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Utopia versus dystopia: Professional perspectives on the impact of healthcare artificial intelligence on clinical roles and skills

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A R T I C L E I N F O

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A B S T R A C T

Background: Alongside the promise of improving clinical work, advances in healthcare artificial intelligence (AI) raise concerns about the risk of deskilling clinicians. This purpose of this study is to examine the issue of deskilling from the perspective of diverse group of professional stakeholders with knowledge and/or experiences in the development, deployment and regulation of healthcare AI.

Methods: We conducted qualitative, semi-structured interviews with 72 professionals with AI expertise and/or professional or clinical expertise who were involved in development, deployment and/or regulation of healthcare AI. Data analysis using combined constructivist grounded theory and framework approach was performed concurrently with data collection.

Findings: Our analysis showed participants had diverse views on three contentious issues regarding AI and deskilling. The first involved competing views about the proper extent of AI-enabled automation in healthcare work, and which clinical tasks should or should not be automated. We identified a cluster of characteristics of tasks that were considered more suitable for automation. The second involved expectations about the impact of AI on clinical skills, and whether AI-enabled automation would lead to worse or better quality of healthcare. The third tension implicitly contrasted two models of healthcare work: a human-centric model and a technology-centric model. These models assumed different values and priorities for healthcare work and its relationship to AI-enabled automation.

Conclusion: Our study shows that a diverse group of professional stakeholders involved in healthcare AI development, acquisition, deployment and regulation are attentive to the potential impact of healthcare AI on clinical skills, but have different views about the nature and valence (positive or negative) of this impact. Detailed engagement with different types of professional stakeholders allowed us to identify relevant concepts and values that could guide decisions about AI algorithm development and deployment.

1. Introduction

Healthcare applications of Artificial intelligence (AI) are rapidly increasing in number and value. AI broadly refers to interrelated technologies that can perform tasks normally requiring human intelligence [1]. Image-based diagnosis and screening, on which medical specialties such as radiology and pathology rely, is considered the most successful domain of such medical AI applications to date [2].

Abbreviations: AI, Artificial Intelligence; ML, Machine Learning; CVD, Cardiovascular disease.

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Diagnostic and screening applications of ML are generally intended to aid clinicians by augmenting their skills, but future automation of clinical tasks is also possible.

Machine learning (ML) is a set of approaches to AI that are designed to solve specific tasks by learning patterns from data, rather than by following explicit rules [1]. Diagnostic and screening applications of ML are generally intended to aid clinicians by augmenting their skills. In addition, there are those who envision AI as a way to humanise medicine by freeing clinicians from time-consuming and rote tasks, enabling them to spend more time with patients [3]. Progress has been made in improving the accuracy of AI detection of diseases including breast cancer and cardiovascular disease [4,5], especially in areas involving visual detection of abnormalities and generating clinical reports [6]. Other areas that may be amenable to AI automation are clinical tasks considered to be repetitive and cumbersome, and those that do not require complicated clinical reasoning [7].

There is a fairly extensive literature on the role and impact of automation on skills in non-healthcare industries. In manufacturing, for example, the tasks considered most automatable are those that are predictable and require consistent or uniform performance [8]. Advances in AI—also referred to as "smart"—automation have led to systematic investigation of the likelihood of automation in different occupations, based on a view of occupations as "evolving combinations of detailed tasks, skills and/or environments" [9]. Researchers seek to map these components of occupations, and thus determine which components are most amenable to automation, generally assuming that tasks, rather than entire occupations, are most likely to be automated [9,10]. The likely effect of automation on any profession is currently contentious and a topic of ongoing research. Some scholars argue that activities common to the professions—those that require "flexibility, judgment and improvisation"—should continue to be done by humans [11], and that automating such activities risks undermining performance and outcomes. Such concerns are especially apparent in healthcare: it has been argued that features of healthcare work make automation impossible or undesirable [12,13]. Some experts argue, for example, that healthcare is "care" work, not only in delivering care but also via "caring for", "caring about", "being careful" and "being caring" [14].

The role of healthcare AI in augmenting skills and automating tasks raises concerns about its potential to deskill, and in certain cases even replace, healthcare workers. Deskilling refers to workers experiencing "reduced discretion, autonomy, decision-making quality and knowledge as they perform their jobs" [15]. In healthcare, deskilling may result in deterioration of clinical skills, compromising decision making across various stages of clinical management, and potentially undermining patient safety. In addition, AI-enabled automation raises fears about workforce replacement, especially in medical disciplines that rely on pattern recognition [16]. With the development of AI in imaging applications and interpretation reportedly approaching human capability [17], discussion of the impact of AI on workforce and professional skills has been particularly active in radiology [1819]. While some studies flag the risk of AI in deskilling clinicians [16,20,21], most studies claim that AI is unlikely to result in workforce replacement given the slow development and uptake of healthcare AI applications [22], and the combination of cognitive and emotional skills needed to perform healthcare work [7].

An important motivating question in the literature on the automation of work is: can this task be automated? Asking this question requires detailed observation and classification of the many hundreds of tasks that constitute the practice of an occupation, and then the analysis of their suitability for automation [9]. Current literature on task automation [23,24], including in healthcare [9,25], suggests that approaches to the evaluation of the potential to automate tasks could be done from an authoritative or objective position. Willis and colleagues, for example, proposed a mixed-method modelling that rated automatability of tasks in general clinical practice, with a focus on administrative tasks rather than direct clinical care [9]. This study aims to complement that important body of research, asking more interpretive and normatively inflected questions from the point of view of the professionals involved in or affected by automation. Consistent with this aim, we examined the views of diverse professional stakeholders, addressing three questions from their perspectives:

1. Should clinical tasks be automated?
2. Will the implementation of healthcare AI lead to clinical deskilling?
3. What values are most important in making judgements about healthcare automation?

In asking these questions, we aimed to help explain the diversity of normative views and judgements of professionals about the automation of clinical tasks, complementing existing work on the feasibility of automation of different clinical tasks.

2. Methodology

This study was approved by the University of Wollongong and Illawarra and Shoalhaven Health District Social Science Human Research Ethics Committee (ethics number 2020/264). [26]For purposes of recruitment, interview discussion and analysis, we used the CONSORT-AI (Consolidated Standards of Reporting Trials–Artificial Intelligence) definitions of AI and ML: AI broadly as interrelated technologies that can perform tasks normally requiring human intelligence; and ML as a set of approaches to AI that are designed to solve specific tasks by learning patterns from data, rather than by following explicit rules.[1] We conducted qualitative, semi-structured interviews with a diverse group of professionals involved in developing, selling, regulating, or implementing healthcare AI, as further outlined below. Interviews were broad ranging, focusing on the ethical, legal and social implications (ELSI) of implementing AI in healthcare. One key issue discussed extensively by informants was the potential relationship between automation and clinical skills, with the data from these discussions as the focus of this paper.

2.1. Recruitment and sampling

We sought to recruit local and international participants. We aimed to access participants with specialist AI expertise and/or professional or clinical expertise; our inclusion criteria required that informants be involved in some way in the development, deployment and/or regulation of healthcare AI, and were at least knowledgeable enough to be informative about the potential implications of AI in their field. The sampling strategy was designed both to elicit diversity of views, and to allow comparisons between stakeholder groups. Initially we recruited via an expression of interest to participate on Twitter and in newsletters and mailing lists of AI, breast screening and CVD organisations in Australia (the latter being areas where discussion of impending AI deployment is common). We also directly approached experts with relevant public profiles and invited them to participate. Over time, our sampling became more theoretically informed [27], and we invited experts who might help us address gaps in our analysis.

2.2. Data collection

YSJA performed semi-structured interviews via Zoom or telephone, taking between 20 and 90 min. The question guide covered views about healthcare AI development in Australia and internationally, imagined futures for healthcare AI, how AI might or might not change things for clinicians and service users, key ethical issues and how they should be addressed in practice, and AI regulation.[26,28,29] Not all participants were asked all questions, either because they had limited time and we had recruited them to answer particular questions, or because they were recruited later in the study and we had already reached theoretical saturation for some categories.

2.3. Data analysis

With participants' consent, interviews were audio-recorded and transcribed. All participants were assigned a code that included their participant number and a summary of their roles; all transcripts were de-identified using these codes before analysis. Analysis combined approaches from constructivist grounded theory [27] and the framework approach [30,31]. The analysis steps were: 1) coding interview transcripts; 2) memo-writing on each interview to develop an analytic understanding of how that informant strengthened the data on existing categories or added new categories to the analysis; 3) organising findings into a framework, including both analytic summaries and data excerpts; 4) memo-writing on each of the core concepts in the analysis. Codes and key themes were generated both deductively—that is, based on concepts from the bioethics and AI ethics literature [26,29,32]—and inductively [28]. Data analysis was performed concurrently with data collection and data collection was modified to reflect insights from the developing analysis. Analysis was led by YSJA in collaboration with SC, with feedback from the research team.

3. Results: Contestations and interpretations

Theoretical saturation of core concepts was reached after interviews with 72 participants. The majority of participants (n = 54) worked in general diagnosis and screening, the rest were involved in breast cancer (n = 10) and CVD (n = 8) diagnosis and screening, respectively (Table 1). While most participants tended to have multiple forms of expertise, they could be classified based on self-identified primary roles, namely clinicians (n = 22), regulators (n = 17), developers/data scientists (n = 10), researchers (n = 8), healthcare administrators (n = 5) and consumer representatives (n = 3).

Core themes under AI's impact on clinical skills included conceptions of clinical skills and tasks, deskilling, and healthcare work, as well as views on the impact of AI automation on the human-technology division of labour. Informants' views on the likely impact of AI on clinical skills were informed by a broad set of background expectations about the future trajectory of healthcare AI. This included assumptions about whether AI would revolutionise healthcare or be just another incremental shift, analogous to the introduction of any new medical technology. Relatedly, participants had different views regarding whether AI should be treated in exceptional ways, or should be managed in much the same way as any other new technology (for example in terms of regulation, quality assurance or implementation).

In our detailed analysis below, we focused on three contested areas in participants' views about the impact of AI on clinical skills. The first concerned whether automation should occur in healthcare, and more particularly, which clinical tasks should or should not be automated. The second revealed opposing expectations regarding the impact of AI on clinical skills (deskilling versus upskilling), and on the relationship between skill acquisition and loss. The third area of contest implied a set of underlying values about what is most important in healthcare work, relating these values to judgements about AI roles, clinical skills and the acceptability of automation.

3.1. First area of contestation: Should clinical tasks be automated?

Participants' views on whether clinical tasks should be automated often drew on background assumptions about which skills and tasks were more, and less, amenable to automation. Whether a task could be automated was generally taken to rely on a cluster of characteristics of that task. These characteristics included the complexity and variability of the task, the degree to which the task required holistic interpretation, how intellectually challenging it was, how fulfilling the task was, and how prestigious it was, as outlined in Table 2. There were no notable patterns of views based on expertise: the distinctions in Table 2 were common across interviews.

There was no clear delineation between tasks deemed automatable or non-automatable; rather, the patterns in Table 2 are clusters of characteristics which were emphasised differently by different informants. As shown, this clustering was not simply about the nature of the task itself (e.g. whether it was simple or complex), it also reflected sociotechnical contexts and sociocultural judgements (e.g. low-prestige versus high-prestige tasks). The participants often assumed that the implementation of AI would inspire new types of skills or new levels of specialisation for humans, benefiting every-one.

So radiologists, their role will have to change. Rather than learning how to recognise patterns and match patterns, a computer can do it for them, so they'll have a different role. Just like pathologists now have a different role. In the past they had to mix reagents and things, now the machine does it for them and tells them the result. But the confidence intervals are given, so they have a different role, a more advisory role probably. Informant 48, clinician.

It seems to me that if AI does, in fact, live up to at least some of its promise and hope, that there will be a need for [healthcare AI] to become like, its own maybe sub discipline or specialty, I think. We're living in a moment, which in my mind I imagine as being analogous to sort of the invention of the X-ray, right, as the X-ray is the – an X-ray machine is the technology. And then it's sort of like, well, we can do all sorts of things with X-rays. And it's actually quite complex and involved and then there is sort of a needing to formalise the radiology discipline. Informant 58, developer.

Views about which tasks were suited to automation often appeared in informants' normative judgements about which clinical skills or tasks *should* be automated, summarised in Fig. 1.

There were three broad positions represented in the data. A small

Table 2
Clusters of characteristics associated with clinical tasks considered more, and less, suited to automation.

Better suited to automation	Less suited to automation
Simple	Complex
Repetitive	Variable
Literal	Holistically interpretive
Less intellectually rigorous	More intellectually rigorous
Tedious or mundane	Fulfilling
Unrewarding for the clinician	Rewarding for the clinician
Low prestige	Prestigious

Table 1
Summary of participants' expertise.

Primary role	Examples	General	Breast	CVD	Total
Clinicians	Radiologists, GPs, emergency physicians, cardiologists, oncologists, imaging specialists	14	4	4	**22**
Consumer representatives	General healthcare consumers, members of health consumer organisations	3	0	0	**3**
Developers	Computer scientists, health informaticians, software engineers	8	0	2	**10**
Entrepreneurs	medical officers in medical technology companies, start-up CEOs	7	0	0	**7**
Regulatory experts	Policy makers, policy officers, lawyers	16	1	0	**17**
Researcher	Academics or professional researchers outside the university sector	6	0	2	**8**
Healthcare administrators	Screening program managers	0	5	0	**5**
		54	10	8	**72**

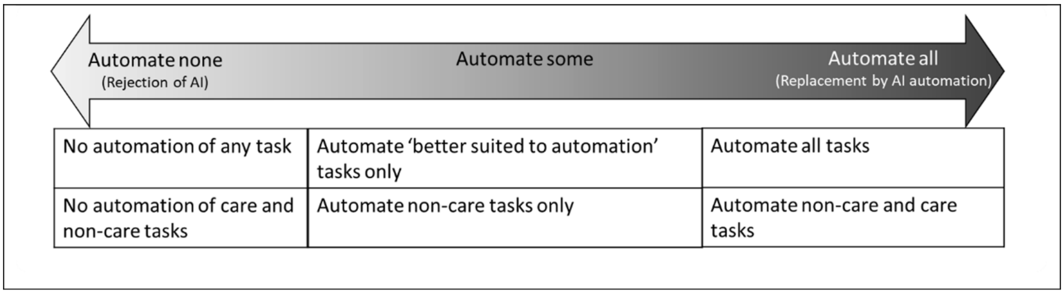

Fig. 1. Normative judgements about whether clinical tasks should be automated.

number of informants fell into two extremes: on the one hand, that there should be no automation, on the other, that as much as possible should be automated. The majority of the informants fell between these two positions, taking what we refer to as the 'automate some' position, which was of two kinds: one that emphasised automating only those tasks most amenable to automation, and another emphasising a moral difference between care and non-care tasks.

3.1.1. 'No automation' view

Those who held the 'no automation' view tended to equate clinical practice to the exercise of unique human skills that cannot and should not be automated: that is, they held that automating any aspect of clinical work would degrade clinical services. This was an implicit rejection of the distinction between tasks more and less suited to automation, via an implied slippery slope: AI automation—even of tasks better suited to automation—would lead to automation of roles and/or deskilling.

[Deskilling in AI] is really just an extension of a problem that's already well manifested. Clinicians who are being honest will admit … they have lost a lot of their hands-on skills and their human skills and their ability to read results for themselves instead of just seeing what is bold on the text – on the test results and going, "Oh, the computer tells me that's wrong." Their physical examination skills, their physical observation skills, they say, are less used and less in tune than they were 30 years ago. Informant 45, consumer representative.

These informants highlighted the subjective, creative and holistic aspects of clinical work that could not be replicated by an AI. Automation, on this view, would inevitably remove clinicians from healthcare systems and dehumanise healthcare.

But the advantage of the radiologist is … they are able to put all the other information together and synthesise it into a diagnosis, but not just what the imaging shows, it's which imaging people should have, the pre-test probability of an investigation. Informant 12, screening program manager.

And other thing too is that machine doesn't have intuition, whereas humans have. So when you see, I guess, you go to a good clinician that he or she may be able to pick up certain things that machine doesn't pick up, especially after talking and looking at your facial aspect of things, or look at body language. They can then lead on to something else, which machine can't do that. Informant 18, consumer representative.

3.1.2. 'Automate all' view

On the other extreme was the 'automate all' view, which held that there were no unique or special clinical skills that needed to be preserved, or clinical tasks that should only be performed by human healthcare workers: anything that could be automated should be automated. In a way similar to the 'no automation' view, this view implicitly rejected the distinction between tasks that were more and less suited for automation (summarised in Table 2). Some informants across different types of expertise added a caveat that AI automation should only happen if it leads to better outcomes (such as greater accuracy and efficiency).

Well, I think in the end if there is a tool that does a job better than a person who does it, then it's hard to argue the person should be doing it, and that is applicable across the board everywhere, but I think that the things that artificial intelligence certainly is being used for at the moment are still fairly narrow applications and questions. Informant 34, clinician and developer.

If a skill or task is increasingly being replaced by software, it means it's not worthwhile for physicians to do those tasks (paraphrased). Informant 43, regulatory expert.

Moreover, some of those who held the 'automate all' view made no distinction between care and non-care tasks if automation could improve or ensure access to healthcare services. In this specific context, participants conflated "access to health services" and "access to care work", implying that the "care" aspect in healthcare is no more or less than receiving a healthcare service regardless of who or what provides that service.

[AI automation] could help with equity between developing countries and rich countries. So for example, the breast example I was talking about before, it's expensive to have radiologists to check breast scans or mammograms. So if we could automate some of that and make that really cheap, then computers could help with that. And then they can give a similar care that we have in developed countries to developing countries. Informant 29, developer.

[I]n rural and developing countries, remote locations where there is no access to healthcare, now we have an application which provides the same level of care that you would have to travel if not thousands of kilometres, hundreds of kilometres and stay overnight in a new place to access that care and then come back. Informant 7, entrepreneur.

3.1.3. 'Automate some' view

Between these two more extreme positions was a set of 'middle ground' positions reflecting the views of many informants that some but not all clinical tasks should be automated. There were two types of logic underpinning the normative distinction between tasks that were, and were not, amenable to automation. The first tracked the clusters of characteristics in Table 1: the implication here was that only tasks well suited to automation should be automated. This first type of logic implies that clinical decision making requires contextualised reasoning, which currently appears to be a human advantage over AI.

So [AI] models are good in very specific little areas, but they don't have the understanding. They don't identify patterns, and even the image stuff, they don't understand and identify patterns with meaning in the same way that we do—humans do. So I think for some very narrowly constrained problems, they're going to be good at that. Informant 29, computer scientist.

I mean, AI and ML, still they're confined to reasonably narrowly defined tasks. So I think in terms of replacing the gestalt and the – and the ability to integrate and conceptualise and be able to conduct abstract reasoning, well no computer, no ML is going to be able to do that. Informant 41, clinician.

The second underpinning logic to the 'automate some' middle ground view relied on a different distinction: between those tasks that did and did not require care. Unlike the conception of care in the automate all view, care in this sense referred to what is understood in literature as the humane and culturally appropriate treatment of patients [33]. On this view, tasks that require direct engagement with patients or healthcare consumers should be preserved for humans, while other tasks should be delegated to machines where possible. This meant that decisions about automation in healthcare should be bounded by consideration of the relational or care aspects of the clinical task in question. If tasks require or are improved by the presence of clinical skills related to communication and care (e.g., a human touch, empathy and/or physical intimacy), they should not be automated.

But the other thing that probably can never be replaced is the communication of those findings back to the person and to their GP and to the other members of the multidisciplinary team. That communication at the moment anyway could not be replaced. Informant 49, clinician.

I still think in times of, you know, pain and fear and whatever, people are going to want to talk to humans. I don't think anybody is going to, you know, not in the next 100 years, is going to have surgery, have their cancer treatment and yada-yada, without having a long chat with a human first. Informant 55, entrepreneur and clinician.

Thus, the middle ground position showed two types of logic that relied on assumptions about what was particular or valuable about humans: contextualised reasoning and relational or care work.

3.2. Second area of contestation: Will AI lead to deskilling?

Informants' views were divided between two contrasting positions about the potential impact of healthcare AI on clinical skills, such as clinical reasoning skills involved in diagnostic and screening procedures. The utopian view was that AI could enhance existing clinical skills and systems, while the dystopian view was that AI would lead to replacement of tasks or roles by automation. As with the first area of contestation, there were no clear patterns based on area of expertise.

3.2.1. The dystopian view of AI's impact on human clinical skills

On the *dystopian view,* healthcare AI would lead to deskilling, or deterioration in clinical skills. This was often explained with reference to the history of automation in general. On this view deskilling was a negative consequence. It was assumed that the deterioration in human clinical skills would have a negative impact both on clinical practice and on patient experience and outcomes. As such, the dystopian view was congruent with the 'no automation' view discussed above, which equated clinical practice to the exercise of unique human skills that cannot and should not be automated. There were at least three key aspects to deskilling according to the dystopian view. First, deskilling could lead to loss of control over the clinical process.

I do see it as a problem when we start losing the skills to interpret the data ourselves and then, if you can't interpret this data yourself, and you don't know what's going on in the black box, then yes, that's a huge challenge. Informant 26, clinician.

The second aspect of the dystopian view was the loss of expert skills by clinicians developed in part by 'doing their time' on basic tasks. If basic tasks were delegated to AI (e.g., patient interview skills and observational skills for physical examination) humans would lose opportunities for learning associated with those tasks. Consequently, humans might not develop high-level skills (e.g., expert clinical reasoning skills) to the same extent:

Every-one is different and there is a subjective element to breast screen radiology and to interpreting results and the more you do it the more you hope that you improve and that's why we have such an accreditation system with all the thousands and thousands of reads…. [A]nd can an AI system actually improve on that, I don't know? Informant 10, regulatory expert.

My research has shown that the higher the case load, the better you get at this. It's not years of experience, right? So if you kept [mammography readers] at a lower threshold of reading cases, but they read a large number of cases, you know, they read sort of a baseline or threshold cases over the next 20 years, it won't actually improve them being able to find the cancer. What they actually need is high case numbers. So if you're taking away high case numbers from them to reduce the workload, you actually have the potential to deskill in that visual perception task. Informant 33, clinician.

The third aspect of the dystopian view was the risk for both *automation bias* and *confirmation bias.* This was seen as a human tendency potentially exacerbated by widespread AI use, but also as arising from the greater processing speed and data volume associated with AI applications, making it impossible for humans to 'keep up with' AI. Here informants were concerned that automation bias would contribute to the loss of a particular kind of clinical skill: critical thinking skills. The poorer the performance of the AI, and the less mature the systems, the more harmful this could be to patients. However even for high-performing AI it remained a problem:

We tend to believe machines more than we would humans and we tend to follow their advice even if it is wrong, so that's a tendency that humans have, and so even if a model is 99 % accurate, how are you going to deal with the 1 % of cases where it's not going to perform? Informant 6, developer.

Clinicians [will] overly trust [machines] on the expected result. So if you suspect it's a cold, and the app tells you it's a cold, you're going to believe it, even if it's a positive [COVID] result, you're going to believe it much more than if the app says, no, no, it's actually COVID, and [you] should have a look at this. Informant 21, entrepreneur.

Yeah, I think [automation bias] will happen, for sure, because… if the AI is like 100 to 1000 times faster than a human … a human is not capable of seeing that many images … Humans get fatigued, computers don't. So there will come a point where I think if the results are good from the computer that humans would just default to it… Informant 28, clinician.

One outlier informant proposed that automation bias was simply the machine version of an existing problem: that 'irresponsible' clinicians might rely on the reports of others to make recommendations rather than make their own decisions. However, most informants saw automation bias as a particular problem that could be worsened by AI.

3.2.2. The utopian view of AI's impact on human clinical skills

In contrast to the dystopian view, with its emphasis on what might be lost, the *utopian* view emphasised the potential for gain. On this view, the implementation of AI would lead to upskilling of clinicians, either *directly* through enhancement of skills or *indirectly* through the delegation of tasks/roles. One way that AI could directly upskill clinicians was by personalising their education and training. Here the AI improved the clinician's own skill and remained extrinsic to the human decision-maker:

So we're using AI to, if you like, understand your reaction with specific image types, then rapidly to try and say, "Okay, well, [this person] is not good at looking at cancers in the upper left lung, and [they're] pretty hopeless down near the diaphragm on the right-hand side." Informant 9, Radiographer and researcher.

And so, part of my role is in education to look and train radiologists and radiographers to understand … how AI can improve image quality… such as optimisation of algorithms, exposure indices, filters, co-registration for hybrid imaging and the use of AI for radiomic data. Informant 33, clinician.

The other form of direct upskilling was via decision support systems, where the addition of an AI increased the accuracy of human decision making. Unlike the enhancement in education and training route, where the AI was extrinsic to the human, the enhanced decision support route created a human-AI cyborg that was a better decision-maker than the human or the machine alone:

The [clinician] that uses the computer to support [their] decision making is now benefiting from the experience of every-one and going to a computer alone doesn't build that confidence that I think people need. Using AI to look at X-rays to alert radiologists to the pathology because this doesn't match the pattern, is far better than radiologists looking at all the films by themselves. Informant 31, regulatory expert.

…in terms of reassuring people, I think it's always important to go back to this being a "hey, wait a minute" kind of thing. I think that's so valuable. That somebody's reading an X-ray or an echo, and they hit the normal button and the machine says, "hey, wait a minute". And they might ignore that, but if they've come off a whole day of reading a hundred echo cardiograms, they might be just a bit tired and they might have missed something, and the machine could identify it for them. So that's a good thing. Informant 27, clinician.

The utopian view also suggested that if AI did those tasks that were better suited to automation (see Table 2), clinicians could focus on more fulfilling or complex tasks and/or seek further specialist training. Here the AI was extrinsic to the clinician, and allowed the clinician to undertake more difficult, desirable and rewarding tasks. This could enhance clinicians' experience of their own work, provide them with new opportunities, and prevent burnout:

So whenever there is a mundane activity, I think there is a real benefit for that. So for example, image recognition of melanoma … is [a] no brainer… if you can have your machine learning identifying 90 % of cases then you leave that mechanical and mundane work to the machines. Informant 3, entrepreneur.

I'm hoping that a really successful solution frees up some time for the clinicians to, you know, that cliché of putting the care back into healthcare, to actually go back to that and not spend all our time on computers or data entry or looking at normal studies. I mean, I think that causes burnout … if we could have a really great solution that … captures some time for the clinicians [to spend] with the patient or really concentrating on those more complex things that require human creativity to solve, that would be a really positive thing. Informant 5, clinician.

Indirect upskilling could also occur if AI would take over clinical roles (not just clinical tasks), enabling clinicians to transition into roles some participants believed to be far more fulfilling and complex, and financially rewarding.

…for radiologists… what they call the high-volume, low-yield tasks could be replaced by an AI and that in turn there may be greater scope for radiology to grow into areas such as interventional radiology, which actually pays a lot of money. Informant 33, clinician.

… I think the message to me is that, don't be frightened that you're going to lose a job, your job will just change and you may even be able to do things which are more interesting at a higher level, than you are doing now. Because let's face it, there are jobs now that are pretty boring. So if you can automate them and then allow people to apply their brains and their thinking skills to then higher order functions, well I think most people would be happy about that, even if they then get an increase in wage to go with it, it's a win/win for everybody. Informant 41, clinician.

Unlike direct upskilling, indirect upskilling appeared to require at least some deskilling. Some informants argued that the process of losing skills and jobs to give way to new ones has historically been part of healthcare work as an evolving practice. There were at least two assumptions in this position. First, the introduction of new technology that could take over some clinical tasks would mean clinicians would no longer perform those tasks, and over time, they would lose the skills needed to do those tasks. The second assumption was that those skills lost over time were not important to the performance of clinical work.

When we were looking for protein or sugar in the urine, we had these paper sticks that you had to dip in and then you had to compare the colour to a scale. All of that now seems almost medieval, because all of that has become quantified and automated, and so in a biochemistry lab or a clinical biology lab, the doctors there are still working. It seems that their professional focus has shifted a little bit from doing manual things, to supervising the production process, and I think also in a lot of medicine, that is going to happen. Informant 59, clinician.

Thus, some informants welcomed deskilling, arguing that it was necessary to advance the field of medicine and healthcare work.

3.2.3. Assumed mechanisms for clinical skill development

These different views of AI's impact on clinical skills were based on a range of assumptions about how skills develop in the clinical professions (Fig. 2). This is important because it provides one avenue by which the claims of the dystopians and the utopians might be tested.

On the dystopian view, clinicians gain their expertise through experience. They begin by performing basic tasks requiring basic skills; over time, the task and skills become more complicated until the clinician becomes expert. Basic skills thus provide the essential foundation of expertise. The path to expertise is not straightforward, involving learning by doing, making mistakes, and receiving feedback from colleagues and senior staff. Automation through AI potentially removes the foundational stage of clinical learning, resulting in dehumanised clinicians who might be worse learners and decision makers.

[I] acknowledge the expertise that the humans have, and really underline there that we're actually getting rid of the rats and mice in your work … you've trained for a squillion years to do this, and so now we want to be able to focus your expertise on it. [But] some might argue that it's all that kind of rats and mice that helps them learn to be good at the more complex stuff. Informant 11, screening program manager.

These aspects of the dystopian view were at odds with the utopian view of *indirect* upskilling – where automation could free a highly specialised clinician to focus on only the most rewarding elements of their practice. If either of these views is correct it will have significant implications for clinical services. If the utopian conception of *direct* upskilling via AI personalising and speeding up human training is correct, dystopian concerns may be unfounded. If the utopian vision of a cyborg decision-maker is correct, any loss of human skill will be unproblematic

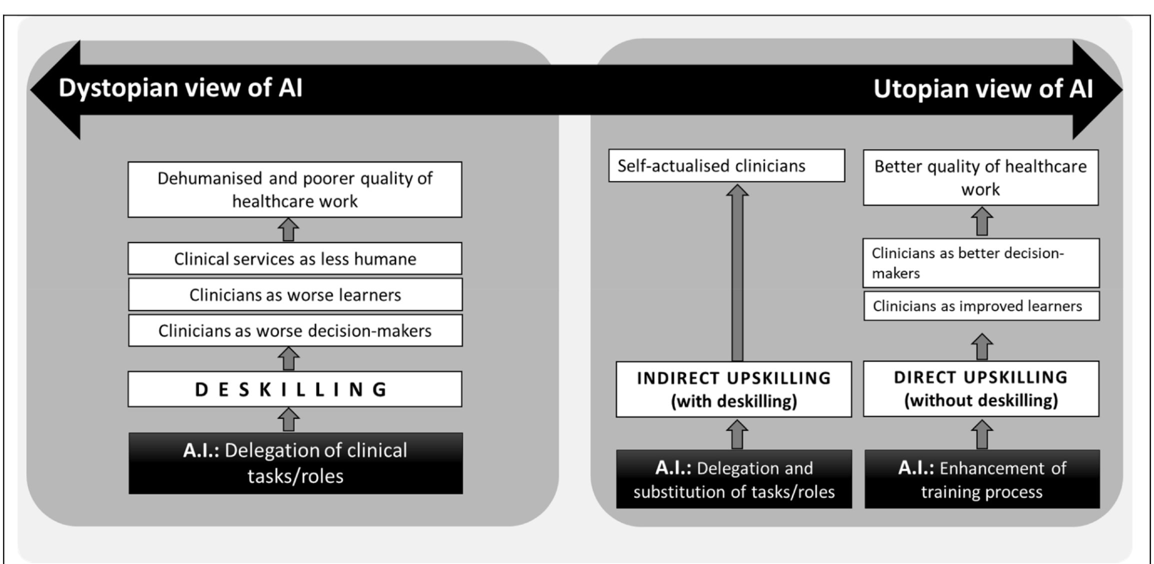

Fig. 2. Dystopian versus utopian views – implications regarding skills acquisition.

– as long as the cyborg continues to function.

3.3. Third area of contestation: Values in healthcare and healthcare work

To bring these analyses together, we consider how views about the nature of clinical tasks—and skills required to perform those tasks—appeared to map over normative positions about the implied values in healthcare work (see Fig. 3).

Implicit in the "automate all" view, held by a small heterogenous group of informants, was a consequentialist position that upheld the value of clinical outcome and clinical performance.

We've got to weigh the benefits coming out of use of technology. It's always there is going to be some to an option of anything, any new intervention or technology. So, if the benefits outweigh the downsides, I wouldn't be so much worried about [the problem of deskilling]. Informant 7, entrepreneur.

Stethoscopes are going to be redundant, because you've got handheld devices that can tell you what's going on much better. … It's just the way it is. Informant 48, clinician.

On this view, healthcare changes, knowledge changes, practice changes, everything changes. The skills needed for healthcare delivery are constantly changing, implying that deskilling was a non-issue, and to a great extent, an inevitable aspect of reskilling and change in focus of skill. The future of healthcare might include humans and might include AI; it was irrelevant what kinds of actors are implicated in healthcare in the future. What mattered was that those actors achieve desirable outcomes. This view offered a picture of medicine that valued outcome and performance of the clinical process (particularly valuing accuracy and speed)—even at the expense of human involvement.

In the other extreme, the small number of heterogenous informants who held the "no automation" view appeared to be more concerned with deskilling, as in their view it could compromise how clinicians perform their roles (including with respect to traits seen as unique to humans and necessary in clinical work, e.g. human intuition and empathy).

It's like, "Oh, how great would it be to take the humanity out of medicine? Oh, wait how terrible would it be to take the humanity out of the system?" Like, that's literally – they get caught with a different sort of attachment. It's because it depends what you mean by "humanity", because you can mean "humanity" to mean care and compassion and kindness or you can take "humanity" to mean human fallibility. And we'd be great without one, but not great without the other. Informant 45, consumer representative.

This view offered a picture of medicine that valued contextualised reasoning, as well as the care and relational aspects of healthcare work—further implying that the best possible clinical outcomes cannot or should not be achieved at the expense of a human touch. A slippery slope argument appeared to underpin the concern about AI automation: AI automation could lead to deskilling and more automation (to the point of automating roles not just tasks), all of which could risk removing the human and relational aspects of healthcare work.

if we make everything electronic, make everything automatic, and if we don't have humans trained, then where are we heading? I mean it's a real concern, I think. … So much so that we don't train human beings anymore. I think it's a real problem. Informant 51, developer.

Those in the middle, the "automate some" view, generally supported automation of tasks more than automation of roles.

Radiologists are under pressure to get through this huge volume of normal mammograms to find the needle in the haystack. And if you make the haystack smaller, then radiologists will probably get better at finding cancers because they have less of the thousands and thousands of normal ones to get through and I think a similar thing is going to happen with most areas in medicine and so that will mean that we have more time to dedicate towards things like counselling the patient, doing procedures, like the biopsies that it's going to be a long time before a robot can do that. Informant 63, clinician.

This view implied an idealised vision of AI upskilling humans, claiming that time freed by AI would lead to pursuit of tasks that are more meaningful, require intellectual rigour and increase the professional fulfilment of humans. In addition, this view did not seem to rely on or commit to a consistent notion of healthcare work, and instead took a problem-solving or practical position by focussing on specific solutions that AI can offer and the problems in healthcare work that AI can solve.

4. Discussion

Our analysis revealed three key contentious issues that participants cared about: 1) which tasks should be automated, 2) whether AI will lead to deskilling, and 3) which values should underpin healthcare.

The first contentious issue arose from competing normative views about the proper extent of AI-enabled automation in healthcare work, and which clinical tasks should or should not be automated. We identified two distinctions made by participants. In one view, participants referenced a set of characteristics that may distinguish those healthcare tasks that are amenable to automation from those less amenable to automation (see Table 2 for a summary). In another view, participants distinguished between patient care and non-care tasks, with the distinction depending on whether a task required relational skills and human-to-human contact. Across the spectrum of these views, participants appealed to the moral value of care and the need to preserve it when arguing for or against AI-enabled automation. However, there were varying conceptions of care. 'Care' could refer to relational, affective and interpersonal aspects of health service provision; 'care' could also refer simply to health service provision. Some participants were

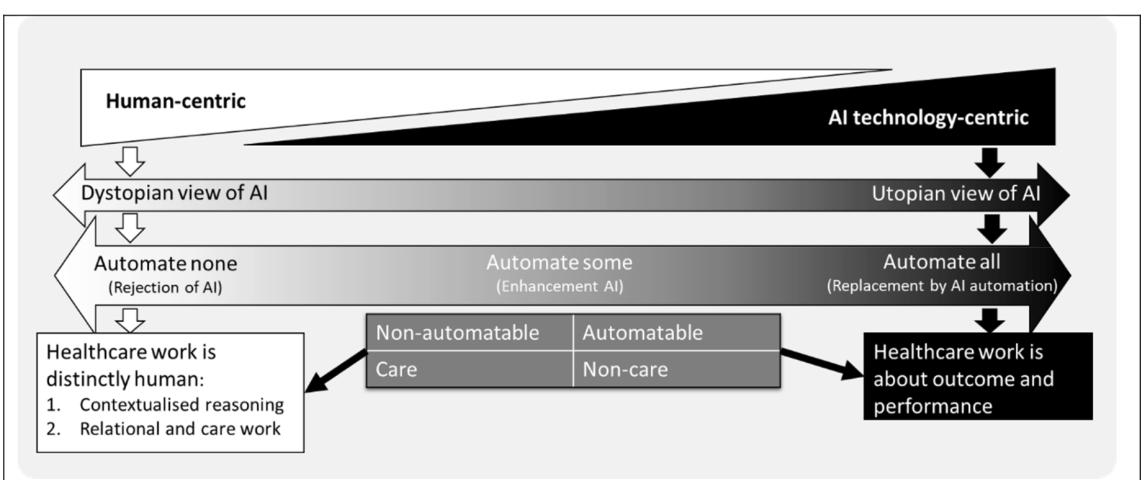

Fig. 3. Relationship between views on clinical skills and views about the role of AI.

uneasy about AI automation as it might undermine the care aspects of clinical work (in the relational sense), while others supported AI automation as it would increase care by ensuring access to services in underserved areas (the second sense of 'care'). This distinction is morally significant in establishing the ethics of AI applications in healthcare, particularly if AI-enabled automation has the potential to reduce our understanding of care to service provision alone—a view potentially consistent with economically rationalist market logics. Moreover, care in the first sense is a strong feature of healthcare work that is not present in most industries that have embraced AI automation (e.g., banking and finance, manufacturing, and information technology).

The second contentious issue entailed expectations about the impact of AI on clinical skills, and whether AI-enabled automation could lead to worse or better quality of healthcare, which we characterise as the dystopian and utopian views, respectively. While establishing the actual trajectory of clinicians' roles in the context of AI automation is beyond the scope of this paper, current threads in the literature may shed light on the range of views presented by the participants. One potentially relevant area of study is on theories and practices in the development, acquisition and maintenance of clinical skills. For example, one model of understanding clinical reasoning characterises the plurality of conditions for developing skills, including intuition, emotions and contextual factors, among others [34]. Another area of study is the impact of healthcare innovations, including automated decision aids, on clinical skills. The phenomenon of deskilling is not exclusive to AI, and has been demonstrated in previous healthcare innovations, including electronic medical records and clinical practice guidelines [35], as well as early warning scores [36].

The third contentious issue relied on assumptions about the underlying values and priorities in healthcare and healthcare work that AI-enabled automation may or may not uphold. One view endorsed a human-centric model of healthcare that framed clinical skills and tasks as distinctly human and required contextual reasoning and relational work. The other view upheld a technology-centric model of healthcare, which mainly focused on clinical outcome and performance. This point of divergence implied stakeholders conceptualised concern for patient welfare in different ways depending on what values they wished to uphold in healthcare. Participants who supported AI-automation appealed to patient welfare by ensuring more efficient clinical processes and positive clinical outcomes. Those who were critical of AI automation argued that AI could undermine patient welfare by removing the humane and relational aspects of healthcare work. We argue that these two views should not be considered a zero-sum game. It is reasonable that people expect both humane and effective health services, and that both sets of values should guide the adoption of healthcare AI. If this is accepted, it means that we should consider adopting AI applications only if they improve outcomes without undermining relational aspects of care work. In addition, our analysis highlights the need for interdisciplinary engagement early in the development process. Development of AI-enabled automation tools should be informed by conceptual and normative considerations of what type of clinical task the AI system is supposed to automate. As such, experts across different disciplines—data science, clinical medicine, ethicists, consumers—have a role to play in the development of healthcare AI.

A key contribution of our study is to make a preliminary call to distinguish two concerns in the evaluation of AI automatability of tasks in healthcare: feasibility and justifiability. Proposed classification systems of automatability in healthcare tend to focus on the criterion of feasibility, that is to determine whether tasks *can or cannot* be automated [9,25]. Our study focuses on the criterion of justifiability, that is, based on the perspectives of different types of professional stakeholders, how do we distinguish tasks that *should and should not* be automated. The concern about justifiability of automation echoes views regarding healthcare work and how it differs from other occupations, such as the nature of clinical reasoning or the relational component of patient care [14]. To address concerns about feasibility and justifiability, AI research and development requires an interdisciplinary approach to evaluate automatability of tasks in healthcare work. Experts from different disciplines tend to have divergent notions of tasks and ways of classifying tasks. AI developers from fields such as data science and software engineering may not be familiar with the intricacies of healthcare work, requiring engagement with healthcare workers and health consumers who are more knowledgeable of or have experience with tasks in healthcare.

In addition, our findings highlight the role of interdisciplinary work since task classification in healthcare, such as the distinction between "administrative" and "clinical" tasks, is not straightforward. In literature, administrative tasks are those associated with clerical, financial or documentary management within the healthcare system or clinic, while clinical tasks are those that involve preparation, provision and/or maintenance of different types of medical interventions from screening to diagnosis and treatment [37]. In reality, however, this distinction is blurred since activities and skills for either type of task bleed into the other. For example, the clerical task of medical history taking is administrative, but requires some level of clinical skills and reasoning to identify essential health information to probe further [38,39]. Th complexity of the distinction between feasibility (what can be automated) and justifiability (what should be automated) is just one example of the kinds of problems that require nuanced conversations between AI developers, regulators, clinicians and patients or healthcare consumers about how to protect valued aspects of healthcare work.

Across the three areas of contestation, the diverse views did not necessarily track in a predictable way with participants' expertise or roles in the health system for several reasons. First, most participants had multiple roles and expertise (for example, one participant was both a clinician and a developer). Second, lack of consistent tracking between and within types of experts suggests that there may not be settled views on the topic of clinical deskilling. This diversity suggests there is currently little consensus about the application of AI to healthcare, and a need for an ongoing inclusive dialogue on these issues.

Our study has several strengths and limitations. To our knowledge, this is the first in-depth study to investigate multiple stakeholders' views about the impact of AI on clinical skills. Our findings showed that concern about clinical deskilling associated with AI healthcare applications was shared by professionals across different types of expertise and domains of the healthcare system. Our analysis offered insights into the conceptual assumptions that underpin clinical skills and tasks, including categorisations of tasks depending on whether they are or should be automated. However, our results should be interpreted in the context of some limitations. While we made all efforts to define and clarify AI during the interviews, the concept remained too broad partly due to the limited deployment or applications of AI in healthcare, particularly in Australia where AI development has been relatively slow. Some participants who are involved in the acquisition, deployment or regulation of healthcare AI systems were not all familiar with the technical details of AI, and may have expressed views that were speculative. In turn, some informants with technical AI expertise were not experts in clinical skill development or automation of tasks, so this reflects common understandings in relevant professionals engaged in practice rather than the views of content experts on clinical skills. Finally, our analysis could be strengthened by situating concerns about deskilling in specific areas of the healthcare system. Different clinical specialties have varying norms of clinical education, skills acquisition and maintenance, and interaction with medical technology. Different areas of the healthcare system (private clinics versus hospital institutions; government versus private healthcare providers) vary in the deployment and administrative oversight of novel technologies, which may entail varying impact of technologies on clinical skills.

5. Conclusion

Our study showed a diverse group of professional stakeholders involved in healthcare AI development, acquisition, regulation and deployment cared about the impact of healthcare AI on clinical skills. Stakeholders, however, were divided on how to approach the risk of clinical deskilling associated with AI-enabled automation. Our results showed three core concerns: the extent to which AI-enabled automation should occur in healthcare work; a spectrum ranging from utopian to dystopian views of the risk of deskilling due to AI automation; and contrasting views about the values that should underpin healthcare work.

Given rapid advances in healthcare AI, it is urgent to address the risk of deskilling. By conducting, to our knowledge, the largest and most in-depth study on this topic to date, we have grounds for suggesting specific considerations in the future development of healthcare AI systems. These include: 1) automating only those healthcare tasks best suited to automation (see Table 1); 2) developing tailored AI-based training systems to upskill human providers (see Fig. 2); 3) evaluating which healthcare tasks—even if mundane—may be necessary for humans to continue to undertake to develop or retain their higher-order skills, noting these may vary between clinical specialties (see Fig. 2); 4) considering automation of tasks where that would allow human clinicians to focus on more satisfying work, with the caveat that; 5) AI systems should be able to demonstrate both improved outcomes for patients *and* negligible impact on the relational and care aspects of healthcare (see Fig. 3). These recommendations reflect the concerns of the participants: whether they are justifiable and operationalisable will require further theoretical and practical research. Future research could also examine the actual impact of implemented AI systems on clinical skills, including whether the resulting practices are more closely aligned to the dystopian or the utopian view, as well as other impacts including on clinical outcomes and patient experience.

Summary Table.

What was already known about the topic:

Healthcare applications of Artificial Intelligence (AI) in healthcare are increasing.

Critics are concerned that implementing AI-enabled decision support systems and automation risks deskilling clinicians.

What this study added to our knowledge:

Large, in-depth study of the perspectives of different implicated professionals about the expected impact of healthcare AI on clinical skills.

New normative typology of clinical tasks that should and should not be automated, from the perspective of stakeholders.

Competing values that underpin judgements about which healthcare tasks should be automated.

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