

WELLBEING, CARE AND ROBOTS

PROSPECTS FOR GOOD WORK IN THE HEALTH AND SOCIAL CARE SECTOR

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CUSP An ESRC Research Centre Working Paper Series ISSN: 2397-8341

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Publication

Druckman A and S Mair 2019. Wellbeing, Care and Robots: Prospects for good work in the health and social care sector. CUSP Working Paper No 21. Guildford: University of Surrey. *Online at: www.cusp.ac.uk/publications.*

Acknowledgements

The financial support of the Economic and Social Research Council for the Centre for the Understanding of Sustainable Prosperity (CUSP) (ESRC grant no: ES/M010163/1) is gratefully acknowledged. We are also grateful to members of CUSP, to the participants of the CUSP *Health and Social Care Multi-Disciplinary Workshop* held on 28 February 2019, and to Prof Payam Barnaghi for the presentation he gave at the workshop.

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Abstract

It has been posited that the health and social care sector may become a 'sweet spot' of good work, in that it will provide plentiful, good quality jobs that are associated with low environmental impacts. To explore this hypothesis, in this paper we address two questions: to what extent will jobs in the health and social care sector be displaced through technological advances such as in artificial intelligence (AI) and robots? And to what extent may the remaining jobs provide 'good' work? Our findings are mixed, with the general consensus being that rather than destroying jobs, technological advances will change the function and nature of jobs. The primary reason for this is the irreplaceability of genuine human interaction by machines. Therefore, as human interaction is likely to be an important component of future jobs, and it is also considered an important feature of 'good' jobs, it is likely that remaining jobs will be generally of good quality.

1 | Introduction

In *Prosperity without Growth* (Jackson 2017: 220) Tim Jackson posits that community-centred enterprises delivering local services such as education, care, craft, creativity and culture hold the promise to contribute to human flourishing, to provide meaningful work and also have relatively low carbon footprints. These types of enterprises are referred to as the 'sweet spots of good work' and it is these which may form the basis of a more sustainable future economy. The properties of a sweet spot in this context can be summarised as:

- a) the work is associated with relatively low environmental impacts;
- b) will provide high numbers of jobs in future as the jobs will not be highly vulnerable to displacement of workers due to technological change;
- c) The work is 'good'—in other words it provides meaningful work with social interaction.

The aim of this report is to explore whether the health and social care sector will fulfil the properties of a 'sweet spot' in future, in particular examining (b) and (c), with (a) having been to a certain extent been explored elsewhere (Jackson et al. 2015), and being beyond the scope of this paper.

The paper therefore addresses the following research questions:

- To what extent will jobs in the health and social care sector be displaced through technological advances such as in artificial intelligence (AI) and robots?
- To what extent may the remaining jobs in the health and social care sector provide 'good' work?

This is potentially a very far-ranging study, and therefore it is important to set out some of what is omitted. Most importantly, the economics of the system is largely considered to be outside the scope of the paper. This is a key omission as, arguably, it is economic aspects that drive all change. Instead we rely on reviewing exercises done by others. A more comprehensive investigation of the topic requires a detailed modelling exercise to be carried out to explicitly explore the questions at hand.

The paper is organised as follows. In Section 2 we consider what 'good work' is, and why good work is important, before going on to explore the current determinants of good work in the health and social care sector. In Section 3 we explore current and future technological change in the health and social care sector, first by reviewing developments in the various fields of the sector, and then we look at the acceptability of technological advances to patients and doctors/nurses and carers. Section 4 considers the numbers of jobs that may be available as we move into the future, and whether the jobs that remain will be good jobs. Section 5 concludes.

2 | Job satisfaction in the health and social care sector

2.1 What is 'good work', and why is good work important?

Employment is important not just because it provides a livelihood, but it is also a key contributor to positive subjective wellbeing (Diener 2000; Taylor 2017). Subjective wellbeing is often conceptualised as having two main components: hedonic wellbeing and eudaimonic wellbeing (Deci and Ryan 2008), and, in particular, work can contribute to eudaimonic wellbeing. According to theories of eudaimonia, subjective wellbeing involves being a fully functional person, and actualisation of one's potential and vitality¹ (Ryan and Deci 2001). Work can contribute to eudaimonic wellbeing through

¹ | Vitality can be described as the experience of possessing enthusiasm and spirit (Ryan and Frederick 1997).

provision of feelings of being competent in carrying out ones' tasks, having autonomy in the way that one carries out one's job, and through interactions with others. These three factors (competence, autonomy and relatedness) are key components of eudaimonia (Sheldon et al. 1996; Ryan and Deci 2001; Kasser 2017; Schwartz and Waterman 2006). Furthermore, many other factors have been shown to increase happiness at work, such as job security, working hours, the provision of training, understanding one's role, and understanding one's line manager (O'Donnell et al. 2014; Hofstetter and Madjar 2003; Csikszentmihalyi 1997; Origo and Pagani 2009; Burchell et al. 2014).

Good work	Bad work
Good wages	Poor wages
Good working hours	Poor working hours
High levels of safety	Low levels of safety
Autonomy	Powerlessness
Interest	Boredom
Self-esteem	Low self-esteem and shame
Self-realisation	Frustration
Work–life balance	Overwork
Security	Risk
Involvement, Social Interaction	Social Isolation
Output is good quality	Output is good quality
Output contributes to the common	Output fails to contribute to the wellbeing of
good	others

Table 1. A conceptualisation of good and bad work.Adapted from Hesmondhalgh and Baker (2011: 39, Table 1)

However, good work is more than about the happiness of the worker. To be classified as 'good', work should produce high quality output, and also make a positive contribution to the wellbeing of society (Hesmondhalgh and Baker 2011). In other words, jobs that produce inferior outputs, degrade the environment and/or increase inequalities (for example) should not be classified as 'good' jobs. Hesmondhalgh and Baker (2011) developed a model of good work, based largely on the work of Blauner (1964)². In their model,

² | Blauner, R. 1964. *Alienation and Freedom: The Factory Worker and His Industry*. Chicago, IL: University of Chicago Press.

which is summarised in Table 1, work is considered to be good or bad based on a balance between the factors shown in the table. This model is useful as we can use it to distinguish factors of good work in jobs in the health and social care sector. We return to this later in the paper.

2.2 A review of the determinants of good work in the health and social care sector

In this section we briefly review the determinants of good work in various health and social care professions, starting with doctors and physicians, followed by nurses, and then care workers. We use job satisfaction as an indicator of good work here. While this is not a comprehensive indicator of good work, we assume that all work in the health and social care sector contributes to societal wellbeing. Furthermore, the literature reviewed below shows that producing work of poor quality impacts job satisfaction. Hence job satisfaction is considered an appropriate indicator of good work for the purposes of this paper. It is important to note that this section looks at the current (and recent past), but not at how job satisfaction might change in future due to, for example, the uptake of new technologies, or changes in the numbers in the workforce.

2.2.1 Doctors and physicians

Job satisfaction amongst doctors and physicians has been found to be strongly positively correlated to hourly wage (Dale et al. 2015; Leigh et al. 2009). Job satisfaction has also been found to be negatively correlated to working high numbers of hours per week, and workload intensity and volume (Dale et al. 2015; Leigh et al. 2009). Job satisfaction also varies according to speciality within the field. For example, in the USA, geriatricians and paediatricians report generally very high job satisfaction, while neural surgeons, and obstetrics and gynaecology specialists report poor job satisfaction (Leigh et al. 2009). The differences can be linked to specific aspects of each speciality, as well the way wages, hours and workload plays out in each field.

In geriatricians high job satisfaction can be attributed to relatively regular working hours, good personal relationships with their patients, and a feeling of satisfaction that they are needed personally and societally (Cravens et al. 2000; Leigh et al. 2009; Shah et al. 2006). With paediatricians the high job satisfaction is attributed to the special relationships that can be built up with child patients, along with the generally 'joyful' nature of children (Leigh et al. 2009; Crew Nelms 2004), the opportunity to have an impact on many aspects of the child's life (Crew Nelms 2004), the challenge of working with children (Crew Nelms 2004), and a general lower perception of stress than in other fields (Leigh et al. 2009).

In the obstetrics and gynaecology field, low job satisfaction can be attributed to emotional exhaustion (Becker et al. 2006), fear of malpractice lawsuits (especially in the USA) (Becker et al. 2006), loss of autonomy via lack of control over schedule and work hours (Leigh et al. 2009; Keeton et al. 2007), lack of adequate time with patients (Kravitz et al. 2003), and restricted availability of high-quality ancillary services (Kravitz et al. 2003). For neurosurgeons, factors contributing to low job satisfaction also include emotional exhaustion, and uncertainty regarding future earnings (Klimo et al. 2013). For both neurosurgeons and obstetrics and gynaecology specialists, low pay when compared to other specialities was a factor (Klimo et al. 2013; Leigh et al. 2009). Leigh also posits that low job satisfaction in these fields is also due to these specialities being regarded as 'top-tier', but, in reality, gaps between outcomes and aspirations are experienced, with expectations not generally being met (Clark and Oswald 1996; Leigh et al. 2009).

2.2.2 Nurses

It is commonly acknowledged that the shortages of nurses in many Western countries is due to low job satisfaction (Currie and Hill 2012). The most common cause of the low job satisfaction is stress, with other factors also including high workload and working hours, management style experienced, role conflict and ambiguity in the role, lack of organisational commitment, poor relationships with fellow workers and managers, and emotional exhaustion (Franklin 2014; Lu et al. 2012; Zangaro and Soeken 2007; McVicar 2016; Coomber and Barriball 2007; Currie and Carr Hill 2012).

The link between pay and nurses' job satisfaction is contested (Currie and Carr Hill 2012; McVicar 2016). For example, pay is found by Coomber and Barriball (2007) and Lu et al (2012) to be a factor whereas Currie and Carr (2012) and McVicar (2016) state in their reviews that the evidence on the linkage between pay and job satisfaction is unclear.

2.2.3 Care workers

Care workers include personal care workers, nursing assistants and nurse aides, working in a variety of settings, such as hospitals, clients' private homes, and residential care homes (Squires et al. 2015).

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In a systematic review of care workers in residential long term care settings, Squires et al (2015) found that factors contributing to job satisfaction included empowerment, autonomy, workload and facility resources. In particular, workload has, as expected, a negative relationship to job satisfaction, and this is related to the shortage of care workers in the UK and lack of (public and private) funding (Roberts et al. 2019). This has resulted in frequent inadequate provision of care, with care workers often being expected to complete home visits in just 15 minutes (Bloodworth 2018; Roberts et al. 2019).

Although pay is not shown to be an important factor in job satisfaction in the studies reviewed by Squires et al (2015), low pay and poor working conditions are associated with high turnover and shortage of care workers (Bukach et al. 2017; Whitebook and Sakai 2003; Roberts et al. 2019). Indeed in the UK over 50% of all care workers are paid less than the real living wage (Roberts et al. 2019). A theoretical basis for this claim can be found in the economic literature on efficiency wages, which argues that workers are more reluctant to quit in jobs that pay wages above the market average (e.g (Yellen 1995)). One potential reason for the discrepancy between job satisfaction, pay and turnover in the care sector is intrinsic motivation. It has been argued that care workers may view their work as a public service, and find job satisfaction more in the fact that they are helping people than in the relatively poor monetary rewards (Folbre and Smith 2017; Morgan et al. 2013). So why is there a high turnover? The suggestion is that turnover rates occur despite often high job satisfaction. Care workers may be satisfied with their jobs, but unable to make ends meet on their low pay (Morgan et al., 2013). As a result they are forced out of work they find satisfying by their inability to make a living.

2.2.4 Summary

When we attempt to map the findings discussed above onto the framework of good and bad work developed by Hesmondhalgh and Baker (2011), we can see that where the output is of low quality, job satisfaction is reduced. We also find that working hours and workload, and autonomy are all factors that influence job satisfaction amongst care/medical professionals, as expected according to the framework.

However, while pay is an important factor in doctors' and physicians' job satisfaction, findings are mixed concerning its importance for nurses, and it is not found to be a factor for care workers. According to Hesmondhalgh and Baker's (2011) framework pay should be a factor in job satisfaction, however,

this is contested. For example, a meta-analysis of studies found that job satisfaction is only marginally related to pay level (Judge et al. 2010). The reason why pay may be a predictor of job satisfaction is that, theoretically, one expects a positive relationship between pay level and pay satisfaction, and pay satisfaction is found to be a predictor of overall job satisfaction (Judge et al. 2010). In contrast, we can draw from the psychology literature. In this literature pay is classed as an extrinsic motivation/reward, with extrinsic motivations/rewards being known to be less likely to be associated with high subjective wellbeing than intrinsic motivations/rewards (Dittmar et al. 2014). This suggests that doctors and physicians are more likely to be extrinsically motivated than care workers (Malka and Chatman 2003). It is also possible that the findings show a gender issue, with doctors traditionally being male, nurses and care workers female. Nursing and care work is often considered to be less reliant on diagnostic skills and more on social skills. The latter are traditionally considered feminine skillsets and are typically ignored and undermined in capitalist economies, not being considered true 'skills' (Plumwood 1993; Dengler and Strunk 2017). It may also indicate an educational issue, with doctors having more training. Further discussion of these issues are beyond the scope of this paper.

Our findings also highlight that other factors are important contributors to job satisfaction for the health and social care workers, which are not included in Hesmondhalgh and Baker's (2011) framework. These are stress and emotional exhaustion for doctors, physicians and nurses, organisational commitment for nurses, and fear of malpractice lawsuits amongst doctors and physicians. This not too surprising: Hesmondhalgh and Baker's framework was developed for the creative industries. So, this emphasises the differences between work in the health and social care sector and other sectors.

3 | How might technological advances affect future jobs in the health and social care sector?

Technological developments that are already being implemented in the health and social care sector, and which hold a great deal of potential for future advances, include AI, virtual and augmented reality, gathering and use of big data, machine learning and robotics (Manyika et al. 2013). For example, AI is being used to develop drugs by screening thousands of compounds to find those that have the required properties to treat a particular condition (Fleming 2018).

In this section we discuss developments first in the fields of medical diagnosis and surgery. Then we move on to provision of physical care through 'carebots', provision of mental care through socially assistive robots (SARs), and then we look at how 'softbots' are developed to meet emotional needs.

3.1 Medical diagnosis

Artificial intelligence, machine learning and use of big data are growing fields of research in medical diagnosis (Ford 2015; Choy et al. 2018; Krittanawong 2018; Choyke 2018). Currently physicians use personal histories, individual biomarkers, simple scores, scans and physical examination of patients to make a diagnosis (Krittanawong 2018; Choy et al. 2018). In contrast, artificial intelligence uses complex deep learning algorithms drawing on big data, which can include extensive datasets based on evidence from millions of patients and published research results (Krittanawong 2018). As emphasised by Ford (2015), use of automation is drawing on far larger, and more up-to-date, datasets than can be processed by any one human being. We give several examples below.

Use of deep neural networks³ enables visual diagnosis of skin cancer (the most common human malignancy) to be carried out to an accuracy equal to that of trained skin-cancer doctors (Esteva et al. 2017). This can be done through a smart-phone app and may therefore in future provide widely available diagnoses (Esteva et al. 2017). Another example of use of deep neural networks is to detect cartilage lesions within the knee joint on MR images, and this has been done with high overall diagnostic accuracy (Liu et al. 2018).

A 'TriageBot' is being developed to be able to decide the order of treatment of patients arriving at hospital emergency departments (Benton 2011). The TriageBot gathers both logistical and medical information, as well as taking diagnostic measurements, from an incoming patient. Using AI, it can give tentative, possible diagnoses that are currently given to the triage nurse (or, as envisaged in future developments, to a diagnostic system) (Wilkes et al. 2010). It will also monitor patients waiting for care, and alert staff when a patient's condition deteriorates and may become acute (Benton 2011).

³ | An artificial neural network is an attempt to simulate the network of neurons that make up a human brain so that a computer will be able to learn and make decisions in a humanlike manner (Marr 2018). A deep neural network is a neural network with more than two layers (techopedia.com 2019).

Furthermore, TriageBot can give recommendations for non-physician care (Wilkes et al. 2010). The system is still under development, with Benton (2011) having stated that it will be "*five to 10 years before it is widely available*". However, a search for "TriageBot" on Google (19.07.19) has not revealed this predicted wide availability.

Babylon have developed an on-line AI powered triage and diagnostic system called 'Chatbot' (Razzaki et al. 2018), which was rolled out in several parts of the UK as part of the NHS's 111 telemedicine service (Heather 2018). Razzaki et al (2018) reported that the system has accuracy comparable to human doctors (in terms of precision and recall). They also report that the triage advice recommended by the AI system was, on average, safer than that of human doctors, when compared to the ranges of acceptable triage provided by independent expert judges, and that the advice had only a minimal reduction in appropriateness (Razzaki et al. 2018). However, this report should be treated with caution: the lead author and eight of the paper's other authors work for Babylon, although four of them work for hospitals and/or academic institutions. Indeed, the NHS suspended the rollout of Babylon Health's 'GP at Hand' service in January 2018, due in part to concerns that it is likely to attract younger, healthier patients rather than those with complex and/or special needs, and might therefore lead to inequality in service provision and potentially inequality in patient outcomes (Heather 2018; Cusano 2018).

How good and appropriate such medical diagnosis systems are is contested. For example, the robustness of the Babylon system has been disputed (Torjesen 2018). Furthermore, Matthew Noble, Associate Medical Director of Babylon Health, stated that AI "*cannot replace the physical, human care that comes from being examined in person by a GP*" (Armstrong 2018). This is because it is unlikely that a system of sensors linked to an AI system can yield the valuable information that traditional physical examinations can provide, especially, for example, in examinations that involve high-level interaction and critical thinking in areas such as neurology (Krittanawong 2018). However, it is likely that, as noted by Ford (2015:156), automated systems will be used increasingly for providing 'high quality second opinions'.

A further limitation of these advances in medical diagnosis is that, according to some researchers, a machine cannot engage with patients emotionally or gain their trust. This is, however, contestable, and we will return to this subject in Section 5. In an opinion piece for the British Medical Journal (BMJ) Margaret McCartney (2018) commented that AI has the potential to speed up healthcare and make it safer, but warned that appropriate systems must be put in place to test and certify the safety of systems (see also Krittanawong (2018)). This is discussed further in Section 5.

Before closing this section on medical diagnosis, it is worth reiterating that while technological developments have the ability to perform substantially more diagnoses with limited human involvement, this may have the knockon effect of increasing the demand for care, particularly in cases where symptoms are not diagnosed early enough for preventative measures to be put in place.

3.2 Surgery

Automated robot assisted surgery is minimally-invasive surgery using highdefinition cameras and micro-instruments to enter the human body through small incisions, thus replacing the eyes and hands of the surgeon (Diana and Marescaux 2015). Additionally, surgical robots are being developed to carry out suturing of wounds (Ford 2015).

Diana (2015) asserts that use of minimally invasive surgery techniques enables reductions in surgical trauma and incision-related complications. This reduced hospital stays, resulting in fewer jobs in post-operative-care. Although there are still problems with the safety of minimally invasive surgery (Alemzadeh et al. 2016), according to Diana and Marescaux (2015), developments in augmented reality offer the prospect of a "major revolution to increase safety and deal with difficulties associated with the new minimally invasive approaches" (Diana and Marescaux 2015). However, Ford (2015:161) posits that for the 'foreseeable future' it seems "inconceivable that any patient would be allowed to undergo an invasive procedure without a doctor being present and ready to intervene".

Robot assisted surgery is being developed in many fields. We consider the case of rectal cancer here, in which robotic surgery is considered to be at the cutting edge (Zhang et al. 2016). A meta-analysis of studies has found that robot assisted surgery results in similar outcomes in the long-term as the outcomes of laparoscopic surgery (Ohtani et al. 2018). Another meta-analysis of studies, this time of colorectal cancer, showed that robot-assisted is a promising surgical approach with its safety and efficacy comparable to that of laparoscopic surgery (Zhang et al. 2016). From this it is concluded that robot assisted surgery may be an acceptable surgical

treatment option compared to laparoscopic surgery for these cancers (Zhang et al. 2016; Ohtani et al. 2018).

3.3 Providing physical care-'carebots'

'Carebots' are "robots intended to assist or replace human caregivers in the practice of caring for vulnerable persons such as the elderly, young, sick, or disabled" (Vallor 2011). For example, RIMAN is a robot developed to help lift patients, having skin-like soft, tactile sensors to enable safe and dexterous manipulation (Mukai et al. 2008). 'Robear' is a plastic and metal robot with a cute polar-bear-cub face, which can lift patients in and out of bed, placing them into a wheelchair or assisting them if they are unsteady on their feet (Davies 2016:60). Vishal et al (2017) are developing a robot system that dispenses medication to patients in a hospital or care home by analysing the position of each bed and matching the medicine intake using image-processing concepts. Another system, developed by Ahn et al (2015) measures patients' vital signs and reports the results. Other carebots are being developed that help with feeding and bathing (Gallagher et al. 2016).

Commenting in the Nursing Standard (2014+) James Buchan (2017) commented that while carebots may supplement the work of nurses and carers, *"they are unlikely to be a substitute for them"*. One of the reasons for this is that carebots involved in lifting patients need to be extremely heavy and therefore will be mainly deployed in care homes and hospitals (Ford 2015). According to Ford (2015:162) the realisation of a "*multitasking robot that can autonomously assist people … remains far in the future"*.

3.4 Providing mental care—socially assistive robots (SARs)

Socially assistive robots (SARs) have a wide variety of uses. For example, many older people suffer from isolation and mental impairment, including dementia, and socially assistive robots are particularly useful in these situations (Sorell and Draper 2014). SARs are also useful in other conditions, such as in treating depression (Bennett et al. 2017).

Paro Robot is an SAR that has been commercially available in Japan since 2005 (Sabanovic et al. 2013). Being in the form of a furry, baby seal, it provides visual, auditory, olfactory and tactile stimulation, it responds to being petted by moving its tail and opening and closing its eyes, and its compact size allows it to be held, hugged and passed around (Sabanovic et al. 2013; Sorell and Draper 2014). In trials where Paro is used to deliver multi-sensory behavioural therapy (MSBT) to elderly people with dementia,

it has been shown to successfully provide therapeutic benefits, with participants showing higher levels of engagement with their environment and with other people (Sabanovic et al. 2013). Moreover, people not involved directly in the study also showed increased levels of engagement too (Sabanovic et al. 2013). A further noteworthy result was that levels of activity increased over the seven weekly sessions, and this was interpreted as showing that it was not due to the novelty of Paro (Sabanovic et al. 2013). Paro has also been used in trials with adults in their own homes suffering from clinical depression (Bennett et al. 2017), with the results suggesting that Paro is effective in reducing depression for most patients, and that it can also be used to monitor depression levels and send alerts when necessary (Bennett et al. 2017).

3.5 Meeting emotional needs—'softbots'

Psychotherapeutic avatars, or 'softbots' are emotionally sensitive robots (Hamet and Tremblay 2017). They can take a human form (humanoid) or take the form of an animal (in a form such as that taken by Paro as described above). When taking the form of an animal, some studies have suggested that the softbot can perform the therapeutic functions of a pet without the drawbacks of having a real animal to care for (Sorell and Draper 2014).

Softbots are used to improve patients' socio-emotional engagement. For example, if the patient is a child, the softbot can be programmed to playfully interact with a child during a hospital stay. This has been found to improve the child's overall hospital experience, including reducing stress, helping to educate and entertain the child, and reducing feelings of social isolation (Jeong et al. 2018). This has benefits not only for the patient, and the child's family, but also for the professional care teams.

A particular feature of a softbot is that softbots can have 'presence'. Sorell explains this as:

"What is meant by 'presence' is the kind of co-location of a thing with a person that brings it about that the person no longer feels alone. A child co-located with a bed will probably feel alone, even if the bed is comfortable and familiar. But a child co-located with a bed and a familiar cuddly toy will probably feel that they are in the presence of something or someone, even though the cuddly toy is inanimate and inert and has degenerated after years of handling to a lump of cloth." Sorell (2014: 184). Paro and ACCOMPANY are both examples of robots that have presence. ACCOMPANY, a humanoid softbot, is particularly sophisticated in this sense in that it can follow an elderly person around, appearing to take an interest in the activities being carried out, being able to show displeasure in the actions of the elderly person when appropriate according to its algorithms, and also prompting the elderly person to undertake beneficial activities (Sorell and Draper 2014).

3.6 Acceptability of technological innovations

There are two aspects of the acceptability of technological innovations: one is how acceptable is it to the *providers* of care. The other is how acceptable is it to the *receivers* of the care, with Kuo et al (2009) having found that male patients are more likely to have a positive attitude toward robotic carers than females, although they found no difference between age groups.

1	The <i>objectification</i> of the elderly as "problems" to be solved by technological means.
2	The potential for carebots to either enhance or restrict the capabilities, freedom, autonomy, and/or dignity of cared-fors.
3	The potential of carebots to enhance or reduce <i>engagement</i> of cared-fors with their surroundings
4	The potential of carebots to enhance or intrude upon the <i>privacy</i> of cared-fors.
5	The <i>quality</i> of physical and psychological care robots can realistically be expected to supply.
6	The potential of carebots to either reduce or enhance cared-fors' levels of <i>human contact</i> with families and other human caregivers.
7	The potential of carebot relations to be inherently <i>deceptive</i> or <i>infantilizing</i> .

Table 2. Concerns that should be taken into account in design of carebots.Source: adapted from Vallor (2011)

Sorell (2014) makes the distinction between whether the robot is designed with user-centredness or carer-centredness, and argues that, from a moral standpoint, the default position should be a user-centred design. However, if the user's behaviour may present a danger to him/herself or to others, it is then considered morally acceptable for the robot to include functions that override the autonomy of the user (Sharkey and Sharkey 2012).

Vallor (2011) sets out concerns that should be taken into account in the design of carebots, as shown in Table 2. There is no inherent reason why, with due care, these potential downfalls cannot be avoided, or, at the very least, minimised. However, Gallagher (2016) points out that the elderly rely on human carers to "*pick up on subtle cues regarding capabilities and to communicate in an emotionally engaged and meaningful way*" and she asserts that, while robots may be able to undertake the physical tasks of lifting and so on, automated systems will not be able to replace human interaction and instead she advocates 'productive human and carebot collaboration'.

4 | Future jobs in the health and social care sector

The health and social care sector employed 3,375,000 people in the UK in 2017, this being 11% of total employment—see Table 3. The highest proportion of employment in the sector is in Caring Personal Services (1,336,000 people, 40% of jobs in the sector), with Nursing and Midwifery Professionals coming next at 702,000 (21%). Health Professionals is the next biggest category, and this includes Medical practitioners, Psychologists, Pharmacists and Ophthalmic opticians: this category only makes up 17% (563,000) of which 48% are Medical Practitioners (271,000).

EMP04: ALL IN EMPLOYMENT BY STATUS,	OCCUPATION & SEX					Unite	ed Kingdom
Quarter 2 : Apr-Jun 2017					Thousands (000's), not seasonal	lly adjusted
ALL	Total in employment	E	Employees		S	elf-employed	(
Standard Occupational Classification							
(SOC 2010):		Full-time	Part-time	Total	Full-time	Part-time	Total
Total UK Employment	31,996	19,988	6,997	27,002	3,423	1,381	4,814
Health and Social Care 614 Caring Personal Services	1,336	773	508	1,281	29	22	52
614 Caring Personal Services	1.336	773	508	1.281	29	22	52
223 Nursing and Midwifery Professionals	702	466	225	691	7	5	11
221 Health Professionals	563	342	99	441	78	43	122
244 Welfare Professionals	205	148	45	193	7	*	12
321 Health Associate Professionals	180	99	31	130	25	25	50
222 Therapy Professionals	154	78	42	120	15	19	34
2442 Social workers	116	87	25	112	*	*	5
118 Health and Social Services Managers and Directors	105	88	11	99			5
9271 Hos pital porters	15	14	•	15	•	*	•
Total in Health and Social Care	3,375	2,094	986	3,082	161	114	289

Table 3. UK Employment by Status, Occupation & Sex.Source: ONS (2018)

4.1 The challenge of making predictions—a word of warning!

It is widely acknowledged that making predictions about future advances in technology is extremely difficult (Frey and Osborne 2017) and that predictions are generally poor (Armstrong and Sotala 2015). For example, Marvin Minsky, who won the 1969 Turing Award for his pioneering work in AI (Dennis 2019), claimed in 1970 that by the end of that decade *"we will have a machine with the general intelligence of an average human being"* (Jacko 2012; Herzfeld 2002; Bigus et al. 2002). But this still has not happened. Nevertheless, despite being aware that predictions are often incorrect, the following section reviews current predictions in the literature, but the reported results should be viewed with possible inaccuracies in mind.

4.2 A review of studies on future jobs

When considering how susceptible jobs are to technological advances, it is helpful to characterise jobs as a bundle of tasks to be carried out, and these can be classed in various ways. An example adapted from Eurofund (2018) and Frey and Osborne (2017) is:

- Routine tasks
 - Physical
 - Intellectual
- Non-routine tasks
 - Physical
 - Intellectual
- Social tasks

In general, routine tasks are easy to automate, with physical routine tasks already having been largely automated already, particularly where it has been economically profitable to do so (Eurofund 2018). Automation of intellectual routine tasks is well underway (Eurofund 2018). The labour market is therefore now largely comprised of non-routine physical and intellectual tasks and social tasks (Eurofund 2018). Non-routine physical tasks are those that require hand-eye co-ordination and manual dexterity. Machine learning, more advanced sensor technology, and use of big data are already beginning to be developed that will contribute to the automation of jobs in this category, such as minimally invasive surgery (Eurofund 2018; Diana and Marescaux 2015). Non-routine intellectual tasks that include creativity and problem solving are more challenging to computerise, but again, advances in AI and deep learning, for example, are enabling these tasks to be automated. Social tasks have traditionally been considered the most challenging to automate, and many researchers suggest that these are unlikely to be automated (e.g. Eurofund 2018). For example, in The Rise of the Robots, Ford (2015:157) discusses the possibility of a new class of medical care professionals who will carry out the routine tasks that include interacting with and examining patients, leaving the challenging diagnostic tasks to a computer. These new professionals would have a Masters or 4 year undergraduate qualification—in other words, far less training than medical doctors currently receive. Ford envisages that these professionals will communicate their findings to an automated diagnostic system, and that once these diagnostic systems have reached a high level of accuracy, any need for a human doctor to oversee the diagnosis will become redundant. Despite this, there is increasing evidence that even social tasks are beginning to be successfully automated, with, as described in Section 3.4, examples of social tasks being carried out to good effect by robots such as Paro (Sabanovic et al. 2013; Jeong et al. 2018).

The graphics shown in Figures 1 and 2 below depict similar classifications. In particular, the Bank of England graphic (Figure 1) highlights that technological skills such as designing, programming and controlling computers and robots are still expected to be needed in 2030, even though these tasks are capable of being automated to a certain extent (Bank of England 2019; Eurofund 2018). Further discussion of this is outside the scope of this paper.



Figure 1. What does the future hold? Source: Bank of England (2019)



Figure 2. Jobs of the future: some occupations will grow, others will decline, and new ones we cannot envision will be created. Source: McKinsey Global Institute, Manyika (2017)

The UK Commission for Employment and Skills (UKCES) commissioned a foresight report on the future of jobs and skills in the UK in 2030 (Störmer et al. 2014). Their study is based on expert input from key groups including business, trade unions and academia, as well as a detailed and comprehensive review of the literature. The study presents four plausible scenarios of what the UK's work landscape might look like in 2030. The four scenarios are Forced Flexibility, The Great Divide, Skills Activism, and Innovation Adaptation. The technological assumptions in each are summarised in Table 4. The types of disruptive innovations considered in the Skills Activism scenario includes advances of AI in medical diagnosis, and robotics in surgery, enabling improved outcomes, as well as use of robots in nursing and care work. The report also considers developments in preventative health care, such as micro-robots internally patrolling bodies and carrying out maintenance and repair tasks. The report suggests that by lowering health care costs (in line with Baumol's (2012) hypothesis), uptake of such technologies could lower the tax burden and/or enable more time to be spent on the 'soft' aspects of social care.

Forced	The Great	Skills	Innovation
Flexibility	Divide	Activism	Adaptation
Focus on incremental innovation in UK businesses, across almost all UK sectors	Radical innovation in life and material sciences driving economic growth	Disruptive IT automation restructures professional tasks	Wide integration of cost-efficient ICT technologies to enable business survival

Table 4. A summary of the assumptions concerning innovation in the UKCES ReportScenarios. Source: Adapted from Störmer (2014:46)

The UK Commission for Employment and Skills also commissioned a project called 'Working Futures 2014 to 2024' which made quantitative assessments of employment in the UK labour market 2014-2014 (UK Commission for Employment and Skills 2016; Wilson et al. 2016). The projections are based on the use of a multi-sectoral, regional macroeconomic model, combined with occupational, replacement demand and qualification modules.⁴



Fig 3. Employment levels by gender and status, 2004-2024 - Health and social work. (FT: Full time; PT: Part time; SE: Self-employed). Source: UK Commission for Employment and Skills (2016)

⁴ | More specifically, the results are based on "latest official employment data, including the results from the Labour Force Survey and the emerging findings from the 2011 Census. The latest stance of government policy is taken into account by factoring in the consequences of the various government public spending measures and other official policy statements. The projections are based on the Cambridge Econometric (CE) macroeconomic forecasts, produced in the summer of 2015 (produced using MDM - CE's detailed multi-sectoral dynamic macroeconomic model (MDM-E3), MDM C152REG (revision 12956), conducted in January 2016)." (Wilson et al. 2016:6)

The report states that "*The detailed projections present a carefully considered view of what the future might look like, assuming that past patterns of behaviour and performance are continued over the longer term. The results should be regarded as indicative of general trends..... If policies and patterns of behaviour are changed then alternative futures can result.*" (Wilson et al. 2016:iii). This makes it clear that the modelling is based on business as usual, with only incremental technological change as manifested already in the data up to 2014.⁵ It therefore does not take into account the prospects for increased rates of technological change (and certainly not radical technological change). The graphs shown above in Figure 3 should be interpreted in this light. From the graphs it can be seen that UKCES expect a slight increase in full-time and part-time jobs in the health and social care sector, rather than a decrease that might perhaps be predicted under conditions of radical technological advances.



Figure 4. Probability of computerisation. Source (Frey and Osborne 2017: Fig 3 page 265) Understanding care work of the future: towards the sweet spot?

⁵ | A search for the terms 'robot' and 'artificial intelligence' in Wilson et al (2016) and in the accompanying technical report did not yield any results.

Complementary to the UKCES reports, Frey and Osborne (2017) developed a framework for assessing how susceptible different types of jobs in the USA are to computerisation. They applied their framework to 702 occupations for the US labour market. The framework is based on assigning categories to job-types according to (a) whether the tasks involved can be 'sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment', and also according to 'the perception and manipulation, creativity and social intelligence required to perform the tasks' (Frey and Osborne 2017:263). Assignment was done in-part based on data and in-part by expert consultation.

They find that whereas 47% of US employment is automatable in the next decade or two, jobs in the health and social care sector are relatively unsusceptible to computerisation.⁶ This is shown above in Figure 4 where most of the 'Healthcare, Practitioners and Technical' jobs are in the 'Low' probability of computerisation category (<0.3% probability). The authors note that computer-controlled machines will be increasing able to undertake tasks currently requiring human mobility and dexterity, and AI will enable tasks that require social intelligence to be increasingly carried out by computers. In contrast, jobs involving '*development of novel ideas and artefacts are least susceptible to computerisation*' are assessed to be less susceptible to computerisation (Frey and Osborne 2017:266), in-line with the discussions above and the graphic in Figure 2.

Given current predictions for automation in the sector, the jobs that remain are likely to have some aspects of good jobs, and some aspects of bad jobs. To understand this further we propose an augmented version of Hesmondhalgh and Baker's (2011) framework (Table 5). This framework codes Hesmondhalgh and Baker's into three components (which in cases overlap), 1) Job Satisfaction 2) Livelihood and 3) Social Usefulness. Taking these three components we can begin to see how automation may impact the 'goodness' or 'badness' of care work, identify tensions and complements, and make suggestions for action.

^{6 |} In this report, computerisation refers to Machine Learning and Mobile Robotics.

Component	Good work	Bad work	
1	High levels of safety	Low levels of safety	
1	Autonomy	Powerlessness	
1	Interest	Boredom	
1	Self-esteem	Low self-esteem and shame	
1	Self-realisation	Frustration	
1	Work–life balance	Overwork	
1	Security	Risk	
1	Involvement, Social Interaction	Social Isolation	
1	Low Stress/time and support to	High Stress/emotional exhaustion	
1,2	Good wages	Poor wages	
1, 2	Good working hours	Poor working hours	
1, 2	No risk of personal liability	High risk of personal liability	
1, 3	Output is good quality	Output is good quality	
1, 3	Output contributes to the common good	Output fails to contribute to the wellbeing of others	

Table 5. A conceptualisation of good and bad work in the care sectors.

Adapted from Hesmondhalgh and Baker (2011: 39; Table 1). Component 1 = Job Satisfaction 2 = Livelihood and 3 = Social Usefulness.

Let us start with component 1, job satisfaction. Some of remaining jobs are expected to be those that include high amounts of human interaction and require properties such as empathy. Consequently, we can see these jobs will fulfil the properties of 'involvement' and 'social interaction', which correspond to job satisfaction in our framework. Other remaining jobs are expected to require human judgement and creativity which can contribute to autonomy, interest, self-esteem and self-realisation. Again, these are components of the job satisfaction element of good work in our framework.

A degree of automation and AI may also improve job satisfaction by increasing component 3, the quality of output/social usefulness of the work. As discussed, social usefulness is a particularly important element of job satisfaction for some groups of care workers. By improving health outcomes, technology can therefore improve both of these elements. For example, Carebots can monitor patients and alert workers when adverse conditions are detected.

Use of AI systems to give second opinions may give workers stronger legal protection, and reduce their liability for mistakes, thereby increasing the livelihood component of the work (2). Certainly, such systems are thought to reduce stress and alleviate fears of legal action against workers (Eurofund

2018). However, these measures may also reduce other elements of job satisfaction. In particular they raise fears about privacy and autonomy of workers. For example, use of sensors that monitor workers' actions can be thought of as intrusive, and potentially misused (Eurofund 2018:18). They can also risk the privacy of the patient, and thus raise issues of trust. We return to this in the next section.

We must also note that it is unclear how AI will impact other key aspects of the livelihood component, in particular, the issue of wages which drive many care workers out the sector. In theory the use of AI could reduce costs, freeing up resources to improve wages. However, by reducing the 'hard' diagnostic skills used by care workers and shifting the work further into the soft skills of social interactions and empathy, AI and automation could drive down wages. This is not inevitable, but would require a changing of the dominant political economy to place increased value on the traditionally feminine skillsets that have been historically undervalued (Dengler and Strunk 2017; Plumwood 1993).

5 | Discussion and conclusion

Before concluding this paper, it is vital to reiterate the limitations of this investigation: the topic is wide ranging and fast moving, and this review has merely scratched the surface. To address the topic more thoroughly a modelling exercise is required, in which the relationships between the financial drivers of technological change (such as capital costs, labour costs, demographic change) and other drivers and barriers (such as the rate and acceptability of technological change, levels of trust, and so on) are modelled.⁷ Such a model would incorporate lessons from Baumol's (2012) 'Cost Disease'. It may also address, for example, Avent's (2016) 'employment trilemma' in which he proposes that new forms of work are likely to satisfy at most two of the following three conditions: 1) high productivity and wages, 2) resistance to automation, and 3) the potential to employ massive amounts of labour. However, even after such a modelling exercise, estimates of the effect of technological change on the quantity and quality of jobs will still be highly uncertain.

A key factor that may influence the number and nature of jobs in the sector is the way in which ethical concerns issues are handled. As stated by Taddeo and Floridi (2018), ethical regulation on design and use of AI to protect

^{7 |} This could be done in, for example, a system dynamics or agent based modelling framework.

individual's rights and protect social values is vital, if complex (Taddeo and Floridi 2018). Initiatives such as AI4People launched by European Parliament in 2018 therefore have an important role to play. AI4People is a multi-stakeholder forum, bringing together actors interested in shaping the social impact of new applications of AI. It includes the European Commission, the European Parliament, civil society organisations, industry and the media (Atomium European Institute for Science Media and Democracy 2019). Its goal is "to create a common public space for laying out the founding principles, policies and practices on which to build a 'good AI society'. For this to succeed we need to agree on how best to nurture human dignity, foster human flourishing and take care of a better world. It is not just a matter of legal acceptability, it is really a matter of ethical preferability" (Floridi et al. 2019). The forming of this body and similar organisations reminds us that we have the power of decision making over our future. Given a better understanding of potential developments and institutions that allow for collective decision-making, we could opt for a promising future rather than one driven by ad-hoc whims of technologists.

This review of the literature has revealed a common consensus that rather than destroying jobs as predicted by some (see for example, the McKinsey report (Manyika et al. 2017)), technological advances will change the function and nature of future jobs, but a large scale loss of jobs in the health and social care sector is not likely to occur. As expressed in the recent IPPR Report, '*The Future is Ours'*, jobs will be "reallocated rather than eliminated" (Roberts et al. 2019). This is for several reasons, the primary one being the irreplaceability of genuine human interaction (which includes, of course, empathy) by machines, and also the valuable role of human judgement and explanation (Haldane 2018:14).⁸ This offers some confidence that future jobs in the sector will be 'good' jobs as they will, in particular, involve social interaction, which is a feature of Hesmondhalgh and Baker's (2011) framework (Table 1).

Now, before closing, we need to turn to an important aspect of a sweet spot of good work as we understand it (see Section 1) that has not been further addressed in this paper, namely: the association with relatively low environmental impacts. It is common knowledge that robots and AI systems require high use of energy and materials, and thus cause environmental harm (Clift and Druckman 2015; Jackson 1996). We need to be aware of this

⁸ | We also envisage jobs developing technology for the sector, but we classify these jobs to be in the technology sector, not the health and social care sector.

when considering the nature of future jobs as they may be associated with high detrimental environmental impacts.

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