The Efficient Doctor-Patient Relationship: A Value-Based Framework for Person-Centred Healthcare in the Age of Artificial Intelligence

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Aurelia Sauerbrei

The Nuffield Department of Population Health
St Cross College
University of Oxford

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Abstract

We know that the doctor-patient relationship contributes to improving patient outcomes. Policymakers and professional bodies expect the integration of artificial intelligence (AI) in healthcare to enhance doctor-patient relationships in an efficient way. Promissory discourse has largely focused on the efficiency gains from AI, often assuming that these gains will straightforwardly be reallocated to benefit doctor-patient relationships, yet offering little explanation of how this reallocation would occur in practice. In contrast, the bioethics literature has focused mainly on concerns specific to AI systems, such as explainability and its effects on the doctor-patient relationship, often treating these issues in isolation and neglecting to consider them within the broader context of resource allocation decisions. This leaves a gap in understanding **how the doctor-patient relationship can be integrated into a healthcare context that strives for AI-supported efficiency**.

To address this gap, I use a combination of theoretical and empirical work. I start by **theoretically exploring the relationship between the doctor-patient relationship and efficiency.** I develop the theoretical framework of the *efficient doctor-patient relationship*, which provides an understanding of the link between efficiency and the doctor-patient relationship in the healthcare context. I argue that, rather than understanding the doctor-patient relationship and efficiency as conflicting or complementary concepts, the doctor-patient relationship should be incorporated into our understanding of efficiency. In practice, this means that resources should be allocated to the doctor-patient relationship when the latter can contribute to maximising outcomes that matter to patients.

I then gather qualitative data through semi-structured interviews to **explore how clinicians and AI developers understand AI to impact healthcare practices.** In the subsequent discussion, I bring together the theoretical and empirical work to gain an empirically grounded

understanding of the role of AI within the *efficient doctor-patient relationship*. Two findings emerge from my analysis. First, AI can enhance the efficiency of the doctor-patient relationship through the saving and reallocation of resources. But, importantly, how to reallocate resources should depend on the outcomes that matter to various patient clusters. Second, AI tools can affect the efficiency of the doctor-patient relationship itself, by changing the dynamics of the interaction. For example, the design of a tool, such as whether it is a black box or explainable, can alter the efficiency of the relationship.

These findings help shape policy. To integrate the doctor-patient relationship into a healthcare context that strives for AI-supported efficiency, resources should be allocated to the relationship when the latter can contribute to maximising outcomes that matter to patients. Decision-makers must first assess whether the AI system in question saves resources that could be reallocated. If so, reallocation should be driven by the needs of specific patient clusters. Furthermore, policymakers need to consider AI tools' direct effect on the doctor-patient relationship and evaluate these together with other effects beyond the doctor-patient relationship to maximise patient outcomes with available resources.

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1. Introduction

1.1. AI Spring

The history of artificial intelligence (AI) has been characterised by alternating periods of "winters," marked by declining enthusiasm and slowed progress, and "springs", marked by rapid advancements and optimism about its potential (Toosi, Bottino et al. 2022). We are currently witnessing an "AI spring". This latest surge in AI development has generated immense promises, with AI systems being hailed for their ability to revolutionise industries, streamline processes, and solve complex global challenges (Gruetzemacher and Whittlestone 2022, Vasant, Weber et al. 2022). As AI capabilities continue to grow, the optimism surrounding its transformative power drives further innovation and significant investment, positioning AI as a critical component of future technological progress. This new spring of AI is characterised by the rising deployment of a broad range of transformative AI systems which display "human-like" intelligence, such as, for example, Open AI's Generative Pre-trained Transformer (GPT), which now underpins offerings in companies ranging from Morgan Stanley to Duolingo or Stripe (Bommasani 2023). Given the transformative power of these new technologies, there is a growing demand for policy that ensures their ethical implementation (European Commission 2024).

The current AI spring has also significantly impacted healthcare, where the integration of AI systems promises to enhance medical diagnostics, streamline administrative tasks, and improve patient outcomes (EIT Health and McKinsey & Company 2020). From AI-driven diagnostic tools that can analyse medical images with unprecedented accuracy to predictive algorithms assisting in treatment decisions, hospitals and clinics are increasingly adopting AI systems to improve efficiency, reduce costs, enable more personalised treatment, and reduce the burden of medical errors (Topol 2019, Alowais, Alghamdi et al. 2023). The healthcare sector, known for

its complexity and resource demands, is now at the forefront of AI innovation, with potential breakthroughs that could reshape patient care and healthcare delivery. One area of high promise within healthcare is the potential ability of AI systems to save time by taking over tasks traditionally performed by humans and reallocating it to give "the gift of time", enabling doctors and patients to develop meaningful relationships (Topol 2019).

1.2. AI as a solution to the deterioration of the doctor-patient relationship

Evidence shows that the doctor-patient relationship is important because it improves outcomes that matter to patients (El Nawawi, Balboni and Balboni 2012, Kelley, Kraft-Todd et al. 2014, Sabety 2023). The doctor-patient relationship refers to the partnership between the patient and the clinician (BMA 2024). This partnership is described by the British Medical Association (BMA) as characterised by mutual respect, open and honest communication, as well as respect for the privacy, dignity, and choices of patients (BMA 2024). These characteristics are discussed extensively in the bioethics literature, which explores the key elements and necessary personal attributes for successful doctor-patient relationships (Meinhardt and Landis 1995, Jeffrey 2016, Håkansson Eklund, Holmström et al. 2019).

However, personal attributes alone are not enough for successful doctor-patient relationships. Having additional time enabling clinicians and patients to interact meaningfully has been cited as a significant factor in enabling the doctor-patient relationship and ensuring its benefits can be fully realised (Dugdale, Epstein and Pantilat 1999, Noseworthy 2019). In the UK, it is becoming more difficult for clinicians[1] to invest in building a strong relationship with their patients because they have less time for it as workload and administrative burdens increase

[1] Note on language: throughout the thesis, healthcare professionals will be referred to as "clinicians" to include those who, while not necessarily doctors, are involved in the broader doctor-patient relationship, which encompasses all providers of direct patient care. Furthermore, AI used in healthcare will be referred to as "AI tools" or "AI systems".

(Banerjee and Sanyal 2012, Chipidza, Wallwork and Stern 2015). This can lead to poorer health outcomes due to missed opportunities, medical errors, and dissatisfaction for patients and physicians alike (Noseworthy 2019). In recent years, policymakers and various stakeholders in the field of emerging technologies have proposed that artificial intelligence (AI) offers a potential solution to the problem of clinicians lacking sufficient time to engage in meaningful patient relationships. The expectation is that by automating specific processes, time will be saved, and this can be reallocated to the doctor-patient relationship. This would be an efficient way to improve the doctor-patient relationship, as no additional resources would need to be deployed to achieve this. Unfortunately, there is currently no convincing evidence showing that the deployment of AI in healthcare will lead to improved relationships due to time reallocation.

John McCarthy, often regarded as the father of AI, described AI as a machine behaving in a way that would be called intelligent if a human were so behaving (McCarthy, Minsky et al. 2006). His definition serves as the foundational basis for understanding AI throughout this thesis. While AI systems are not (yet) standard in the UK, the NHS is actively pursuing increasing uptake of AI (NHS England 2019). The NHS long-term plan published in 2019 presents the long-term goals of the NHS. One chapter of this 7-chapter document is dedicated entirely to "digitally-enabled care", which the NHS writes will go mainstream across its organisation (NHS England 2019). In practice, this means that, in ten years, the NHS wants to offer a "digital first" option for most patients, which should allow for longer and more meaningful consultations with clinicians when patients need it (p.92). Furthermore, predictive tools will be used to better plan care at the population level, and decision-support systems guided by AI will increasingly be deployed (p.92).

To support the NHS digital transformation described in the above-mentioned long-term plan, the NHSX was set up in 2019, and in 2022, the unit started working as part of the "NHS

Transformation Directorate". The Transformation Directorate has been distributing £123 million worth of awards to 86 projects in the last years to help accelerate the testing and evaluation of new technologies that meet the aims set out in the NHS Long Term plan (NHS 2022). A rapid analysis of the list of award recipients offers interesting insights. As appendix 5 shows, most of the systems funded between 2020 and 2021 in order to become an integral part of the UK healthcare system share two characteristics:

1. They are used for diagnostic/decision-making purposes. The most funded tools are the systems used for technical tasks, triage, monitoring, prevention, and organisation. However, they are a small minority compared to diagnostic and/or decision-making tools. These five types of tools represented 18 awards versus 58 for diagnostic and/or decision-making tools.
2. Although some systems are designed for the patients to be the primary users, they are a minority compared to the number of tools funded for clinicians as primary users. This means that patient-led systems do not currently seem to be a priority for the Transformation Directorate.

In line with the NHS Long-Term Plan, the AI-enabled diagnostics tools that support clinicians (forming the majority of funded tools) are expected to provide more accurate diagnostics and do so more efficiently (NHS 2022).

The promise that AI can improve the efficiency of healthcare, leading to gains in various aspects of healthcare, including the doctor-patient relationship, makes AI particularly appealing to policymakers (Carroll 2022). Once a healthcare system invests in an AI tool, the system should theoretically enable clinicians to achieve *more* with the *same* resources (time, money, etc.). This matters because efficiency has been linked to improved quality of care and health outcomes (Bose 2021). Many commentators accept that the pursuit of efficiency in healthcare should be a central objective of policymakers and managers (Cylus, Papanicolas and Smith 2016, The

Economist 2023). Furthermore, in a public system like the NHS, it is crucial to ensure that public funds are used judiciously. This is because available resources tend to be more limited and to maintain citizens' willingness to support the system, without which the long-term future of the health system could be jeopardised (Smith 2012). Theoretically, an efficient system makes the best possible use of resources to achieve goals (Thomas and Chalkidou 2016). This implies that waste is reduced to a minimum.

As a result of the need to maintain citizens' support and the limited availability of resources, ensuring efficient use of resources to make the most of them becomes even more critical, especially in the post-COVID era, when healthcare systems worldwide, including the NHS, struggle to meet patients' needs (Bohr and Memarzadeh 2020, Spatharou, Hieronimus and Jenkins 2020). In 2024, life expectancy in the UK dropped to its lowest in a decade, with the COVID pandemic cited as a major reason, but also the lack of resilience of the healthcare system (Thomas 2024). Besides the aforementioned erosion of the doctor-patient relationship (Friedberg, Chen et al. 2013, Fogel and Kvedar 2018, Ward 2018, Davis 2019), there is evidence of many diagnostic errors (Cheraghi-Sohi, Holland et al. 2021) and backlogs negatively affecting the health outcomes of patients and causing needless suffering (Iacobucci 2021, BMA 2023). To make matters worse, the NHS is grappling with escalating costs, partly attributed to the ageing population (Bohr and Memarzadeh 2020) and sustained underspending per head on healthcare (Charlesworth and Rebolledo 2022). Amidst these systemic challenges, questions arise about whether the resources allocated to the NHS are being used optimally, that is, whether the system is achieving the best possible outcome with the resources at hand (Oliver 2022, Triggle 2024). In other words, is the system efficient? This has important consequences because a lack of efficiency results in unnecessary suffering, given that, at its core, efficiency is about making the best possible use of the available resources (Cylus, Papanicolas and Smith

2016). A lack of efficiency, therefore, indicates that resources are not used in the best possible way.

Given the crucial importance of efficiency, efforts to improve the eroding doctor-patient relationship should be considered within a context of efficiency. In other words, improvements in the doctor-patient relationship should be approached as part of a model that prioritises maximising the impact of available resources rather than as an initiative that consumes excessive resources without careful consideration of their optimal use. An increasing number of policy documents and business materials marketed by stakeholders in the field of new technologies and healthcare propose that AI can address problems in healthcare efficiently, including clinicians not having enough time to engage in meaningful relationships (Topol 2019, EIT Health and McKinsey & Company 2020).

1.3. The vision of policy and professional documents

The proposed vision in policy and professional documents is that AI can help save time, and this saved time can be reallocated to developing the doctor-patient relationship. This would, therefore, be an efficient way of improving the relationship and overall outcomes because no additional resources are needed. The Topol review is an influential policy document put together under the leadership of MD Eric Topol, which explores how healthcare can be prepared for the inclusion of new technologies, including AI. The report aims to provide a guide on how the NHS can make the most of these new technologies in order to improve healthcare services (Topol 2019). In 2020, one year after the publication of the review, the NHS Health Education England noted that interest in the review was expanding, with several related initiatives taking place at different levels of the healthcare system (Health Education England 2020). In the letter to the Secretary for Health and Social Care, which forms the foreword of

the report, Topol states that the document is predicated on five presuppositions, the fourth of which states that

"A marked improvement in the patient-clinician relationship is possible, owing to the gift of time delivered by the introduction of these technologies. This will bring a new emphasis on the nurturing of the precious inter-human bond, based on trust, clinical presence, empathy and communication." (Topol 2019)p.6

The presupposition that AI can improve relationships between patient and clinician assumes that the introduction of new technologies, including AI, can give the *gift of time,* where time is understood in this context as a vector for the provision of the "precious inter-human bond based on trust, clinical presence, empathy and communication".

Topol is one of the leading figures arguing for the link between AI and the "gift of time." However, this claim is frequently made in the policy and the broader professional literature (e.g. business, mainly tech or pharmaceutical company reports). For example, a report by GE Technologies in collaboration with MIT Technology Review titled "The AI effect: how artificial intelligence is making healthcare more human" dedicates a section to "More time means more meaningful relationships" (GE Healthcare and MIT Technology Review 2019). Based on survey data, the report claims that saved time by automation, for example, becomes a gift and enables the clinician to spend more time developing a relationship with the patient. Similarly to the claims made by GE Technologies and MIT Technology Review, a report by the leading management consultancy Boston Consulting Group (BCG) states that the automation of various processes by AI systems results in clinicians devoting more time to patients (Boston Consulting Group 2023). EIT and the consultancy McKinsey claim that "AI can help improve the experience of healthcare practitioners, enabling them to spend more time in direct patient care" (EIT Health and McKinsey & Company 2020) p.4. As mentioned previously, what these

reports have in common is that they show that improvements in the doctor-patient relationship following the introduction of AI result from improved efficiency.

How exactly can AI help save resources which can be reallocated to the doctor-patient relationship? According to policy and promotional documents, resources are saved because AI can replace humans in specific tasks, achieve more, or do better than the status quo. This can range from taking over administrative tasks, resulting in less time writing reports (GE Healthcare and MIT Technology Review 2019), to helping clinicians diagnose patients accurately and quickly. Topol advocates for an "up-to-date" practice of medicine, asking, "Why would you listen to a heart when you have an ultrasound in your pocket?" referring to AI-powered devices which perform much better in studies than human clinicians in detecting heart anomalies (Gullo 2011, Associated Press 2019). IBM suggests that many studies show that AI diagnostic systems can outperform human clinicians, leading to better care without needing additional time (IBM Education 2023). EIT Health, a body of the European Union, is a 'knowledge and innovation community' (KIC) of the European Institute of Innovation and Technology (EIT), mentions diagnostics as a key area where AI can make a positive difference (EIT Health and McKinsey & Company 2020). The majority of policy documents on the topic of diagnostic AI systems mention the potential to improve diagnostic quality, meaning that diagnoses could become more precise and accurate (Topol 2019, EIT Health and McKinsey & Company 2020, Department of Health and Social Care and Barclay 2023).

A turn to the medical literature, which is cited in policy and professional documents, shows that it is rich in accounts promoting AI as a great time saver, creating space for more meaningful and empathetic relationships to be developed with patients (Chen 2017, Fogel and Kvedar 2018, Aminololama-Shakeri and López 2019, Davenport and Kalakota 2019, Topol 2019, Dagher, Shi et al. 2020, Nelson, Pérez-Chada et al. 2020, Hung, Chen et al. 2021). There is already some

evidence to suggest that AI can save doctors' time. Printz explains that the AI system Watson for Oncology needs 40 seconds to capture and analyse data and then generate treatment recommendations based on the available data (Printz 2017). In comparison, manually collecting and analysing the data takes an average of 20 minutes, decreasing to 12 minutes when oncologists become more familiar with cases (Printz 2017). Other studies have also shown that using AI reduced the overall workload of clinicians while improving screening performance (McKinney, Sieniek et al. 2020, Al-Zaiti, Martin-Gill et al. 2023, Lauritzen, Lillholm et al. 2024). It is unclear, however, if this saved time will be used to enhance the doctor-patient relationship and if these tools affect the relationship in other ways.

At the same time as suggesting that saved time will be reallocated to the doctor-patient relationship, policy and professional documents also understand the use of AI as leading to better care through time savings, which can be allocated to ensure timely access to care. It is said that this would lead to more productivity in terms of increasing patient throughput (EIT Health and McKinsey & Company 2020). For example, this can be made possible if an AI-enabled system speeds up the diagnostic process, allowing a patient to start treatment quickly.

The Topol review suggests that AI can significantly improve the speed, accuracy and scalability of medical data interpretation (Topol 2019). A global consultancy McKinsey & Company report claims that AI can improve operations and efficiency and, therefore, help meet the increasing demand for healthcare driven partly by an ageing population (EIT Health and McKinsey & Company 2020). SCC, a software integration firm, mentions the ability of AI tools to analyse images accurately, leading to faster diagnoses and, ultimately, better care. This is because clinicians will be able to, for example, identify clinical trials for which their patient is eligible quicker than without using AI (SCC 2019). A 2021 press release by the Department of Health and Social Care (DHSC) claims that technology, among other changes, will help the NHS

"increase efficiencies (…) and increase activity levels to tackle rising backlogs." According to the statement, AI will contribute to "tackle growing waiting lists and treat around 30% more patients who need elective care by 2023 to 2024." The belief in the power of AI to cut backlogs enabled the unlocking of over £36 billion in funding to "do things differently" and "help the NHS get back on track" (DHSC 2021). A further statement in March 2023 by the DHSC together with NHS England and MP Steve Barclay, stated that thousands of patients will benefit from quicker diagnoses thanks to AI-enhanced care (DHSC, NHS England and Barclay 2023).

Policy and professional documents suggest that AI systems will lead to both faster care and improved doctor-patient relationships, but scepticism exists regarding the feasibility of achieving both objectives simultaneously. The view that the deployment of AI in healthcare will lead to faster care only is put forward by bioethicists Sparrow and Hatherley, who suggest that the economics of healthcare, especially in for-profit environments, will dictate that more patients will pass through the system and more tasks will need to be taken on by individuals (Sparrow and Hatherley 2020). They, as well as others, argue that there is no reason to believe that the time saved by the use of AI will result in more empathetic doctor-patient relationships but instead, it will allow higher patient throughput (Sparrow and Hatherley 2020, Sauerbrei, Kerasidou et al. 2023, Tan, Stretton et al. 2023). Topol (the author of the previously mentioned influential Topol review) is certainly not oblivious to market laws and has suggested in an interview by O'Connor that doctors must get together to create a movement demanding that time saved is not used to get more patients through the system (O'Connor 2019). Sparrow and Hatherley have a pessimistic outlook on the ability of doctors to initiate change, at least in the US context. Using several historical examples (such as universal basic healthcare), they argue that doctors have been unable to motivate any changes under any administration in the US (Sparrow and Hatherley 2020).

1.4. The problem

An initial exploration of the claims made in the policy and professional documents as well as some of the corresponding responses in the bioethics literature, shows that the integration of AI takes place within a complex moral world with apparently conflicting values and incentives. If AI does save resources, it is unclear whether these resources will and should be allocated to promote values traditionally perceived to be associated with efficiency, for example, speed, accuracy, and cost-reduction or whether they should be reallocated to promote relational values such as empathetic and compassionate doctor-patient relationships. While both options potentially offer benefits for patient outcomes, the benefits of increased throughput, for example, are easier to calculate than the benefits of the doctor-patient relationship. As a result, healthcare managers face difficulties when deciding what to prioritise and need to ensure that the benefits of the doctor-patient relationship are realised while operating within resource-constrained environments. Therefore, this thesis aims to find out **how the doctor-patient relationship can be integrated into a healthcare context that strives for AI-supported efficiency.**

The next section provides an overview of how this thesis addresses this aim.

1.5. Thesis overview

Chapter 2 analyses the literature in two parts. The first part examines the concept of the doctor-patient relationship and why it holds significance in healthcare, laying the foundation for understanding the importance of preserving its benefits in an AI-enhanced healthcare system. The second part reviews the existing literature on how the use of AI may impact this relationship. My analysis highlights the need for a more integrated understanding of the relationship between the doctor-patient relationship and efficiency within the context of AI deployment in healthcare. This understanding is necessary to address the overarching aim of

how the doctor-patient relationship can be integrated into a healthcare context that strives for AI-supported efficiency.

Chapter 3 describes the methodology. A theoretical analysis combined with an empirical study is best suited to find out how the doctor-patient relationship can be integrated into a healthcare context that strives for AI-supported efficiency. This is to ensure that the study outcomes are theoretically robust and practically informed, providing valuable information amidst the prevalent speculation in the AI field. The chapter details the data collection process, including semi-structured interviews with AI developers and clinicians. It concludes with an explanation of the data analysis process and the approach to integrating empirical findings with the theoretical framework in the subsequent discussion.

Chapter 4 introduces the concept of the *efficient doctor-patient relationship* as the theoretical framework to analyse my empirical data. This chapter begins by exploring various definitions of efficiency in healthcare. I adopt the Value-Based Healthcare (VBHC) model, which frames efficiency in terms of improving patient outcomes relative to costs. I combine this concept with the understanding of the doctor-patient relationship established in Chapter 2. This integration leads to an important theoretical contribution, the framework of the *efficient doctor-patient relationship* which takes into account values that are not traditionally associated with efficiency.

In **Chapter 5,** I analyse the data gathered through interviews with clinicians and AI developers to understand their experiences with AI systems in healthcare. The chapter is structured around key themes that emerged through coding, with a focus on how AI affects clinical practices and the doctor-patient relationship.

Chapter 6 draws on my theoretical and empirical work. It applies the framework (Chapter 4) to the gathered data (Chapter 5) to understand **how the doctor-patient relationship can be integrated into a healthcare context that strives for AI-supported efficiency**. More specifically, using the theoretical framework, I investigate how AI can affect the efficiency of the doctor-patient relationship to understand how we can preserve and value the benefits of the doctor-patient relationship, thereby maximising patient outcomes within an AI-driven, resource-constrained healthcare environment. I examine the gap between policy expectations, such as AI freeing up time for enhanced doctor-patient relationships, and the actual experiences of clinicians and developers. I also investigate other ways AI is perceived to impact the efficiency of the doctor-patient relationship.

Chapter 7 concludes the study. Based on the discussion, I make suggestions for healthcare managers to help them integrate the **doctor-patient relationship into a healthcare context that strives for AI-supported efficiency.** This proposes an approach to optimise the efficiency of the doctor-patient relationship, ensuring that patient-valued outcomes are achieved within an AI-enhanced healthcare system. The thesis ends with limitations and related avenues for further research.

2. Literature gap

The previous chapter showed how professional and policy-oriented documents explain how AI is expected to impact the doctor-patient relationship. Moving beyond these high-level discourses, this chapter delves into the academic literature in order to explore current understandings of the role of the doctor-patient relationship in healthcare, more generally and in the context of AI, more specifically. This is important to define *why* we should care about ensuring the benefits of the doctor-patient relationships do not get sacrificed in an AI-enhanced healthcare system, *what* we already know on the matter, and *what* we do *not* know yet.

2.1. Understanding the doctor-patient relationship in a person-centred model

To investigate what "the doctor-patient relationship" means, I used a critical narrative approach, meaning that I analysed the literature critically and compared and contrasted different views to develop an understanding of the doctor-patient relationship. I used various bodies of literature, including bioethics, medical and nursing, and some key texts from the health policy literature. I start with a short note on terminology, as this thesis uses the term "doctor-patient relationship" throughout and, importantly, in a way that encompasses the "person-centred care" model.

2.1.1. Person-centred doctor-patient relationships: terminology

The concept of the doctor-patient relationship can encompass a wide range of interactions and models. However, my focus is specifically on the person-centred approach, which prioritises individual patient values, preferences, and experiences as central to delivering effective care (NHS Health Education England 2022). The reason why I analyse the concept of the doctor-patient relationship through the lens of the person-centred model is that such a model is widely accepted in Western medicine as being the gold standard, setting the standards for ideal care (Institute of Medicine 2002, Department of Health 2012, The Health Foundation 2016).

Person-centred care is an emerging and evolving concept, and different countries and institutions use different terminology to describe it. Some speak of personalisation, relationship-centred care and, in Scotland, mutuality (The Health Foundation 2016). Most commonly, the term "*person*-centred care" is often used interchangeably with "*patient*-centred care" (Castro, Van Regenmortel et al. 2016, The Health Foundation 2016). A limited amount of literature attempts to differentiate between "person-centred care" and "patient-centred care", but also other concepts such as "patient empowerment" and "patient participation" but there is currently no agreement on how the concepts may differ, principally because, in practice, terms tend to be used interchangeably (Starfield 2011, Castro, Van Regenmortel et al. 2016, The Health Foundation 2016, Håkansson Eklund, Holmström et al. 2019). For example, on the NHS webpage entitled "developing patient-centred care", they cite a resource by the National Health Foundation entitled the "person-centred care resource centre" (NHS 2022). The assimilation of these terms is also evident in the academic literature; for example, in a broad literature review on patient-centred care, Kitson et al. use "patient-centred care", "person-centred care", and "person-focused" care as their initial search strategy to define a single concept (Kitson, Marshall et al. 2013). The broad range of terms used is not necessarily negative. Mitchell, Cribb and Entwistle (2023) argue that maintaining a variety of vocabulary, rather than trying to enforce the use of a single term, can enable nuanced and context-sensitive communication. In this thesis, I only use the term "person-centred care" for consistency. Although, as Mitchell, Cribb and Entwistle (2023) pointed out, understandings of this model vary, I aim to find the common points between various understandings of person-centred care. This will help me situate the doctor-patient relationship within this specific model, not others, often viewed as outdated models, such as the paternalistic model.

2.1.2. Understanding the concept of person-centred doctor-patient relationship

Historically, doctors were expected to make decisions in the best interest of their patients without involving them in the decision-making process (Ha and Longnecker 2010). The doctor knew best, and the patient was expected to follow the doctor's recommendations. This model is usually called the paternalistic model in the bioethics and medical literature (Kaba and Sooriakumaran 2007, Lazcano-Ponce, Angeles-Llerenas et al. 2020). The latter can be traced back to the Hippocratic oath which was written between the fifth and third century BC. The aim of the oath was (and still is to an extent) to set the standards of conduct for doctors. This was especially relevant when medicine was not regulated to the extent it has been since the middle of the 20th century. Today, the Hippocratic oath has arguably lost some relevance due to modern developments in bioethics (Indla and Radhika 2019). The oath supports a paternalistic model of healthcare in which beneficence is key, but patient autonomy has no place (Edelstein 1943). The Hippocratic oath is not the only factor contributing to the continued relevance of the paternalistic model into the 20th century. According to Coulter and Oldham, in the UK, the birth of the NHS resulted in grateful patients who, in some cases, received treatment that they could not previously afford (Coulter and Oldham 2016). They link this phenomenon to attitudes of acceptance vis-à-vis healthcare professionals and, therefore, a natural acceptance of the paternalistic model. Doctors' decisions would remain unchallenged as they were believed to know best (Coulter and Oldham 2016).

The second half of the 20th century saw a gradual shift away, in cultural narratives, practices, and scholarship, from the traditional, paternalistic model ('the doctor knows best'), towards a new model favouring shared decision-making, where the patient is involved in all decisions about her medical care (Eastwood 1986, Assal JP 1987, Tattersall 2002, Susskind and Susskind 2015). Though criticised by some as burdening patients and ultimately not being the optimal way to act in patients' best interests (Coulter 1997, Mol 2008), this new model is widely accepted

as ethically appropriate in the bioethics and medical community and is enforced by law (Coulter and Oldham 2016). The emphasis on shared decision-making has led to a new model characterising the doctor-patient relationship called "person-centred care" or "patient-centred care". The doctor-patient relationship plays a crucial role in enabling person-centred care, as it provides the foundation for understanding and responding to patients' individual needs, values, and preferences.

A review in the nursing field by Byrne et al. found that, while no single definition of person-centred care is available in nursing, three different themes come up systematically. The first one is "people", the second one is "practice", and the third one is "power" (Byrne, Baldwin and Harvey 2020). "People" refers to two subcategories: recognising uniqueness and partnerships. The former understands that each person has their own wants, needs, and desires. This understanding of the person as unique is important as it leads to tailored care (Byrne, Baldwin and Harvey 2020). Partnership refers to the relationship between the healthcare professional and the person as a way of "facilitating information, knowledge, and decision making" (Byrne, Baldwin and Harvey 2020). The second theme, "practice", encompasses "doing" and "space", and the third theme "power" encompasses "power over one's care" and "power to practice person-centred care". Power over one's care refers to the power balance between clinicians and patients, which should allow the patient to be fully involved in decision-making. In contrast, power to practice person-centred care refers to the need for healthcare systems to commit to person-centred care in order for person-centred care to actually be practised. The "practice" theme is particularly relevant as it refers to the relational factors necessary to practice person-centred care. Different authors attribute different kinds of characteristics which they believe are necessary for the practice of person-centred care. For example, communication, respect, compassion, non-judgemental behaviour are commonly described as necessary for the practice of person-centred care in the nursing literature (Byrne, Baldwin and Harvey 2020). These are

all relational factors that are expressed through the relationship between the doctor and the patient.

The themes identified by Byrne et al. can be found in Lusk and Fater's concept analysis. They identify the following elements: encouraging patient autonomy, caring attitude of the nurse, and individualising patient care by the nurse (Lusk 2013). While these themes are not phrased in the same manner as Byrne et al. and differences exist (for example, Lusk and Fater emphasise patient autonomy whereas Byrne et al. write about "power over one's care", or Lusk and Fater mention the caring attitude of the nurse whereas Byrne et al. highlight the importance of "partnerships"), these authors fundamentally agree that the person-centred care model respects patient uniqueness and encourages effective communication between the healthcare professional and the patient (Lusk 2013, Byrne, Baldwin and Harvey 2020). Within these components, empathy is frequently cited as important. Brown et al. define empathy as the ability to imagine what someone else may be feeling or thinking and consider it a crucial component of person-centred care (Brown, Agronin and Stein 2020). This can help understand the patient's unique values and preferences. They link the importance of empathy as an inter-personal quality to the studies demonstrating the benefits of empathy, such as better treatment adherence and more accurate diagnoses (Decety and Fotopoulou 2014, Riess 2018). However, they acknowledge the limitations of such studies due to the lack of a clear, single definition of empathy (Brown, Agronin and Stein 2020). Byrne et al. equally consider empathy to be an important element of the doctor-patient relationship (Byrne, Baldwin and Harvey 2020) as well as McKinnon who considers empathy a powerful tool to inform practice (McKinnon 2018).

The previously mentioned components of person-centred care, such as communication, respect, compassion, non-judgemental behaviour, and empathy, are widely mentioned in the nursing literature with varying emphases (Kvåle and Bondevik 2008, Morgan and Yoder 2012,

Kitson, Marshall et al. 2013, Edvardsson 2015, Ross, Tod and Clarke 2015) which depend on factors such as authors own beliefs but also context (e.g. person-centred care in cancer care versus intensive care (Kvåle and Bondevik 2008, Jakimowicz and Perry 2015). Therefore, nursing literature authors use different terminology to define person-centred care and emphasise different elements. However, core attributes remain the same and can be found in major nursing conceptual analyses. These are (1) partnerships (including effective communication) between the healthcare professional and the patient, (2) respecting the patient's uniqueness (including their values and preferences), and (3) shared-decision making between the healthcare professional and the patient, by involving the patient in the decision-making process regarding their healthcare (Lusk 2013, Byrne, Baldwin and Harvey 2020). These core attributes are mostly enacted through the relationship between the doctor and the patient.

Castro et al. explain that patient participation in their care is a crucial antecedent of person-centredness, as well as communication between patients and caregivers (Castro, Van Regenmortel et al. 2016). For example, a systematic review by Dahm and Cattanach shows that the way in which diagnostic uncertainty is communicated makes a difference in the doctor-patient relationship. Patients dislike when the topic of uncertainty is avoided and prefer an honest conversation about it. Equally, patients have more confidence in their doctor when diagnostic evidence from examinations is shown (Dahm, Cattanach et al. 2023). The authors also find that there is literature showing that diagnostic uncertainty can in some cases be linked to improved doctor-patient relationships, especially when linked to open communication (Dahm, Cattanach et al. 2023). This shows that part of the quality of the doctor-patient relationship relies on open and honest communication, no matter the level of certainty associated with diagnoses.

Furthermore, a caring environment is also described as important, where everyone's choices and values are respected. This facilitates the healthcare professional's ability to be empathetic,

compassionate, respectful, and non-judgmental (Castro, Van Regenmortel et al. 2016). Because person-centred care is an approach that tries to adopt the patient's perspective and understand their expectations and preferences, having the skill to listen to patients, treat them with respect and dignity, and be empathetic is important (Castro, Van Regenmortel et al. 2016). When asking healthcare professionals how they understand person-centred care, respondents also consistently ranked "listening to the patient and incorporating their preferences and needs to be important principles of shared decision making" highly, right after "treating patients with dignity and respect" (Berghout, van Exel et al. 2015). Here again, having the ability to listen, understand, and incorporate personal preferences can be facilitated by empathetic relationships, which enable the healthcare professional to gain a deep understanding of patient preferences.

Scholl et al., in the medical literature, outline four principles for person-centred care, including (1) essential characteristics of the clinician, referring to a combination of personal qualities and technical knowledge; (2) the clinician-patient relationship referring to a reciprocal relationship emphasising mutual understanding; (3) regarding the patient as a unique person which highlights the importance of personal values and preferences; (4) Biopsychosocial perspectives entails taking into account the broader personal circumstances of the patient (Scholl, Zill et al. 2014). The four principles can be regarded as related. For example, rather than being a principle, the second dimension (clinician-patient relationship) could be conceptualised as a prerequisite for the first, third and fourth principle, that is, understanding the uniqueness of the patient and their respective circumstances and having the personal qualities to do so. Without a successful relationship, a doctor cannot understand the uniqueness of their patient and their respective circumstances.

In the social science literature, Mead and Bower identify five principles of person-centred care. The first is the biopsychosocial aspect, which, like Scholl et al., refers to the broader

circumstances of the patient. The second is the "patient as person" aspect, which can be compared to Byrne's "People" principle or Scholl et al.'s "patient as a unique person" principle, in that it recognises the patient "as an experiencing individual", or active subject not just a passive object experiencing illness (Mead and Bower 2000). The third principle, sharing power and responsibility, relates to Scholl et al.'s conceptualisation of the doctor-patient relationship and Byrne et al.'s understanding of "partnerships". The fourth principle, the "therapeutic alliance", is related to the previous "sharing power and responsibility" principle, again overlapping with Scholl et al. and Byrne et al.'s relational principles. The fifth principle, the "doctor-as-person" principle, emphasises personal qualities and is therefore consistent with Scholl et al.'s "essential characteristics of the clinician" but less relevant to Byrne et al.'s model.

Across the medical, nursing, and social science literature, there are many variations in how person-centred care is being described, but the core principles remain the same. At its core, person-centred care is about partnerships, including good communication, and respect for the patient's uniqueness, which can be accessed through empathetic care and shared decision-making between the healthcare professional and the patient. In such a model, the doctor-patient relationship plays a crucial role. The nursing literature broadly agrees that the doctor-patient relationship is important and particularly helpful in understanding the patient in his unique circumstances.

In the UK, The Health Foundation, an independent charity that aims to bridge academia and practice in order to inform effective policymaking, describe person-centred care in the following way:

"In person-centred care, health and social care professionals work collaboratively with people who use services. Person-centred care supports people to develop the knowledge, skills and confidence they need to more effectively

manage and make informed decisions about their own health and health care. It is coordinated and tailored to the needs of the individual. And, crucially, it ensures that people are always treated with dignity, compassion and respect" (The Health Foundation 2016)

This definition encompasses all aspects repeatedly found in the academic literature. It suggests that the healthcare professional and the patient should work collaboratively (an element also emphasised by the King's Fund, another independent charity (The King's Fund 2011), and that the patient is unique and requires tailored care as opposed to a "one size fits all" approach. The Health Foundation also argues that empathy is crucial for person-centred care in order for clinicians to be able to manage relationships and respond in appropriate ways (The Health Foundation 2021).

In the UK, person-centred care has been further defined and encouraged by several policy papers by the Department of Health (DoH) (Department of Health 2012, Scholl, Zill et al. 2014). The DoH claims that informed and shared decision-making is key to person-centred care (Department of Health 2012), which again, inevitably puts significant weight on the doctor-patient relationship, and specifically on the doctor reaching a high level of understanding of the patient in order to share the burden of decision-making with them. This high-level of personal relationship is also made explicit by the Alzheimer Association, which defines person-centred care as a "philosophy of care built around the needs of the individual and contingent upon knowing the person through an interpersonal relationship"(Fazio, Pace et al. 2018).

It is striking that the core attributes of person-centred care are enacted through the doctor-patient relationship. This relationship serves as the primary vehicle for expressing key elements such as empathy, trust, and individualised care, which lie at the heart of person-centred care. Through open communication and shared decision-making, doctors can tailor their approach

to meet each patient's specific needs and preferences. Therefore, the quality of this relationship is central to the effective delivery of person-centred care.

So far, the person-centred doctor-patient relationship has been described in terms of micro-level factors. Shared decision-making, empathetic care, and effective communication are all attributes that manifest themselves within a relational context. These are crucial for the practice of person-centred doctor-patient relationships and explain why there is a significant body of literature arguing that medical students should be selected based on their personal characteristics, for example, their ability to be empathetic, rather than purely intellectual skills (Chen 2017, Colm and Mary 2020, Sauerbrei, Kerasidou et al. 2023). However, these interpersonal skills can only be practised if broader systemic conditions allow their practice (Kerasidou, Bærøe et al. 2020). Healthcare systems need to value such relationships in the first place and make them a priority. A major systemic driver for the practice of person-centred doctor-patient relationships is the availability of sufficient time, as time gives the necessary space for meaningful relationships (Dugdale, Epstein and Pantilat 1999). Of course, clinicians with particularly good relational skills may be able to achieve more meaningful relationships in less time, meaning that more prolonged interactions do not necessarily guarantee better relationships (Elmore, Burt et al. 2016).

Nevertheless, more time at least provides the opportunity to build these relationships. Time is needed for appropriately understanding a patient's uniqueness, for practising empathetic care, which leads to an understanding of individual values that can help guide clinical decisions, and sufficient time for all patients as opposed to a select few ensures that the benefits of the person-centred doctor-patient relationships are reached system-wide. Time is, therefore, a key enabler for the person-centred doctor-patient relationship and its associated benefits. However, as mentioned previously, nowadays, time is often insufficient for doctors to develop the type of

empathetic and compassionate relationship with their patients that is necessary for person-centred care (Friedberg, Chen et al. 2013, Fogel and Kvedar 2018, Ward 2018, Davis 2019).

In summary, we know from the various bodies of literature on person-centred care that the same core attributes are always present. First, the emphasis is placed on *partnerships* based on effective communication between the healthcare professional and the patient. Second, *respecting the patient's uniqueness* (including their values and preferences) is another crucial aspect of this model. Third, *empathy* is often mentioned as an important value enabling the clinician to understand her patients deeply. Finally, *shared decision-making* between the healthcare professional and the patient is another key element of person-centred care, where *effective communication* plays, also a crucial role. The doctor-patient relationship is an important vehicle for enabling these various attributes and is, therefore, a relationship that emphasises *effective communication (including empathy) and shared decision-making, aiming to respect the patient's uniqueness*. This is the understanding of the doctor-patient relationship I use throughout the study.

The enablement of the person-centred doctor-patient relationship is driven both by micro-level factors, practised at the level of the relationship itself, and macro-level factors, specifically sufficient time. Sufficient time is necessary for the practice of these relational aspects. In the next section, I investigate why the person-centred doctor-patient relationship is an important and valuable goal for healthcare systems and, therefore, why we should aim to uphold this relationship, even within resource-constrained healthcare systems.

2.1.3. Relevance and importance of the person-centred, doctor-patient relationship

Why should we care about the person-centred doctor-patient relationship? Why is it ethical to improve or maintain the benefits of such a relationship within cash-strapped healthcare

systems? The person-centred doctor-patient relationship has been linked to improved health outcomes, warranting a focus on it (Kelley, Kraft-Todd et al. 2014). Conversely, a poor doctor-patient relationship can negatively impact health outcomes, making it essential not to neglect this aspect of care even within limited resource settings.

Four key factors can be found in the literature to explain the link between the person-centred doctor-patient relationship and improved health outcomes. First, through effective communication, patients can better understand their illness and the benefits and downsides of treatment, resulting in better treatment adherence (Zolnierek and DiMatteo 2009, Stavropoulou 2011). Increased adherence can also be explained by patients feeling genuinely understood and supported by their clinician (Zolnierek and DiMatteo 2009). Second, through communication and empathy, clinicians can understand what matters most to patients and can, therefore, help them make choices to maximise their well-being in ways that they feel comfortable with (BMA 2024). Third, the relationship plays an important part in understanding the nature of symptoms and apprehending underlying pathologies (Chew-Graham, May and Roland 2004, Kelley, Kraft-Todd et al. 2014). Fourth, there is a "caring effect". Limited evidence shows that when patients perceive their clinician as empathetic, their illness resolves quicker (Rakel, Barrett et al. 2011). A similar effect has been found when the clinician is warm, friendly, and reassuring (Blasi, Harkness et al. 2001). Further indirect links exist between the doctor-patient relationship and improved health outcomes, such as reduced staff burnout and malpractice risk (Gluyas 2015, Drossman and Ruddy 2020). These factors show that the person-centred doctor-patient relationship currently matters at various stages of the clinical interaction between a patient and a doctor.

Health outcomes are a useful metric by which to consider whether person-centred doctor-patient relationships should be pursued. However, the doctor-patient relationship can also be

considered beneficial in-and-of itself, without directly impacting health outcomes. It could impact other outcomes that matter to patients, such as wellbeing. Feeling "cared for" can be important for patients. For example, in palliative care, there are often no expectations for health outcomes to improve. However, clinicians can help improve the wellbeing of their patients, for example, by providing spiritual support (El Nawawi, Balboni and Balboni 2012). There is also evidence that emotional support, particularly compassionate care, is an important factor in end-of-life care (Wenrich, Curtis et al. 2003). There is something unique about the caring aspect of the doctor-patient relationship, as its impact differs from the roles it plays in diagnosis, treatment decisions, and treatment adherence, where the relationship primarily serves functional and decision-making purposes. Caring, on the other hand, transcends the functional requirements of clinical interactions. It addresses the patient's holistic needs, including emotional and psychological aspects, which may indirectly contribute to recovery but also enhance the patient's overall experience, irrespective of health outcomes (Balint 1957, Cassell 2004).

By transcending functional needs, caring also appears to be uniquely human (or animal) to the extent that it does not seem replaceable by other tools. Though "caring robots", for example, have been designed and tested in areas such as elderly care, there are significant doubts about whether non-humans can truly care (Turkle 2011, Sharkey and Sharkey 2012, Wright 2023). For example, it has been argued that while machines can simulate care, they cannot truly replicate human interactions' emotional depth and relational qualities (Turkle 2011). Therefore, the caring aspect of the doctor-patient relationship holds intrinsic value beyond improving health. Caring addresses emotional, psychological, and spiritual needs, enhancing patients' well-being and overall experience. Though machines may replace functional tasks in medicine, there are doubts about whether they can genuinely care.

Despite the importance of the doctor-patient relationship in many clinical cases, it is equally important to recognise that empirical evidence shows that for some patients, speed and convenience can be preferred and prioritised over relational aspects (Hunter, Weber et al. 2009, Cordina, Fowkes et al. 2022). For example, while some argue that telemedicine can harm the doctor-patient relationship (Menage 2020, Andreadis, Muellers et al. 2023), a survey indicates that over half of respondents preferred telemedicine appointments, with the preference being especially strong among those under 65 and in higher income brackets (Cordina, Fowkes et al. 2022). Therefore, all aspects of the doctor-patient relationship do not seem to be valued in the same way by all patients.

Therefore, the person-centred doctor-patient relationship is beneficial insofar as it is associated with improved outcomes mainly through enhanced treatment adherence, a deeper understanding of patient priorities for meaningful health outcomes, and more accurate diagnoses. There are also further benefits, such as reduced staff burnout. The doctor-patient relationship can also be valuable in and of itself, particularly when feeling "cared for" through compassionate care leads to increased wellbeing, as observed notably in palliative care. There is also evidence that not all patients value the doctor-patient relationship equally. However, given the many advantages of the doctor-patient relationship identified in the literature, it is ethically imperative to strive to uphold and strengthen this relationship when it benefits patients to ensure optimal health outcomes.

Figure 1: The benefits of the person-centred doctor-patient relationship throughout and beyond the clinical encounter

Components of the clinical encounter	Benefits of Person-Centred Doctor-Patient Relationship
Diagnosis	Clinician and patient communicate well to understand the patient's symptoms, history, and personal context, leading to a more accurate diagnosis.
Treatment decision	Clinician and patient collaboratively decide on treatment, considering the patient's values and preferences. A genuine understanding through empathetic care ensures the treatment aligns with patient goals.
Treatment adherence	Clear communication helps the patient understand the role, purpose, and importance of adhering to the prescribed treatment.
Caring	A clinician providing a warm, friendly, empathetic, and compassionate attitude can improve patient wellbeing (not necessarily strictly health outcomes)

Based on the literature, **Figure 1** represents a highly schematised version of a clinical encounter which can be characterised by the diagnosis, the treatment decision, and the treatment adherence stage (which goes beyond the direct encounter). While all these steps are iterative, the "caring" stage in particular cuts across the various stages of the encounter. In other words, the caring element can be present across all stages (and sometimes beyond if the other components are not present) of the care pathway. The table illustrates how the doctor-patient relationship positively impacts each stage of the clinical encounter: diagnosis, treatment

decision, and treatment adherence. The column on the right describes how aspects of person-centred relationships, such as effective communication, empathy, and collaboration between clinician and patient, can improve the accuracy of diagnosis, ensure treatment decisions align with the patient's values, and promote better adherence to the prescribed treatment. Additionally, the caring element, characterised by a warm, friendly, and empathetic attitude, is shown to have a positive influence across all stages, ultimately enhancing outcomes. Importantly, not every clinical encounter will possess all these elements, nor will all patients value and benefit from all these elements. For example, in some encounters, the diagnosis is already known. In others, caring may be the only required step (Wenrich, Curtis et al. 2003).

To conclude the first part of this chapter, the doctor-patient relationship is a fundamental aspect of healthcare that involves effective communication, mutual respect, shared decision-making, and empathetic and compassionate care centred around the unique needs and preferences of the patient. The doctor-patient relationship is fundamental to achieving various patient outcomes such as health and wellbeing. It is linked with better treatment adherence, facilitates a deeper understanding of patient priorities, and contributes to more accurate diagnoses. Beyond these measurable benefits, the caring aspect of this relationship holds intrinsic value, addressing emotional and psychological needs that machines may be unable to replicate. Although not all patients prioritise the relational aspects of care, particularly in contexts where speed and convenience are desired, the ethical imperative remains to uphold and strengthen person-centred relationships wherever they benefit patients.

2.2. The doctor-patient relationship in the context of AI-enhanced care

Having acquired an understanding of the doctor-patient relationship and its importance in healthcare, this section investigates how the bioethics literature envisions AI impacting the doctor-patient relationship and in what ways this resembles or differs from the expectations

outlined in policy and professional documents presented in the introduction. As a reminder, many policy and professional documents expect AI to enable an efficient enhancement in meaningful doctor-patient relationships because AI systems are said to save resources (such as time) which can be reallocated to the doctor-patient relationship. They also expect AI to enable faster care, reducing backlogs and wait times between diagnosis and treatment. Some expect that the introduction of AI systems in healthcare will have a negative impact on the doctor-patient relationship because any saved resource will be directed towards increased patient throughput (Sparrow and Hatherley 2020). It is unclear how healthcare policies can balance the benefits of faster care with the preservation of the benefits of the doctor-patient relationship within the context of an efficient system. By turning to the bioethics literature, I map out the current knowledge on AI and its impact on the doctor-patient relationship and investigate potential gaps regarding the effect of AI on the doctor-patient relationship in the context of efficient care.

To this end, I conducted a critical narrative review through searches on PUBMED, Philpapers, SCOPUS, Web of Science, and Google scholar in April 2021 with an update in June 2024 (keywords used can be found in the appendix).[2] I then used a snowball strategy to capture the broader implications of the impact of AI on the doctor-patient relationship. This means that some of the studies that were captured by this review are not strictly in the field of bioethics but social science studies treating bioethics topics. The review is divided into three sections based on the themes that emerged from the literature. The first addresses the issue of autonomy and shared decision-making raised by using AI in clinical settings. The second discusses AI and

[2] This section of the thesis is a modified and updated version of a paper that appeared in Sauerbrei, A., Kerasidou, A., Lucivero, F. *et al.* The impact of artificial intelligence on the person-centred, doctor-patient relationship: some problems and solutions. *BMC Med Inform Decis Mak* **23**, 73 (2023). https://doi.org/10.1186/s12911-023-02162-y

the issue of explainability, and the third explores the role of AI in healthcare, especially focusing on the impact of assistive and replacement models on the doctor-patient relationship.

2.2.1. Patient autonomy and shared decision-making

As discussed in the first part of this chapter, patient involvement in decision-making is a central aspect of shared decision-making in the doctor-patient relationship (McDougall 2019). Increasing the patient's autonomy by encouraging their involvement in decision-making processes is a powerful pushback against the outdated paternalistic model of care (Kilbride and Joffe 2018). Elwyn et al. argue that shared decision-making rests on the acceptance that individual self-determination is a good and, therefore, desirable goal (Elwyn, Frosch et al. 2012). Thus, supporting patient autonomy is important within this framework (Elwyn, Frosch et al. 2012).

Some AI tools may potentially increase patient autonomy and, therefore, the practice of shared decision-making (Žaliauskaitė 2020). Zaliauskaite discusses patient autonomy within the context of technological advances and argues that an effective way to ensure patient's autonomy is the implementation of legal instruments such as informed consent, advance directives and Ulysses contracts (a contract to bind oneself in the future) (Žaliauskaitė 2020). She suggests that technologies such as mobile apps that are used by patients for self-monitoring (collecting any form of health data) may increase autonomy and, in the best case scenario, shift the doctor-patient relationship towards a customer-service type format, where both sides have a balanced distribution of rights and responsibilities, and thereby an equal input/share in the decision-making process (Žaliauskaitė 2020). However, one could argue that it is questionable whether a balanced distribution of rights and responsibilities is feasible in a doctor-patient relationship which is commonly characterised by the vulnerability of the patient towards the doctor and epistemic imbalances (Fricker 2007, Carel and Kidd 2014, Heggen and Berg 2021). Additionally,

there seems to be a risk that such a relationship becomes purely transactional and subject to market pressures. In contrast, Manrique de Lara and Peláez-Ballestas (2020) present a perspective within the context of big data and data processing in rheumatology and argue that relationships must preserve fiduciary duties. According to them, this is necessary in order to protect the promise of an ethical relationship of trust between doctors and patients.

A more fundamental problem arises when considering the type of patient autonomy an AI tool can support within a framework of shared decision-making. Whereas policy and professional documents tend to frame the deployment of AI in healthcare and its associated efficiency savings in a mostly unproblematic manner, the bioethics literature warns that it is unclear how an algorithm could take the preferences of different people (e.g. regarding treatment goals) into account (McDougall 2019), which matters in the case of diagnostic tools that provide treatment recommendations. This could give rise to a new form of paternalism in which the AI makes decisions on behalf of patients and doctors. The difference with the old form of paternalism is that this time, the paternalistic relationship would be vis-à-vis the AI, not the doctor. In other words, "doctor knows best – but the computer knows more and makes fewer mistakes" (McDougall 2019, Arnold 2021). This new form of paternalism would be fundamentally at odds with the principle of shared decision-making. Jotterand and Bosco (2020) as well as Rainey and Erden (2020) share similar concerns, explaining that in the context of neurotechnology in psychiatry, AI tools are potentially dangerously reductive. This is because they are unable to comprehend social, psychological, biological, and spiritual dimensions. Therefore, they, too, argue that AI tools should be designed to allow for value plurality (Jotterand and Bosco 2020, Rainey and Erden 2020).

McDougall uses IBM Watson as an example to argue that AI machines should be designed and built in a way that allows for value plurality, namely the ability to take into account different

patients' preferences and priorities. IBM Watson's role is to rank treatment options based on outcome statistics presented in terms of 'disease-free survival' and to show a synthesis of the published evidence relevant to the clinical situation (McDougall 2019). While, at the outset, this seems to be a typical example of the type of AI system that policy and professional documents refer to when explaining that AI can help save resources, McDougall argues that the treatment ranking by IBM Watson should be driven by individual patient preferences (e.g., one patient might choose further treatment whereas another might choose palliation). Without taking into account value plurality, there is a real risk of the AI's decisions undermining the patient's autonomy (McDougall 2019). There might, however, be a place for AI to improve doctor-patient relationships by supporting decision-making processes. A report by the WHO suggests that, in some cases, an AI providing explanations about treatment options could be beneficial for the doctor-patient relationship, as this might improve communication between clinician and patient if the clinician can go through these options and explain them to the patient (World Health Organization 2021).

Black box AI tools are arguably particularly threatening to shared decision-making as the absence of explainability might hurt patient autonomy by preventing the patient from making informed decisions (Molnár-Gábor 2020). Doctors may have more time to spend talking to patients, but if they are unable to provide the necessary explanations about certain treatment decisions/ prognoses and/or diagnoses suggested by the AI, the benefits of extra time may be limited (Carter, Rogers et al. 2020). The issue of lack of value-plurality can be further exacerbated by black box systems, which may, besides failing to consider individual values, hide biases. A further topic addressed in the bioethics literature is bias and fairness. This issue has also been brought up in relation to the doctor-patient relationship in an EU report by Mittelstadt (2021). AI systems can perpetuate existing biases in healthcare data, leading to disparities in care. For example, suppose training data does not adequately represent the populations the AI

system will be used on. In that case, the AI may make less accurate predictions, which is an especially relevant concern for underrepresented groups (Benzinger, Ursin et al. 2023). Furthermore, ensuring that AI benefits all patients equitably is a significant issue. There is an ongoing debate about how to design and implement AI systems that do not exacerbate health inequalities (Leslie, Mazumder et al. 2021). There is literature on how to build new technologies on adequate datasets, which could lead to a reduction in biases (Abràmoff, Tarver et al. 2023), and efforts are ongoing to ensure new technologies do not reproduce biases stemming from humans (Ganapathi, Palmer et al. 2022). Given the evidence, AI is rightly criticised for the risks associated with bias. However, human clinicians are also biased, often unconsciously, and humans can be inconsistent (Reason 2000, Dekker 2011, FitzGerald and Hurst 2017). Even if AI systems can be built in a way that minimises biases, studies have shown that humans are more accepting of human errors than errors made by technology (Dietvorst, Simmons and Massey 2015). This seems to indicate that patients value their relationship with their human clinician and may prefer AI to be used in an assistive context rather than as a full replacement for the human clinician.

In summary, the emerging literature is divided on whether AI will enhance the doctor-patient relationship by encouraging shared decision-making through increased patient autonomy or create a new form of paternalism by hindering value-plurality and sometimes dangerously making biased recommendations. This divergence highlights the importance of critically examining the potential risks associated with each individual AI system prior to its introduction in care pathways to ensure that technological advancements serve the diverse needs and values of patients.

2.2.2. Algorithmic explainability

AI systems can be seen as a new third actor in the two-way doctor-patient relationship. Just as the doctor-patient relationship is founded on trust (Chin 2001), patients and doctors alike must be able to develop a trust relationship with the AI tool they are using, meaning that they believe that it will act in the expected way. For someone to warrant trust, they need to demonstrate their trustworthiness. One way of doing this is by indicating their reliability. In the case of AI, this might require features such as explainability, validity and freedom from algorithmic bias, as well as clear pathways of accountability (HLEG) 2019). AI tools do not always conform to these values. For example, AI tools are not necessarily built to be transparent (Hagendorff and Wezel 2019, Bjerring and Busch 2021). The continuous search for increased accuracy often compromises AI's explainability**.** From a performance perspective, the best AI tools are, therefore, not necessarily explainable (Amann, Blasimme et al. 2020). Triberti et al. argue that the lack of explainability could lead to a phenomenon of "decision paralysis" due to the trust issues for the users of the AI tool, generated by the lack of explainability (Triberti, Durosini and Pravettoni 2020).

The issue of AI explainability raises a number of ethical questions, including whether it would be justifiable to dismiss the use of highly efficient AI on explainability grounds. Ho argues that uncritical deference to doctors over (unexplainable) AI tools that have outperformed humans may lead to preventable morbidity and is ethically irresponsible (Ho 2019). According to this view, the deployment of an AI tool might end up becoming compulsory as a matter of due diligence (Kolanska, Chabbert-Buffet et al. 2021) and its use might effectively become an epistemic obligation (Bjerring and Busch 2021).

Others argue that explainable AIs might give rise to a more productive doctor-patient relationship by increasing the transparency of decision-making. Mabillard et al. propose a

framework of "reasoned transparency", which entails elements such as abundant communication about AI tools and services and reassurance on data confidentiality (Mabillard, Demartines and Joliat 2021). In a reasoned transparency framework, explainable AI is seen as a powerful tool due to its increased transparency and, therefore, its ability to generate trust relationships between the AI, the doctor and the patient. This is because the doctor can give much more precise information and explain, for example, which specific parameter played a role in an AI tool's prediction (Mabillard, Demartines and Joliat 2021).

Even in cases where AI tools' output is not directly explainable, probabilities are, and doctors may be able to justify diagnoses and explain procedures in a manner understandable to patients, even if the latter are unfamiliar with statistical jargon. Similarly, patients might be happy to develop a trust relationship with the AI tools that they use as part of their self-management and retain a trust relationship with their doctor, on the grounds of explanations of probabilities and statistics the doctor provides. This will depend on medical education changing accordingly, as discussed below.

Kerasidou suggests that there might be a shift away from human-specific skills in an AI-assisted healthcare system if patients and healthcare systems start to value the increased accuracy and efficacy of AI tools over relational values such as interpersonal trust (Kerasidou 2020). In this context, AI tools do not necessarily need to be explainable (or transparent) to improve the doctor-patient relationship, especially if they systematically out-perform human doctors. Patients and doctors alike might start perceiving trustworthiness as based on the level of certainty or accuracy offered by AI tools, as opposed to a high level of transparency. According to Banja, if our primary interest is clinical accuracy, then "just like Watson on *Jeopardy!*, AI is going to win the machine-versus-human contest every time" (Banja 2019) (p.34). He further suggests that AI technologies are held to an unfairly high standard as excessive attention is paid

to their errors instead of human errors. In this context, one could argue that AI tools do not necessarily need to be explainable (and therefore transparent) to improve the doctor-patient relationship, especially if they systematically out-perform human doctors. Patients and doctors alike might start basing their trustworthy relationship on the understanding that AI tools offer a high level of certainty as opposed to a high level of transparency. De Lara et al. explain that medicine is already full of black boxes (Manrique de Lara and Peláez-Ballestas 2020). For example, not all doctors and patients need to understand how electromagnetic radiation works when dealing with an MRI machine. Bjerring and Busch, however, argue that AI is a different type of black box (Bjerring and Busch 2021). They explain that, currently, there is always a human in the loop who is able to give an explanation of how technology works (for example, there will be an engineer able to explain how an MRI machine works), but this cannot be said of some AI systems (Bjerring and Busch 2021).

Beyond issues relating to accuracy and efficiency, explainability is also linked with the problem of accountability. Carter et al., discussing AI-assisted breast cancer diagnostic tools, suggest that a lack of explainability is problematic if the doctor is expected to take responsibility, i.e., be accountable, for decisions involving AI systems (Carter, Rogers et al. 2020). Furthermore, it is unclear to whom responsibility for AI-mediated decisions should be delegated and how the interactions between AI tools and doctors will develop, given this uncertainty (Grote and Berens 2020). A shift in the attribution of responsibility from the doctor to other stakeholders (e.g. AI developers, vendors) may have a negative impact on the doctor-patient relationship as traditional systems of accountability become compromised. This has been recognised as an issue at the policy level, with a report by the EU Parliament warning that introducing new stakeholders in medical decision-making processes adds complexity to a historically relatively straightforward relationship between two actors, the clinician and the patient (EU Parliament 2022).

Generally, therefore, the argument is that due to their lack of transparency and difficulties surrounding systems of accountability, unexplainable, black box AI could have a negative impact on the doctor-patient relationship. On the other hand, the use of highly efficient, albeit unexplainable, AI tools could be morally justified – and indeed encouraged – given the potential health benefits resulting from their accuracy. Further research is necessary to determine how different types of AI tools should be used in different clinical situations.

2.2.3. Assistive vs. replacement models

Many have observed that the impact of AI on person-centred doctor-patient relationships is likely to depend on the role it occupies in clinical contexts, assisting versus replacing human practitioners. The ideal role of AI in healthcare is currently unclear (Triberti, Durosini and Pravettoni 2020). Yun, Lee, et al. shed some light on the current dynamics between AI machines and people (Yun, Lee and Kim 2021). Using a combination of a behavioural and MRI-based neural investigation, they found that, generally, participants demonstrated an intention to follow the advice of a human doctor rather than an AI machine. In the behavioural experiment, they found that participants' self-reported willingness to follow AI recommendations increased if the AI was able to conduct personalised conversations. However, they were still likelier to state they preferred human doctors' recommendations. In a second experiment using neuroimaging, they identified the neurocognitive mechanisms that underlie responses to personalised conversation conducted by AI tools versus human doctors (Yun, Lee and Kim 2021). They found inconsistencies with the first experiment: participants' brain responses showed apathy towards medical AI tools, even when using personalised conversational styles. Human doctors, in contrast, elicited a pro-social response. This experiment suggests a future where AI may be better accepted by patients if it acts as an assistant to human doctors rather than replaces them. Furthermore, a review investigating patients' and the publics' attitudes towards AI found that

while AI was viewed positively overall, participants strongly preferred AI tools to be assistive, with only a minority believing that the technology should either fully replace the doctor or not be used at all (Young, Amara et al. 2021).

Several studies in the field of mental health support the view that AI can only have a positive impact on the doctor-patient relationship in an assistive role by improving openness, communication, and avoiding potential complications in interpersonal relationships (Trachsel, Gaab et al. , Eysenbach, Wright et al. 2018, Szalai 2020). For example, supporting the view that AI can only positively impact the doctor-patient relationship in an assistive role, Szalai argues that AI-based addendum therapy for patients with borderline personality disorder can be beneficial (Szalai 2020). This is done using algorithms capable of identifying the emotional tone of a narrative and fine-grained emotions. Patients may be more willing to disclose information to the AI than to the human doctor, even when they know the human doctor can access the information. On the other hand, Luxton warns of the risk of AI tools replacing human doctors, arguing that the imperfection of the psychotherapist is an essential part of the healing process. He argues that patients must be warned, and stakeholders must be mindful of the ethical implications of using these types of AI tools for mental healthcare (Luxton 2014).

There is some evidence that clinicians also believe that assistive AI may have a positive role to play in doctor-patient relationships. An exploratory survey conducted with general practitioners in the UK showed that they, too, believe in a restricted role of AI within general practice (Kool, Laranjo et al. 2019). Opinions were extremely varied regarding how AI tools may be incorporated into practice. The overwhelming majority of the respondents were sceptical about the ability of AI tools to help with diagnoses, save time, etc. (Kool, Laranjo et al. 2019). Interestingly, however, the study shows that the views of GPs are often far removed from those of AI experts (Kool, Laranjo et al. 2019). The latter forecast that primary care will be radically

transformed as evidence suggests that mHealth tools enable patients to monitor key variables without the need for traditional check-ups. Mihai warns, though, that this may backfire as patients might worry obsessively about continuous monitoring, which is likely to be counterproductive (Mihai 2019), presumably because this might unnecessarily increase the demand for healthcare services as a result. To mitigate this phenomenon, strategies could be put into place where the readings are automatically sent to the doctor but only visible to the patient if they so wish, and alerts are only sent in cases of emergency. These views suggest that AI tools can only positively impact the doctor-patient relationship if they are used in an assistive manner, that is, ensuring human-to-human empathetic relationships are preserved. Karches argues that AI should not replace the human doctor, particularly in caring for people with chronic and terminal illnesses, as human doctors are able to "offer wisdom and compassion from his or her own experience of being human" (Karches 2018) (p.108). Therefore, (preferences for) the use of AI may be influenced by illness type (Karches 2018) and the level of empathy required (Liu, Keane and Denniston 2018).

In summary, if public acceptability of AI tools is a concern, current evidence seems to suggest that introducing them in an assistive capacity in healthcare is less likely to have a negative impact on the doctor-patient relationship. Assistive tools, especially explainable ones, may even support empathetic and trust-based doctor-patient relationships by giving sufficient space to the doctors to perform their role. They can also promote shared decision-making by allowing doctors and patients to take their own preferences into account. It is likely that the use of AI tools in healthcare may spread as patients and doctors adapt to their use. Indeed, Banja observes that humans are robust anthropomorphisers, meaning that they attribute human characteristics to non-human entities. Thus, the acceptance of AI tools is very likely to increase over time (Banja 2019).

2.3. The gap: linking the impact of AI on the doctor-patient relationship with efficiency

As highlighted in Chapter 1, policy and professional documents frequently view enhanced doctor-patient relationships as a byproduct of improved efficiency. It explores important concerns about whether the time saved by AI will be redirected toward enhancing the doctor-patient relationship, as policy and professional documents presented in the introduction often suggest. However, I showed that there is scepticism that, instead of promoting stronger relationships, healthcare systems may prioritise increasing patient throughput, which is another advantage frequently cited in those same documents. Additionally, as discussed in this chapter, the bioethics literature contributes with a critical assessment of the promises outlined in policy documents. While AI holds the potential to support shared decision-making and patient autonomy, it also risks introducing new forms of paternalism, especially when algorithms lack explainability or fail to account for value plurality. Ethical challenges related to transparency, accountability, and bias further complicate the use of AI, as these systems may reinforce disparities in care and erode trust between patients and healthcare providers, therefore harming doctor-patient relationships.

Although the bioethics literature emphasises the importance of the doctor-patient relationship for patient outcomes, it does not sufficiently examine how efficiency factors into this relationship, particularly in the context of AI. Closing this gap in the bioethics literature is critical, as understanding the interplay between AI, efficiency, and the doctor-patient relationship is key to understanding how the doctor-patient relationship can be integrated into a healthcare context that strives for AI-supported efficiency. This is also important given that AI is often introduced into healthcare pathways with the primary goal of increasing efficiency.

As previously noted, the doctor-patient relationship is known to benefit patient care, while efficiency is vital in order to make the most of available resources in healthcare systems. Though the bioethics literature has contributed significantly to understanding AI's impact on the doctor-patient relationship, a key gap remains:

- The bioethics literature does not sufficiently explore the relationship between efficiency and the doctor-patient relationship in the context of AI-enhanced care. It is necessary to understand this relationship in order to address the overarching aim of this thesis, which is to understand **how the doctor-patient relationship can be integrated into a healthcare context that strives for AI-supported efficiency**. As a result of this gap, it is crucial to:
    a. **Theoretically explore the relationship between the doctor-patient relationship and efficiency.**
    b. **Empirically explore how clinicians and AI developers understand AI to impact healthcare practices.** This is because much of the literature is speculative and lacks grounding in real-world experiences of AI deployment in healthcare. This is understandable, given the novelty of AI in medical practice, but it limits our understanding of its actual impact on the doctor-patient relationship and efficient care.

The next chapter will present the methodology to address the aim of this thesis.

3. Methodology

Chapter one has identified the following problem: **how can the doctor-patient relationship be integrated into a healthcare context that strives for AI-supported efficiency?** It is unclear at this stage whether and if resources saved by AI systems will and should be allocated to values traditionally perceived to be associated with efficiency, for example, speed, accuracy, and cost-reduction or whether these resources should be reallocated to relational values such as empathetic and compassionate doctor-patient relationships. The problem is that AI integration in healthcare systems occurs within a complex moral world with apparently conflicting values. Because the values traditionally associated with efficiency are easier to quantify, it is easier to justify a focus on these. In contrast, it is more difficult to know how to ensure that the benefits of the doctor-patient relationship are realised and patient outcomes are maximised. A literature search revealed a gap that must be addressed to determine how the doctor-patient relationship can be integrated into a healthcare context that strives for AI-supported efficiency. Though the bioethics literature has contributed significantly to understanding AI's impact on the doctor-patient relationship, it does not sufficiently explore the relationship between efficiency and the doctor-patient relationship in the context of AI-enhanced care. This requires a theoretical examination of the relationship between the doctor-patient interaction and efficiency, alongside an empirical investigation into how AI is perceived to impact healthcare practices. Integrating these two components allows me to address the central aim of the study effectively.

This chapter describes and justifies the research methods used in this study. The purpose of the research design is to ensure that the results of the study are theoretically robust and practically informed, grounding expectations in current practices, which is important amidst the prevalent speculation in the AI field. I start by reiterating the study's central aim and two related objectives. This is followed by a discussion of the methodologies chosen to achieve these aims

and objectives, including explanations of why these methodologies are particularly suitable and how they work together.

3.1. Aims and objectives

My study aims to understand **how the doctor-patient relationship can be integrated into a healthcare context that strives for AI-supported efficiency.** In order to address this aim, I need to:

a. Theoretically explore the relationship between the doctor-patient relationship and efficiency
b. Empirically explore how clinicians and AI developers understand AI to impact healthcare practices.

I combine theoretical analysis with empirical research, employing qualitative interviews. A proper understanding of how the doctor-patient relationship can be integrated into a healthcare context that strives for AI-supported efficiency requires theoretical engagement with the concept of efficiency and its relationship with the doctor-patient relationship, as well as collection and analysis of the views and perceptions of different stakeholders. Interweaving theoretical analysis and empirical research generates theoretically robust and contextually informed conclusions (Dunn, Sheehan et al. 2012), which ultimately enables me to make useful recommendations regarding how to maximise the benefits of the patient-centred doctor-patient relationship while ensuring the efficiency of the system. I now present the various steps I take to complete this study.

3.2. Definition 1: the doctor-patient relationship

The doctor-patient relationship is a key concept and, therefore, must be defined precisely. I did this as part of my literature review in chapter 2. I defined the doctor-patient relationship as a type of relationship that puts an emphasis on partnerships based on effective communication between the healthcare professional and the patient. Respecting the patient's uniqueness (including their values and preferences) is a crucial aspect of this relationship, as well as shared decision-making between the healthcare professional and the patient where effective communication plays, again, a crucial role. The enablement of the doctor-patient relationship is driven both by micro-level factors, practised at the level of the relationship itself, and macro-level factors, specifically sufficient time. Sufficient time is necessary for the practice of these relational aspects.

3.3. Definition 2: efficiency

The literature review in chapter 2 highlighted the need to better understand how the doctor-patient relationship relates to the concept of efficiency. Efficiency is, therefore, the second key concept of this thesis. While I defined the doctor-patient relationship in the literature chapter, I provide a detailed definition of efficiency at the beginning of my theoretical framework (chapter 4). I explore different perspectives on what constitutes an "efficient" healthcare system, clarifying the varying definitions of efficiency and identifying the definition of efficiency this study will employ.

3.4. Theoretical framework: integrating the 'doctor-patient relationship' and 'efficiency'

To achieve my first objective, understanding how the doctor-patient relationship and efficiency relate, I develop a framework that integrates the two concepts. As a result, I start by analysing theoretically the relationship between efficiency and the doctor-patient relationship. The Value-

Based Healthcare (VBHC) model is introduced as the framework from which I derive my understanding of efficiency and combine it with the doctor-patient relationship. The understanding of the relationship between these two concepts, efficiency and the doctor-patient relationship, gives rise to the theoretical framework. While analysing this theoretical relationship provides a general theoretical framework, it lacks specificity in the context of AI and does not provide information on how this relationship may be enacted in practice. This is why my next step is to conduct an empirical study to ground the framework in real-life practices and ultimately enable me to make theoretically sound and practically informed recommendations.

3.5. Qualitative study: applying the new framework in the context of AI

Qualitative methods are the most appropriate given the aim and objectives of this study. This is because a qualitative study allows for depth of understanding and the identification of the reasons *why* a phenomenon happens (Clark, Foster et al. 2021). In the context of this study it enables me to understand the practical experiences of users and developers of AI and explore what stakeholders perceive to be important with respect to their practice and why they hold these viewpoints.

3.5.1. Semi-structured interviews

Empirical data collection options are numerous, and choosing the right methodologies was an instrumental part of this study. An important consideration in selecting the right method was the novelty of AI in healthcare. I used semi-structured interviews because my focus was on the depth of exploration and the unique experiences each interviewee might have with AI systems. Given that both clinicians and AI developers may interact with the technology in distinct ways, it is important to capture the nuances of their perspectives in a detailed and flexible manner. Semi-structured interviews allow me to delve into these individual experiences, uncovering insights that might not emerge in a group setting, such as focus groups, where personal

viewpoints could be overshadowed or influenced by others. Interviews as a data collection method allow for an in-depth understanding and "seeing through other people's eyes". The flexible, but not totally unstructured, nature of the semi-structured interviews allowed me to explore emerging themes while also grounding my inquiry in the pre-existing theoretical concepts identified in the literature review and theoretical framework chapters (Clark, Foster et al. 2021). This approach enabled me to move between the data and the theory, as new insights from the interviews inform and specify the theoretical framework. Importantly, however, obtaining in-depth data from interviews is only helpful in so far as the choice of interviewees is appropriate and serves the objectives of the study. I now explain my sampling strategy.

3.5.2. Sampling frame

From the overview of the landscape of AI in the UK in chapter 1 and the analysis of the literature and current context in terms of policy and business documents, it emerged that the most relevant AI systems currently used in the NHS are clinician-mediated diagnostic systems. In terms of the feasibility and applicability of my study to the current context, I actively looked for interviewees who were developing or using such systems. My inclusion criteria limited the sampling frame to clinicians working with AI systems in their practice and AI developers working on the development of systems to be used in the healthcare context. My starting point was a case study, which will be described in the next section, followed by a snowball sampling methodology, meaning that I asked my interviewees at the end of each interview if they could suggest further relevant interviewees.

3.5.3. Starting case study: a cardiology diagnostic tool

A spin-off of the University of Oxford that developed an AI system to help diagnose patients with heart disease was identified as the main case study. This company has two products. The first one automatically interprets echocardiogram scans with precision and accuracy, calculating the most common measurements in diagnosing heart health. The second product combines AI

with stress echocardiography to detect earlier signs of coronary artery disease. It has been shown to provide more sensitivity compared to manual reads.

Given the type of AI tools currently being deployed in the NHS, as described in Chapter 1 and **Figure 6** in the annexe, the tools developed by this spin-off provide a relevant case study, as they align with the general characteristics of the technologies the NHS appears interested in funding. The tools developed by this company are mediated by clinicians and are used to help them diagnose patients. Furthermore, this case study was accessible as it is a spin-off from the University of Oxford, facilitating initial contact. The case study is data-rich, as it was a recipient of a phase 3 and phase 4 award in 2020 NHS transformation directorate award (full information in the appendix), meaning that the AI systems were actively used in trials and had several AI developers available to talk about the development of the tool.

The next step was to conduct semi-structured interviews with various stakeholders of the company as my primary case study. Besides the developers, I was able to talk to clinicians using the system as part of the trial the company was conducting within the NHS. As this single case study did not provide enough interviewees, I broadened my search and used a snowball sampling strategy to recruit further participants.

3.5.4. Snowball sampling

The Oxford spin-off initially provided the contact details of their AI developers and clinical advisors. I then used a snowball sampling strategy to continue recruitment. When recruitment started to slow down, I contacted AI companies that had recently won phase 3 and phase 4 NHS Transformation Directorate awards and prioritised AI tools mediated by clinicians and used for diagnostic and/or decision-making purposes. Throughout the process, I mainly interviewed two key groups: AI developers and clinicians.

AI developers:

The focus of these interviews was on understanding how developers, who are at the very start of the AI implementation process, think about the use of AI systems. They are in a unique position to understand the potential shortcomings and advantages of the tools and may be able to give a different perspective on how they see AI systems affecting the doctor-patient relationship and efficiency. The interviews took place until I reached theoretical saturation.

Clinicians using AI tools:

The focus is on generating an understanding of how the AI system has impacted the care for their patients, if at all. Given the recent introduction of AI systems, clinicians using these are in a unique position to compare the current situation with the one before the introduction of the AI system. They are also the "middle-point" between the system and patient levels. They are, therefore, uniquely positioned to address both perspectives: the system-level view of healthcare efficiency and the patient-centred focus on care, bridging the gap between overarching healthcare policies and individual patient experiences

The snowball sampling strategy allowed me to talk to other people who did not fit the abovementioned groups. For example, AI compliance specialists or product managers could give broader perspectives on the deployment of AI tools, such as understanding the goals behind the implementation of AI systems in the healthcare sectors (e.g. improving the doctor-patient relationship by saving time or improving cost-savings by seeing more patients more quickly).

Figure 2 shows the list of interviewees who participated in the qualitative study, and **Figure 3** shows the types of questions I asked during the interviews. Given the semi-structured nature of the interviews, questions changed slightly as the research project progressed and depending on the interviewee. For example, this initial interview guide referred specifically to the Oxford

spin-off products, whereas later interviews no longer focused on the AI systems developed by this company. Later, interviewees came from various fields, including neonatal care, gastroenterology and oncology.

Figure 2: list of interviewees

N °	Role (Clinical or tech)	Type of AI used/role within tech company
1	Clinical	AI for cardiology
2	Clinical	AI for cardiology
3	Tech	Director of AI and computer vision engineering
4	Clinical/Tech	Clinical research scientist at tech company
5	Clinical/Tech	Senior clinical research scientist at tech company
6	Neither	Research Ethics Committee member (expert)
7	Neither	Research Manager at the NHS AI Lab Ethics Initiative
8	Tech	PMO team, project management lead
9	Tech	Data engineer
10	Tech	Compliance manager
11	Tech	Computational biology
12	Tech	Director of a biomedical imaging team
13	Tech	Statistician for brain imaging research
14	Clinical	AI for oncology
15	Clinical	AI for polyp detection
16	Clinical	AI for lung nodules
17	Clinical	AI for Genomics
18	Tech	AI for endoscopy
19	Clinical	AI for obstetrics
20	Clinical	AI for fetal ultrasound
21	Clinical	AI for endoscopy

Figure 3. sample questions for semi-structured interviews

Questions for clinicians
Do you feel the [Company X] tool informed or shaped your clinical decision-making?
How confident did you feel about the feedback/information you received from the [Company X] tool?
Did the tool have any effect on how much time it took you to make decisions about a patient's care? a. If yes, did the tool mean you took more/less time? b. If it saved time, what were you able to do with this time instead? c. If it took more time, what tasks were you unable to complete as a result?
Did you speak to any colleagues about using the AI tool? a. What was this experience like?
Did you speak to any patients about using the AI tool? a. What was this experience like? b. Did you get asked any questions? How did this go? d. Could anything have been improved here?
What impact do you think the AI tool might have on patient's access to stress echocardiograms across the NHS?
What factors currently impact patient's access to stress echocardiograms? How might the AI tool help overcome these?
Is anything else needed for the AI tool to help improve patient access to care?
Has your perception of using AI tools changed over time?
Are there any other factors that would help you to feel more confident or comfortable in using the AI tool as part of the NHS patient care pathway?
Are there any changes that would need to be made at your Trust/organisation to facilitate the AI tool's use?
What impact could using AI tools in healthcare, like the [Company X] tool, have on patient care and clinical decision making? a. Would patient care be improved/worsened as a result of AI tools? b. What are some of the benefits of using AI tools? What are some of the potential risks?
Would you like to share any other thoughts or suggestions with the research team?

Questions for AI developers
What impact do you think AI Tools (such as [Company X] tool) can have on patient care? a. Why or why not? In what ways?
How do you decide what to prioritise when building an AI tool?
When you go to the doctor, what matters to you? 1. Do you think having a good relationship is important?
What are the key concerns of clinicians/patients in using AI in healthcare? 1. Are there any things that can be done to overcome these concerns?
What are your key concerns when developing AI for healthcare?
In your view, what could be done to overcome these concerns?
If you (as a company) have to set the ethical standards to ensure that the doctor-patient relationship is not lost, what would you do?

3.5.5. Ethics approvals, procedures, and consent

Ethics approval was obtained through the University of Oxford prior to the start of the interviews. Informed consent was obtained from the research participants via an emailed consent form before the interview, which they had to sign electronically. In some cases, when participants did not return a signed form, the content of the information sheet was reiterated at the start of the interview and consent was obtained orally and recorded.

All interviews were audio recorded. This is because, given the type of questions that were asked, often encouraging the use of concrete examples and stories, participants' answers were dense and rich in detail. An external device was used for these recordings. Audio recordings were stored in a folder on the university-approved Nexus365 and were destroyed when the transcripts were produced. The resulting transcripts are also stored in a folder on Nexus365.

If a participant requested their interview transcript, I would share this with the participant and give him/her the option to identify sections as 'off the record'. While interviewees were offered the opportunity to view the transcripts on request, it was made clear to them that they would not have access to the analysis of the transcripts and would not be able to alter the interpretation of the data.

All identifiable data (consent forms) will be destroyed or deleted approximately three years after the thesis submission. Contact details were deleted at the end of the study. Linkage codes and audio recordings have all been deleted as soon as the recordings have been transcribed.

3.5.6. Data analysis

All the interviews were first transcribed. Next, I read each interview transcript twice to identify the main points and subjects. Once this was finished for each interview, a summary of all the key concepts and subjects was created. This gave me an overview of the entire data set before the coding and analysis started, allowing me to approach the data with an awareness of the themes that had emerged over the entire set of interviews.

After reading the transcriptions and developing an awareness of the main topics of the interviews, I broke down the data into components, coded it and managed it using the NVivo coding software. Codes were then grouped into broader concepts. I went through this process until I reached theoretical saturation, in other words, until new data no longer illuminated concepts (Clark, Foster et al. 2021) (p.569). Comparing the available data highlighted the collected data's similarities, differences, and relationships. The findings of my empirical analysis were used for my next step, which was the discussion in which I investigated how the empirical data fit the theoretical framework presented in chapter 4 and the literature analysed in chapter 2.

3.6. Integrating the empirical findings and theoretical framework

In the discussion (chapter 6), I focus on weaving together the empirical findings with the theoretical framework and relevant literature. I begin by revisiting the patterns and themes that emerged during the data analysis. As part of the iterative process, I engage in a dynamic back-and-forth between theory and data. By using this process, I aim to integrate empirical evidence with theoretical concepts in a flexible manner. As a result, the discussion emphasises how the data informs the theoretical understanding to the context of AI in healthcare, highlighting the contributions of my research to both empirical knowledge and conceptual development in the field.

I aim to present the findings of my discussion as initial analyses of an exploratory study rather than ultimate truths that must be taken at face value. My goal is to contribute to an ongoing conversation, recognising the complexity and evolving nature of the subject matter. By framing my results as part of an exploratory process, I seek to highlight the potential for further research and dialogue rather than offering prescriptive or absolute ethical judgments. It appears important to recognise that the topic of this research project is relatively new in the world. Artificial intelligence is a comparatively young technology and even younger in the everyday medical context. Its youth brings some difficulties: first, there is a lack of literature informed by practice. While we can speculate on the various impacts of AI based on current evidence and theoretical knowledge, there is a benefit from "going into the field" and finding out the real-life experiences of various stakeholders. As such, we can map the moral domain and perhaps notice that the real-world context brings new or other ethical challenges that had not been thought about in the theoretical literature. Therefore, I aim to make the theory context-appropriate and identify how this contribution can be helpful to policymakers and healthcare managers by proposing policy recommendations at the end of the study. In recognition of the need to

explore this topic further, I end the thesis with suggestions for further research based on shortcomings of this research project.

4. Theoretical framework

What makes the deployment of AI particularly appealing in healthcare is the promise of increased efficiency. This is because AI is said to help achieve more without needing as many resources as would be necessary if hiring new full-time employees (FTEs), for example (EIT Health and McKinsey & Company 2020). This would be a good thing since, according to Cylus et al., evidence suggests that a lack of efficiency is a significant problem in all health systems (Cylus, Papanicolas and Smith 2016). They provide evidence from the World Health Organization, which has been corroborated by the Organisation for Economic Co-operation and Development (2010) to show that many healthcare systems could benefit from a better use of their resource.

However, the concept of efficiency in healthcare remains complex and contested. Traditional approaches often emphasize speed, productivity, and resource optimisation, but these views may overlook the relational aspects of care that are vital to patient outcomes. For example, the doctor-patient relationship, while seemingly less "efficient" because of its time-consuming nature, has been shown to play a crucial role in improving care quality and outcomes that matter to patients, as discussed in chapter 2.

The first part of this chapter investigates how efficiency is currently understood within healthcare, exploring different perspectives on what constitutes an "efficient" healthcare system. This exploration clarifies the varying definitions of efficiency and helps identify the need for a more comprehensive approach. In the second part of the chapter, the ***efficient doctor-patient relationship*** is introduced as a theoretical framework to further our understanding of the relationship between the doctor-patient relationship and efficiency. This will also serve as a framework through which the empirical data of the qualitative study will be analysed. This

framework is grounded in the Value-Based Healthcare (VBHC) theory. VBHC offers a broader understanding of efficiency by focusing on improving patient outcomes relative to the costs of care. In this model, outcomes such as the quality-adjusted life year (QALY) metric are not prescriptive. Rather, they are developed by taking into account what matters to patients, making it a suitable lens for assessing the dual impact of AI on operational efficiency and other outcomes, such as relational ones.

4.1. What is efficiency in healthcare?

The meaning of efficiency will be discussed in depth in the rest of the chapter, but at a very basic level, efficiency can be understood as the best way to use the available resources (Thomas and Chalkidou 2016). Another option to improve healthcare services would be increasing the available resources. While discussions exist on whether the UK could, in fact, afford to increase NHS funding (Edwards 2022), there will never be completely unlimited funding available, meaning that questions pertaining to the allocation of resources will always exist.

The meaning of efficiency can vary considerably. Historical analysis of efficiency has traced variations of the term back to Aristotle (Alexander 2009). Modern use of the word is rooted in the Industrial Revolution when machinery waste was seen as an undesirable side effect. Gerard Joseph Christian, a machine theorist, described a good machine as producing the greatest mechanical effect while using the least amount of fuel (Christian 1822). Efficiency could be precisely calculated in mathematical terms with the aim of minimising loss in perceived useless, extraneous motion (Alexander 2009).

Today, the prevailing interpretation of efficiency remains a legacy of the Industrial Revolution, characterised predominantly by an engineering perspective. Textbooks and dictionaries often define efficiency as *technical* efficiency (Rutgers and van der Meer 2010). This refers to the

relationship between resource input and output. For example, a machine produces the largest amount of goods with available time, materials, labour, etc. (Cambridge Dictionary). As the name indicates, *technical efficiency* is a specific type of efficiency. It does not fit all the contexts within which efficiency is being used, and a single definition of efficiency does not exist upon which the academic community agrees. Heyne argues that *technical efficiency* is meaningless to the extent that, from a strictly physical standpoint, all processes are perfectly efficient. Heyne reminds us that the ratio of physical output (ends) to physical input (means) necessarily equals one, as the fundamental law of thermodynamics states (Heyne). Then, if an engineer judges one machine to be more efficient than another, it is because one machine produces more *useful* work output per unit energy input than the other. Useful is an evaluative term. This reflects a subjective element in defining what is considered 'efficient' in a practical context as there needs to be an agreement on what is useful. Judging a machine's, or any process's, or system's efficiency only becomes relevant if a valuation is attached to a process, a *goal*. Waldo suggests that things are not simply 'efficient' or 'inefficient.' They are efficient or inefficient for given purposes, and efficient for one purpose may mean inefficient for another (Waldo 2017). This understanding makes efficiency neutral in relation to the valued outcome or *goal*. In other words, it suggests that efficiency itself does not inherently favour any particular type of *goal* (Simon 1976). This leads to the critical questions: what is the *goal*, and who is responsible for determining the nature and weight of the *goal* that is valued (Heyne)?

Economic gains, such as profits, are often highlighted when assessing the goal of various processes (Rutgers and van der Meer 2010). This focus can be defined as *economic efficiency*, where the evaluation of processes prioritises their financial effectiveness and benefits (Kalirajan 1989). This understanding of efficiency is arguably a poor guide to public policy, including healthcare, as it ignores values beyond monetary value. Ignoring these non-monetary values can lead to decisions that undermine social well-being, equity, and ethical considerations, which are crucial

for comprehensive and just policymaking. Heyne provides the following example to illustrate this problem:

"The wealthy dowager who bids scarce milk away from the mother of an undernourished infant in order to wash her diamonds is promoting economic efficiency (…) such dramatic examples can remind us that economic efficiency is not the highest good in life, but that does not mean we should discard the concept."(Heyne)

Given the shortcomings of *economic efficiency* (a form of technical efficiency with monetary value as its valued outcome) in specific contexts such as in public policy, which includes healthcare, Rutgers and van der Meer advocate for a distinct interpretation of efficiency. Their approach departs from the traditional, modern focus rooted in the Industrial Revolution and engineering. Instead, they draw upon a historical framework, tracing back to the ideas of Aristotle. This alternative perspective offers a richer understanding of efficiency. It entails "a broad value spectrum: abilities to act, to act timely, knowledgeable, with integrity, and so on" (Rutgers and van der Meer 2010) p.774. This approach is not convincing in terms of its usefulness, as they recognise that the broadness of the concept renders it vague, making it difficult to use it in practice. This is an ongoing problem with efficiency, which requires balancing "reductionism and indeterminacy" (Mitchell, Crowe et al. 2024) p.16.

The challenge then becomes to find a way to reconcile efficiency with its use in healthcare as part of the public sector, which does not aim to make a profit but rather focuses on the public good. The challenge lies in defining precisely what is *useful* in the healthcare context; in other words, there needs to be a clear goal against which the efficiency of a system or process can be evaluated. As mentioned previously, determining this goal is an evaluative process because it

involves making value-laden decisions. In other words, ""doing efficiency" is always also "doing ethics"" (Mitchell, Crowe et al. 2024) p.17.

The Healthcare Financial Management Association (HFMA) is a charitable organisation that provides support and guidance to the healthcare community. Its aim is to promote professional standards and innovation in financial management and governance across the UK health economy. The HFMA borrows their definition of efficiency from the National Audit Office (NAO) and defines it as 'the relationship between the output from goods or services and the resources to produce them – spending well' (HFMA 2024) p.190. They add that this definition effectively means that efficiency is "about doing the same while minimising waste or costs – there is no reduction in quality" (HFMA 2024) p.190. The problem is that it is not clear what the *goal* is. According to NHS, its main aim is to provide high-quality services for all (NHS England 2024), which is presumably the goal to which these definitions refer. However, this goal is too broad to effectively operationalise efficiency. This ambitious aim encompasses a vast array of services and patient needs, making it challenging to set specific, measurable targets for efficiency improvements. As a result, in the UK, the efficiency of the healthcare system is often calculated using efficiency targets, which, on the contrary, are very narrow and easier to calculate. For example, increasing the number of beds for unit resource (Anandaciva 2023). This may be efficient from a number of beds' perspective, but it does not necessarily mean that outcomes will improve for patients. Another problem with using a narrow approach is the Jevons paradox (Polimeni 2008). The paradox states that any efficiency gains with which a resource is being used result in increased consumption of that resource (Polimeni 2008, Ettinger 2022). For example, if an MRI machine becomes cheaper and faster, the logical outcome should be that resources are saved while at the same time keeping health outcomes the same or improving them. The paradox is that instead of decreasing overall healthcare costs, the

efficiency of MRI technology leads to increased usage and, in some cases, higher overall costs for healthcare systems as more patients undergo scans.

In order to avoid the problem of optimising the efficiency of specific metrics, which do not necessarily contribute to overall outcomes, Ettinger suggests that an allocative efficiency approach would enable patients to receive interventions that provide the most value instead of many that may not be valuable to the patient (Ettinger 2022). The following anecdote illustrates this:

"My grandad is in his mid-80s. He has atrial fibrillation, diabetes and is becoming frailer and frailer. Two weeks before Christmas he had a visit from a speech therapist as he was having problems swallowing. I am told the therapist was wonderful. They were clearly good at their job and listened attentively to his needs. The speech therapist gave my grandad some verbal advice and left him a leaflet. Whilst this was helpful, my grandad complained the benefit to him was minimal. This was not a new experience for him. In the last three months he had, on top of two hospital trips, visits from physio, speech, and occupational therapists. They all left him with similar advice and the same problem. Only minimal benefit for a lot of effort." (Ettinger 2022)

Allocative efficiency is about allocating resources in such a way that the combination of interventions provides maximal health benefits for the population (Ettinger 2022). Determining what constitutes an optimal allocation of resources is intricate, as it involves weighing individuals' and society's diverse needs, preferences, and values. Moreover, healthcare outcomes are influenced by various factors, including medical progress, patient demographics, and evolving treatments. Balancing outcomes appropriately involves making value-laden decisions. For example, how does the system value equity in relation to health outcomes for specific rare diseases? Funding expensive research for diseases suffered by few may result in fewer funds to ensure fair access to healthcare services. Of course, healthcare decisions are rarely this

straightforward and involve multiple factors, which must all be balanced to create the best possible overall outcome. When reaching the optimal balance (or getting as close to it as possible) of interventions in line with the goal of maximising health benefits, the healthcare system can be said to be in a state of *allocative efficiency*. At this point, each individual process within the larger mix can be reviewed for its *technical efficiency*, ensuring that the outcome remains *allocatively efficient*. Balancing these considerations and striving for an equilibrium between different forms of efficiency is a dynamic challenge for healthcare systems, including the NHS (Healthcare Financial Management Association 2023).

Instead of focusing so much on individual metrics, as is the case today in the NHS, a combination of *allocative* and *technical* efficiency, as I represented graphically in **Figure 4** below, can be viewed as ensuring optimal resource use for healthcare quality while prioritising interventions for maximum societal health benefit. This dual approach balances effective resource allocation and other important healthcare values, such as equitable service distribution (Neville and Ricozzi 2023). Given that *allocative efficiency* arises when the right mix of services is provided, there is a responsibility at the governance level to get this mix of services or interventions right and identify exactly what the *goal* is. *Technical efficiency*, on the other hand, is more likely to arise at the "single process level", for example, the practitioner level. *Technical inefficiency* could be the result of wrong incentives, poor management, or poor information.

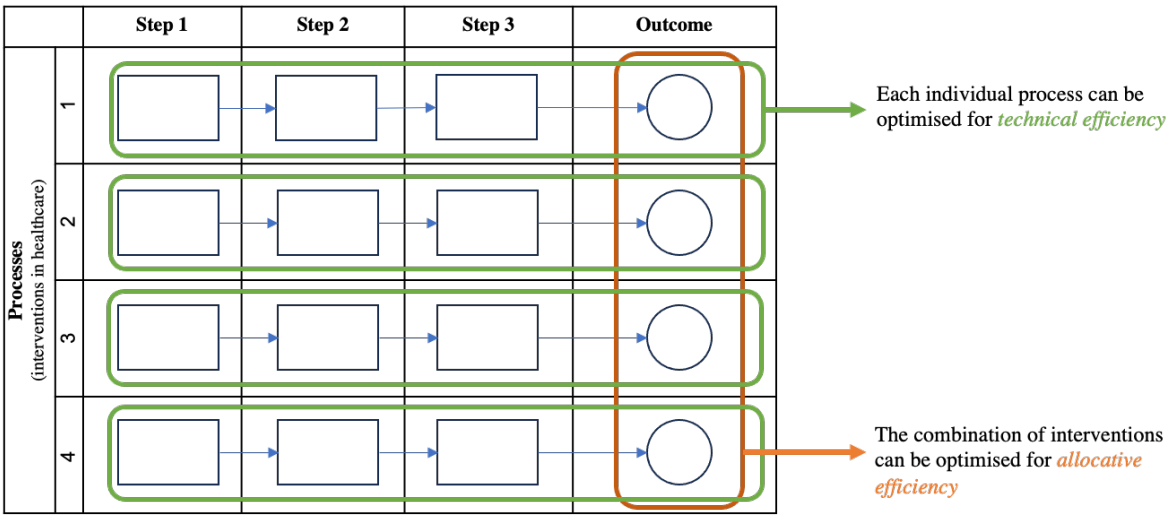

Figure 4: *In this figure, I show that allocative efficiency and technical efficiency work together in order to optimise a pre-determined outcome*

4.2. Allocative efficiency, valued health system goals, and control

The concept of *efficiency* (*allocative* or *technical*) is closely linked with the idea of control. At the *technical,* single-process level, this can be explained by the requirement of absolute mastery and the capacity to govern each constituent element within that process. For example, "attempts to increase the engine's efficiency require observing it closely enough to find avenues of greater control. Efficiency operates as a technique of control by providing a model of how a machine or process should function and a technique for measuring how closely that function matches the model. The model thus functions as a benchmark or yardstick." (Meijers 2009)(p.1011).

Regarding *allocative efficiency*, decisions relating to the values with which processes should align and establishing the right programme mix to support these pre-determined values are not automatic. They require active decision-making and are, therefore, in the control of the decision-maker(s), not the healthcare staff. For example, a GP can ensure that the processes within his own practice are efficient. If a patient requires a renewal of their medication for a chronic condition, the GP can streamline the procedure from the patient's initial request for a new prescription to the actual issuance of the prescription, ensuring the process is as *technically*

efficient as possible. However, the GP cannot decide what the right mix of programmes for the entire NHS looks like. Instead, these are decisions made at different levels of the system governance level and are political, value-laden decisions. The overall funds available to the NHS are voted on by parliament. Though healthcare is largely a devolved matter in the UK, through the UK Department of Health and Social Care (DHSC), the UK government sets the overall health strategy for the UK. The DHSC supports the ministers and is accountable to the parliament and the taxpayers for the health and care system. Smaller local commissioning groups have some freedom over local fund allocation decisions within the bounds of the priorities set by the DHSC.

The DHSC's responsibilities include "supporting and advising ministers" and "setting direction" (Department of Health and Social Care 2024). The UK government, through the DHSC, therefore, has c*ontrol* over determining the mix of programmes the NHS should strive to be *allocatively efficient*. The government is ultimately in charge of determining the mix of programmes proposed by the NHS. The government plays a significant role in the relationship between the efficiency of the system and the resources it manages, including time, through the *control* it can exercise over these. Within this context, determining a "valued outcome" or *goal* is key to making a healthcare system efficient by allocating the right mix of interventions to achieve this pre-determined outcome. Yet this is highly complex due to resource constraints, the inherent tension between individual and population-level priorities, and the challenges of measuring health outcomes accurately.

As mentioned previously, the NHS states on its website that its goal is to provide high-quality services for all (NHS England 2024). The NHS Long-Term plan provides more details (NHS England 2019). It outlines several detailed strategies to achieve its goal of providing high-quality services for all. For example, it includes commitments to adopt digital technologies, emphasises

the importance of preventative care and integrated care systems to reduce hospital admissions and ensure that patients receive appropriate care in the most efficient setting (NHS England 2019). These initiatives are aimed at ensuring that high-quality healthcare is accessible and sustainable across the NHS. However, the complexity of too many details prevents the operationalisation of efficiency in practice. As mentioned previously, the focus on all these intermediary outcomes, such as reducing hospital admissions or increasing the number of hospital beds, is not a good way to evaluate the efficiency of the healthcare system and has been criticised as taking the focus away from what truly matters (Porter 2010).

If "providing high-quality services for all" is too broad a *goal* for efficiency in healthcare and intermediary outcomes are inadequate, the HFMA introduces the concept of value as a helpful tool (HFMA 2024) p.188. Value-based healthcare (VBHC) offers a constructive framework to conceptualise and achieve efficiency in healthcare by aligning patient-centred outcomes and focusing on delivering high-quality care, but it has not yet been adopted in the everyday language of the NHS (Hurst, Mahtani et al. 2019). VBHC, as defined in Porter and Teisberg's *Redefining Health Care*, builds on the principles of allocative efficiency by ensuring that healthcare resources are distributed in a manner that maximises health outcomes (Porter and Teisberg 2006). Allocative efficiency focuses on optimising the allocation of resources to achieve the greatest overall benefit, emphasising the overall welfare of the population (Kaplan and Porter 2011). VBHC extends this by prioritising patient-centred outcomes and directing resources toward treatments and interventions that provide the highest value in terms of both quality and cost. This approach ensures that investments in healthcare are made where they can achieve the most significant impact on patient health and well-being, thereby enhancing the overall efficiency of healthcare delivery (Porter 2010, Porter and Lee 2013)

4.3. Value-based healthcare

Value-based healthcare (VBHC) is an approach to medical care that prioritises patient outcomes relative to the cost of delivering those outcomes, focusing on maximising the value derived from healthcare expenditures. This approach was developed by Porter and started from the observation that stakeholders in healthcare have several, often conflicting goals ranging from access to services to cost containment, safety, patient-centeredness, satisfaction, and so on. These intermediary goals are clearly outlined in documents such as the NHS Long-Term Plan (NHS England 2019). Despite the numerous intermediate goals, lack of clarity about "final" goals has led to divergent approaches, gaming of the system, and slow progress in performance improvement (Porter 2010). The purpose of VBHC is to incentivise healthcare providers to deliver high-quality care that improves patient health and well-being. In other words, this is a model of healthcare where the goal of healthcare is unambiguous and straightforward, making it very clear what the *goal* of efficiency is: achieving high value for patients where value is defined as the health outcomes achieved per dollar spent (Porter 2010). Importantly, achieving value is not necessarily about providing a high volume of services, rather, it is about providing the best possible combination of services to achieve the best possible health outcomes per dollar spent. Since value is defined as outcomes per dollar spent, it encompasses the concept of efficiency (Porter 2010). To reframe Porter's conceptualisation of value in terms of efficiency, efficiency is achieved when the best possible outcome (for the patient), the *goal*, is achieved per pound spent.

VBHC can be seen as building on the concept of allocative efficiency, as both concepts share the goal of optimising health outcomes per pound spent. The goal of allocative efficiency is to create the right mix of programmes to enhance population health. However, this broad scope involves balancing numerous factors, such as cost-effectiveness, equity, and population health

needs, making the goal abstract, complex, and difficult to work with in practice. VBHC takes a more individual approach rather than a large population-based model and goes a step further by clarifying *how* health outcomes can be optimised for individual patients, thereby clarifying how the goal of healthcare should be conceptualised, which, in practice, makes it easier to improve efficiency.

In his framework, Porter defines outcomes that matter most to patients by focusing on clinical results, functional status, sustainability of health, and patient-reported experiences. To ensure these outcomes are tailored to individual patients, Porter advocates for the use of Integrated Practice Units (IPUs), which are specialised, multidisciplinary teams providing care for specific conditions throughout the entire cycle of care. This holistic approach considers all aspects of a patient's journey, from diagnosis through treatment and recovery, and incorporates patient involvement to align care with individual values and needs. By consistently measuring and reporting outcomes at the individual patient level and using personalised treatment plans, VBHC's framework ensures that healthcare delivery is responsive to the specific characteristics and preferences of each patient. A possible criticism is that it will never be possible to truly cater to what matters to individual patients (Steinmann, van de Bovenkamp et al. 2020). A proposed solution is to focus on groups of patients sharing similar characteristics, and who are likely to broadly share similar goals (Porter 2010). For example, a child who has diabetes is likely to have different priorities than a retired person who has diabetes. This patient-centred focus, supported by continuous improvement through detailed outcome measurement, shifts the emphasis from volume to value, achieving the best outcomes at the lowest cost for each patient.

It is important to recognise that this conceptualisation of efficiency, which prioritises outcomes that matter to patients, inherently involves a significant normative decision in defining the goal (Mitchell, Crowe et al. 2024). Even though I have argued that this *goal* seems to be an

appropriate one in healthcare, especially compared to its alternatives, it is crucial to acknowledge that efficiency gains are not unequivocal improvements but rather involve trade-offs that must be carefully considered. Because there is a need to operationalise efficiency in a practical way, this inevitably results in a narrower understanding of efficiency, excluding some of the values that one might wish to incorporate. Mitchell, Crowe et al. (2024) raise the important point that those with decision-making power must remain alert to the limitation of models of efficiency as decision-making tools.

4.4. The efficient doctor-patient relationship

Chapter 1 demonstrated that policy and professional documents view improvements in the doctor-patient relationships as resulting from efficiency. When AI saves resources, these can be allocated to the doctor-patient relationship. However, some of the literature on the doctor-patient relationship covered in chapter 2 pointed towards the idea that good doctor-patient relationships save money and improve health outcomes through various mechanisms (Kelley, Kraft-Todd et al. 2014, David Meltzer, Gregory Ruhnke et al. 2023). Porter's framework emphasises the importance of focusing on final outcomes rather than intermediary outcomes. Intermediary outcomes are immediate results of healthcare processes and interventions. These outcomes are important for monitoring and improving specific aspects of care. However, excessive focus on intermediary outcomes can overshadow the importance of final outcomes, which are the ones that ultimately matter to patients. Porter uses the following example: "radiologists focus on the accuracy of reading a scan, for example, rather than whether the scan contributed to better outcomes or efficiency in subsequent care. Cancer specialists are trained to focus solely on survival rates, overlooking crucial functional measures in which major improvements vital to the patient are possible" (Porter 2010). A good doctor-patient relationship is a classic example of an intermediary outcome, according to Porter's framework. It facilitates important elements of healthcare, such as effective communication, which

enhances adherence to treatment plans. This is important because this intermediary outcome has an impact on the final outcome, the ultimate measure of healthcare success. However, overly prioritising intermediary outcomes, such as the doctor-patient relationship, can overshadow the importance of the final outcome: enhancing the overall health as defined by patients.

By clustering patients into groups, the VBHC model makes space for recognising that the needs of patients vary, including the need for the doctor-patient relationship as an important intermediary outcome. In some cases, the doctor-patient relationship takes much more space as it will be a crucial contributory element to improving the final outcome of improving health as defined by the patient. In some other cases, the doctor-patient relationship will make a minimal contribution to improving health as defined by the patient. The literature in chapter 2 on the doctor-patient relationship provides some clues. For example, there is some evidence to suggest that through effective communication, patients can better understand their illness and the benefits and downsides of treatment, resulting in better treatment adherence (Zolnierek and DiMatteo 2009, Stavropoulou 2011). This indicates that patients needing to adhere to treatments are likely to benefit disproportionately from a meaningful relationship because this relationship helps them reach their health outcomes. Furthermore, for some patient clusters, such as those with metastatic cancer, Porter recognises that aspects such as survival or degree of recovery have little relevance (Porter 2010). However, other aspects, such as reducing discomfort, may be more important for this cluster. In such cases, a meaningful doctor-patient relationship is crucial, as it can significantly contribute to achieving these patient-centred outcomes.

By acting as an intermediary outcome, the doctor-patient relationship helps achieve the final outcome of enhancing health as defined by the patient and can, therefore, be prioritised

depending on the situation. In other words, by recognising that the need for the doctor-patient relationship varies based on patient clusters, the doctor-patient relationship can be framed in terms of efficiency. For example, in cases where the doctor-patient relationship plays a significant role in reaching the final outcome, it is efficient for the doctor-patient relationship to use more resources. When a patient needs to achieve long-term adherence to treatment to see an improvement in health, the doctor-patient relationship may be instrumental in reaching this outcome, justifying the allocation of additional time to it. However, since every patient cluster is unique, some might not require as much relational attention. In these cases, less resources can be spent on the doctor-patient relationship.

By varying the resources spent on the doctor-patient relationship on a case-by-case basis (or cluster-by-cluster basis), the doctor-patient relationship can be made efficient. This is because the use of resources can be optimised depending on the situation. By asserting that AI has the potential to give time back for the doctor-patient relationship, policy documents fail to differentiate between various situations. These documents create the impression that increasing doctor-patient interactions is always beneficial. However, within an efficient system, additional time for the doctor-patient relationship is not always necessary, but can be instrumental for patients to achieve health outcomes. Therefore, the doctor-patient relationship should be viewed as an intrinsic part of an efficient healthcare system. In other words, efficiency should not be viewed in isolation of the doctor-patient relationship.

4.5. Conclusion

The framework of the *efficient doctor-patient relationship* provides a robust approach for analysing the doctor-patient relationship in the context of efficiency in healthcare. This framework views the doctor-patient relationship as an integral part of efficiency. Unlike other definitions, VBHC stands out as a basis for understanding efficiency in the healthcare context because it clearly

outlines the specific goal of healthcare. By understanding allocative and technical efficiency, it becomes evident that clearly defining the goal of efficiency is crucial. However, many discussions of efficiency in the healthcare context, including those by institutions like the HFMA, often fail to provide a clear definition, leaving the concept too vague and of limited use in its practical applications. The VBHC framework fills this gap and provides a clear pathway to efficiency by defining the *goal* of healthcare as achieving health outcomes that matter to the patient or patient clusters. By attaining these outcomes within the resources made available, optimal efficiency (relative to the established *goal*) is achieved.

Intermediary outcomes, such as the doctor-patient relationship, play a crucial role in achieving the ultimate goal of improving person-centred health outcomes. However, the primary focus should remain on optimally using resources to reach this final goal, ensuring that resources are allocated across intermediary outcomes in a way that best supports this goal. Making the doctor-patient relationship efficient should, therefore, be an important goal for decision-makers in the field of healthcare if the outcomes that matter to patients are the primary concern. In the following, I use the term *efficient doctor-patient relationship* to refer to the doctor-patient relationship when it contributes to maximising the goals that matter to patients.

In Chapter 6, I deploy the *efficient doctor-patient relationship* framework to analyse the data gathered through interviewing clinicians using AI as well as developers. Analysing my qualitative data using this framework helps me understand how AI tools in healthcare can affect the efficiency of the doctor-patient relationship and what this means for patient outcomes. This analysis helps us understand when and how AI could contribute to more tailored relational care, where the valuable aspects of the relationship are maintained, ultimately optimising patient outcomes in an efficient manner. Furthermore, the analysis of the empirical data helps me specify the theoretical framework for the specific context of AI deployment in healthcare.

5. Interviews

I collect qualitative data through semi-structured interviews to **explore how clinicians and AI developers understand AI to impact healthcare practices.** Through the snowball sampling strategy, I have also interviewed one person in the field of AI governance, who could share his perceptions regarding the aims of introducing AI in healthcare, and one person in a research ethics committee who provided his own experiences relating to the use of AI in healthcare. This chapter is organised into sub-chapters based on the themes uncovered through the data analysis, which employed coding techniques, as described in the methodology chapter (Chapter 3). Exploring these real-world perspectives ensures that the subsequent discussion is contextually informed and grounded in real-world experiences. This is especially important given the novelty of AI systems and the fact that much of the existing literature remains speculative, lacking direct engagement with the real-world implementation of AI in healthcare. The clinicians interviewed in this study have used AI systems in their practice, while the developers interviewed were engaged in developing these systems.

5.1. Reallocation of time

As shown in Chapter 1, policy documents claim that the use of AI in healthcare leads to time savings, which then leads to the reallocation of time to the doctor-patient relationship. According to these documents, this mechanism means that using AI directly leads to improved doctor-patient relationships. The interviews aimed to understand how clinicians' experiences and perceptions of using AI in their day-to-day practice and AI developers' intentions aligned with these high-level visions.

One of the theoretical aims of AI is to provide more personalised care

Some interviewees, including the next interviewee who works in the field of AI governance, hope that time saved by AI systems can be allocated to "a more personal way of providing care". He explains that this is one of the hopes associated with the use of AI systems:

> *"By having AI perform some tasks that are now taking time and resource and effort from the clinicians or other sort of professionals, then* ***it would allow, you know, that time (…) to go into a more personal kind of way of providing care.*** *And I think that's actually what a lot….I think that's the intention, you know, that's what we're trying to do"*
> *Interviewee 7 – AI governance*

This interviewee shows that there is a will to improve specific aspects of the doctor-patient relationship at a systemic level. However, often, developers did not focus specifically on how their systems could improve relational aspects. Rather, the key focus of many developers was to create precise, accurate, and consistent tools that can help clinicians enhance their clinical abilities and improve patient health outcomes. As one of the AI developers noted:

> *"If you can get the level of an AI high enough that this determination is correct,* ***you can, in my opinion, reduce the risk of cancer, or cancer evolving****."*
> *Interviewee 18 – AI developer*

AI developers, unless prompted, never viewed the improvement of the doctor-patient relationship as a particularly important aim. The focus is mostly on creating tools that can be validated and help clinicians perform better, for example, in terms of diagnostic accuracy.

The impact of AI on the doctor-patient relationship depends on decisions made by management at the system level

An interviewee explained that he found it impossible to say how time saved by AI will be used in the future. He believed that medicine is likely to change so significantly that it is impossible to determine at this point whether specific activities which are currently considered important will still be needed.

> "The **current healthcare practice we have will not be the same**. So trying to fix, I guess what I'm really saying is that actually we've now got cars and we're trying to plump them on steam engines and actually it's all changing. (…) And **I think this**

> **conversation about "the algorithm is taking three minutes off that doctor time" or whatever it is…It may be that doctor time isn't used at all in that area of disease** (…) but **I think it's all going to change**. I think with cancer and stuff like that, it is going to be changing with the blood biomarkers. So you take 30 ml of blood and you look for circulating tumour DNA and you look for protein biomarkers because tumours and things like that, or heart failure secretes different proteins and so it's quite complicated…**I think to suggest that algorithms are just going to make people have five minutes more per patient…maybe they won't be seeing those patients**"
> *Interviewee 16 – Clinical researcher*

This researcher foresees radical changes in the way healthcare will be provided, making it impossible to predict exactly how much time AI tools can save, and how this saved time can be reallocated. He suggests that there is a possibility that some doctors will not need to see patients at all.

Unlike the above quote, most interviewees believe that the impact of AI systems is predictable, because it is dependent on the priorities of healthcare systems. Clinicians showed scepticism when discussing whether time saved by AI tools can be reinvested in the doctor-patient relationship. Allocating resources to one area of healthcare, such as increased throughput, will be at the expense of a different area, and decisions related to resource allocation will depend on priorities. This clinician argues that speeding up processes will likely result in losing out on something else that matters, such as empathetic relationships.

> *"There is an argument that it might be able to speed things up. But then* ***that would probably be at the expense of something else, which might be the expense of having, you know, (…) the time we have, we can use more empathetically for the patient to sort of talk through what's the finding within the results rather than having to sort of be a bit vague about your answer so you can be more clear and have time.*** *I guess you could argue that actually if you don't want to introduce that, you could shorten it down. Just be able to give the results and then save time. Sure.* ***But then actually the AI is losing something by doing that*** *(…)* ***It depends on your priorities!"***
> *Interviewee 8 – Clinician*

System priorities, set by management, are important in attempting to pre-determine the impact of AI. For example, in some healthcare systems, the benefits of the doctor-patient relationship

resulting from extra time will likely be short-lived, as management will realise they can save money instead. This points towards the influence of healthcare systems' management, the lack of agency of clinicians over their schedule, and the inability of AI systems to "automatically" improve the doctor-patient relationship without the involvement of the healthcare system, headed by management:

> *"You could potentially save a couple of minutes in a 25 minute exam. Doesn't sound like a lot,* ***it's a significant bit of extra time that you can then do other stuff, like communicate with the patient, explain things to them. Yeah, I think it's a potential benefit. That allows people to do what people are best at, which is to communicate, to explain, to talk patients through things****. Rather than to do repetitive manual tasks. Now then truth is if you do have a consistent time saving,* ***it's likely that you won't get more time to talk to the patient at all. Because the management will realise that there are two minutes of efficiency saving*** *that you can have that will just then disappear. But sure, at least in the interim period, it would be helpful".*
> *Interviewee 20 – Clinician*

This interviewee explains that the extra time AI could help gain, which he sees as a real possibility following his own experience with AI systems, would enable clinicians to do "what people are best at", namely, communicate with patients. However, he notes that ultimately, management decides the type of impact AI tools can have through their decision to reallocate resources to areas considered more important.

What happens to the time that AI systems help clinicians to save? A developer highlights that as soon as the time to visit a patient decreases, the time could be spent to "get through as many people as possible". This is dependent on the system and could have a positive or negative connotation:

> *"****We'd like to think that it would be different in the UK than say in the US because of the patient structure.*** *But that's heavily predicated on "You would like to think that". Obviously, you can look at that as a negative, that they're just trying to get through as many people as possible. If they're getting money for that, then that's a financial incentive.* ***But if they're trying to get through as many people as possible, maybe that will reduce the burden on the overall health system.*** *If we're overburdened, maybe if they have more time and they can get through more people, maybe more people will be seen. It's not a financial thing. It could be both, but yeah,* ***it's definitely a***

concern and it's probably the reality, whether that's a positive or a negative is probably depending on how you look at it."
Interviewee 5 – Clinical researcher within an AI development company

According to this participant, the extra time could be used to see more patients more quickly. This quote shows that speeding up processes can be seen positively or negatively. It can mean shorter consultation times with the negative impacts this could have on the doctor-patient relationship, for example, but it can also help clear backlogs, which is positive as patients do not have to wait as long before receiving care. This interviewee also highlights how different healthcare structures may create different outcomes on the impact of AI systems following their integration. Other interviewees also emphasised the different impacts AI systems can have depending on the type of healthcare system in which they are implemented. In other words, depending on the system, resources may be allocated differently based on the system's priorities.

The healthcare system's influence on decisions regarding resource allocation

AI developers recognised that the impact of their AI systems on healthcare is largely determined by the governance of the healthcare systems in which they are implemented. This means that AI systems can optimise various aspects of healthcare depending on the specific policies, regulations, and structures of the healthcare environment in which they are used. Comparisons were often made between the US and UK healthcare system to illustrate this:

"Let me give you the nice version and I'll tell you some of the slightly dark realities of the American healthcare system. But ***it's largely about kind of optimising the clinical care pathway. So, if we have these tools that are able to automate measurements and generate things faster, they're more liable to be used in something like the NHS, whereas right now they don't do a lot of extra analysis, they just eyeball things and that tends to work.*** *(…) The other thing you can do is (…)* ***you can come up with this triaging thing. (…) We're working on doing the cost implications of that. You can imagine that might save money, right? (…)*** *In America (...)* ***you can end up in quite dark places where you're trying to charge for more exams****. You're trying to end up with more exams in a given pathway and trying to get them to do more tests.* ***And that's generally how the American healthcare system works. That's why they do lots of things because they can then charge. (…)*** *They could argue that helps patient care. There'll be more accurate. Maybe they are more likely to pick*

> *up disease, but then there will be people who will be healthy, and you know, they don't need more stress.* ***That's an interesting ethical gray area and the American healthcare system very much feeds that, whereas the NHS (…) they are trying to save as much as possible, which has its own problems as well"***
> *Interviewee 1 – AI developer*

By comparing the UK system with the US system, this interviewee shows how one AI system, for example, the one developed by his company, can impact a specific system differently. In this case, it is not the AI system that shapes the impact, but the system that determines what kind of impact it wishes the AI to have. In the US, it looks like the AI system can be used to do more exams, which results in more income for the healthcare system, potentially better health outcomes, but also potentially unnecessary stress for the patient. On the contrary, in the UK, the same AI tool can be used to avoid patients having to do extra exams. This developer explains that AI can be used differently, and have a different impact depending on which healthcare system the AI is implemented in. In essence, the impact of AI is not fixed by itself but is largely fixed by the healthcare system into which it is being integrated. Going back to the two previous quotes by clinicians, they found that the healthcare system is not geared towards investing time in the doctor-patient relationship, no matter the capabilities of the AI system. Here, the AI developer confirms that a single AI can be used for very different purposes depending on the system in which it is being implemented. In other words, if the system does not value the doctor-patient relationship, it is unlikely that the integration of AI systems can improve doctor-patient relationships through the reallocation of resources such as time. As the next section will show, my interviewees viewed the healthcare system and management as having an influence not only on the type of impact AI systems have, but also on the very development of the systems.

5.2. Systemic priorities and AI development

An AI system is often viewed as a solution that can be integrated into the existing healthcare framework to generate incremental improvements, rather than fundamentally transforming the healthcare system as a whole. Interviewees stated that AI should be built to fit into current

systems seamlessly and should not act as disruptors, even though the general consensus among interviewees seems to be that we are stuck in a "Sisyphus-type cycle", meaning that, as medicine can do more and more, new technologies will always play catch up with the increasing workload.

Several interviewees explained that AI systems are designed in a way that clinicians do not have to change their way of working. The workflow remains exactly the same, with no time being gained but also no time lost.

> *"In conceptualising how you use this tool (…) what you want to do is introduce something, which means* ***they don't need to change what they're doing***. ***They can keep doing what they're doing, and they just have this additional information,*** *which we've been able to achieve. But as a result, you don't allow more time or create more time. Which is a good thing, right."*
> *Interviewee 8 – Clinician*

In this case, the AI system gives additional information without using more time or changing the way clinicians are working. There is no ambition to improve other aspects, such as facilitating improvements in the doctor-patient relationship. The interviewee sees this as a positive element, because more can be done within the same amount of time. AI developers often brought up that they try to build tools that fit seamlessly in the current workflows:

> *"Instead of disrupting because I think* ***basically disrupting requires too many stakeholders.*** *And yes,* ***it's nearly impossible to change some of the existing workflows because of regulatory processes, because you might need to run big clinical trials or do like, it might require like someone to own the entire pipeline*** *of things to do that type of change (…) I think the way we try to think about the models is like something that is* ***super hard to change is workflows and the way people are working today***. *So* ***what we have been trying to do is not to change that.*** *To basically create models that…for example, these models for radiotherapy* ***you don't need to click any buttons. When they open the image, they already have the contours done… it has to be seamless for the user*** *(…) like they don't see any buttons or anything like that. That's the key thing, create something that helps them* ***without having to change the way they work***."
> *Interviewee 12 – AI developer*

The seamless fit into the current system described by this interviewee can be seen as a positive, because, according to the interviewee, changing the way the system as a whole works would require too many changes and the involvement of many stakeholders. Because this would be hard, developers explained that they tried to interfere as little as possible in the current workflows. This idea of seamlessness was developed further by other interviewees. For example, one developer explained that the AI company's most significant intellectual property is not the AI system itself, but rather the way it integrates perfectly in current workflows.

> *"Their AI is important, but it's really the smallest, It's a relatively minor part. And their key intellectual property are the systems that they have developed. This is for identifying lung nodules or scoring lung nodules from CT, because it turns out it is very often that you can find a little lump. Is it benign? Is it just a knot of tissue or is it actually cancerous?* ***And they developed a system that tightly integrates into the imaging workflow of a radiologist****. And they said that is their real intellectual property that basically says…so basically the radiologist finds it, puts a little hoover over it and then it gets this score up on it based on the AI. And so that I thought it was really impressive that* ***it wasn't some fancy deep learning this or that is their key technology. It's just the, in some ways graphical user interface, and human interface design for the workflow in a hospital for a neuroradiologist****... In this case a pulmonary radiologist."*
> *Interviewee 13 – Researcher and AI developer*

What these quotes all show, is that there are no incentives to build AI systems that could disrupt the current ways of working. On the contrary, the last quote seems to indicate that the least disruption, the better. A clinician also indicated that the integration of AI has not changed the way clinics work in any way, confirming that AI developers are successfully working on making the integration of AI as seamless as possible.

> *"The clinics run exactly the same"*
> *Interviewee 8 – Clinician*

In the previous section, interviewees remarked that AI systems themselves do not determine whether time can be given back to the doctor-patient relationship. Rather, this is a decision made at the management level. What this section shows, is that beyond the inability of AI systems themselves to instigate change, there is also no incentives for developers to build

systems that could disrupt current practices. In other words, if the doctor-patient relationship is currently not prioritised in healthcare systems, developers have no incentive to build AI systems that support the development of a meaningful doctor-patient relationship. The lack of incentive is especially strong because most companies building AI tools are for-profit companies that have financial motivations and must therefore build tools that are attractive to the healthcare system (the client). This creates the risk that the systems are built with this objective in mind, rather than having a genuinely positive impact on healthcare. For example, some areas of healthcare might require disruption in order to improve healthcare provision. The primary concern of financial profit over clinical benefit has been highlighted by developers, as exemplified by the quotes below. Furthermore, there is also a strong incentive to try to get the AI systems on the market as quickly as possible, without the systems being properly developed. This has been recognised as a pitfall by some developers:

> "**Biggest pitfall is an easy one for me. And that is corporate greed.** And (…) **the capitalist system means you have to try and work so fast to get some money that things are at risk of not being properly developed.** That's my biggest risk (…) that's my biggest concern: **the corporate drive to make money often predominates or overtakes the clinical question you're trying to answer** (…) we're a startup company. So we basically are on **a running timeline of 18 months before we go bankrupt**."
> Interviewee 4 – AI developer

> "So there is a risk (…) **the marketing and the commercial side** of the product of AI"
> Interviewee 5 – Clinical researcher within an AI development company

The above quotes show the concerns of developers that AI systems built within for-profit environments might not always centre around the clinical problems they are trying to solve but rather are driven by money. Intuitively, it seems like this problem could be solved by creating AI systems for healthcare outside of a for-profit environment. However, places such as

universities often do not have the capacity to feasibly bring AI systems onto the market due to financial and administrative barriers:

> *That is an extremely difficult documentary level of evidence burden to try and meet. And* ***even meeting the lowest barriers for medical device regulation for something you would want to actually put out there and usable for by the community is from experience almost infeasible in an academic setting*** *(…) It's an enormous documentary burden. It's end to end documentation of every step and processes in place along every step (…)* ***When you don't have funding and the people time to do that, it's just, it's not really doable.***
> *Interviewee 11 – Clinical researcher in a university*

AI developers have highlighted that AI tools developed within private companies are subject to the same market-driven incentives as any other product, where financial profit often takes precedence. This focus on profitability is particularly acute for startups operating under tight timelines, where the pursuit of clinical benefits may, at times, be relegated to secondary importance. In contrast, while not-for-profit environments might ideally prioritise clinical benefits, they face significant challenges in bringing AI tools onto market due to the extensive documentary and regulatory burdens involved.

The data indicates that more significant, systemic change is avoided because of the magnitude of the work this would require. Regulatory changes, involvement of stakeholders, resistance to change, have all been mentioned as reasons for the lack of higher-level change. As a result, if AI systems are to be adopted, interviewees feel like they must be built in a manner that integrates as easily as possible into the current healthcare system, which means that AI systems are designed to support the healthcare system's current state without causing disruption. I showed previously that interviewees believe that healthcare management favours timely care over doctor-patient relationships, meaning that AI developers aim to build systems that support the goal of timely care over other goals, such as the development of meaningful doctor-patient relationships that do not seem currently a priority to healthcare managers.

Increased throughput can be viewed as a positive and tends to be favoured over the doctor-patient relationship

Interviewees frequently mention that the use of AI tools can help save time and view this as a positive development, as more patients can be screened more quickly. The next quote exemplifies this.

> "I mentioned before that our pre-readers usually can **sit down for 45 minutes to an hour to look through a patient video.** Whereas if the artificial intelligence, if we get to a point where it helps them find all the findings that they needed to find in, say, 10 minutes, **they can get six patients done in an hour rather than one.**"
> *Interviewee 9 – AI developer*

The view that more reads per clinician is a positive aspect of AI is shared by clinicians. This improvement has been qualified as "improved workflow":

> *"But there's also the understanding that the AI will provide that value-base to care. It will allow **more reads** per clinician, it will **allow increased automation**, **improved workflow**."*
> *Interviewee 14 - Clinician*

In addition, saved time can be used to get patients onto treatment quicker. Following the introduction of AI systems, some interviewees experience improvements in the time It takes for patients to start their treatment:

> "If we want to use radiotherapy to try and cure somebody of cancer, then from the day that we make that decision, **the patient should be on treatment within 31 days. But with this technology and others, we're trying to halve that time so the patients with the most fast-growing tumours can get onto treatment within 15 days. Because if you're waiting to start curative treatment, it's a horrible time.** And we know that every day that goes by, for the fastest-growing tumours, you're 2% like less likely to control the disease. So we really try, **it really makes a difference to try and get the patients onto treatment as quickly as possible**"
> *Interviewee 14 – Clinician*

The centre where this clinician works is trying to halve the waiting time for patients to get treatment. This means that the AI system improves the quality of care for the patient by enabling the redistribution of resources (saved time) to reduce waiting times.The next quote reflects the

same idea, from the AI developer side who developed the technology used by the clinician above.

> "I think it would be good if we could show that **this reduces the waiting times to get to treatment.** So there are some goals in terms of, I think basically from diagnosis to treatment, it has to be less than 31 days"
> *Interviewee 12 – AI Developer*

Several AI developers view the faster diagnoses enabled by certain AI systems as a major positive point. This is because interviewees understand the role time plays in healthcare as a key determinant of patient outcomes, as exemplified by the next quote:

> "I think speed is probably one of the key things, we know that with a lot of diseases, **if things go undiagnosed for a long time and they usually are, the quicker you get identified as having some sort of condition, you can manage that. And usually the better the outcomes.** So yeah, in that sense, I think it's a speed thing as well as an ease."
> *Interviewee 5* – Clinical researcher within an AI development company

The importance of speed was also underlined by this AI developer, who goes a step further and suggests speed can always be improved.

> "I mean the biggest benefit is **faster results from a doctor.** I think you can always get diagnoses faster"
> *Interviewee 1 – AI developer*

It was a general trend during the interviews that, especially AI developers, were more enthusiastic about the ability of AI to speed up processes rather than its ability to give time back to the doctor-patient relationship. However, another aspect that interviewees highlighted, is that an increase in patient throughput enabled by AI is not always positive, and can also in some cases prevent good patient care. This will be the topic of the next section.

Too much focus on throughput can prevent good patient care

Ultimately, interviewees showed an awareness that there is a dilemma when deciding how to reinvest resources that the AI saves. They view several potential positive outcomes following

the integration of AI systems, and the reallocation of resources to the doctor-patient relationship is only one of the possibilities, which has proved to be less popular for interviewees than the speeding up of processes. However, the dangers of too much focus on speed have been highlighted by interviewees as well. Saved resources will not necessarily be allocated to the doctor-patient relationship and the increase in throughput can be seen as a risk, as it can prevent patient care:

> *"I think there's a real role for that in terms of kind of efficiency savings and things like that. And I guess maybe that's something for the broader health policy to think through that if,* ***if this technology did save time, how do you just avoid the situation of just having the radiologist to sit in front of a screen even more. Like, how do you give that time back to the patient care or other things that matter,*** *rather than just adding another 100 cases to the load"*
> *Interviewee 10 – Compliance manager in an AI development company*

Overall, interviewees highlighted that the integration of AI in healthcare is intended in part to enhance the doctor-patient relationship by reallocating saved time to improve this relationship, besides other very important elements such as speed of diagnoses. However, interviewees noted that healthcare systems' current values and priorities often do not support this aim. They also noted that the management leading healthcare systems ultimately determines where resources saved by the AI system will be reallocated. It also determines the incentives that drive the development of AI systems, encouraging for-profit companies to build AI systems that seamlessly fit within current workflows. As a result, interviewees suggest that the time saved through AI is frequently redirected towards increasing throughput, which currently seems to be a key priority of healthcare systems, as opposed to the doctor-patient relationship, which does not seem to be a priority. While interviewees acknowledged that these reallocations can enhance patient outcomes, they also warned of potential risks. An excessive focus on throughput can compromise personalised care, resulting in less individualised attention by clinicians for single patients. Thus, despite the expressed hope to reinvest time savings into doctor-patient relationships, interviewees explained that systemic priorities tend to favour other aspects of care

such as speed of diagnoses over relational aspects of care. While the reallocation of resources saved by AI were not understood as having a strong link with improved doctor-patient relationships, interviewees highlighted another mechanism through which relationships between clinicians and patients could be improved. This will be presented in the next section.

5.3. Additional information provided by the AI and the doctor-patient relationship

AI can provide additional useful information to the clinician

Some interviewees explain that when AI systems provide additional information to help them with a diagnosis within the same time it usually takes them to complete this task, this positively impacts patient care. According to some interviewees, the AI tool can improve quality by providing additional information within the same timeframe as the one usually used by the clinician to complete a task. This also means that using this type of AI tool does not introduce delays in care pathways:

> *"Within that very standard timeframe that we're already doing,* ***we also have an AI bit of additional information added in****. So that's a real plus I think."*
> *Interviewee 8 – Clinician*

This next quote reflects the same idea of improved quality within the same timeframe:

> *"****It does improve quality,*** *that's for sure. It does the* ***same thing better in the same timeframe*** *as we do it without AI."*
> *Interviewee 15 - Clinician*

Interview data suggests that participants associate using AI with enhancing the quality of care. This perceived improvement is attributed to AI's capacity to provide additional information while operating within the time constraints normally adhered to by clinicians. The idea that AI can improve the quality of care is widely shared among interviewees, as exemplified by the next quote:

> *"It's really* ***assisting the endoscopies and it will provide more quality.*** *There are now currently multiple studies specifically in colorectal cancer screening that show that* ***AI is really elevating the level of the endoscopist toward an expert endoscopist.*** *So everybody becomes an expert actually in endoscopy. So* ***every patient more or less has the same quality of endoscopy. (…) So I think there's a true value of AI, like being a supporter and assistant of the endoscopies to make sure that your endoscopy in the morning is as qualitative as the last one of your day*** *where you want to go home, it's ten to four and you have to get your children and you want to be quick. And so of course, that diminishes your quality of endoscopy (…) I think AI can assist there.* ***Improve quality****"*
> *Interviewee 15 - Clinician*

This quote refers to a system that can help highlight the presence of polyps during endoscopies. The interviewee explains that there are two ways the AI can help raise the quality of care. First, AI systems are implicitly seen as having an assistive role that can help clinicians detect polyps during endoscopies. The AI system provides information to the clinician, who uses it to improve her judgment. According to the interviewee, this can elevate an average clinician to an expert clinician. As a result, a clinician who is less skilled, for example, due to less experience, will be able to perform as well as a highly experienced and skilled clinician. Second, this clinician suggests that AI can help reduce errors by introducing more consistency. He recognises that a human can be inconsistent throughout the day, and using this AI system can ensure that the level of quality of endoscopies remains consistent, no matter the time of the day.

The idea that AI can help mitigate human inconsistency came up often during interviews. Some explained that AI systems could have a guiding role, effectively giving the clinician additional information by guiding her in the right direction, which, in the context of polyp detection, helps detect them in a way that benefits patients.

> *"I like the thing we're doing right now, developing a clinical support tool that helps the clinician detect polyps, because as you might know,* ***detection of polyps is very very different inter operator.*** *So some people have a very high abnormal detection rate. Some people have a very low abnormal detection rate.* ***It depends on their skill level (…) So yeah I think that if we can develop an AI system which can run on the site and which can guide the clinician, hey, look again there, or maybe you should resect this as well, that might benefit the patients****."*
> *Interviewee 21 – Clinician*

The ability of AI to provide information to the human clinician raises questions about how this information is being used and how this influences the clinician's decision-making process. This will be covered in the next section.

The additional information provided by AI systems is linked with increased clinician confidence

The use of some diagnostic AI systems can result in increased clinician confidence resulting from additional information, with one clinician specifically mentioning the impact this can have on younger doctors who will inevitably have less experience to draw on:

> *"And I then go look at the information and what the AI is doing is it's writing* ***another bit of information****, which is saying to me,* ***giving me reassurance that I got it right****."*
> *Interviewee 8 – Clinician*

> *"I imagine for a younger doctor,* ***it will give you more confidence****"*
> *Interviewee 8 – Clinician*

The reassurance and confidence expressed in these quotes have frequently been linked to improved relationships with patients throughout the interviews. Clinicians feel that the AI system provides them with a level of certainty that enables them to improve their relationship with the patient, as this certainty can be reflected in the discussion with the patient. It is unclear from the interviewee's experience whether the added reassurance improves the doctor-patient relationship, or whether the clinician herself just *feels* better about the relationship:

> *"So indeed,* ***endoscopists feel really much reassured*** *using, being assisted by AI systems. And* ***that indeed can improve the relationship with your patient*** *because you can say, okay, I thought it was there, the computer says it, I think we are quite sure that there is a suspicious lesion that has to be treated and et cetera, etc."*
> *Interviewee 15 – Clinician*

The next quote reflects a very similar idea, namely that the added information provided by the AI system can reassure the clinician, who can then be more confident, which in turn, according to some interviewees, positively affects the doctor-patient relationship:

> *"I think that's even true at my level as well. I think* ***if it agrees with what you're saying, that reassures you and you can be more relaxed and actually your interaction with the patient probably becomes more clear and there are less caveats and less other things you are trying to bring into the conversation*** *(…) If you're very confident, you can be more clear with the patient and explaining what's going on. It also gives you some reassurance that you don't need sort of…that actually you're making the right decision for the patient* ***so it potentially then frees up the opportunity to have that conversation more about what is going to happen for that patient and seeing how that fits into their sort of life experience, what that means. So it all comes from the confidence really, I think. Yeah, the reassurance that you're making the right decisions."***
> *Interviewee 8 – Clinician*

The interviewee explicitly mentions the idea that more time can be spent having a conversation about what will happen to the patient and how this fits into their life experience rather than having to bring in other things into the conversation resulting from uncertainty. Since there is more clarity around the diagnosis, conversation time can be spent focusing on the patient experience. It is important to note here that the doctor is referring to a system that helps him get the diagnosis right, but does not make suggestions regarding treatments or patient management.

Another clinician in the field of obstetrics spoke about the benefits reassurance could have on doctors, midwives, and also patients. It is worth noting that this obstetrician is speaking about a system which has not yet been used routinely in her own practice:

> *"So* ***if I could have something to help midwives, doctors and even I would include patients feeling that they are more reassured that we are doing the right thing, I think would be great****. (…) sometimes you have a trace that doesn't look that good, you do a c-section and the baby comes out crying and it's perfectly fine, and you just feel like, why did I do this? Did I do the right thing?* ***the patient may even come back to you and ask for answers.*** *So why did you section me? Why didn't you allow me to give birth vaginally? That was my dream.* ***And you look at it and sometimes you can't explain,*** *but of course you probably did the right decision because if you allowed that baby for five more hours or eight more hours, because sometimes labours take 60….that baby probably would struggle and wouldn't come out in the same condition, but because you intervened earlier it was absolutely fine.* ***If I could have that kind of support telling me: do a c-section, you are doing the right thing, there's a high risk of this baby being compromised. It just gives you that reassurance that…it would be great to just have someone telling you that you're doing the right thing"***
> *Interviewee 19 – Clinician*

In this extract, the clinician speaks of the difficult relations that can arise with patients when it is difficult to justify certain decisions. In her opinion, AI systems could reassure the clinician that she is doing the right thing. Given her experience of difficult conversations with patients, it is likely that such a tool could facilitate discussions with patients, or, as she suggests, reassure the patients themselves directly.

> *"We know the AI isn't right all the time and the doctors aren't right all the time. So I think the combination of the two is really interesting. So you know, there are grey areas.* ***The ones which are obvious either way are great and you get reassurance about that, and it's the ones in the middle, which make you just focus a little bit more*** *about which those might be"*
> *Interviewee 8 –Clinician*

Clinicians using AI tools that provide them with additional information feel like they can have a better relationship with their patients. This is because they feel reassured when the AI tool supports their decision-making. This translates into more confidence which is then reflected in the quality of the conversation with the patient. AI developers, although not using the tool in a patient-facing capacity, agree with this outlook, mentioning that more information can facilitate communication between the clinician and the patient:

> *"But in essence, most of these tools are just sort of, hopefully, a better type of ruler. It's just another measuring device. The hope is that they will become better and get better measures and* ***therefore improve confidence in diagnoses and of course, help technicians be more confident that they are doing the right thing."***
> *Interviewee 11 – AI developer/Clinical researcher*

> *"I can believe that actually, and certainly in my sphere,* ***using the detection algorithms that it makes people feel more confident."***
> *Interviewee 16 – AI developer/Clinical researcher*

These quotes both link the additional information provided by the AI with increased confidence for the clinician, but also for the technicians using the tools. They link this increased confidence with the perception that it can support a better relationship with their patients.

> *"More information is good (…) So, yeah,* ***I think it could improve confidence and it could improve the relationship. For sure. Especially if it's tangible, you can show them on a screen that they're in the red or they're in a danger zone and maybe that's helpful.*** *I think it depends on the information presented. Or even the bedside manner of the clinician."*
> *Interviewee 4 – AI developer/Clinical researcher*

Besides the positive link between more information resulting from using AI and an improved doctor-patient relationship, this interviewee emphasises the importance of presenting the information clearly to the patient to positively impact the doctor-patient relationship and the importance of the clinician's bedside manners. He is showing that additional information in itself does not improve the doctor-patient relationship unless the clinician already has adequate personal qualities.

Interviewees, both clinicians and AI developers, have linked AI systems to enhanced doctor-patient relationships by its ability to provide additional information, thus improving the clinician's confidence and reassurance. However, the personal attributes ("the bedside manners") of the clinician have been highlighted as a factor, suggesting that AI's potential to improve these relationships is contingent upon the clinician's interpersonal skills.

The additional information provided by AI impacts decision-making

AI systems could provide information to the clinician in different ways. For example, hypothetically, a clinician could have to emit a hypothesis before receiving input from the AI system. In some cases, the additional information provided by the AI system is given upfront to the clinician. In other words, the clinician theoretically does not need to formulate a hypothesis, as the AI tool will provide an explicit diagnosis:

> *"It's more of a case of the* ***AI guiding them to what this person might have or what this image might be,*** *rather than the doctor coming to the conclusion of, this person has diverticulosis let's*

> *see if the AI agrees, because* ***the clinician has already seen what the AI sees*** *if that makes sense"*
> *Interviewee 9 – AI developer*

This experience does not reflect the way all AI systems used by interviewees work, as a number of systems do not provide specific diagnoses but rather provide more discrete pieces of information. However, this quote shows that AI is seen, again, as able to provide additional information. It also raises questions about the AI's method and sequence of information delivery. For example, whether it might be more advantageous for clinicians to initially propose a hypothesis followed by AI input or, alternatively, for clinicians to validate AI suggestions. Such considerations bring concerns regarding confirmation bias to the forefront (Bashkirova and Krpan 2024). For example, if the clinician agrees with the AI's diagnosis without first independently evaluating the patient's symptoms and forming her own hypothesis, there is a risk of falling into a pattern of confirmation bias. This scenario could potentially lead to a situation where the clinician might overlook or undervalue critical patient information that does not align with the AI-generated conclusions. This quote, therefore, besides underlining the potential benefits of additional information the AI can provide, also raises questions about the importance of scrutinising the order and methodology of information exchange to mitigate the risk of confirmation bias. Within this context, AI developers raise questions about the order in which clinicians should use AI systems in their decision-making process. The next quotes highlight the potential issues that may arise in the decision-making process when using AI systems.

> *"Obviously there is a bias effect in it, isn't it? And whether you, the doctors should make your decision first, then refer to the algorithm, and then when it confirms or refutes their opinion, if it refutes it, they can go back and determine whether the algorithm is correct or not.* ***If it confirms their opinion, then it counts as though it's the second opinion, and you get a confirmation of faith, but you'd also get a confirmation bias, wouldn't you****? So one just has to be wary"*
> *Interviewee 16 – AI developer/Clinical researcher*

This developer suggests that even if a clinician forms his own opinion first, using the AI a posteriori can result in either confirmation of faith or confirmation of bias. For example, if both the clinician and the AI are wrong, the clinician will feel reassured in her decision after checking the AI system because the AI system will confirm the wrong opinion, presumably not incentivising the clinician to question her opinion should she be unsure. The idea of overreliance on the AI system has been brought up by several interviewees:

> *"There's a real balance to be struck with these technologies around overreliance versus scepticism and yeah,* ***I think it's great if they provide confidence, but you know, what would you do if it was a junior doctor? And they were so unsure that they couldn't even challenge the system.*** *They just went with what it said. And so I hear stories like that, and I think it sounds really positive, but you know, I think going one layer deeper just to see how they're interacting with it over time.* ***If they see the same thing from the system for 12 months, would they stop challenging their own judgment?*** *Like what's the long-term view of these things?"*
> *Interviewee 10 – Compliance manager in an AI development company*

Here, the interviewee questions the impact of long-term use of AI systems, particularly for less experienced doctors. Unlike the previous quote, she does not mention confirmation bias, but rather, worries about less experienced clinicians being unable to challenge the AI system and automatically going with the information provided by it.

A clinician viewed the use of an AI system as positive in terms of decision-making. He talked about the information AI provides as "hard" information. In this clinician's experience, this is a good thing in comparison with the additional information another colleague, for example, could provide. He explains that a clinician will try to reach an agreement with another clinician, whereas an Al system will not feel pressured by a human clinician. In other words, a clinician will feel more comfortable questioning and disagreeing with the AI system than with a human colleague. Equally, the information the AI system provides is not susceptible to being influenced by human behaviour and the AI is therefore perceived as providing "hard" information:

> *"I think the colleague in the room, there is a human interaction, which means* ***they get led by one or the other person****. So if you have a colleague in the room, there's a tendency to* ***want to try and agree with the other colleague*** *to be honest, actually, there is a collaborative field, so you both come*

> *to a kind of feeling that it's right, whereas the AI is "hard***". You know, it's not going to be influenced by whether you're smiling at them or whether they can sense that you're worried about the decision. They will just say yes or no**. *(…) So although it's tempting to say, oh, this is second read, it isn't actually, it's a very clear kind of,* **it's a much harder piece, which is actually useful in terms of making you focus on what's going on**."*
> *Interviewee 8 – Clinician*

The quote shows that the clinician felt that he found it easier to challenge the results of an AI system than a human, indicating that, perhaps, when the clinician is unsure, he will still question the AI system more than a human colleague. However, it seems likely that in cases where the clinician is certain but wrong, an AI providing wrong information will misplace the clinician's confidence. While the clinician perceived the AI's non-human nature as an opportunity for more rigorous interrogation of its outputs, the developers regard AI utilisation as risky due to the danger of uncritically accepting its information.

Despite the risks associated with confirmation bias highlighted by the developers, several clinicians found that using AI to confirm their findings is a source of reassurance and confidence, which helps them improve their relationship with patients. AI developers were generally sympathetic to this idea, despite their worries.

Additional information provided by AI and bias in the algorithms

Another risk of using an AI tool as part of the decision-making process, which has been raised several times by both clinicians and AI developers, is the risk of using untransparent, biased algorithms. A clinician highlights these issues as a challenge for the future:

> *"I think it's going to be* **the bias reduction** *and then that ability to be able to generate* **truly transparent inference** *from an AI algorithm that is going to be the challenge of the future."*
> *Interviewee 14 – Clinician*

Several developers were acutely aware of the issue of bias. Some qualified this issue as the biggest threat that currently exists with AI in healthcare:

> *"The biggest threat? (…)* ***models being biased*** *in some way for different ethnic groups. I think that's a big problem.* ***Underrepresented groups, and not just ethnic, but comorbidities*** *that it might be some disease that for us very obviously affects someone in a certain way,* ***but the AI just doesn't hadn't seen it. So it doesn't know****. That's very hard to deal with because those are always going to be educated on data."*
> *Interviewee 1 – AI developer*

This quote highlights the issue of bias in AI models, particularly concerning their potential to disadvantage certain ethnic groups and individuals with specific comorbidities systematically. The challenge lies in the reliance of AI on data for learning, which may not adequately represent all patient demographics or the full spectrum of medical conditions, thus limiting the AI's ability to help diagnose or help treat underrepresented populations accurately.

Both clinicians and AI developers are aware that a major current problem with the use of AI in healthcare is bias and the difficulty of mitigating this. Since diagnostic tools can influence decision-making processes, this is a noteworthy problem.

5.4. Other ways in which AI can contribute to health outcomes

Saving time can enhance patient experience by reducing the need for additional testing

According to some AI developers, the time that AI systems can save can enhance patient experience. This can happen when using AI systems enables patients to skip tests. The next quote shows that, for heart disease, tests can quickly become invasive, given the difficulty of identifying the problem. In this context, using an AI system can help bypass some of these unpleasant tests for some patients and determine the diagnosis earlier.

> *"Someone comes in (…) then they start to have all these tests and they can quickly get quite invasive because we don't necessarily know what's going on. These things are certainly, you know, hard to determine. So* ***some of our tools, particularly the (edited out), which is on trial with the NHS can help determine whether they are more or less likely to have coronary artery***

> ***disease (…) So if it says it's a negative, it's definitely a negative. So to them, we do much less invasive tests.*** *We just do what's called a resting echocardiogram, where we just measure the heart.* ***If it says negative, we send them home****, you know, you're okay, you get to go (…) If it's positive, then we can send them for a stress echocardiogram, where we actually stress the heart with chemical agents or exercise, and that's quite an unpleasant experience."*
> *Interviewee 1 – AI developer*

Avoiding unnecessary tests saves time for both the patient, who does not need to undergo as many tests, but also for the clinician, who does not need to perform as many tests. It also improves patient experience, because the patient does not need to endure as many tests. In this context, AI tools help to improve the quality of care by improving patient experience.

The next interviewee is a developer who is part of a team that developed a capsule with a camera which is ingested by people for GI cancer screening. If the screening is clear, the patient will not need to undergo further testing in the form of a colonoscopy, which is only necessary if a procedure has to be done.

> *"I think, at least a few years ago, there was about 600,000 in the colonoscopy waiting list. And* ***a lot of those people in the waiting list didn't actually need a colonoscopy. They might have just needed a screening, which is what a capsule can provide. There is no point in a patient going in and having a colonoscopy and nothing to be done, or taken out****."*
> *Interviewee 9 – AI Developer*

This AI tool seems to improve the patient experience by enabling patients to skip unnecessary procedures and shortening waiting times.

AI can bring additional consistency, reducing errors

An interviewee working in obstetrics highlighted the main benefit of AI as its capability to enhance the care of newborns at risk of complications due to errors. She stated that her main reason for engaging in AI research is to address these issues and improve newborn outcomes:

> *"I think the most important thing for me,* ***the impact that it (AI) has is the reason why I joined the project, to have an impact in maternity care****. I don't know if you have any awareness of this (…) so you have a baby that is absolutely fine, goes into labour and has (…)*

> *complications. But the ones that die and they don't even deliver,* ***it's a lot because of errors*** *(…). So we are clearly still having a lot of problems with this kind of population"*
> *Interviewee 19 – Clinician*

This interviewee views using AI as a way to improve newborn population outcomes. She identifies errors as a cause of unborn infant death and views AI as an opportunity to create an impact in this field. The next extract, also from a clinician, similarly discusses the main benefits of using AI as its impact on various outcomes.

> *"So* ***all technologies and drugs ultimately are there to improve outcomes.*** *And that's what I'm interested in: improving outcomes. And* ***those outcomes may be the patient experience. It may be death rates. They may be heart attack rates, cancer rates.*** *That's what I always think. What's the vision, what's the end goal? And how are we going to get there?"*
> *Interviewee 2 – Clinician*

This interviewee shows awareness that there are many ways to define outcomes that go beyond objective metrics, such as life expectancy. For example, he includes patient experience as a possible outcome that AI can improve. The next quote shows that, according to the interviewee, the value of the AI tool is in its ability to improve disease detection and, by extension, improve health outcomes.

> ***"****If you can get the level of an AI high enough that this determination is correct,* ***you can, in my opinion, reduce the risk of cancer, or cancer evolving****."*
> *Interviewee 18 – AI developer*

The data presented above shows that some interviewees believe that the role of AI tools is to improve outcomes. This can be at the individual level (e.g. a patient getting diagnosed more accurately) or at the population level (e.g. increasing life expectancy in a region of the country). The AI tool (as a "technology") is understood as a means to achieve an end, improving specific outcomes. The outcomes mentioned by these clinicians, lowering the number of heart attacks, cancers, or deaths and improving patient experience, are important aims for the NHS as these

contribute to improving their overall goals as established in the constitution (Department of Health & Social Care 2021).

Besides clearing backlogs, interviewees mentioned other ways in which saving and reallocating time could benefit patient care. For example, this AI developer was hopeful that resources saved by AI could translate into improved quality because the clinician can use the time saved by the AI to do quality-improving activities, for example, by creating more complex treatment plans. However, this is still hypothetical:

> *"But it (the saved time) also allows them to create more complicated plans.* ***So that could help in terms of creating better plans. Because they can now do more structures****. So if you have more…if you can delineate more healthy tissue so for example, for head and neck, they were telling me that they would like to segment lymph nodes and things like that, that they don't do today because, it will take too much time. Now with the models, they might be able to do those manually."*
> *Interviewee 15 – AI developer*

AI can improve the quality of care for all

A clinical researcher engaged in AI development spoke about the benefits of using AI technology to minimise cross-centre variations in the quality of care. She explains there is a potential for centres that underperform to raise their quality. In her opinion, this would help make care more equitable:

> *"It's mostly about* ***improving care or enhancing the quality of care and in the same way, making care equitable, if that makes sense*** *(…)* ***in big well-resourced settings, you have a different level of care than in poorly resourced settings****. Even within us, within a country.* ***So some of these tools can be used to enhance access and equity to care,*** *(…)****I strongly believe in the use of technology to try and level the playing field a little bit, but not by pushing good hospitals down, but hopefully by making hospitals that are not so good come up a little bit.*** *And it's certainly true that some of the early AI systems you probably won't need in centres of excellence, because they're already very good at what they do.* ***But they can be particularly valuable in centres where maybe care is a little more variable.***
> *Interviewee 20 – AI developer/Clinical researcher*

This interviewee explains that quality of care is not only understood at the patient level and the impact that AI tools can have on a single patient, but also at the system level, and the variations that can exist within a country, for example, depending on how well-resourced centres are. She takes a systemic approach to understanding the quality of care. She explains that AI tools can impact equity by improving the quality of care across different socio-economic backgrounds and geographical areas. She explains that AI tools can improve the quality of care in more poorly-resourced settings. By doing so, these centres can be raised to the level of expert centres (which she understands as centres which perform well according to NHS standards). The expert centres might not need the tools (yet), as they already operate at a high level of quality. As a result, some AI tools can, in her opinion, make healthcare more equitable by improving the quality of care across centres, no matter how well-resourced they are. This assumes that the more poorly resourced centres can afford the AI tool(s).

5.5. AI can improve outcomes efficiently

In some cases, interviewees see AI tools as having the potential to save resources by fully replacing the clinician:

> "We work with two systems. One is providing like a scoring between zero and 255. And so it's really quantifying the disease activity on a histological scale. So **we won't need the pathologist anymore in the future,** or at least as a hypothesis"
> *Interviewee 15 – Clinician*

In the next quote, the clinician talks about the problem of understaffing. He emphasises the magnitude of the issue and explains that, as a consequence, people die because of medical errors. Within this context, he sees two solutions which can improve quality. The first would be to hire more human professionals (who are currently not available) or to implement AI tools. He goes on to explain that AI tools are cost-effective solutions, which are therefore advantageous over human resources.

> "*And we've also got to be fundamentally aware that* ***there aren't enough doctors, there aren't enough nurses and there is lots of data that a lot of people in the UK and in the US have died because of medical errors****. There are not enough people to do echocardiography in the UK. So I would anticipate, and I'm just going to throw out a figure,* ***we could probably need a thousand people.*** *If we had a thousand people who could perform echocardiography across the UK, we could swallow that up immediately. That isn't going to happen.(…) I said at the beginning,* ***if we had a thousand more echocardiographers in the country, we could mop them up and I'm sure we could improve quality. That's massively expensive, inefficient. AI can improve outcomes cost-effectively."***
> *Interviewee 2 – Clinician*

Besides introducing the idea that some jobs, or at least, part of jobs, can be automated, the above quote refer to cost-effectiveness as a key function of AI tools. Cost-effectiveness often comes back as an important positive impact of AI. The previous quote especially shows that quality can be improved by increasing the number of human professionals rather than implementing AI. However, according to the interviewee, AI tools have the added advantage of being efficient and cost-effective.

The next quote, from an AI developer, shows that he also views AI's ability to save resources as a key advantage. He views that as a primary advantage, coming before any qualitative improvements to care.

> *"For me, just using the technology properly,* ***it gives benefits in terms of saving time and money.*** *Um, and if you can go on to do amazing things beyond that, then brilliant!"*
> *Interviewee 4 – AI developer*

Another perspective is that using an AI tool is helpful in so far as it can do a job that nobody wants to do. In this case, the AI tool essentially replaces the human clinician in a specific part of the care pathway, not with the primary objective of making the pathway more cost-effective, but rather to get rid of a task "nobody wants to do":

> *"You know, the stuff that's going to get automated now is very much imaging and radiology, right? Which, anybody who doesn't work there sort of thinks it's a bit boring and a waste time. There might be people who might lose jobs because manual processing is required, but I will say I'm not sure that's true.* ***I think that bit, it's just a bad job that no one really wants to do.*** *And they will still have to acquire images. Like, you know, still have a job to do that.* ***It's just that boring quantification. They can just get a report immediately.****"*
> *Interviewee 1 – AI developer*

AI developers envision the resource-saving aspect of AI tools as positive. Clinicians gave a more nuanced account, explaining that this aspect might be useful in the context of insufficient staff or LMICs but also understanding that resource-saving tools can be implemented in systems that are actively seeking a reduction in headcount.

Improving healthcare goals and resource savings often go hand in hand

So far, I have separated instances where clinicians and AI developers spoke of AI tools' ability to reach healthcare goals, such as improving the quality of care, and instances where AI saves resources, such as replacing human clinicians. However, in many cases, AI tools were spoken about both in terms of their ability to help reach healthcare system's quality goals, and resource saving terms. In the next quote, the clinician speaks of determining what better clinical decision-making is, and suggests that there is both an element of better outcomes for the patient, but also of rapidity of decisions. Using a triaging tool as an example, she shows that this can provide information to the clinicians regarding the level of complexity of cases while at the same time saving time because the clinician does not have to spend time on the easier cases. The focus of the human clinician can therefore be entirely on the trickier cases. This is what the interviewee characterises as "better-quality clinical decision".

> *"This is ultimately what better clinical decision-making is. And what I think that we struggle ourselves with is the idea: what is a better-quality clinical decision? You know, and that can mean a number of things, right?* ***It can mean, I think the obvious one is a better outcome for the patient. Whether that means increased survivability, you know, longer progression. That's one level of better. But when you look at the NHS and the workflow, what we want, is also more rapid decision, right? We want clinicians to spend their time on complex and***

> ***tricky cases that really benefit from half an hour very intense discussion. And one of the things that we we're considering is if we can use the machine learning to kind of categorize patients (…) so we don't spend a huge amount of time on those cases because we know that they're straightforward, but we can also flag up the more tricky cases*** *that do need that time spent on them that do need those extensive discussions. So that's another way we're looking at better decision-making. But also it's about more efficient decision making."*
> *Interviewee 17 – Clinician*

This clinician, therefore, makes the case that this AI tool is both about improving the quality of the decision-making process "better decision-making" but also about saving, or optimising, resources "more efficient decision-making". Triaging tools are not unique to possess both the quality-improving and the resource-saving elements. Many of the quotes presented in the previous sections can usually be linked to both resource saving and quality improving aspects. While a tool can be primarily quality-improving, it is likely that as a result of quality improvements, the tool can also make secondary resource savings. The next quote exemplifies this overlap:

> "I think AI can assist there: **improve quality and be, at the same time, time reducing** because you will be sure that you have qualitatively well seen the endoscopy or the colon and can be quite sure that you did not miss too many things. I think you're completely right saying that **it will be time saving as well as cost saving.** If we need less biopsy, if we need less polypectomies, since the system can say, this is a benign polyp, you can just leave it in. This is a malignant polyp, you have to take this out, so that's something that is cost saving. **Time saving and will improve quality for the patient. And that's the, I think, true value of AI.** (…) **So the system performs better in the same time as we do it without the system. So it outperforms humans in the same time. So actually it is time saving because we would need more time to reach to the same level of detection, to reach to the same level of experience as the AI system does it in our time**."
> *Interviewee 15 – Clinician*

In this quote, the clinician explains that the quality-improving aspects of the AI tool he is using are inextricably linked with the resource-saving aspects. The resource-saving capacity of the tool, in the form of saved time, is an indirect impact of the tool which directly results from the quality-improving features of the tool. Through improving the quality within the same amount of time, the resource of time is effectively being saved. This is because without the AI tool,

more time would be needed in order to reach the same level of quality. This logic could be applied to many of the quality-improving tools. For example, by providing additional information, the AI tool effectively saves resources as more time would be needed to provide the same level of quality without the help of the AI tool. As a reminder, another way that AI tools can improve quality is by accurately diagnosing patients faster and/or getting them onto treatment faster. While this ultimately improves the quality of care, this also results in saved resources in the form of time which can be allocated to other areas. As a result, many tools that help improve the quality of diagnoses also help save resources, although these can, in some cases, be less immediately obvious. In scenarios where the use of AI tools result in resource savings, the crucial task arises of deciding how to allocate these saved resources effectively to optimise healthcare goals. This strategic redistribution is essential for maximising the benefits of AI in reaching the goals healthcare as outlined in the NHS constitution. The next section presents interview data related to the redistribution of resources saved by AI tools and asks, in the first instance, whether it is possible to predict how saved resources will be redistributed.

5.6. Medicine as an exponential science

Some interviewees are pessimistic about the positive impact the introduction of AI, by itself, can have on solving key healthcare systems problems, such as reducing backlogs. In this context, any resource the AI tool can save will quickly be taken up by the need to provide more healthcare rather than better healthcare. In the next quote, the clinician explains how constant expansion is an intrinsic part of medicine.

> *"It's a feature of medicine. Basically* ***medicine is now picking up disease at an earlier and earlier stage. And the spectrum of interventions, of course, in medicine is increasing more and more.*** *When my father was a doctor and somebody came into hospital with a heart attack, you put them into bed and you gave them aspirin because that's all you could do. Now there are 50, 60 different things that you can do to optimize the care of somebody who comes into hospital with a heart attack. (…)* ***Medicine is an exponential technology.*** *In one way, it's just that people don't really think about it.* ***You have people think about motor cars or the internet or mobile phones as an exponential technology, but actually the truth, same thing is true of medicine***

> ***(…) There's a need for increased human intervention in radiology****, simply because radiology can do more than ever."*
> *Interviewee 14 – Clinician*

This vision of medicine as exponential has important implications for the ability of AI to enhance healthcare. This clinician explains that medicine can do more and more, and often earlier, regarding the number of interventions available for any given condition. I asked the clinician whether he thought that AI tools could help us get to a point where speed targets are met (e.g. getting patients onto treatment within the target time) at which point, any incremental resource savings could theoretically be poured into more qualitative aspects of healthcare, such as the doctor-patient relationship. The clinician was pessimistic about this and observed that technology will always be playing catch-up with the workload. The idea that medicine is exponential is related to the constant need for "more", in terms of capacity and resources:

> *"I think it's this constant,* ***a bit like Sisyphus rolling his ball up the hill and it rolls back down again*** *and it's… basically you have a problem.* ***You become rate limited, technology disrupts that, allows you to go faster, then you have more activity, demand goes up*** *and then you need to… and it just… that seems to be my observation of working in medicine, really."*
> *Interviewee 14 - Clinician*

This clinician used the myth of Sisyphus, who is eternally condemned to roll a boulder up a hill only for it to roll down each time it nears the top, to make sense of the cyclical challenges faced in the field of medicine. The clinician observes that each problem addressed through technological advancements initially increases capacity. However, this improvement paradoxically leads to higher demand and activity, eventually outpacing existing technological solutions and creating a new bottleneck. This problem-solving cycle, followed by increased demand and the subsequent need for further innovation, is seen as a constant dynamic in medical practice. It underscores the continuous struggle against the limitations of current technology and the perpetual quest for improvement, much like Sisyphus's endless effort.

Another clinician confirms this position, explaining that, in his experience, the workload has always been a problem. While it has not significantly worsened over the years, it also has not improved. Rather, it goes through better and worse phases.

> *"I think **there's an ebb and flow of it.** But see, I think right now there's quite a lot of patients, a lot of demand. I know waitlists are stretching out. You know, I know that it's happened in years gone by as well, so **I think it's an ongoing problem**."*
> *Interviewee 8 – Clinician*

These extracts show that AI tools that help save resources enable healthcare systems to catch up with the ever-increasing demand. However, interviewees seem sceptical about the power of AI to introduce change significant enough for "spare" time to be available to spend time on qualitative aspects of healthcare, such as building relationships with patients, for example. AI tools are, therefore, not seen as being able to disrupt healthcare systems significantly. Rather, it looks like, for these clinicians, AI tools will simply become part of the system and bring resource savings, without themselves initiating drastic changes to the system itself. According to interviewees, it looks like healthcare systems are stuck in a loop where all potential gains made by AI tools will be automatically assigned to clearing backlogs and meeting time goals (e.g. number of days between diagnosis and treatment start). However, most interviewees expressed hopes beyond mere resource savings for AI. How AI tools can contribute to the goals of healthcare, as perceived by interviewees, will be covered in the next section.

5.7. Summary of interview findings

This chapter has delved into the experiences and perspectives of clinicians and AI developers regarding the impact of diagnostic AI systems, particularly diagnostic systems, on healthcare practices and the relationship between doctors and patients. The thematic analysis of interview data revealed several key insights that we can bring back to our understanding of the role of AI in improving the doctor-patient relationship within the context of efficient healthcare systems.

First, while AI systems have the potential to save time, the reallocation of this saved time towards more meaningful interactions between doctors and patients is not straightforward. Clinicians and developers noted that systemic priorities and management decisions within healthcare settings play a crucial role in determining how these time savings are utilised. Many interviewees using AI systems in their practice did not experience a clear improvement in their relationship with patients as a result of reallocated time. On the contrary, interviewees expressed scepticism that any time saved by AI systems would be reinvested in improving relationships with patients, suggesting instead that it is often redirected towards improving timely care through an increase in patient throughput. Despite this, some interviewees remained hopeful that AI could eventually allow clinicians to spend more time interacting with patients.

Clinicians also highlighted the increase in confidence resulting from the use of AI tools, which can make them more certain and precise in their communications. This increased confidence, stemming from the additional information provided by AI, was seen as a positive factor. Furthermore, the chapter discussed the potential for AI to bring consistency and reduce human errors in clinical practice. However, concerns about biases in AI algorithms and the risk of over-reliance on AI systems were also prominent themes. Interviewees emphasised the need for transparency and rigorous testing to ensure that AI systems do not perpetuate existing disparities or introduce new ones.

In terms of efficiency, the interview study highlighted that while AI systems can lead to resource savings, such as time and costs, these benefits are often seen through the lens of improving overall system productivity, such as patient throughput, rather than specifically enhancing doctor-patient relationships. The ability of AI systems to facilitate faster diagnoses and reduce waiting times was frequently mentioned, underscoring the technology's potential to streamline healthcare processes.

Ultimately, the data underscored the complexity of integrating AI into healthcare. According to interviewees, while AI holds significant promise for improving diagnostic accuracy and operational efficiency, its impact on the doctor-patient relationship is mediated by broader systemic factors. The subsequent discussion integrates the learning from the interviews with the framework of the efficient-patient centred relationship in order to address the central aim of this study.

6. Discussion

This chapter uses the *efficient doctor-patient relationship* framework developed in Chapter 4 to analyse the qualitative interview data presented in Chapter 5. The purpose of bringing together the theoretical and empirical work is to gain an empirically grounded understanding of the role of AI within the *efficient doctor-patient relationship,* and ultimately understand **how the doctor-patient relationship can be integrated into a healthcare context that strives for AI-supported efficiency**. I highlight some implications of the findings for policy at the end of the chapter.

As a reminder, the *efficient doctor-patient relationship* framework developed in Chapter 4 posits that the resources allocated to doctor-patient relationships should vary depending on the specific needs of patient clusters and their contribution to achieving patient-centred outcomes. In this framework, the doctor-patient relationship is considered an intermediary outcome that facilitates important aspects of care, such as effective communication and treatment adherence; how beneficial it is varies across patient clusters. By varying the resources allocated to the doctor-patient relationship by patient cluster, efficiency in healthcare can be maximised, ensuring that resources are directed towards where they have the greatest benefit.

6.1. Saving and reallocating resources

A central claim made in policy and professional documents is that time saved by AI systems will be reinvested in the doctor-patient relationship. Investigating how that relationship appears to play out in practice, as experienced by interviewees, through the lens of the *efficient doctor-patient relationship* framework provides information on the implications of AI integration for both efficiency and person-centred doctor-patient relationships.

6.1.1. Policy expectations vs. interviewees' views

In accordance with policy documents, interviewees mentioned three ways in which AI can enhance the use of time in healthcare:

1. **Improved diagnoses**: AI has the capacity to process large amounts of data and enables doctors to access valuable information to help them diagnose patients.
2. **Save and reallocate time:** some AI systems can help speed up processes. The time saved can be used in one of two ways.
    a) **Increased patient throughput**: some AI systems can help speed up processes. The time saved can enable doctors to see more patients within the same amount of time.
    b) **Increased time for patient interaction**: By saving time, some AI systems enable doctors to spend more time with each patient, which can result in improved doctor-patient relationships.

In all three cases, AI enables doctors to do *more* with their time: access *more* data, see *more* patients, and spend *more* time with their patients.

The interviewees who use AI in their practice viewed the two first outcomes, improved diagnoses and increased patient throughput, as noticeable changes following the introduction of AI systems. The healthcare system can become more efficient by achieving more with the available resources through improved diagnoses. Clinicians explained that, by using an AI system, they could achieve better diagnoses within the same time as before the adoption of the AI system. This idea of improved diagnoses is consistent with the claims made in policy documents. Policy documents tend to focus on the ability of AI systems to make diagnoses more accurate (Topol 2019). In contrast, interviewees illuminate *how* the accuracy and consistency of some of the diagnoses can be improved. Clinicians explain that they find it very useful when an AI system provides additional information. Clinicians have expressed this

additional information as helping them be more consistent and do better within the same timeframe. The idea that an average doctor or diagnostician can be raised to an expert level through AI systems has been raised. It shows that some clinicians highly value using AI systems in diagnostic contexts.

Interviewees frequently mention that the time-saving capacity of AI systems is linked to decreasing patient waiting times. Clinicians and developers explain that these waiting times can be reduced by AI enabling tasks to be done quicker and by using well-functioning diagnostic tools that ensure patients do not have to undergo as many diagnostic procedures. A clinician using AI technology in cancer care has cut the time to get patients onto treatment after the diagnosis. Ultimately, his clinical team aims to halve the wait time put forward in official NHS guidelines. AI developers were on the same page, viewing the speed AI can generate as a positive goal and one they aim towards, as they understand the benefits of fast diagnoses. Given the links between the speed of treatment and health outcomes, when AI systems save time that can be used to diagnose and treat patients faster, this could lead to improved system efficiency. This is because health outcomes (the presumed *goal* or *valued outcome* of most patients using the healthcare system) improve without additional resources besides the investment in the AI system. In other words, more can be achieved with the available resources, which aligns with the claims made in policy and business documents.

In contrast with the expectations expressed in policy documents, according to interviewees, extended doctor-patient interaction resulting from more time does not seem to be an obvious result of introducing AI systems in care pathways. Rather, it is perceived as a hypothetical benefit. It is theoretically possible to allocate more time to the doctor-patient relationship following the introduction of AI systems. However, interviewees emphasise that this requires system-level decisions about resource allocation. In other words, saved time does not seem to

be automatically allocated to the doctor-patient relationship after introducing AI systems in care pathways. The current benefits of deploying AI in care pathways, as observed by interviewees, are limited to improved diagnoses resulting from additional information and/or increased patient capacity. This contrasts with the position of several policy documents, which assume that the introduction of AI will lead to improved doctor-patient relationships through 'the gift of time'.

The idea that the impact of AI systems on the doctor-patient relationship is determined at the decision-making level and not by the AI system itself extends beyond the doctor-patient relationship. Interviewees remarked that the purpose for which an AI system is being used, and therefore the impact it has, depends on the environment within which it is being deployed. The scepticism of all interviewees (clinicians and developers alike) regarding the time-saving abilities of AI and the subsequent potential giving of time to the doctor-patient relationship points towards the idea that current system incentives do not encourage such a use of time. Rather, incentives seem to push towards a more one-sided use of time to see patients more quickly and cut waiting times and procedures. Such a use of time can contribute to increased system efficiency. However, not all situations warrant extra speed. In some situations, such as when a clinician mentions that he does not have time to explain procedures to a patient who might then come back more frequently, the most efficient outcome would be to allocate this time to the doctor-patient relationship rather than speed. Whereas Chapter 4 showed that the *goal* of efficiency is case-dependent, based on the priorities of patient clusters, the introduction of AI in the NHS seems to point towards a blanket impact of saved resources being allocated to speed, rather than the doctor-patient relationship, which is not always the most efficient use of resources.

Interviewees highlight that there are advantages to allocating resources to various areas, including speed (e.g. increasing patient throughput) and the doctor-patient relationship. Analysis through the *efficient doctor-patient relationship* framework shows that, rather than adopting a blanket approach, resources should be directed to where they provide the most value and help achieve the desired outcomes. The doctor-patient relationship literature identifies several mechanisms that benefit patients, as shown in section 2.1.3 **Figure 1**, and when a new AI system is introduced, it is important to assess how it may impact these benefits. For example, good communication can improve the quality of diagnoses. If the AI takes over the diagnosing process, the importance given to the doctor-patient relationship could be reconsidered or reduced for that specific instance. The *efficient doctor-patient relationship* framework developed in this thesis treats the doctor-patient relationship itself as efficient, meaning that preserving it should not be a default decision but a deliberate one based on the doctor-patient relationship's contribution to outcomes.

6.1.2. Paradox of timesaving

Non-patient-facing tasks like administrative work do not directly contribute to the doctor-patient relationship, in the sense that this is not work that the patient often sees happening in front of their eyes, even if these tasks can also contribute to a productive and effective doctor-patient relationship. When these tasks are replaced by an AI, the reallocation of the saved time to the doctor-patient relationship is relatively straightforward. However, more often than not, this is not the type of work that is being replaced. When policy and professional documents suggest that AI can save time on tasks such as diagnoses, which can then be reallocated to meaningful doctor-patient relationships, a paradox is created. The paradox lies in the suggestion that AI can save time on tasks traditionally performed by humans that are central to the doctor-patient relationship, then reallocating this saved time back to the relationship itself. One example of this paradox is that good communication is an important component of accurate

diagnoses, which contributes to the development of a meaningful doctor-patient relationship (Chew-Graham, May and Roland 2004). By automating or accelerating this stage, AI can unintentionally diminish opportunities for these relational interactions.

Analysis of this paradox through the developed *efficient doctor-patient relationship* framework helps navigate this issue. If there are ways in which an AI system can provide the same benefits to the patient as a human clinician would, and the AI does it using fewer resources, then it seems that replacing certain aspects of the doctor-patient relationship with AI may be efficient. However, when is this the case, and when is it not?

Interviewees have noted the varying levels of emphasis that can be put on the doctor-patient relationship. One interviewee commented that he found it unnecessary and counterproductive to speculate about the ways in which AI systems may or may not give time back to the doctor-patient relationship. This is because, in his opinion, medicine is bound to change significantly. There will be instances, he explains, where a human doctor might no longer be necessary at all. Another clinician explains that one has to recognise that many people die of medical errors. He explains that this could be solved by hiring many more human clinicians. However, he argues this is massively expensive and, therefore, not a good solution. He found AI to be a more promising way forward than human clinicians.

Furthermore, several developers believed that the doctor-patient relationship is of secondary relevance compared to other factors, such as access to timely care. However, the person-centred doctor-patient relationship is at the centre of the theoretical framework developed in Chapter 4, as it has been found to benefit patient outcomes (Kelley, Kraft-Todd et al. 2014). AI might be able to replace bits of diagnostic processes, as explained by interviewees, but AI is unlikely to be able to empathetically care for patients, which has been shown to be important for health

outcomes (Decety and Fotopoulou 2014), nor are AI systems currently able to grasp patients' value plurality (McDougall 2019), although this may change in the future. Many clinicians also view the doctor-patient relationship as a matter of ongoing importance. Clinicians still hope AI will afford them more time to spend with patients, allowing them, for instance, to explain treatment options and procedures in greater depth.

Notably, interviewees who cared a lot more about timely care and interviewees who cared mainly about the doctor-patient relationship do not necessarily seem to disagree entirely but rather seem to have two distinct understandings of the doctor-patient relationship. The first group, which comprises interviewees who mainly view the benefits of timely care, talks about the doctor-patient relationship in superficial terms. They view it as a currently necessary interaction between humans, as humans are instrumental in achieving a specific action. For example, one of the interviewees referred to the need for more echocardiographers. Until recently, humans were the only ones able to read and interpret such images. Therefore, a relationship between the echocardiographer and the patient exists to the extent that the echographer reads and interprets the image in the patient's presence.

Another clinician and AI researcher explains that, in the future, 30 ml of blood will be enough to look for circulating tumour DNA and protein biomarkers because tumours or heart failure secrete different proteins. As a result, he suggests that clinicians will no longer be necessary for certain procedures and areas of healthcare. This clinician refers to a new methodology that does not involve human clinicians to the same extent. These interviewees seem to refer to the doctor-patient relationship at the most basic level as an interaction between a doctor and a patient to achieve an act of clinical relevance. Some interviewees appear to be comfortable replacing this type of interaction with AI systems. This is especially more relevant given that the counterfactual is not necessarily that the clinician is replaced by software. As suggested by an

interviewee, it could be that an entire methodology changes and that a small sample of blood is passed through an AI system to quickly and accurately diagnose a patient, meaning that the quality of the diagnostic process would improve by taking out at least some human element. This phenomenon is not unique to AI. Throughout history, many tasks that once required clinicians have been replaced by often more accurate "human-less" solutions. For instance, the diagnosis of uncomplicated urinary tract infections no longer requires a human clinician.

These evolutions of the doctor-patient relationship, where the AI can convincingly replace some human tasks, can lead to efficient doctor-patient relationships. However, this partial substitution should not compromise the intrinsic value of the doctor-patient relationship. In other words, if the integration of AI systems as partial replacements for human clinicians results in a decline in patient health outcomes, such as, for example, patients stopping their adherence treatments, then this integration does not increase efficiency. Instead, it highlights a critical flaw in the implementation process, underscoring the necessity of maintaining the doctor-patient relationship in healthcare to ensure patient compliance and overall well-being. It is therefore necessary to determine if and whether parts of the care pathways can be replaced by AI systems without compromising the benefits resulting from the doctor-patient relationship.

As described in Chapter 2, according to the literature, four key factors can explain the link between the doctor-patient relationship and improved health outcomes. First, through effective communication, patients can better understand their illness and the benefits and downsides of treatment, resulting in better treatment adherence (Zolnierek and DiMatteo 2009, Stavropoulou 2011). Increased adherence can also be explained by patients feeling genuinely understood and supported by their clinician (Zolnierek and DiMatteo 2009). Second, through communication and empathy, clinicians can understand what matters most to patients and can, therefore, help them make choices to maximise their well-being in ways that they feel comfortable with (BMA

2024). Third, the relationship plays an important part in understanding the nature of symptoms and apprehending underlying pathologies (Chew-Graham, May and Roland 2004). Fourth is the "caring effect". Evidence shows that when patients feel like their clinician is empathetic, their illness resolves quicker (Rakel, Barrett et al. 2011). A similar effect has been found when the clinician is warm, friendly, and reassuring (Blasi, Harkness et al. 2001). Some of these aspects seem to be replaceable by AI systems. For example, early evidence shows that AI can be used to help patients understand the benefits and downsides of their treatment, which helps with treatment adherence (Ayers, Poliak et al. 2023). However, AI does not seem to be able to convincingly capture human values and preferences yet (McDougall 2019) nor can it adequately care (Turkle 2011).

Figure 5: AI systems' potential to replace specific components of the clinical interaction

Component of the clinical interaction	Benefit of the Person-Centred Relationship	Evaluation criteria for AI systems
Administrative work	Not *directly* relevant	Can AI effectively complete the clinician's administrative work?
Diagnosis	Clinician and patient communicate well to understand the patient's symptoms, history, and personal context, leading to a more accurate diagnosis.	Can AI accurately gather and interpret patient data, including subtle contextual factors that a human clinician would recognise?
Treatment decision	Clinician and patient collaboratively decide on treatment, considering the patient's values and preferences. A genuine understanding through empathetic care ensures the treatment aligns with patient goals.	Can AI support shared decision-making by incorporating patient values, preferences, and context in treatment recommendations?
Treatment adherence	Clear communication helps the patient understand the role, purpose, and importance of adhering to the prescribed treatment.	Can AI systems effectively communicate treatment plans and ensure adherence through follow-ups or reminders?
Caring	A warm, friendly, and empathetic attitude	Can AI systems be warm, friendly, and empathetic?

Figure 5, adapted from the literature on the doctor-patient relationship presented in Chapter 2 and the input of interviewees, helps to understand where AI may have a role in making the

relationship more efficient by simplifying the clinical encounter into five key components: administrative work, diagnosis, treatment decision, treatment adherence, and caring. Each component outlines the benefits of the patient-centred doctor-patient relationship and provides evaluation criteria for AI systems to determine where they can replace human input. Importantly, when AI convincingly replaces one part of the interaction, such as diagnosis, it does not mean that all other parts, like caring, should remain intact. The continuation of these aspects depends on the outcomes that matter most to the patient. For example, while some patients may highly value empathy and emotional care, others may prioritise speed of care over the need to feel cared for. This approach allows for a more nuanced application of AI in healthcare, focusing on improving efficiency without sacrificing patient-centred care where it matters most. Whereas current evidence points toward the fact that steps such as diagnoses could convincingly be replaced by AI systems in situations where the choice of treatment requires significant value input or in cases where patients benefit from caring from a clinician, time saved through diagnosis by AI, for example, should be reallocated to these specific activities in order to ensure that the outcomes that matter to patients are realised.

6.1.3. How blanket approaches limit efficiency

According to the developed *efficient doctor-patient relationship* framework, one size does not fit all. In Chapter 4, efficiency in healthcare was described as maximising outcomes with the available resources. In a value-based healthcare model, outcomes are defined in accordance with the needs of specific subgroups (for example, children with chronic conditions such as asthma). This means that *goals* need to be tailored to specific patient clusters. This requires the balancing of different values and interventions in order to reach optimal outcomes with the available resources.

When analysing the doctor-patient relationship in Chapter 2, I pointed to some literature showing that the benefits of the doctor-patient relationship on health outcomes are situation-dependent. For example, compassionate care, an important part of the doctor-patient relationship, is perceived as particularly important in palliative care (Sinclair, Beamer et al. 2017). Another example is the case of patients who are difficult to diagnose, especially with symptoms that are hard to describe. In this case, there is an expectation that the doctor-patient will make a significant positive difference due to improved communication (Chew-Graham, May and Roland 2004, Kelley, Kraft-Todd et al. 2014), although these specific benefits may disappear in the face of accurate AI diagnostic softwares. Furthermore, the benefits of empathetic care in order to find the most appropriate course of action are well demonstrated. However, there seems to be space, in some cases, for the doctor-patient relationship to take a backseat in more straightforward instances. One example of this could be a simple fracture due to an accidental fall. To the extent that this case is medically simple and not traumatic for the patient, there do not appear to be significant benefits associated with a meaningful doctor-patient relationship in this specific event. On the contrary, this might be a situation where the patient prefers faster care and fewer interactions, leading to a more rapid return to "normal" life and activities. For example, convenience and speed, rather than relational aspects, have been found to be important factors in patient satisfaction in the context of retail health clinics, which are health centres located in retail locations such as pharmacies, grocery stores and department stores (Hunter, Weber et al. 2009). Systematically giving time back to the doctor-patient relationship is not always the best option, as this assumes that all doctor-patient interactions require particularly meaningful relationships. The interventions and values to optimise outcomes with the available resources, therefore improving efficiency, are situation-dependent. The interviewees' observations that the healthcare system is taking a blanket approach to the reallocation of time savings to timely care does not seem to be the most efficient approach and

omits that the doctor-patient relationship, too, can lead to more efficiency in a Value-Based Healthcare framework, as described in Chapter 4.

By analysing the expectations set out by the policy and professional documents with the interview data through the lens of the *efficient doctor-patient relationship*, I find that there is a lack of nuance in how AI systems are deployed and a lack of reflection surrounding their intended impact. Importantly, the *efficient doctor-patient relationship* framework reveals that AI's potential to improve patient outcomes is not fully realised because the reallocation of saved resources is not directed toward enhancing the doctor-patient relationship when this would be efficient. AI systems are deployed within existing pathways, and the notion that their use could automatically lead to improved relationships does not take into account the strong systemic incentives to increase aspects of care such as patient throughput. While these incentives are not always wrong and can, in many cases, contribute to improved patient care, this is not always the case. As mentioned, when the doctor-patient relationship contributes to the outcomes that matter to the patient, allocating saved resources to this relationship can be the most efficient way forward. Using the framework highlights the need for nuance and thoughtfulness when determining the reallocation of resources saved by AI, whereas the policy and professional documents and the experiences of interviewees highlight a seemingly lack of nuance when integrating AI systems in care pathways.

6.1.4. Conclusion

The mechanism of saving and reallocating time as a way for AI to affect the doctor-patient relationship has been clearly outlined in policy and professional documents. While interviewees agree with this mechanism in principle, they point towards the idea that saved resources are generally not reallocated to the doctor-patient relationship. The data suggests that this is due to systemic incentives, which push developers to develop AI tools that prioritise speed and

accuracy and push clinicians to see more patients rather than spending more time with any one patient. Viewing this situation through the lens of the *efficient doctor-patient relationship* suggests that systemic incentives should be aligned with the outcomes that matter to patients. In other words, any saved resources should be reallocated in a way that maximises the outcomes that matter to patients. What this means is that, sometimes, the doctor-patient relationship will have to be prioritised over other values, such as speed, as the relationship will make a significant contribution to outcomes. Equally, at other times, saved resources should not be reallocated to the doctor-patient relationship but rather to other aspects of care, such as patient throughput. Finally, as AI's performance increases, there will be tasks that have traditionally been performed by clinicians, which will be taken over by AI systems. Viewed through the lens of the *efficient doctor-patient* framework, this is beneficial only if the use of the AI tool contributes to enhancing the outcomes that matter to patients.

While the mechanisms behind AI deployment often seem to overlook the complexity of resource allocation for patient outcomes, the data suggests that the effect of AI on the doctor-patient relationship does not necessarily depend only on saving and reallocating time. The *efficient doctor-patient relationship* framework emphasises that to maximise patient outcomes, reallocation decisions must be made based on the needs of patient clusters as opposed to taking a blanket approach for all patients, and interview data suggest that changes in this relationship can be achieved through mechanisms like increased clinician confidence. This shows that there is reason to investigate whether efficiency in the doctor-patient dynamic can be maintained or enhanced without solely relying on resource reinvestment. The following section explores how AI systems, by boosting clinician confidence, can improve doctor-patient relationships efficiently.

6.2. Direct effects of AI on the doctor-patient relationship

While the previous section focused on AI tools' potential indirect effects on the doctor-patient relationship through the freeing up and reallocating of time, this section discusses how AI tools might directly impact the interactions between clinicians and patients. While the dynamics and systemic incentives surrounding reallocation are generally underexplored, the more direct effects that features of AI tools can have on the doctor-patient relationship have received considerable attention, as described in Chapter 2. Therefore, to complement the existing literature, I focus this section on the underexplored direct effects that arose during interviews.

6.2.1. Additional information and clinician confidence

If the relationship between AI and improved doctor-patient relationships does not seem straightforward in practice, interview data has shown that there might be another mechanism, besides saving and reallocating time, that leads to an improved doctor-patient relationship in an efficient way, but these have received no attention in the literature and policy documents. Many interviewees, clinicians and developers proposed that AI systems can improve the doctor-patient relationship by increasing clinician confidence through the AI system's ability to provide valuable information.

The proposed mechanism looks like the following: a clinician uses an AI system, which provides her with additional information. Without this additional information, the clinician feels more insecure about her diagnosis. Some of the interviewed clinicians indicated that this affects their relationship with the patient because they feel this diagnostic uncertainty prevents them from spending time talking to patients about things that matter to them. One clinician specifically said that he feels the need to add caveats to the conversation when he is unsure of his diagnosis, taking time away from focusing on the unique needs of each patient. By using a validated AI system that provides diagnostic information, interviewees believe that the doctor-patient

relationship can be improved. Furthermore, these AI systems have been noted in interviews for their ability to provide additional information within the same timeframe required for a clinician to see a patient. Consequently, if these systems enhance the doctor-patient relationship, they do so efficiently. This efficiency stems from the fact that no additional resources are required, thereby enabling healthcare providers to achieve more with the same resources. I investigate the claim made by interviewees regarding the potential of AI systems to improve the doctor-patient relationship through the outlined mechanism. To analyse this claim, I start by drawing on the definition of the person-centred doctor-patient relationship previously explored in Chapter 2, which is a relationship that puts an emphasis on effective communication (including empathy) and shared decision-making, aiming to respect the patient's uniqueness.

Good communication is an important part of the person-centred, doctor-patient relationship because it has been linked with improved health outcomes. The empirical data identifies two possible ways in which increased confidence can lead to improved doctor-patient relationships. The first is that the feeling of confidence about the diagnosis helps the clinician develop a better relationship with the patient. The second is that the feeling of confidence in the diagnosis helps the clinician spend less time justifying the diagnosis to the patient and allows for more time to be spent discussing what matters to patients and what the diagnosis means within their life story.

It is unclear at this stage whether an increase in clinician confidence can lead to improvements in the doctor-patient relationship. There is some evidence that a more confident clinician (in self-perception) comes across as "very satisfying" for a patient when discussing difficult matters (Fröjd and Von Essen 2006, De Vries, de Roten et al. 2014). However, there is also literature showing that diagnostic uncertainty is not necessarily detrimental to doctor-patient relationships, especially when linked to open communication (Dahm, Cattanach et al. 2023). This is not always the case and can be dependent on the patient. For example, patients from

professional backgrounds tend to feel a loss of control in the face of diagnostic uncertainty, whereas patients from a lower educational background tend to be more accepting (Dahm, Cattanach et al. 2023). Furthermore, the systematic review by Dahm and Cattanach also shows that it might not be the uncertainty itself that can, in some cases, improve the doctor-patient relationship, instead, it is the way in which it is communicated. Patients dislike when the topic of uncertainty is avoided and prefer an honest conversation about it. Equally, patients have more confidence in their doctor when diagnostic evidence from examinations is shown (Dahm, Cattanach et al. 2023). It therefore appears that (un)certainty itself is not what affects the doctor-patient relationship, but rather the open and honest communication of it. It is unclear, given the literature, whether clinician confidence itself can contribute to an improved doctor-patient relationship, though some benefits may be derived from the ability of the clinician to communicate more openly and honestly.

It is, however, well-documented, as shown in Chapter 2, that when clinicians spend more time providing empathetic care, understanding what matters to patients and addressing their concerns, effectively providing person-centred care, it leads to better health outcomes through an improved doctor-patient relationship. It is, therefore, likely that the feeling of confidence described by clinicians as improving their relationship with patients can be linked to improved doctor-patient relationships through the "classic" mechanism of additional time to provide more personalised care. This is because the doctors have to spend less time justifying their diagnoses and can, therefore, use that "saved" time to discuss topics that matter to the patient.

The interviewees explain that their improved relationships with patients result from the additional information they received from the use of AI systems. They also explain that this does not require additional time. If this is indeed the case, then this means that the use of AI systems contributes to more system efficiency by improving the doctor-patient relationship

without needing additional resources. Additional time is unnecessary. However, depending on whether it is the confidence of the clinician itself that improves the doctor-patient relationship or if it is the time saved as a result of increased diagnostic certainty, the latter case could result in a compromise needing to be made between timely care and the doctor-patient relationship. This is because, as suggested in the previous section, clinician confidence can 'free up' time and mental resources for the clinician to communicate about things that matter to the patient. If this is the case, then the freed-up time could also be used to enhance timely care. Whether the use of AI increases efficiency, in this case, would, again, be situation-dependent, depending on whether patient clusters value the doctor-patient relationship or timely care more in terms of what would lead to the best possible outcomes. If the decision is made according to person-centred health outcomes, as defined by VBHC, then using validated diagnostic AI systems creates additional value without consuming additional resources, which means that any improvements in the doctor-patient relationship or timely care can be done *efficiently* as there is more output (the doctor-patient relationship or increased patient throughput) with the same amount of input (resources).

6.2.2. Clinician confidence and bias

Many interviewees, including AI developers, expressed concern regarding bias stemming from the use of AI systems. The worry is that if the clinician can gain confidence by using an AI system, then this might reinforce biases. Suppose the clinician comes up with a wrong diagnosis, and the AI system happens to be wrong as well, then the clinician will be reinforced in her idea that she is right, even though she is wrong. Similarly, if the clinician is right but puts more confidence in the AI system that happens to be wrong than her own abilities, then the clinician is likely to go with the wrong suggestion made by the AI system. In Chapter 2, I provided a short overview of the risks identified by the bioethics literature regarding bias. The literature warns against the use of biased data to build AI systems, as this can mean that biases are

exacerbated as opposed to minimised (Leslie, Mazumder et al. 2021). AI developers showed a deep awareness of this issue during interviews and seemed to be actively thinking about ways to prevent harmful bias from creeping into the development of AI systems.

The potential benefits of additional clinician confidence in the doctor-patient relationship would arguably be lost if clinician confidence is misplaced in biased data. However, as demonstrated in Chapter 2, human clinicians are also biased, often unconsciously, and furthermore, humans can be inconsistent (Reason 2000, Dekker 2011, FitzGerald and Hurst 2017). It has been argued that the use of new technologies can help prevent bias by ensuring that these technologies are built on adequate datasets (Abràmoff, Tarver et al. 2023). Interviewees suggested that the order of using AI systems could perhaps mitigate risks. For instance, having to come up with a diagnosis before using an AI system can ensure that the AI system remains assistive and means that the AI acts as an additional "check". Furthermore, efforts are ongoing to ensure new technologies do not reproduce biases stemming from humans (Ganapathi, Palmer et al. 2022). Interviewees have also highlighted that AI systems can help human clinicians be more consistent, which can have positive effects on health outcomes. Despite these potential positives, studies have shown that humans are more accepting of human errors than errors made by technology (Dietvorst, Simmons and Massey 2015). In other words, patients may be more accepting of errors stemming from clinician bias or inconsistencies than errors made by an AI system, even if the AI system makes significantly fewer errors than a human. This matters because the potential benefits stemming from the use of AI systems expressed by interviewees can only be realised if these new technologies are accepted by patients.

To summarise, interviewees have highlighted the potential for AI systems to enhance the doctor-patient relationship through mechanisms that have not yet been extensively explored in

published literature or policy documents. The primary mechanism identified by interviewees involves AI systems providing clinicians with additional diagnostic information, which in turn increases clinician confidence. This increased confidence allows clinicians to engage more effectively with patients, allowing them to practice person-centred care by focusing on what truly matters to the patient without the distraction of diagnostic uncertainty, which usually requires time to justify. The gathered data suggests two main pathways through which increased clinician confidence, facilitated by AI, can improve the doctor-patient relationship. First, confidence in diagnosis helps clinicians feel better in their relationship with patients, potentially leading to an improved relationship. Second, it allows clinicians to spend less time justifying diagnoses and more time engaging in meaningful conversations about what the diagnosis means for the patient's life. However, the relationship between clinician confidence and improved doctor-patient relationships requires further investigation. There is some limited evidence suggesting that confident clinicians are perceived more positively by patients (Fröjd and Von Essen 2006). However, there is an established body of literature emphasising the benefits of empathetic care. Further research should determine whether the increased confidence itself directly enhances the relationship or if it is the additional time spent on personalised care that can make a difference.

Another finding is that interviewees indicated that AI systems provide valuable diagnostic information without requiring additional time, thereby improving relationships without necessitating extra resources. This implies a more efficient healthcare system where better doctor-patient relationships are potentially achieved with the same level of input. Nonetheless, despite the potential efficient improvements in the doctor-patient relationship resulting from additional clinician confidence, there are concerns regarding bias in AI systems. The potential for AI to reinforce existing biases if trained on biased data is significant (Leslie et al., 2021). Interviewees and literature alike underscore the importance of developing AI systems that

minimise bias and promote consistency in clinical practice. However, patients' acceptance of AI is crucial, as studies have shown a general preference for human errors over technological ones (Dietvorst, Simmons, & Massey, 2015). Thus, the potential benefits of AI on the doctor-patient relationship depend not only on the technology itself but also on its acceptance by stakeholders. Ultimately, by focusing on clinician confidence, the findings specify and validate the concept of the *efficient doctor-patient relationship* by demonstrating how relational care can be improved without solely relying on time reallocation, providing a more nuanced and flexible approach to efficiency in healthcare.

6.2.3. Characteristics of AI tools

The discussion on AI and confidence and the associated problems that can result from additional clinician confidence highlights the need to investigate how features of the AI systems themselves can impact the doctor-patient relationship and what this means for efficiency.

As a reminder, in the first part of this discussion chapter, I identified that systemic incentives that push towards blanket approaches (e.g. time saved by AI should be reallocated to the doctor-patient relationship or time saved by AI should be reallocated to increased patient throughput) are not useful in order to enhance the doctor-patient relationship efficiently. This is because the reallocation of saved resources must be conducive to the achievement of outcomes that matter to patients, meaning that incentives and care pathways have to be aligned accordingly. However, another important barrier to AI enhancing doctor-patient relationships efficiently is the numerous ethical issues that can emerge from the development of AI systems. There is a broad literature, presented in Chapter 2, on how the very features of AI systems are likely to impact the doctor-patient relationship. Some of these have been described as potentially having a positive impact (e.g. explainable systems), but many have raised concerns with systems that are built as black boxes, as lacking value-plurality, or developed using biased data (McDougall 2019,

Leslie, Mazumder et al. 2021). Such ethical issues have the potential to harm the doctor-patient relationship.

The ethical issues associated with features of specific AI tools have been reinforced by interviewees, particularly developers, who worry a lot about bias and the difficulty in mitigating such problems. They are also aware that clinicians have a strong preference for using explainable AI systems but emphasise the difficulty of creating such tools. Given that we know from the bioethics literature how ethical issues can arise from specific features of AI systems that can harm the doctor-patient relationship, every effort should be made to mitigate such issues. Furthermore, when analysed through the lens of the *efficient doctor-patient relationship*, ethical issues emerging from features of AI systems do not only harm relationships but also efficiency, given that by harming the relationship, its benefits can no longer be realised.

Therefore, if an AI tool has the potential to improve the doctor-patient relationship (for example, by increasing clinician confidence), this positive effect is cancelled out if features of the same AI tool create problems that harm the doctor-patient relationship and, by the same token, efficiency. Furthermore, even if an AI tool saves time and can, in theory, be reallocated to the doctor-patient relationship, this loses meaning if the use of the AI itself threatens essential aspects of the doctor-patient relationship. Therefore, each AI system deployed in care pathways should be carefully evaluated specifically for its potential to impact the doctor-patient relationship through its very features rather than only through its ability to save resources.

6.3. Answering the research question

This study sought to find out **how the doctor-patient relationship can be integrated into a healthcare context that strives for AI-supported efficiency**. In order to address this aim, Chapter 4 investigated how the concepts of the doctor-patient relationship and efficiency relate.

It developed a theoretical framework chapter, proposing that the doctor-patient relationship should be viewed as a component of efficiency and that healthcare systems should strive to make the doctor-patient relationship as efficient as possible in order to maximise patient outcomes.

My next step was to understand the experiences of those developing and using AI systems. I presented the gathered interview data in Chapter 5. Through analysing the interviewees' experiences using the *efficient doctor-patient relationship* framework, this discussion chapter (Chapter 6) offered a nuanced understanding of how the doctor-patient relationship can be integrated into a healthcare system that strives for AI-supported efficiency. This discussion built on existing literature. In the following, I summarise the discussion to provide a succinct answer to my research question.

The doctor-patient relationship can be integrated into a healthcare system that strives for AI-supported efficiency by viewing the doctor-patient relationship itself as efficient. This approach puts outcomes that matter to specific patient clusters at its centre. In the context of AI deployment in healthcare, patient outcomes can be maximised (1) indirectly through the saving and reallocation of resources and (2) through the features of the AI system itself, which may directly affect the efficiency of the doctor-patient relationship.

1) AI can impact the doctor-patient relationship through the saving and reallocation of resources in several ways. Whether the reallocation of resources does, in fact, lead to an increase in the efficiency of the doctor-patient relationship depends on whether such a relationship contributes to enhancing the outcomes that matter to patients. Importantly, recognising that AI systems may adequately replace some aspects of the doctor-patient relationship, as

proposed in **Figure 4,** is an important factor in making the doctor-patient relationship efficient. It is equally important to recognise that not all patients value the doctor-patient relationship similarly. If AI integration leads to a decline in patient outcomes, such as decreased treatment adherence due to the loss of meaningful clinician relationships, it indicates a flawed implementation. It is essential to identify which parts of care pathways can be managed by AI without compromising the benefits of the doctor-patient relationship. By identifying instances where the doctor-patient relationship is crucial to patient outcomes and where it can take a secondary role, as well as determining which aspects can be effectively replaced by AI, the doctor-patient relationship can be made efficient, which can help contribute to the overall efficiency of the healthcare system. Furthermore, for AI to positively affect the efficiency of the doctor-patient relationship, systemic incentives and values need to be aligned to provide the care that will most benefit the outcomes that matter to patients.

2) The features of the AI system itself may impact the dynamic of the doctor-patient relationship. For example, blackbox AI systems risk disrupting communication between clinicians and patients. Besides providing a comprehensive framework for understanding the role of the doctor-patient relationship in the context of AI, my analysis uncovered a mechanism underexplored in the bioethics literature, which is the possibility that AI could improve the efficiency of the doctor-patient relationship by increasing clinicians' confidence through enhanced access to information. According to clinicians, this could mean that they end up spending more time talking to patients about things that matter to them. However, this potential benefit might be limited if management reallocates the time gained from AI efficiencies elsewhere. If

increased confidence on its own were indeed the key mechanism by which AI enhances the doctor-patient relationship, this could be a valuable area for further research. Yet, there are significant concerns about the risks of overconfidence, such as the introduction of bias in clinical decision-making. Interview data confirms the need to assess each AI system prior to its deployment in care pathways for its impact on the dynamic of the doctor-patient relationship. In the context of the *efficient doctor-patient relationship*, such effects have to be balanced with other effects beyond the doctor-patient relationship (e.g. the level of accuracy of the AI system) to maximise patient outcomes with available resources. For example, if health outcomes are a priority, it may be justifiable to use a high-performing black box AI system (in the absence of an explainable alternative), which could have a harmful effect on the doctor-patient relationship but ultimately benefits the outcomes that matter most to the patient in a way that the doctor-patient relationship cannot benefit these outcomes.

By optimising the efficiency of the relationship, we can ensure that the doctor-patient relationship is adequately integrated into a healthcare context that strives for AI-supported efficiency.

Based on the findings of this discussion, the next section presents recommendations aimed at decision-makers who need to decide when to allocate resources to the doctor-patient relationship when introducing a new AI system in care pathways.

6.4. Implications for policy and practice

The primary contribution of this study is the development of the *efficient doctor-patient relationship* framework, which, together with the gathered interview data, advances our

understanding of how the doctor-patient relationship fits within a healthcare context that strives for AI-supported efficiency. This framework challenges the simplistic assumptions in policy documents that AI will automatically lead to better doctor-patient relationships by saving time. Instead, it provides a more sophisticated lens for analysing how AI can enhance or undermine these relationships depending on outcomes that matter to patients within the context of an efficient healthcare system.

By analysing the experiences, views and perceptions of clinicians and AI developers, I identified some of the ways in which AI has been perceived to affect the doctor-patient relationship in practice. The saving and reallocation of time is one way AI can affect the doctor-patient relationship. Another way in which AI can affect the doctor-patient relationship is through the features of the AI systems, which can change the way users feel and interact.

The introduction of AI tools into healthcare systems comes with considerable opportunities and risks for the doctor-patient relationship and, relatedly, overall patient outcomes. Navigating this complex and rapidly evolving environment poses serious challenges for policymakers. This section provides actionable recommendations based on my findings to guide their efforts.

A direct link between AI, efficiency, and improved relationships should not be assumed. Introducing AI tools into healthcare is highly unlikely to automatically reallocate saved time to the doctor-patient relationship, thereby improving efficiency and patient outcomes. While it is reasonable to expect that AI can enhance efficiency by improving outcomes with the same resources or maintaining outcomes with fewer resources, this does not necessarily translate into better relationships. Specifically, it is unclear whether AI actually saves time. Some clinicians report that while they receive more information within the same timeframe, they do not gain "free time" to build stronger patient relationships. Even in cases where time is saved, clinicians often find they cannot dedicate that time to patients.

To enhance the efficiency of the doctor-patient relationship, decision-makers should:

1. Understand whether the integration of an AI system has the potential to save clinicians' time.
    a) **If yes:**
        1. Understand whether the saved time is taken from areas where the doctor-patient relationship plays an important role (e.g. diagnostic as opposed to administrative work) and consider whether replacing a human clinician with an AI system will contribute to enhancing the outcomes that matter to patient clusters.
        2. Understand how the features of the AI tool are likely to change the interactions between the doctor and the patient and evaluate this together with other effects beyond the doctor-patient relationship.
        3. Allocate the saved time to the area that benefits patients the most, according to the preferences of specific patient clusters.
    b) **If no**:
        1. Understand how the features of the AI tool are likely to change the interactions between the doctor and the patient and evaluate this together with other effects beyond the doctor-patient relationship.

Importantly, these steps require **aligning the incentives within healthcare systems with the values and priorities the system seeks to promote**. A key insight from the interview data revealed that, despite policy and professional documents expecting the time saved by AI systems to be reinvested in the doctor-patient relationship, the current healthcare system does not appear to prioritise reallocating this time toward strengthening that relationship. The *efficient doctor-patient relationship* framework emphasises that patient-centred outcomes should drive resource allocation decisions. Aligning systemic values with this framework would necessitate greater flexibility in resource distribution and recognition that aspects of care not traditionally associated with efficiency, such as the doctor-patient relationship, may, in certain cases, represent the most efficient allocation of resources. Overall, achieving an efficient doctor-

patient relationship requires nuanced resource allocation decisions, an aspect often overlooked in current policy discussions surrounding the deployment of AI in healthcare.

A final important point that has emerged from this study is that **medical education should focus on relational aspects of care**. Although this has been brought up in the medical and bioethics literature, this study further highlighted the importance of clinicians' ability to be empathetic and compassionate. This ability is not a "nice to have extra" but a key element in maximising efficiency and patient outcomes in the age of AI. This is because AI systems can take on many of the "knowledge" tasks which have so far been exclusive to clinicians. However, what will remain and make the clinician irreplaceable is her ability to provide empathetic and compassionate care, which will still be a crucial component of healthcare for many patient clusters.

7. Conclusions

7.1. Limitations of this study and further research

This study's findings advance our understanding of how efficiency and the doctor-patient relationship are related in theory and how AI fits within this relationship in practice. The developed *efficient doctor-patient relationship* framework enables us to adequately integrate the doctor-patient relationship into a healthcare context that strives for AI-supported efficiency. It also develops practical recommendations for decision-makers. There are, however, limitations to this study, which could be addressed through further research in order to deepen our understanding of the impact of AI on healthcare.

First, based on one of the findings of the qualitative study, more research could be done on the use of AI systems and the link with clinician confidence and how this affects doctor-patient relationships. This area is currently underexplored and could give rise to meaningful findings within the bioethics literature.

Furthermore, given the (currently) limited uptake of AI in healthcare, this study focused mostly on diagnostic AI systems used by clinicians. This is because these form the majority of AI systems currently used. These are not the only AI systems available, and as time goes by, there is likely to be an increasing uptake of a wide variety of different AI systems in healthcare. Further research should focus on other types of AI systems, such as those mediated by patients.

Patients form an integral part of the doctor-patient relationship. However, they have not been included in this study, given my focus on efficiency and, therefore, on the systemic level of healthcare. Clinicians were especially well placed as intermediaries between patients and the healthcare system, and developers were also acutely aware of system-level incentives driving

their work. Patients do not have a similar "access" to the systemic level. However, given that this thesis proposes that the doctor-patient relationship should be made efficient based on outcomes that matter for patients, further research projects should investigate how various patient clusters value the doctor-patient relationship in different situations.

Next, given the focus on the doctor-patient relationship, this study does not consider other broader ethical risks associated with AI-enhanced healthcare. For example, interviewees have highlighted the risk of creating a two-tiered system depending on who can afford AI systems versus who cannot. Related to the cost issue, this study considers the impact of AI systems post-implementation. For example, the interviewed clinicians already use the system. The AI developers I talked to had already developed tools that are being used in practice. There is, therefore, no consideration in the discussion chapter for the cost of the AI system at the development, uptake, and maintenance stages. Given the focus of this study on efficiency, it would be an interesting follow-up project to determine whether the integration of AI systems truly contributes to better care within the resources allocated to the NHS or whether better care comes at an increase in costs.

Interviewees were overwhelmingly England-based. Given the uniqueness of the NHS, findings from this study may not apply to other healthcare systems. In addition, different regions of the world may have different understandings of what constitutes a "meaningful doctor-patient relationship", affecting the theoretical contributions of this thesis. Further studies could focus on how the incentive structures of different healthcare systems affect AI tools' impact on the doctor-patient relationship. Distinguishing between the largely state-funded systems like that of the UK and primarily private systems like that of the US, could be a good place to start.

7.2. Concluding reflections

This study sought to understand **how the doctor-patient relationship can be integrated into a healthcare context that strives for AI-supported efficiency**.

To this end, I developed the theoretical framework of the *efficient doctor-patient relationship*. The framework views the doctor-patient relationship as an intrinsic part of efficiency. It posits that resources should be allocated to the doctor-patient relationship when doing so contributes to maximising outcomes that matter to patients.

I then empirically explored, through semi-structured interviews, how clinicians and AI developers understand AI to impact healthcare practices. Analysing the gathered interview data using the theoretical framework enabled me to gain an empirically grounded understanding of the role of AI within the *efficient doctor-patient relationship*.

I identify two key mechanisms through which AI can impact the efficiency of the doctor-patient relationship: the reallocation of freed-up resources and the direct influence of AI systems' features on the doctor-patient relationship. Whenever AI frees up resources, the decision on how to reallocate these resources must be based on the needs and priorities of specific patient clusters. Additionally, the features of AI systems, such as whether they are explainable or operate as black boxes, can directly alter the dynamics of the doctor-patient relationship. These effects, too, must be carefully evaluated in terms of how they impact the *efficient doctor-patient relationship*.

These findings have important policy implications and can guide healthcare decision-makers' efforts to maximise patient outcomes when integrating AI tools into healthcare systems.

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8. Appendix

8.1. NHSX/Transformation Directorate Awards

Figure 6 below shows all the awards presented since the AI for Health and Care Awards programme's start in 2020, in all 4 phases. To understand what types of AI tools the UK is funding and planning to deploy within the NHS, I have added two variables to the table below: "Role of AI" and "Primary User." These variables help identify specific AI applications, such as diagnostic tools or organisational aids, and determine their intended users, clinicians, patients, or others. **Figure 7** presents of summary of the type of AI tools funded, and **Figure 8** shows the number of AI tools funded per user type. This information is useful for interpreting policy documents, as it allows us to understand which kinds of AI systems the provided information pertains to.

1) Role of AI: I investigated the function of each AI system. The following were identified as the leading categories:
    - **Diagnostic tool and/or decision making**: the system is used to help diagnose patients or to help with the decision-making process (e.g. what treatment is the most appropriate?). I did not differentiate between diagnostic and decision-making systems as the two are often related. Frequently, a system helping with diagnosing also helps with decision-making, but this is not always the case. For example, while a system might help diagnose a disease, it may not help choosing between treatment options. This distinction does not affect my classification process, as both contribute to the clinician's thought process, with some AI systems contributing to smaller aspects of the thought process (e.g., diagnosis only) and others covering more extensive parts (e.g., diagnosis and treatment recommendations). In both these options, AI systems contribute to the overall thought process of the human clinician, albeit to different extents.

- **Monitoring:** the system monitors a patient (e.g. vital signs).
- **Technical:** the system helps with purely technical matters but does not inform decision-making or diagnosis. For example, tools used to measure organs.
- **Organisational:** the system helps with administrative work, primarily organising staff or patient consultations.

2) Primary user: indicates who the primary user of the technology is. The majority of primary users are either:
   - **Clinician:** the clinician is the primary user.
   - **Patient (with or without a clinician in the loop):** the patient is the primary user. If the clinician is in the loop, the latter has access to the data, and the system is used to complement clinician-led treatment, meaning that the AI system is effectively used as a clinician's aid. The patient is the sole user if the clinician is not in the loop. However, other third parties are occasionally involved, such as pharmacists (for example, when delivering drugs following the detection of infection using an AI-powered app).

Figure 6: Recipients of the AI for Health and Care Awards

Phase	Function of tool	Role of AI	Primary user
2020 (phase 1)	Stewardship of Antimicrobials using Real-Time Artificial Intelligence (SamurAI) - University College London	Diagnostic and/or decision making	Clinician
	Deep learning for effective triaging of skin disease in the NHS - University of Dundee	Diagnostic and/or decision making	Clinician
	A fully automated ultrasound tool to screen for fetal growth restriction (FGR) in the first trimester - University of Oxford	Diagnostic and/or decision making	Clinician

	Personalised Preoperative (Neoadjuvant) Chemotherapy (NACT) to optimise curative treatment in breast cancer - University of Nottingham	Diagnostic and/or decision making	Clinician
	OCTAHEDRON : Optical Coherence Tomography Automated Heuristics for Early Diagnosis via Retina in Ophthalmology and Neurology - Newcastle University	Diagnostic and/or decision making	Clinician
	Improving diagnostic yields of the Faecal Immunochemical Test using artificial intelligence and machine learning- Advanced Expert Systems Limited	Diagnostic and/or decision making	Clinician
	Development of AI techniques to predict eye cancer using big longitudinal data - University of Liverpool	Diagnostic and/or decision making	Clinician
	An artificial intelligence macular disease treatment decision tool for patients with wet age-related macular degeneration, diabetic macular oedema, and retinal vein occlusion - Macusoft Ltd	Diagnostic and/or decision making	Clinician
	Project Rhapsody: Investigating the clinical feasibility of using AI-based deep audio and language processing techniques to diagnose neurological and psychiatric diseases - Novoic Ltd	Diagnostic and/or decision making	Clinician
	AI-enabled point-of-care technology for radiotherapy planning peer review - Mirada Medical Ltd	Diagnostic and/or decision making	Clinician
	Prognosis of epilepsy using at-home EEG monitoring - Neuronostics Limited	Diagnostic and/or decision making	Clinician
	Autonomous cardiac MR acquisition - Barts Health NHS Trust	Diagnostic and/or decision making	Clinician

	Senti: Wearable technology to enable remote precision and predictive medicine for respiratory patients - Senti Tech Limited	Diagnostic and/or decision making	Clinician
	An artificial intelligence algorithm for diagnosing attention deficit hyperactivity disorder (ADHD) in adults - University of Huddersfield	Diagnostic and/or decision making	Clinician
	Woubot: An AI predictive system to produce personalised care recommendations for chronic lower limb wounds - Nine Health Global Ltd	Diagnostic and/or decision making	Clinician
2020 (phase 2)	FORE AI - Odin Vision Limited	Diagnostic and/or decision making	Clinician
	Clinical validation of the AI Clinician decision support system for sepsis treatment - Imperial College London	Diagnostic and/or decision making	Clinician
	Developing Lifelight: A contactless vital signs monitor for CVD screening - Xim Limited	Diagnostic and/or decision making	Clinician or patient
	Digitally adapted, hyper-local real-time bed forecasting to manage flow for NHS wards - University College London	Organisational tool	Neither clinician nor patient
	Interactively trained 'human-in-the-loop' deep learning approach to improve cardiac CT and MRI assessment for accurate therapy response and mortality prediction - University of Sheffield	Diagnostic and/or decision making	Clinician
	Artificial Intelligence to improve cardiometabolic risk evaluation using CT (ACRE-CT) - Caristo Diagnostics Limited	Diagnostic and/or decision making	Clinician
	Dem Dx triage support platform for ophthalmology referrals - Dem Dx Limited	Diagnostic and/or decision making	Clinician
	BioEP: From prototype to clinical evaluation - Neuronostics Limited	Diagnostic and/or decision making	Clinician

	SMARTT critical care pathways - (Safe, Machine Assisted, Real Time Transfer): An artificial intelligence-based decision support tool to enable safer and more timely critical care transfer - University Hospitals Bristol and Weston NHS Foundation Trust	Diagnostic and/or decision making	Clinician
	Prediction and prevention of asthma attacks in children - BreatheOx Limited	Prediction	Patient (with a Clinician in the loop)
	Autonomous telemedicine - cataract surgery follow-up at two NHS trusts - Ufonia Limited		Patient (no Clinician in the loop)
	Natural language processing for real-time data capture in electronic health records to improve clinical care and operational efficiency - University College London Hospitals NHS Foundation Trust	Technical	Clinician
2020 (phase 3)	A study to assess the clinical and cost-effectiveness of the Ibex Medical Analytics - AI System: Histology system in diagnosing clinically important prostate cancer in prostate biopsy tissue - Imperial College London	Diagnostic and/or decision making	Clinician
	Real world testing of PreSize Neurovascular: medical device software to optimise stenting surgeries to reduce complications - Oxford Heartbeat Ltd	Technical/decision making	Clinician
	EchoGo Pro: NHS impact of automating coronary artery disease risk prediction in stress echocardiogram clinics - Ultromics Ltd	Diagnostic and/or decision making	Clinician
	Point-of-care heart failure diagnosis for GP use: Implementation and evaluation of a simple AI-tool into the folio of care pathways serviced by Imperial's Connected Care national GP network	Diagnostic and/or decision making	Clinician

	Evaluation of the DEONTICS AI platform for personalised, evidence-based treatment planning in multidisciplinary cancer care: Increasing compliance with national standards of care and streamlining MDTs in prostate cancer - Guy's and St Thomas' NHS Foundation Trust	Diagnostic and/or decision making	Clinician
2020 (phase 4)	e-Stroke Suite - Brainomix Ltd	Diagnostic and/or decision making	Clinician
	Smartphone albuminuria self-testing - Healthy.io (UK) Ltd	Diagnostic and/or decision making	Patient
	DLCExpert - Mirada Medical Ltd	Technical task	Clinician
	EchoGo Pro - Ultromics Limited	Diagnostic and/or decision making	Clinician
	Automated diabetic retinal image analysis software - Optos Public Limited Company	Diagnostic and/or decision making	Clinician
	Mia Mammography Intelligent Assessment - Kheiron Medical Technologies	Diagnostic and/or decision making	Clinician
	Maximising Hospital Resource - ICNH Ltd (DrHCP)	Organisational tool	Neither clinician nor patient
	RITA: Referral Intelligence and Triage Automation - Deloitte	Triage	Clinician
	Veye - Aidence	Triage and diagnostic tool	Clinician
	Zio Service - iRhythm Technologies Ltd	Diagnostic and/or decision making	Clinician
2021 (phase 1)	Diagnosis of 'glue ear' with AI	Diagnostic and/or decision making	Clinician
	R-CANCER: will improve the quality of decisions made by HCPs when deciding how best to detect and diagnose cancer	Diagnostic and/or decision making	Clinician

	Predicting pre-term labour: explore the use of electrohysterography sensing to predict the pre-term labour of women	Diagnostic and/or decision making	Clinician
	Detecting coronary artery calcification in CT scans	Diagnostic and/or decision making	Clinician
	Decision-making for less-than-perfect kidney transplant matches	Diagnostic and/or decision making	Clinician
	CirrhoCare	Predictive tool	Clinician
	Measuring hip dysplasia in children with cerebral palsy	Technical	Clinician
	PREVAIL - PhototheRapy Enhanced Via Artificially Intelligent Lasers	Technical	Clinician
	panPIERS: app to calculate an individual woman's risk of the complications of pre-eclampsia, including following birth.	Diagnostic and/or decision making	Clinician
	Developing the Blood Pressure Index for improved blood pressure control: provide the public with more useful and AI-driven blood pressure data for self-monitoring	Diagnostic and/or decision making	Patient
	Pathpoint Detect: Pathpoint Detect is a novel, transparent decision support tool for image-based diagnosis in dermatology.	Diagnostic and/or decision making	Clinician
	Monitoring slow-growing brain tumours	Diagnostic and/or decision making	Clinician
	Machine learning to improve the diagnosis of heart attacks	Diagnostic and/or decision making	Clinician
	Issues and themes analysis in complaints: improve the speed, responsiveness and learning from the management of healthcare complaints, picking up key issues in individual cases	Diagnostic and/or decision making	Clinician
2021 (phase 2)	Eye2Gene: determine which genetic condition is causing a patient's inherited retinal disease	Diagnostic and/or decision making	Clinician

	CESCAIL: preliminary analysis on the hours of images taken during capsule endoscopy	Diagnostic and/or decision making	Clinician
	CHRONOS: A machine learning-based clinical decision support for 'digital triage' in secondary mental health care	Triage	
	First PLUS: analyse the size of the placenta during the first trimester as a predictor for Fetal Growth Restriction, a risk factor for stillbirth and other neonatal conditions.	Diagnostic and/or decision making	Clinician
	ImageDx: faster and more accurate testing on cancer biopsy tissue for colorectal, lung and other cancers	Diagnostic and/or decision making	Clinician
	mySmartCOPD: use home monitoring of various health markers, and report them using the MyCOPD app	Monitoring	Patient (with a Clinician in the loop)
	Advance notice of deterioration in cystic fibrosis: predict sudden dips in the health of adults with cystic fibrosis, enabling early intervention and supporting patients to stay well without repeated hospital check-ups.	Monitoring	Patient (with a Clinician in the loop)
	AI Systems for precision blood group matching: genetic blood group typing, automated stocking of blood of different types, and precision matching of patients to blood units	Triage	Clincian
	MyDiabetes IQ: predicting diabetes complications, subtype diagnosis and treatment choices, to support clinicians including non-specialist GPs with managing their diabetes patients	Diagnostic and/or decision making	Clinician
2021 (phase 3)	Wysa: early intervention and support tool for mental health	Self-help	Patient (no Clinician in the loop)

	Lenus chronic obstructive pulmonary disease (COPD) Management Service: uses AI to analyse output from patients' daily monitoring and wearable devices to predict deterioration, and enable targeted intervention by care teams	Diagnostic and/or decision making	Clinician
	DOLCE: helps HCPs make optimal decisions for patients with potentially cancerous lung lesions found in CT scans	Diagnostic and/or decision making	Clinician
	Open-source AI to augment and accelerate radiotherapy workflows: differentiate between tumour and healthy tissue on cancer scans (called 'segmenting'), prior to radiotherapy treatment	Technical	Clinician
	Analysing breast screening X-rays: analysing X-ray images of routine mammograms	Diagnostic and/or decision making	Clinician
	Workforce deployment solutions: ensuring that both logistics and clinical support teams are in the right place at the right time within a hospital, to maximise efficiency	Technical	Neither clinician nor patient (healthcare management)
	ArtiQ.Spiro: interpret and evaluate the spirometry test used to determine lung function	Diagnostic and/or decision making	Clinician
	qER: analyse CT scans in patients with head injuries	Diagnostic and/or decision making	Clinician
	Cogstack Natural Language Processing: clinical coding of medical records aims to enable more efficient analysis, remove errors, free up staff time, and improve research	Technical	Clinician
	CaRi-HEART: detect the invisible signatures of inflammation in the heart as shown in regular CT scans	Diagnostic and/or decision making	Clinician
2021 (phase 4)	DERM: highlight the most likely cancers, and aid in swift and appropriate treatment being	Diagnostic and/or decision making	Clinician

	offered, reducing backlogs in this service and reducing premature deaths		
	eHub: triage and automate GP e-consultation requests	Triage	Clinician
	Chest X-ray analysis: fast-track the diagnosis of suspected lung cancer patients, offering them same-day CT scans	Diagnostic and/or decision making	Clinician
	Paige prostate cancer detection tool: support the interpretation of pathology sample images, in order to more efficiently detect, grade and quantify cancer in prostate biopsies	Diagnostic and/or decision making	Clinician
	Bone Health Solutions: analyse any CT scan to catch undiagnosed spinal fractures, which can be a marker for osteoporosis	Diagnostic and/or decision making	Clinician

Figure 7: Numbers by type of AI tool

Type of AI	Total number
Diagnostic and/or decision making	58
Organisational	2
Prediction	2
Technical	8
Technical/decision making	1
Triage and diagnostic tool	1
Triage	4
Monitoring	2
Self-help	1

Figure 8: User type

Primary user	Total number
Clinician	62
Clinician or patient	1
Patient (with a clinician in the loop)	3

Patient (no clinician in the loop)	3
Patient (with or without clinician in the loop)	1

8.2. Literature review search terms

Figure 9: Search keywords for the bioethics literature review

Database	Search terms
PubMed	("ai"[Title/Abstract] OR "artificial intelligence"[Title/Abstract] OR "algorithm*"[Title/Abstract] OR "machine intelligence"[Title/Abstract] OR "machine learning"[Title/Abstract] OR "computer reasoning"[Title/Abstract] OR "computer vision system*"[Title/Abstract]) AND ("doctor patient relation*"[Title/Abstract] OR "physician patient relation*"[Title/Abstract] OR empathy[Title/Abstract] OR compassion[Title/Abstract] OR "therapeutic relation*"[Title/Abstract] OR "therapeutic alliance"[Title/Abstract])
PhilPapers	ai OR artificial intelligence OR machine and patient doctor relationship OR empathy OR compassion
SCOPUS	("ai"[Title/Abstract] OR "artificial intelligence"[Title/Abstract] OR "algorithm*"[Title/Abstract] OR "machine intelligence"[Title/Abstract] OR "machine learning"[Title/Abstract] OR "computer reasoning"[Title/Abstract] OR "computer vision system*"[Title/Abstract]) AND ("doctor patient relation*"[Title/Abstract] OR "physician patient relation*"[Title/Abstract] OR empathy[Title/Abstract] OR compassion[Title/Abstract] OR "therapeutic relation*"[Title/Abstract] OR "therapeutic alliance"[Title/Abstract])
WebofScience	TS = ((ai OR "artificial intelligence" OR algorithm* OR "machine intelligence" OR "machine learning")) AND TS = (("doctor patient relation*" OR "physician patient relation*" OR empathy OR compassion))
Google Scholar	ai OR artificial intelligence OR machine and patient doctor relationship OR empathy OR compassion