"The Algorithm Will See You Now": Exploring the Implications of Algorithmic Decision-making in Connected Health

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Abstract: Despite abundant literature theorizing on Connected Health innovations to support decision-making, the extant literature provides sparse coverage on users' awareness of algorithmic decision-making. As a result, little is known regarding the role of algorithmically generated insights which directly influence clinical decisions nor the consequences of distancing clinicians and patients from decision-making capabilities. Indeed, recent studies highlight the growing emphasis on algorithmic decision-making but there is a need to raise questions as to how this is impacting on the risk and quality of delivering care. In this article, a summary of key concerns from the literature is provided, and a discussion on the implications of algorithmic decision-making in Connected Health is presented. In addition, a research roadmap is presented to draw more research focus on the role of algorithmically generated insights in Connected Health.

1 INTRODUCTION

Fuelled by ongoing discussions on advancements in technology and data science to facilitate algorithmic decision-making, there is a growing body of literature that expresses the need to explore its implications. Burrell (2016; p.1) argues that "opacity seems to be at the very heart of new concerns about 'algorithms' among legal scholars and social scientists" but we need to focus the discourse on getting inside the algorithms themselves.

An algorithm may be defined as a process or set of rules to calculate or solve a problem which is typically carried out by a computer. Therefore, algorithms can be viewed as a set of step-by-step instructions to achieve a desired result in a finite number of moves (Orlikowski and Scott 2015) which act on data. Using data as input, algorithms produce an output; for example, a risk classification for a loan, or whether an email should be considered as spam. Burrell (2016; p.1) explains that algorithms "are opaque in the sense that if one is a recipient of the output of the algorithm (the classification decision), rarely does one have any concrete sense of how or why a particular classification has been arrived at from inputs". Indeed, technological advances continues to mask our 'black box society' through powerful yet unnoticed algorithms that control how data is collected and processed to present information and ultimately influence decision-making.

While there has been much speculation around the role of technology giants in recent years in collecting all kinds of data about citizens and how the so-called surveillance capitalism is creating another layer of secrecy across society and trust in software solutions, awareness for similar implications in algorithmic decision-making goes undocumented. Yet, the implications of ubiquitous and pervasive digital technologies for healthcare and public health are profound (Lupton 2014).

In this article, we examine some of the assumptions around the role of algorithmically generated insights which influence healthcare decisions through Connected Health innovation.

2 CONNECTED HEALTH

Connected health is a socio-technical model for healthcare management and delivery by using technology to provide healthcare services. The Connected Health phenomena (Carroll, 2016; Carroll

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et al. 2016a) have continued to grow for several reasons including, the growth in mobile phone devices, increased availability of mobile applications ('app') technologies, improved Internet connectivity, growing availability of personal and health-related data, and growing pressures on healthcare providers to seek alternative means to deliver healthcare services. Thus, 'Connected Health' is a term that is used to encompass the wide range of technologies that are used for healthcare such as digital health (Lupton, 2014), eHealth (Oh, 2005), mHealth (Gagnon et al. 2015), health informatics (Coiera, 2015) and health education (Glanz, 2008).

Connected Health technologies are now explicitly designed for medical and health purposes (Carroll and Richardson, 2016a), contributing to the digital health phenomenon that has recently emerged and many of which are controlled by specific algorithmic decision-making techniques. Connected Health technologies may bring other benefits, such as standardized care, and greater control over the delivery of care. Algorithmic decision-making through Connected Health technologies give significant benefits, ranging from improved diagnosis, thereby delivering better patient care and improving the support of clinical decision-making. This enhances hospital productivity, lowers costs, and reduces medication errors (Aron et al., 2011). Algorithmic decision-making in healthcare ought to be viewed as critically important whereby decision-making can have significant consequences, including potentially fatal outcomes, on the quality and safety of care.

In essence, Connected Health is far reaching and focuses on the convergence of digital technologies with health, healthcare, living, and society to enhance the efficiency of healthcare delivery and make medicine more personalized and precise. To enhance the efficiency of healthcare delivery, this places more emphasis on the role of algorithms to gather data and encapsulate a process or set of rules to be followed in calculations or other problem-solving operations (Gruber, 2019), for example, through Connected Health technologies, yet little research has explored the implications of algorithmic decision-making in Connected Health and its impact on decision-making.

2.1 Decision Making in Healthcare

The crucial element of high-quality care in healthcare is the accuracy, efficacy, and expediency of clinical decision-making. It is important, therefore, that we understand both its importance and the range of strategies that are used to make decisions (Croskerry, 2002). Technological advances have encouraged the development of new technologies that drive connectivity across the healthcare sector such as software apps, gadgets and systems that personalise, track, and manage care using just-in-time information exchanged through various patient and community connections (Leroy et al., 2014; Carroll, 2016). This paradigm shift has contributed to advancing healthcare practice, highlighting our growing reliance and need for algorithmic decision-making to support healthcare decisions due to technological advancements such as with artificial intelligence (AI). For example, research explains how the performance of AI algorithms can be highly dependent on the population used in the training sets (for example, algorithm training and testing for cancer screening) to ensure that the results are broadly applicable (Topol, 2019).

The outcome of algorithmic decision has significant implications when individual find themselves at an intersection of medicinal possibilities, diverging pathways have extraordinary and significant results with lasting ramifications. These include, for instance, decision-making in major surgeries, prescriptions to be taken for the rest of a patient's life, and screening and symptomatic tests that can trigger upsetting interventions. But, while there have been benefits, there have been several high profiles and costly technology failures within healthcare in recent years, leading to the importance of having a published and defined algorithmic decision-making structure to decrease the risk of failures (Lepri et al. 2017).

3 'BLACK BOX SOCIETY': ALGORITHMIC DECISION-MAKING IN CONNECTED HEALTH

The last decade has witnessed the widespread diffusion of digitized devices that have the ability to monitor the minutiae of our everyday lives (Hedman et al., 2013) enabling data to flow across devices guided by algorithms to shape information and make decisions and predictions about individuals by recognizing complex patterns in complex datasets.

3.1 Promoting the "Right to Explanation"

Governments have made increasing efforts to protect citizens' rights within the digital world. For example, the European Union's General Data Protection

Regulation (GDPR) provides data protection and privacy for all individual citizens of the European Union and the European Economic Area – which extends to the use of algorithms. Regardless, the use of algorithmic decisions in an increasingly wide range of applications has led some scepticism around technology companies and their growing dominance in our so-called 'black-box society' (Pasquale, 2015). As a result, there has been growing demands for increased transparency in algorithmic decision-making. However, the regulatory requirements around transparency are often unclear and are open to some interpretation; for example, in GDPR (Goodman and Flaxman, 2017). Goodman and Flaxman (2017) explain that regulation efforts such as GDPR place restrictions on automated individual decision-making (that is, algorithms that make decisions based on user-level predictors) that "significantly affect" users. GDPR also presents a requirement on the "right to explanation". As outlined in Articles 13 and 14, when profiling takes place, a data subject has the right to "meaningful information about the logic involved". Goodman and Flaxman (2017) explain that this requirement prompts the question: what does it mean, and what is required, to explain an algorithm's decision?

There have been efforts to categorise barriers to transparency. For example, Burrell (2016) distinguishes between three broad barriers to transparency we can associate with algorithms: (1) opacity as intentional corporate or state secrecy, i.e. where decision-making procedures are kept from public scrutiny (2) opacity as technical illiteracy, i.e. simply having access to underlying code is insufficient, and (3) opacity that arises from the characteristics of machine learning algorithms and the scale required to apply them usefully, i.e. a mismatch between human reasoning and styles of interpretation and machine capabilities. Such barriers to transparency have far reaching consequences across many sectors, especially in healthcare, where one can view it as an evolving critical decision-making system whereby decision often leads to "life or death" outcomes.

3.2 Connected Health as a Safety Critical Decision-making System

Critical systems are systems where failure or malfunction will lead to significant negative consequences (Lyu, 1996). These systems may have strict requirements for security and safety to protect the user or others (Leveson, 1986). By safety critical, we refer to system failure may lead to loss of life or serious personal injury. This is particularly important within a healthcare context where we may view Connected Health as an extension of a safety critical decision-making system.

Within the healthcare sector, the complexity of delivering healthcare services is becoming less clear. This presents new implications for patients, clinicians, and the wider society, given that decisions are increasingly automated, and decision-making algorithms may not always be transparent. Within a healthcare system, many decisions are made by human beings as a result of interpreting medical data and images generated by computer algorithms. Healthcare innovations such as Connected Health promise to increase accuracy and reduce human bias in important decisions. Specifically, within a Connected Health context, algorithmic decision-making occurs when data are collected through digitized devices carried by individuals such as smartphones and technologies with inbuilt sensors built – and subsequently processed by algorithms, which are then used to make (data-driven) decisions. Decisions are typically based on relationships identified in patterns of data - yet decision-makers often ignore or are not fully aware of why such relationships may be present (Mayer-Schonberger and Cukier, 2013). In addition, non-clinical professionals, such as software engineers and data scientists are typically tasked with developing Connected Health solutions. Without clinical input, they may be misinformed on healthcare best practice, medicine management, or simply reinforce existing biases and disparities under the guise of algorithmic neutrality (Carroll and Richardson, 2016a).

3.3 Connected Health Data-driven Decisions

In Connected Health, the phrase "data-driven decision-making" is used, which often alludes to describe how healthcare organisations integrate objective information to inform and improve all sorts of decisions. Data-driven decisions made through digital devices are promoted and trusted on the basis of providing personalised insights on individual behaviour and health status. They also result in the narrowing of their choices while the diffusion of Connected Health devices become normalised across society. However, as clinical practice increasingly adopts Connected Health solutions, we continue to distance clinicians and patients form the mechanics of the decision-making process. Thus, there is a growing power of the algorithm to influence the provision of care, for example, whereby (often untrained) software developers and data scientists play a key and influential role in the provision of healthcare. This raises significant concerns and there is a need to re-examine assumptions around this. Furthermore, ethics and potential unwanted consequences must be considered.

3.4 Risks of Algorithmic Decision-making

Research indicates that users expect that algorithms will help human decision-makers to avoid their own prejudices by adding consistency to make decisions (Zerilli et al. 2018). However, algorithms introduce new risks which often go undocumented as more focus is placed on the Connected Health innovation and devices. Algorithms can replicate institutional and historical biases, amplifying disadvantages lurking in data points like such as health status ratings or scores (Coiera, 2019; Ransbotham et al., 2016). Even if algorithms remove some subjectivity from the care pathways, humans are still very much involved in final decisions. Arguments that cast "objective" algorithms as fairer and more accurate than fallible humans fail to fully recognise that in most cases, both play a role particularity in safety critical healthcare decisions.

On a wider societal level, and arguably a less critical impact, another element of Connected Health promotion that has been led by consumers is self-tracking and new innovations which support mobile devices and associated software that can monitor and measure many aspects of bodily functions and activities and geolocation details. Algorithmic decision-making across Connected Health devices reports on a myriad of body functions, sensations and indicators ranging from blood glucose, body weight body mass index and physical activity, which are monitored through wearable and internal sensors and collected to support decision-making processes. Yet, algorithmic decision-making means that discriminations are increasingly being made by an algorithm, with few individuals actually understanding what is included in the algorithm or even why. Criado Perez (2019) argues, for example, that many such algorithms are based on men-only data, although outputs are used by women. In other words, it is seen as being sufficient that an algorithm is successfully predictive, never mind if the reasons for the associations found in the data from different sources are unknown. We argue that this is likely to create problems when no one in a healthcare system, for example, a hospital context, really understands why some decisions are made nor how they were influenced based on Connected Health algorithms.

4 THE NEXT WAVE OF ALGORITHMIC DECISION-MAKING IN CONNECTED HEALTH

The importance of exploring the implications of algorithmic decision-making in Connected Health will be further realised by the growth of AI and machine learning. AI refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions such as learning and problem-solving. Machine learning is an application of AI that provides systems with the ability to automatically to learn from experience. Therefore, machine learning allows systems to adjust to new inputs and perform human-like tasks through algorithms and statistical models that perform a specific task without using explicit instructions and rely on patterns and inference instead.

Hollis et al. (2019) explains that with more health data availability, and the recent developments of efficient and improved machine learning algorithms, there is a renewed interest for AI in healthcare. In general, the objective of adopting AI in healthcare is to help health professionals improve patient care while also reduce costs. However, the other costs of AI, including ethical issues when processing personal health data by algorithms, should be considered (Hollis et al. 2019).

AI and machine learning are continuing to currently dominate research efforts in healthcare (Gruber, 2019), from planning to care pathway recommendations to predictive analytics. There are emerging research trends which demonstrate how healthcare providers can exploit the use of AI for getting routine results at a faster rate, health insurers can better understand risk assessments, and respond to patient contact call centres and automate drug dispensary in hospital pharmacy. However, algorithms are often trained on "data sets that are riddled with data gaps" (Criado Perez, 2019, p xii), and as they are often 'black-box' systems, users cannot identify nor take these into account when supporting our decisions. While technological advancements such as AI present a new transformative power in algorithmic decision-making, research calls for a regulatory framework related to Software-as-a-Medical-Device (Carroll and Richardson, 2016b). This is important to provide a new approach for Connected Health technologies to offer a more tailored fit to healthcare needs.

5 A RESEARCH ROADMAP

This section summarises some of the main research gaps on the implications of algorithmic decision-making in Connected Health and presents a research roadmap. Scholars are encouraged to consider the following seven key research themes, namely: (i) ethical implications; (ii) open science implications; (iii) accountability and responsibility implications; (iv) ageing implications; (v) data literacy implications; (vi) healthcare professional skills gap; and (vii) regulatory implications associated with algorithmic decision-making in Connected Health.

5.1 Ethical Implications

Technological advancements such as IoT, AI, machine learning and cloud technology, has been one of the most important trends over the past couple years. AI promises to transform society on the scale of the industrial, technical, and digital revolutions before it and will accelerate solutions to large-scale problems in myriad of fields, including healthcare. In addition, IoT technologies are increasingly infusing our lives as the interplay of people, computing, data, and things is continuously evolving. Thus, IT innovation has been developing at astonishing speeds since its inception, often rapidly changing healthcare in new and quite unexpected forms. This raises new concerns around ethical implications. For example, Coiera (2019) explains that while AI will be applied to classic pattern recognition tasks such as diagnosis or treatment recommendation, it is likely to be as disruptive to clinical work as it is to care delivery. In addition, digital scribe systems that use AI to automatically create electronic health records promise great efficiency for clinicians but may lead to potentially very different types of clinical records and workflows.

Other examples include radiology, whereby AI is likely to see image interpretation become an automated process with diminishing human engagement. Thus, there needs to more focus on machine ethics in Connected Health with a view to investigate the role of artificial moral agents, robots or artificially intelligent computers that behave morally or as though moral and indeed challenge the idea that AI can itself be held accountable. Thus, the research question arises: *What are the ethical considerations for algorithmic decision-making within a Connected Health context?*

5.2 Open Science Implications

Open Science is the practice of science in such a way that others can collaborate and contribute, where research data and other research processes are freely available, under terms that enable reuse, redistribution and reproduction of the research and its underlying data and methods. Amidst these activities however, it is worth noting that the Open Science movement is still not universally welcome (Osborne, 2015).

Among the issues raised against Open Science are worries that the movement can unleash into the public domain unprecedented amount of materials beyond our capacity to process them, thereby degrading the peer review quality and adding more stress on the discoverability and spread of new knowledge. However, many scientists surveyed by Mann et al. (2009), identified with Open Science in principle, but have not made any action plan to share their data and software tools because the existing research funding and evaluation structures offer no incentives to justify the extra efforts to circulate their resources. Paton and Kobayashi (2019) explain the ecosystem of software development, data sharing, education, and research in the AI community has, in general, adopted an Open Science ethos that has driven much of the recent innovation and adoption of new AI techniques. However, within the healthcare domain, adoption may be inhibited by the use of "black-box" systems, where only the inputs and outputs of those systems are understood, and clinical effectiveness and implementation studies are missing.

As Connected Health and clinical decision support systems begin to be implemented in healthcare systems around the world, further openness of clinical effectiveness and mechanisms of action may be required by safety-conscious healthcare policy-makers to ensure they are clinically effective in real world use. This leads to a research question: *How can Open Science present an action plan to be transparent on algorithmic decision-making within a Connected Health context?*

5.3 Accountability and Responsibility Implications

Accountability serves to ensure responsible development and use of algorithmic systems such that they improve human rights and benefit society (Nissenbaum, 1994). An important difference between transparency and accountability is that accountability is primarily a legal and ethical obligation on an individual or organisation to account for its activities, accept responsibility for them, and to disclose the results in a transparent manner. Transparency, logs of data provenance, code changes and other record keeping are important technical tools, but ultimately accountability depends on establishing clear chains of responsibility. Accountability ultimately lies with a (legal) person (Cooper, 2011).

Automated decision-making algorithms are now used throughout industry and government, underpinning many processes. Given that such algorithmically informed decisions have the potential for significant societal impact, software developers and product managers design and implement algorithmic systems in publicly accountable ways. Accountability in this context includes an obligation to report, explain, or justify algorithmic decision-making as well as mitigate any negative social impacts or potential harms.

Koene et al. (2019) present an EU initiative for a governance framework for algorithmic accountability and transparency. They describe how algorithmic systems are increasingly being used as part of decision-making processes in both the public and private sectors, with potentially significant consequences for individuals, organisations and societies as a whole. Koene et al. (2019) draw focus on how the same properties of scale, complexity and autonomous model inference, however, are linked to increasing concerns that many of these systems are opaque to the people affected by their use and lack clear explanations for the decisions they make. This lack of transparency increases the risk of undermining meaningful scrutiny and accountability. This is a significant concern when these systems are applied as part of decision-making processes that can have a considerable impact on people's human rights (e.g. allocation of health and social service resources). We posit the research question: *What governance structures are required to ensure accountability and responsible use of algorithmic systems within a Connected Health context?*

5.4 Ageing Implications

Societal, demographic and economic changes have encouraged us to reconsider how we deliver health and social care to older people and their families in our communities (Carroll et al., 2016b). The worldwide increase in the ageing population presents an urgent need for new technologies to improve the quality of life for the elderly. In recent years we have seen the rapid development of healthcare technologies along with the widespread use of the Internet, mobile technologies, data analytics and artificial intelligence in healthcare – moving towards more personalized care. However, we must also consider how do algorithms consider the age and changing healthcare needs of patients. Our research question becomes: *How can we ensure that algorithmic decision-making aligns with the complexity of longevity, i.e. an ageing population within a Connected Health context?*

5.5 Data Literacy and Intelligence

Data literacy is the ability to read, work with, analyse, and argue with data. Much like literacy as a general concept, data literacy focuses on the competencies involved in working with data. For example, at best current science on various machine learning methods described artificial narrow intelligence (ANI), i.e. the first level of intelligence created by humans. This implies that algorithms are useful in recognising patterns and gleaning topics from blocks of text or deriving the meaning of whole documents from a few sentences. With increasing efforts to achieve artificial general intelligence (AGI) to abstract concepts from limited experience and transferring knowledge between domains and then moving towards superintelligence, this has the potential to allow machines to demonstrate some level of consciousness (Goertzel, 2014). There are limited studies which consider how to exploit the rich body of medical evidence to develop frameworks for conceptualising the algorithm itself and support clinical teams, beyond decision support systems (O'Leary et al. 2014). This raises the question: *What are the key requirements between data literacy and intelligence on algorithmic decision-making for stakeholders within a Connected Health context?*

5.6 Healthcare Professionals Skills Gap

Healthcare education is continually evolving to meet the global healthcare needs of society. While there are inherent links between healthcare professionals' educational development and patient safety, there is growing concern regarding the mismatch in healthcare professionals' technological skills and how technological innovators are informed of healthcare needs (Carroll et al. 2018).

There is an opportunity to experiment with algorithmic decision-making in simulated clinical learning environments. For example, university-simulated clinical skills laboratories provide a safe innovation environment for healthcare solution developers to experiment with implementing new algorithms to improve healthcare practice. Thus, we need to understand: *How can we develop healthcare education and training on algorithmics decision-making for Connected Health technology solutions?*

5.7 Regulatory Implications

Connected Health is a rapidly developing field never before witnessed across the healthcare sector. It has the potential to transform healthcare service systems by increasing its safety, quality and overall efficiency (Kvedar et al., 2014). However, as medical devices and algorithms continuously rely more on software development, one of the core challenges is examining how Connected Health is regulated – often impacting Connected Health innovation adoption and usage. Many of these regulatory developments fall under "medical devices", giving rise to Software-as-a-Medical Device (SaaMD) yet we need to re-examine how regulation governs the development and usage of algorithms which guide decision-making processes in practice, for example, the role and impact of GDPR as a requirement on the "right to explanation" in Connected Health innovation. We posit the research question: *What are the key regulatory requirements for algorithmic decision-making for software-as-a-medical device within a Connected Health context?*

6 DISCUSSION & CONCLUSION

The future of Connected Health aims to apply data sciences, machine learning, AI and IoT to tackle the health problems and challenges faced by patients and the care professionals. For example, tracking personalized health indicators regularly such as blood pressure and heart rate can help with the management of the health and well-being of patients with heart issues.

New technologies developed in the digital industry, particularly in the emerging interfacing area between big data and AI, are changing the way healthcare delivery is decided upon and can have an enormous economic impact on healthcare provision. We are witnessing growing research efforts in healthcare in the development of new smart sensing, new algorithms, and new systems or devices for personalised healthcare. One of the fundamentals of these developments is to ensure that healthcare data can be accessed and analysed effectively in order to support accurate decision-making. This article focuses on the algorithmic decision-making process and the need to uncover key enabling and inhibiting factors to support and deliver healthcare services. It is becoming increasingly important for healthcare technologies to invest in technology and to explore how technology may be part of that solution.

We explain that central to Connected Health innovation is the process of algorithmic decision-making. Therefore, it is important that healthcare stakeholders understand the need for improved transparency and ethical considerations in Connected Health algorithms. Therefore, as part of our future research, we propose a research roadmap on key topics. Scholars are encouraged to consider the seven key research themes, namely: (i) ethical implications; (ii) open science implications; (iii) accountability and responsibility implications; (iv) ageing implications; (v) data literacy implications; (vi) healthcare professional skills gap; and (vii) regulatory implications associated with algorithmic decision-making in Connected Health.

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