Salas, R., Cathelineau, X., Weston, R., Johnson, M., D'Hondt, F., Mottrie, A., Hosseini, A., Wiklund, P.N., 2016. Enhanced recovery after robot-assisted radical cystectomy: EAU robotic urology section scientific working group consensus view. Eur. Urol. 70, 649–660. https://doi.org/10.1016/j.eururo.2016.05.020.
Conrad, J.G., Zeleznikow, J., 2015. The role of evaluation in AI and law: an examination of its different forms in the AI and law journal. In: Proceedings of the 15th International Conference on Artificial Intelligence and Law, pp. 181–186. https://doi.org/10.1145/2746090.2746116.
Cronin, R.M., Fabbri, D., Denny, J.C., Rosenbloom, S.T., Jackson, G.P., 2017. A comparison of rule-based and machine learning approaches for classifying patient portal messages. Int. J. Med. Inform. 105, 110–120. https://doi.org/10.1016/j.ijmedinf.2017.06.004.
Dang, T.H.H., Tapus, A., 2015. Stress game: the role of motivational robotic assistance in reducing user's task stress. Int. J. Soc. Robot. 7, 227–240. https://doi.org/10.1007/s12369-014-0256-9.
Danilchenko, A., Balachandran, R., Toennies, J.L., Baron, S., Munske, B., Fitzpatrick, J.M., Withrow, T.J., Webster, R.J., Labadie, R.F., 2011. Robotic mastoidectomy. Otol. Neurotol. 32, 11–16. https://doi.org/10.1097/MAO.0b013e3181fcee9e.Robotic.
Dautenhahn, K., 2013. Human-robot interaction. In: The Encyclopedia of Human-Computer Interaction. Interaction Design Foundation.
Davenport, T.H., Kirby, J., 2015. Beyond automation. Harv. Bus. Rev. 93, 58–74.
Davenport, T.H., Kirby, J., 2016a. Just how smart are smart machines? MITSloan Manag. Rev. 57, 21–25.
Davenport, T.H., Kirby, J., 2016b. Only Humans Need Apply: Winners and Losers in the Age of Smart Machines. Harper Business, New York.
Davenport, R.D., Mann, W., Lutz, B., 2012. How older adults make decisions regarding smart technology: an ethnographic approach. Assist. Technol. 24, 168–181. https://doi.org/10.1080/10400435.2012.659792.
De Benedictis, A., Trezza, A., Carai, A., Genovese, E., Procaccini, E., Messina, R., Randi, F., Cossu, S., Esposito, G., Palma, P., Amante, P., Rizzi, M., Marras, C.E., 2017. Robot-assisted procedures in pediatric neurosurgery. Neurosurg. Focus 42, 1–12. https://doi.org/10.3171/2017.2.FOCUS16579.
de la Paz-Marín, M., Campoy-Muñoz, P., Hervás-Martínez, C., 2012. Non-linear multiclassifier model based on Artificial Intelligence to predict research and development performance in European countries. Technol. Forecast. Soc. Change 79, 1731–1745. https://doi.org/10.1016/j.techfore.2012.06.001.
de León, A.D., Lalla-Ruiz, E., Melián-Batista, B., Marcos Moreno-Vega, J., 2017. A machine learning-based system for berth scheduling at bulk terminals. Expert Syst. Appl. 87, 170–182. https://doi.org/10.1016/j.eswa.2017.06.010.
DeCanio, S.J., 2016. Robots and humans – complements or substitutes? J. Macroecon. 49, 280–291. https://doi.org/10.1016/j.jmacro.2016.08.003.
Decker, M., Fischer, M., Ott, I., 2017. Service robotics and human labor: a first technology assessment of substitution and cooperation. Rob. Auton. Syst. 87, 348–354. https://doi.org/10.1016/j.robot.2016.09.017.
Dedrick, J., Gurbaxani, V., Kraemer, K.L., 2003. Information technology and economic performance. ACM Comput. Surv. 35, 1–28. https://doi.org/10.1145/641865.641866.
Dehais, F., Causse, M., Vachon, F., Tremblay, S., 2012. Cognitive conflict in human-automation interactions: a psychophysiological study. Appl. Ergon. 43, 588–595. https://doi.org/10.1016/j.apergo.2011.09.004.
Dehning, B., Richardson, V.J., 2002. Returns on investments in information technology: a research synthesis. J. Inf. Syst. 16, 7–30.
Del Pino, J.S., Gheorghiu, R., Roman, A., 2012. The rest of me. Futures 44, 730–734. https://doi.org/10.1016/j.futures.2012.04.011.
Dewi, T., Uchiyama, N., Sano, S., Takahashi, H., 2014. Swarm robot control for human services and moving rehabilitation by sensor fusion. J. Robot. 2014. https://doi.org/10.1155/2014/278659.
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. Curr. Cardiol. Rep. 16, 1–8. https://doi.org/10.1007/s11886-013-0441-8.
Dirican, C., 2015. The impacts of robotics, artificial intelligence on business and economics. Proc. – Soc. Behav. Sci. 195, 564–573. https://doi.org/10.1016/j.sbspro.2015.06.134.
Dodig Crnkovic, G., Çürüklü, B., 2012. Robots: ethical by design. Ethics Inf. Technol. 14, 61–71. https://doi.org/10.1007/s10676-011-9278-2.
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.
Doryab, A., Min, J.K., Wiese, J., Zimmerman, J., Hong, J.I., 2014. Detection of behavior change in people with depression. AAAI Work. Work. Twenty-Eighth AAAI Conf. Artif. Intell 12–16.
Drew, J., 2017. Real talk about artificial intelligence and blockchain. J. Account. 224 (22–26), 28.
Drigas, A.S., Ioannidou, R.-E., 2012. Artificial intelligence in special education: a decade review. Int. J. Eng. Educ. 28, 1366–1372.
Du, K.K., Wang, Z.L., Hong, M., 2013. Human machine interactive system on smart home of IoT. J. China Univ. Posts Telecommun. 20, 96–99. https://doi.org/10.1016/S1005-8885(13)60240-X.
Durairaj, M., Ranjani, V., 2013. Data mining applications in healthcare sector: a study. Int. J. Sci. Technol. Res. 2, 29–35.
Edwards, P., Ramirez, P., 2016. When should workers embrace or resist new technology? New Technol. Work Employ. 31, 99–113. https://doi.org/10.1111/ntwe.12067.
El-Najdawi, M.K., Stylianou, A.C., 1993. Expert support systems: integrating AI technologies. Commun. ACM 36, 55-ff. https://doi.org/10.1145/163298.163306.
Enache, A.C., Ionita, M., Sgarciu, V., 2015. An immune intelligent approach for security assurance. In: 2015 Int. Conf. Cyber Situational Awareness, Data Anal. Assessment, CyberSA 2015. https://doi.org/10.1109/CyberSA.2015.7166116.
Excell, P.S., Earnshaw, R.A., 2015. The Future of Computing – the Implications for Society of Technology Forecasting and the Kurzweil Singularity. In: IEEE

International Symposium on Technology in Society (ISTAS) Proceedings, pp. 1–6.
Fahdi, M. Al, 2013. Towards an automated forensic examiner (AFE) based upon criminal profiling & artificial intelligence. In: 11th Australian Digital Forensics Conference. Perth, pp. 1–9.
Fischer, M., 2012. Interdisciplinary technology assessment of service robots: the psychological/work science perspective. Poiesis Prax. 9, 231–248. https://doi.org/10.1007/s10202-012-0113-6.
Frank, L., Klincewicz, M., 2016. Metaethics in context of engineering ethical and moral systems. SS-16-01-. AAAI Spring Symp. – Tech. Rep. 208–213.
Frey, C.B., Osborne, M.A., 2017. The future of employment: how susceptible are jobs to computerisation? Technol. Forecast. Soc. Change 114, 254–280. https://doi.org/10.1016/J.TECHFORE.2016.08.019.
Frude, N., Jandrić, P., 2015. The intimate machine ??? 30 years on. E-Learning Digit. Media 12, 410–424. https://doi.org/10.1177/2042753015571830.
Gilbert, B.J., Goodman, E., Chadda, A., Hatfield, D., Forman, D.E., Panch, T., 2015. The role of mobile health in elderly populations. Curr. Geriatr. Reports 4, 347–352. https://doi.org/10.1007/s13670-015-0145-6.
Goeldner, M., Herstatt, C., Tietze, F., 2015. The emergence of care robotics – a patent and publication analysis. Technol. Forecast. Soc. Change 92, 115–131. https://doi.org/10.1016/j.techfore.2014.09.005.
Gombolay, M.C., Huang, C., Shah, J.A., 2015. Coordination of human-robot teaming with human task preferences. AAAI Fall Symposium Series on AI-HRI. Arlington.
Grace, K., Salvatier, J., Dafoe, A., Zhang, B., Evans, O., 2018. When will AI exceed human performance? Evidence from AI experts. J. Artif. Intell. Res. 62, 729–754.
Haen, C., Barra, V., Bonaccorsi, E., Neufeld, N., 2012. Artificial intelligence in the service of system administrators. J. Phys. Conf. Ser. 396, 052038. https://doi.org/10.1088/1742-6596/396/5/052038.
Hamet, P., Tremblay, J., 2017. Artificial intelligence in medicine. Metabolism. 69, S36–S40. https://doi.org/10.1016/j.metabol.2017.01.011.
Hanson, M.A., Barth, A.T., Silverman, C., 2011. In home assessment and management of health and wellness with BeClose ambient, artificial intelligence. Proc. 2nd Conf. Wirel. Heal. – WH '11 1. https://doi.org/10.1145/2077546.2077574.
He, S., Song, R., Chaudhry, S.S., 2014. Service-oriented intelligent group decision support system: application in transportation management. Inf. Syst. Front. 16, 939–951. https://doi.org/10.1007/s10796-013-9439-4.
Hengstler, M., Enkel, E., Duelli, S., 2016. Applied artificial intelligence and trust: the case of autonomous vehicles and medical assistance devices. Technol. Forecast. Soc. Change 105, 105–120. https://doi.org/10.1016/j.techfore.2015.12.014.
Hilovská, K., Koncz, P., 2012. Application of artificial intelligence and data mining techniques to financial markets. ACTA VSFS 6, 62–77.
Hirsch, P.B., 2017. The robot in the window seat. J. Bus. Strategy 38, 47–51. https://doi.org/10.1108/JBS-04-2017-0050.
Hislop, D., Bosua, R., Helms, R., 2018. Knowledge Management in Organisations: A Critical Introduction, 4th ed. Oxford University Press, Oxford.
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. J. Relatsh. Mark. 12, 223–242. https://doi.org/10.1080/15332667.2013.846735.
Howley, I., Rosé, C.P., 2011. Modeling the rhetoric of human-computer interaction. In: 14th International Conference on Human-Computer Interaction, pp. 341–350.
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. J. Autism Dev. Disord. 46, 2100–2114. https://doi.org/10.1007/s10803-016-2740-6.
IBM, 2017. IBM Policies and Principles [WWW Document]. URL https://www.ibm.com/ibm/responsibility/ibm_policies.html#transparency (accessed 1.15.17).
Iliadis, L., 2014. Special issue of the 8th aiai 2012 (artificial intelligence applications and innovations) international conference. Artif. Intell. Rev. 42, 309–311. https://doi.org/10.1007/s10462-013-9421-z.
James, K.L., Barlow, D., Bithell, A., Hiom, S., Lord, S., Oakley, P., Pollard, M., Roberts, D., Way, C., Whittlesea, C., 2013. The impact of automation on pharmacy staff experience of workplace stressors. Int. J. Pharm. Pract. 21, 105–116. https://doi.org/10.1111/j.2042-7174.2012.00231.x.
Jang, M., Kim, J., 2015. A relationship-based model of robot service personalization. In: The 12th International Conference on Ubiquitous Robots and Ambient Intelligence, pp. 192–193.
Jankel, N.S., 2015. AI vs. human intelligence: Why computers will never create disruptive innovations [WWW Document]. HuffingtonPost. URL http://www.huffingtonpost.com/nick-seneca-jankel/ai-vs-human-intelligence-_b_6741814.html (accessed 7.4.18).
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. Int. J. Adv. Robot. Syst. 11, 1–9. https://doi.org/10.5772/58389.
Jeske, D., Santuzzi, A.M., 2015. Monitoring what and how: Psychological implications of electronic performance monitoring. New Technol. Work Employ. 30, 62–78. https://doi.org/10.1111/ntwe.12039.
Johnson, D.G., 2014. Technology with no human responsibility? J. Bus. Ethics 127, 707–715. https://doi.org/10.1007/s10551-014-2180-1.
Junejo, F., Amin, I., Hassan, M., Ahmed, A., Hameed, S., Author, C., 2017. The application of artificial intelligence in grinding operation using sensor fusion. Int. J. GEOMATE 12, 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. Comput. Human Behav. 71, 291–298. https://doi.org/10.1016/j.chb.2017.02.022.
Kaivo-oja, J., Virtanen, P., Jalonen, H., Stenvall, J., 2015. The effects of the internet of things and big data to organizations and their knowledge management practices. In: In: Uden, L., Heričko, M., Ting, I.H. (Eds.), Knowledge Management in Organizations. KMO 2015. Lecture Notes in Business Information Processing, vol 224 Springer, Cham. https://doi.org/10.1007/978-3-319-21009-4.
Khosla, R., Chu, M.T., Nguyen, K., 2013. Affective robot enabled capacity and quality improvement of nursing home aged care services in Australia. In: Proceedings – International Computer Software and Applications Conference. pp. 409–414. https://doi.org/10.1109/COMPSACW.2013.89.
Kaivo-oja, J., Roth, S., Westerlund, L., 2017. Futures of robotics. Human work in digital transformation. Int. J. Technol. Manag. 73, 176–205. https://doi.org/10.1504/IJTM.2017.083074.
Kile, F., 2013. Artificial intelligence and society: a furtive transformation. AI Soc. 28, 107–115. https://doi.org/10.1007/s00146-012-0396-0.
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. Comput. Educ. 91, 14–31. https://doi.org/10.1016/j.compedu.2015.08.005.
Kinne, E., Stojanov, G., 2014. Grounding drones' ethical use reasoning. In: Association for the Advancement of Artificial Intelligence. Québec City, pp. 231–235.
Kinshuk, Chen, N.S., Cheng, I.L., Chew, S.W., 2016. Evolution is not enough: revolutionizing current learning environments to smart learning environments. Int. J. Artif. Intell. Educ 26, 561–581. https://doi.org/10.1007/s40593-016-0108-x.
Klintong, N., Vadhanasindhu, P., Thawesaengskulthai, N., 2012. Artificial intelligence and successful factors for selecting product innovation development. In: Proceedings – 3rd International Conference on Intelligent Systems Modelling and Simulation, ISMS 2012. pp. 397–402. https://doi.org/10.1109/ISMS.2012.86.
Ko, T., Lee, J.H., Cho, H., Cho, S., Lee, W., Lee, M., 2017. Machine learning-based anomaly detection via integration of manufacturing, inspection and after-sales service data. Ind. Manag. Data Syst. 117, 927–945. https://doi.org/10.1108/IMDS-06-2016-0195.
Kokina, J., Davenport, T.H., 2017. The emergence of artificial intelligence: how automation is changing auditing. J. Emerg. Technol. Account. 14, 115–122. https://doi.org/10.2308/jeta-51730.
Kolbjørnsrud, V., Amico, R., Thomas, R.J., 2017. Partnering with AI: how organizations can win over skeptical managers. Strateg. Leadersh. 45, 37–43. https://doi.org/10.1108/SL-12-2016-0085.
Kowalski, J., Krawczyk, B., Woźniak, M., 2017. Fault diagnosis of marine 4-stroke diesel engines using a one-vs-one extreme learning ensemble. Eng. Appl. Artif. Intell. 57, 134–141. https://doi.org/10.1016/j.engappai.2016.10.015.
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. Behav. Inf. Technol. 33, 1013–1026. https://doi.org/10.1080/0144929X.2014.916351.
Kreps, G.L., Neuhauser, L., 2013. Artificial intelligence and immediacy: designing health communication to personally engage consumers and providers. Patient Educ. Couns. 92, 205–210. https://doi.org/10.1016/j.pec.2013.04.014.
Kudo, F., Akitomi, T., Moriwaki, N., 2015. An artificial intelligence computer system for analysis of social-infrastructure data. In: 2015 IEEE 17Th Conference on Business Informatics, pp. 85–89. https://doi.org/10.1109/CBI.2015.26.

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. J. Robot. Surg. 11, 247–250. https://doi.org/10.1007/s11701-016-0648-y.
Kurzweil, R., 2005. The Singularity is Near: When Humans Transcend Biology. Viking Press, New York.
Kuusisto, J., Meyer, M., 2003. Insights into services and innovation in the knowledge intensive economy. Technol. Rev. 134, 1–63.
Lacity, M.C., Willcocks, L.P., 2016a. Robotic process automation at telefónica O2. MIS Q. Exec. 15, 21–35.
Lacity, M.C., Willcocks, L.P., 2016b. A new approach to automating services. MIT Sloan Manag. Rev. 58, 41–49.
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. J. Digit. Imaging 30, 487–498. https://doi.org/10.1007/s10278-017-9988-z.
Litwin, A.S., 2011. Technological change at work: the impact of employee involvement on the effectiveness of health information technology. Ind. Labor Relations Rev. 64, 863–888.
Loebbecke, C., Picot, A., 2015. Reflections on societal and business model transformation arising from digitization and big data analytics: a research agenda. J. Strateg. Inf. Syst. 24, 149–157. https://doi.org/10.1016/j.jsis.2015.08.002.
Loi, M., 2015. Technological unemployment and human disenhancement. Ethics Inf. Technol. 17, 201–210. https://doi.org/10.1007/s10676-015-9375-8.
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. ARSO, pp. 2–7. https://doi.org/10.1109/ARSO.2011.6301970.
Luxton, D.D., 2014. Artificial intelligence in psychological practice: current and future applications and implications. Prof. Psychol. Res. Pract. 45, 332. https://doi.org/10.1037/a0034559.
Major, L., Kyriacou, T., Brereton, P., 2014. The effectiveness of simulated robots for supporting the learning of introductory programming: a multi-case case study. Comput. Sci. Educ. 24, 193–228. https://doi.org/10.1080/08993408.2014.963362.
Makridakis, S., 2017. The forthcoming Artificial Intelligence (AI) revolution: its impact on society and firms. Futures 90, 46–60. https://doi.org/10.1016/J.FUTURES.2017.03.006.
Mallach, E.G., 2000. Decision Support and Data Warehouse Systems. Irwin McGraw-Hill, Boston.
Macas, M., Lagla, L., Fuertes, W., Guerrero, G., Toulkeridis, T., 2017. Data Mining model in the discovery of trends and patterns of intruder attacks on the data network as a public-sector innovation. In: 2017 4th Int. Conf. eDemocracy eGovernment, ICEDEG 2017, pp. 55–62. https://doi.org/10.1109/ICEDEG.2017.7962513.
Manyika, J., Lund, S., Chui, M., Bughin, J., Woetzel, J., Batra, P., Ko, R., Sanghvi, S., 2017. Jobs lost, jobs gained: What the future of work will mean for jobs, skills, and wages [WWW Document]. URL https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages (accessed 11.7.19).
Marjanovic, O., Cecez-Kecmanovic, D., 2017. Exploring the tension between transparency and datification effects of open government IS through the lens of Complex Adaptive Systems. J. Strateg. Inf. Syst. 26, 210–232. https://doi.org/10.1016/j.jsis.2017.07.001.
Markoff, J., 2016. Machines of Loving Grace: The Quest for Common Grounds Between Humans and Robots. Harper Collins, New York.
Markus, M.L., 2017. Datification, organizational strategy, and IS research: What's the score? J. Strateg. Inf. Syst. 26, 233–241. https://doi.org/10.1016/j.jsis.2017.08.003.
Martínez-Ballesteros, M., García-Heredia, J.M., Nepomuceno-Chamorro, I.A., Riquelme-Santos, J.C., 2017. Machine learning techniques to discover genes with potential prognosis role in Alzheimer's disease using different biological sources. Inf. Fusion 36, 114–129. https://doi.org/10.1016/j.inffus.2016.11.005.
Martínez-López, F.J., Casillas, J., 2013. Artificial intelligence-based systems applied in industrial marketing: an historical overview, current and future insights. Ind. Mark. Manag. 42, 489–495. https://doi.org/10.1016/j.indmarman.2013.03.001.
Mathers, N., Goktogen, A., Rankin, J., Anderson, M., 2012. Robotic mission to mars: hands-on, minds-on, web-based learning. Acta Astronaut. 80, 124–131. https://doi.org/10.1016/j.actaastro.2012.06.003.
McAfee, A., Brynjolfsson, E., 2017. Machine, Platform. Crowd. W. W. Norton & Company, New York and London.
Melville, N., Kraemer, K.L., Gurbaxani, V., 2004. Information technology and organizational performance: an integrative model of IT business value. MIS Q. 28, 283–322. https://doi.org/10.2307/25148636.
Menager, N.E., Coulomb, M.A., Lambaudie, E., Michel, V., Mouremble, O., Tourette, C., Houvenaeghel, G., 2011. Place du robot dans la formation chirurgicale initiale: Enqu??te aupr??s des internes. Gynecol. Obstet. Fertil. 39, 603–608. https://doi.org/10.1016/j.gyobfe.2011.07.025.
Metzler, T.A., Lewis, L.M., Pope, L.C., 2016. Could robots become authentic companions in nursing care? Nurs. Philos. 17, 36–48. https://doi.org/10.1111/nup.12101.
Michelfelder, D.P., 2011. Dirty hands, speculative minds, and smart machines. Philos. Technol. 24, 55–68. https://doi.org/10.1007/s13347-010-0009-0.
Mohaghegh, S.D., 2011. Reservoir simulation and modeling based on artificial intelligence and data mining (AI&DM). J. Nat. Gas Sci. Eng. 3, 697–705. https://doi.org/10.1016/j.jngse.2011.08.003.
Mokyr, J., Vickers, C., Ziebarth, N.L., 2015. The history of technological anxiety and the future of economic growth: is this time different? J. Econ. Perspect. 29, 31–50.
Moniz, A., Krings, B.J., 2014. Technology assessment approach to human-robot interactions in work environments. In: Proceedings – 2014 7th International Conference on Human System Interactions, HSI 2014. pp. 282–289. https://doi.org/10.1109/HSI.2014.6860490.
Morris, K.C., Schlenoff, C., Srinivasan, V., 2017. Guest editorial a remarkable resurgence of artificial intelligence and its impact on automation and autonomy. IEEE Trans. Autom. Sci. Eng. 14, 407–409. https://doi.org/10.1109/TASE.2016.2640778.
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: Proceedings – IEEE International Workshop on Robot and Human Interactive Communication. pp. 580–585. https://doi.org/10.1109/ROMAN.2014.6926315.
Naik, G., Bhide, S.S., 2014. Will the future of knowledge work automation transform personalized medicine? Appl. Transl. Genomics 3, 50–53. https://doi.org/10.1016/j.atg.2014.05.003.
Newell, S., Marabelli, M., 2015. Strategic opportunities (and challenges) of algorithmic decision-making: a call for action on the long-term societal effects of "datification" J. Strateg. Inf. Syst. 24, 3–14. https://doi.org/10.1016/j.jsis.2015.02.001.
Nezhad, H.R.M., 2015. Cognitive Assistance at Work, in: AAAI 2015 Fall Symposium. pp. 37–40.
Nielsen, J.A., Andersen, K.N., Sigh, A., 2016. Robots conquering local government services: a case study of eldercare in Denmark. Inf. Polity 21, 139–151. https://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. ISPRS Int. J. Geo-Inf. 5, 66. https://doi.org/10.3390/ijgi5050066.
Nomura, T., Kanda, T., Yamada, S., Suzuki, T., 2011. Exploring influences of robot anxiety into HRI. In: Human-Robot Interaction (HRI), 2011 6th ACM/IEEE International Conference On. pp. 213–214. https://doi.org/10.1145/1957656.1957737.
Noor, A., 2011. Intelligent adaptive cyber-physical ecosystem for aerospace engineering education, training, and accelerated workforce development. J. Aerosp. Eng. 24, 403–408. https://doi.org/10.1061/(ASCE)AS.1943-5525.0000128.
Ohlsson, S., 2016. Constraint-based modeling: from cognitive theory to computer tutoring – and back again. Int. J. Artif. Intell. Educ. 26, 457–473. https://doi.org/10.1007/s40593-015-0075-7.
Parasuraman, R., 1997. Humans and automation: use, misuse, disuse, abuse. Hum. Factors 39, 230–253.
Parasuraman, R., Sheridan, T.B., Wickens, C.D., 2000. A model for types and levels of human interaction with automation. IEEE Trans. Syst. Man Cybern. - Part A Syst. Humans 30, 286–297. https://doi.org/10.1109/3468.844354.
Paré, G., Trudel, M.-C.C., Jaana, M., Kitsiou, S., 2015. Synthesizing information systems knowledge: a typology of literature reviews. Inf. Manag. 52, 183–199. https://doi.org/10.1016/j.im.2014.08.008.
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. Int. J. Des. Nat. Ecodynamics 11, 230–238. https://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. Curr. Surg. Reports 5, 17. https://doi.org/10.1007/s40137-017-0180-7.
Pieters, W., 2011. Explanation and trust: what to tell the user in security and AI? Ethics Inf. Technol. 13, 53–64. https://doi.org/10.1007/s10676-010-9253-3.

Pinkwart, N., 2016. Another 25 Years of AIED? Challenges and opportunities for intelligent educational technologies of the future. Int. J. Artif. Intell. Educ. 26, 771–783. https://doi.org/10.1007/s40593-016-0099-7.
Queenan, C., Kull, T., Devaraj, S., 2016. Complements or substitutes? Culture-technology interactions in healthcare. Decis. Sci. 47, 851–880. https://doi.org/10.1111/deci.12199.
Raheem, A.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 J. Urol. 4, 116–123. https://doi.org/10.1016/j.ajur.2016.09.012.
Reeves, J., 2016. Automatic for the people: the automation of communicative labor. Commun. Crit. Stud. 13, 150–165. https://doi.org/10.1080/14791420.2015.1108450.
Richert, a, Shehadeh, M., Müller, S., Schröder, S., Jeschke, S., 2016. Robotic workmates: Hybrid human-robot-teams in the industry 4.0. In: Proceedings of the International Conference on E-Learning, ICEL. pp. 127–131.
Ross, C., Swetlitz, I., 2017. IBM pitched its Watson supercomputer as a revolution in cancer care. It's nowhere close [WWW Document]. Stat. URL https://www.statnews.com/2017/09/05/watson-ibm-cancer/ (accessed 1.15.18).
Russell, S., Hauert, S., Altman, R., Veloso, M., 2015. Ethics of Artificial intelligence [– Take a stand on AI weapons –] [– Shape the debate, don't shy from it –] [– Distribute AI benefits fairly –] [– Embrace a robot-human world –]. Nature 521, 415–418. https://doi.org/10.1038/521415a.
Russo, L., Rosa, S., Maggiora, M., Bona, B., 2016. A novel cloud-based service robotics application to data center environmental monitoring. Sensors 16, 1255–1273. https://doi.org/10.3390/s16081255.
Samani, H., 2016. The evaluation of affection in human – robot interaction. Kybernetes 45. https://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. Int. Conf. E-Learn. 299–303.
Sananès, N., Garbin, O., Hummel, M., Youssef, C., Vizitiu, R., Lemaho, D., Rottenberg, D., Diemunsch, P., Wattiez, A., 2011. Setting up robotic surgery in gynaecology: the experience of the Strasbourg teaching hospital. J. Robot. Surg. 5, 133–136. https://doi.org/10.1007/s11701-010-0231-x.
Sayers, W., Savić, D., Kapelan, Z., Kellagher, R., 2014. Artificial intelligence techniques for flood risk management in urban environments. Proc. Eng. 70, 1505–1512. https://doi.org/10.1016/j.proeng.2014.02.165.
Schryen, G., 2013. Revisiting IS business value research: what we already know, what we still need to know, and how we can get there. Eur. J. Inf. Syst. 22, 139–169. https://doi.org/10.1057/ejis.2012.45.
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.
Semerjian, A., Pavlovich, C.P., 2017. Extraperitoneal robot-assisted radical prostatectomy: indications, technique and outcomes. Curr. Urol. Rep. 18, 1–7. https://doi.org/10.1007/s11934-017-0689-4.
Sendra, S., Parra, L., Lloret, J., Tomás, J., 2018. Smart system for children's chronic illness monitoring. Inf. Fusion 40, 76–86. https://doi.org/10.1016/j.inffus.2017.06.002.
Shahriar, M.S., Rahman, M.S., 2015. Urban sensing and smart home energy optimisations: a machine learning approach. IoT-App 2015 - Proc. 2015 Int. Work. Internet Things Towar Appl. co-located with SenSys 2015, 19–22. https://doi.org/10.1145/2820975.2820979.
Sheridan, T.B., 2016. Human-Robot Interaction: status and challenges. Hum. Factors 58, 525–532. https://doi.org/10.1177/0018720816644364.
Sheridan, T.B., Parasuraman, R., 2005. Human-automation interaction. Rev. Hum. Factors Ergon. 1, 89–129. https://doi.org/10.1518/155723405783703082.
Skulimowski, A.M.J., 2014. Future Prospects of Human Interaction. In: International Conference on Adaptive and Intelligent Systems. Bournemouth, pp. 131–141.
Smith, H.J., Dinev, T., Xu, H., 2011. Theory and review information privacy research: an interdisciplinary review. MIS Q. 35, 989–1015.
Soh, C., Markus, M.L., 1995. In: How IT creates Business Value: A Process Theory Synthesis. Association for Information Systems, Amsterdam, pp. 29–41. https://doi.org/10.1504/IJSTM.2010.029673.
Stalidis, G., Karapistolis, D., Vafeiadis, A., 2015. Marketing decision support using artificial intelligence and knowledge modeling: application to tourist destination management. Proc. – Soc. Behav. Sci. 175, 106–113. https://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 J. Res. Dev. 59, 10:1–10-9. https://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. Int. J. Account. Inf. Syst. 22, 60–73. https://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. J. Exp. Psychol. Appl. 17, 71–96. https://doi.org/10.1037/a0024170.
Tarafdar, M., Beath, C.M., Ross, J.W., 2017. Enterprise cognitive computing applications – opportunities and challenges. IT Prof. 19, 21–27. https://doi.org/10.1109/MITP.2017.3051321.
Taylor, A.K., Cotter, T.S., 2014. Human-Machine Intelligence Interaction in Aviation. In: Proceedings of the American Society for Engineering Management. p. 1.
Tepeš, M., Krajnik, P., Kopač, J., Semolič, B., 2015. Smart tool, machine and special equipment: overview of the concept and application for the toolmaking factory of the future. J. Brazilian Soc. Mech. Sci. Eng. 37, 1039–1053. https://doi.org/10.1007/s40430-014-0229-9.
Torras, C., 2015. Social robots: a meeting point between science and fiction. MÈTODE Sci. Stud. J. 5, 111–115. https://doi.org/10.7203/metode.82.3546.
Tsang, Lincoln, Kracov, Daniel A., Mulryne, J., Strom, Louise, Perkins, Nancy, Wallace, Victoria M., 2017. The impact of artificial intelligence on medical innovation in the European Union and United States. Intellect. Prop. Technol. Law J. 29, 3–12.
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. Int. J. Aviat. Psychol. 22, 120–143. https://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. J. Serv. Res. 20, 43–58. https://doi.org/10.1177/1094670516679272.
Verne, G., Bratteteig, T., 2016. Do-it-yourself services and work-like chores: on civic duties and digital public services. Pers. Ubiquitous Comput. 20, 517–532. https://doi.org/10.1007/s00779-016-0936-6.
Vollmer, A.L., Mühlig, M., Steil, J.J., Pitsch, K., Fritsch, J., Rohlfing, K.J., Wrede, B., 2014. Robots show us how to teach them: Feedback from robots shapes tutoring behavior during action learning. PLoS One 9, 1–12. https://doi.org/10.1371/journal.pone.0091349.
Wang, C.-M., Tseng, S.-H., Wul, P.-W., Xu, Y.-H., Liao, C.-K., Lin, Y.-C., Chiang, Y.-S., Lim, C.-D., Chu, T.-S., FU, L.-C., 2013. Human-oriented recognition for intelligent interactive office robot. In: 13th International Conference on Control, Automation and Systems, pp. 960–965. https://doi.org/10.1093/gbe/evv015.
Webster, J., Watson, R.T., 2002. Analyzing the past to prepare for the future: writing a literature review. MIS Q. 26, 13–23.
Weyer, J., Fink, R.D., Adelt, F., 2015. Human-machine cooperation in smart cars. An empirical investigation of the loss-of-control thesis. Saf. Sci. 72, 199–208. https://doi.org/10.1016/j.ssci.2014.09.004.
Wolbring, G., 2016. Employment, disabled people and robots: what is the narrative in the academic literature and canadian newspapers? Societies 6, 15. https://doi.org/10.3390/soc6020015.
Wood, L.J., Dautenhahn, K., Rainer, A., Robins, B., Lehmann, H., Syrdal, D.S., 2013. Robot-mediated interviews – how effective is a humanoid robot as a tool for interviewing young children? PLoS One 8. https://doi.org/10.1371/journal.pone.0059448.
Xiao, B., Benbasat, I., 2007. E-commerce product recommendation agents: use, characteristics, and impact. MIS Q. 31, 137–209. https://doi.org/10.2307/25148784.
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. Appl. Ergon. 45, 1495–1503. https://doi.org/10.1016/j.apergo.2014.04.012.
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, 1–11. https://doi.org/10.1017/S0263574713001094.
Yampolskiy, R., Fox, J., 2013. Safety engineering for artificial general intelligence. Topoi 32, 217–226. https://doi.org/10.1007/s11245-012-9128-9.
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. https://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. Arch. Pathol. Lab. Med. 139, 929–935. https://doi.org/10.5858/arpa.2014-0478-OA.
Ye, L.R., Johnson, P.E., 1995. The impact of explanation facilities on user acceptance of expert systems advice. MIS Q. 19, 157–172. https://doi.org/10.2307/249686.
You, S., Robert, L.P., 2018. Emotional attachment, performance, and viability in teams collaborating with embodied physical action (EPA) robots. J. Assoc. Inf. Syst. 19, 377–407. https://doi.org/10.17705/1jais.00496.
Yu, Q., Yuan, C., Fu, Z., Zhao, Y., 2012. An autonomous restaurant service robot with high positioning accuracy. Ind. Rob. 39, 271–281. https://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. J. Egypt. Natl. Canc. Inst. 28, 169–174. https://doi.org/10.1016/j.jnci.2016.05.003.
Zheng, L., Chen, L.G., Huang, H.B., Li, X.P., Zhang, L.L., 2016. An overview of magnetic micro-robot systems for biomedical applications. Microsyst. Technol. 22, 1–17. https://doi.org/10.1007/s00542-016-2948-6.
Zheng, X., Lee, M.K.O., 2016. Excessive use of mobile social networking sites: negative consequences on individuals. Comput. Human Behav. 65, 65–76. https://doi.org/10.1016/j.chb.2016.08.011.
Ziuziański, P., Furmankiewicz, M., Sołtysik, A., 2014. E-health artificial intelligence system implementation: case study of knowledge management dashboard of epidemiological data in Poland. Int. J. Biol. Biomed. Eng. 8, 164–171.
Zurek, E.E., Guerrero, G., Reyes, C., Hernandez, R.J., Jabba, D., Wightman, P.M., Salazar, A., Torres, J.E., Nieto-Bernal, W., 2013. Fast identification process of library call numbers for on the shelf books using image processing and artificial intelligence techniques. ISIEA 2013–2013 IEEE Symp. Ind. Electron. Appl. 222–226. https://doi.org/10.1109/ISIEA.2013.6738998.