The impacts, concerns and pitfalls of AI in healthcare diagnostics

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AFFIDAVIT

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ABSTRACT

One of the driving forces for the digitalization of the healthcare environment is Artificial Intelligence (AI). AI is the principle and development of computer systems capable of performing tasks that typically involve human intelligence. AI has facilitated healthcare innovations from drug development and selection to screening clinical trial patients. AI has proved to be effortless, reliable, and accurate in various disease diagnostics especially in medical imaging, neurology, cardiology, diabetes movement disorder and mental health, yet ethical challenges and validation frameworks remain questionable.

With its infinite power, AI has the potential to revolutionize patient healthcare creating a paradigm shift in disease diagnostics. The availability and increase of healthcare data, plus the increase in 21st century computer power, has facilitated the adoption of AI in healthcare diagnostics and fuelled the rapid results and analytic techniques. Addressing the diagnostic performance of AI within a hospital setting across different disease areas, through to the acceptance and reliance of AI and its diagnostic capabilities in digital wearable technology (for example, Apple Watch, Fitbit and other smart devices), AI is allowing patients to track and monitor their own health conditions and disease progression. These wearables can remind patients to take medication, signalling reminders. Some patients, especially those with heart conditions such as Atrial Fibrillation, receive warning alerts through their device which could have lifesaving consequences.

Against this background, this thesis delves into the literature on AI in healthcare diagnostics and penetrates the minds of the patient to gain enriched insights and knowledge across two definitive target groups: Non wearable candidates, and wearable candidates. Through a qualitative research approach using snowball sampling techniques and thematic analysis, this thesis illuminates the patient perspective of AI in diagnostic healthcare within two different mindsets. The aims are to identify what are the frequent applications of AI in the diagnostic healthcare sector, what do patients think of AI in healthcare diagnostics, what factors are driving patients to adopt digital diagnostic wearables to monitor their own health and what are the hindering concerns causing avoidance. The impacts, concerns, and successes of AI in healthcare diagnostics, are identified, showing areas where AI has, in many cases from a diagnostic perspective, outperformed doctors. This thesis will be theoretically underpinned by both the Technology Acceptance Model and the Healthcare Belief Model. One major aim is to bridge the gap in the lack of literature and the scarcity of empirical findings regarding the patient perspective of AI uses in healthcare diagnostics. Additionally, this thesis will lay the foundations for future expansion and investigation around this exciting topic.

Using qualitative research in the form of face-to-face interviews via video links and a snowball sampling approach, 17 sets of patients' opinions regarding the uses of diagnostic wearable devices and the diagnostic capabilities of AI in healthcare have been analysed. The interviews involved candidates who are currently wearing a diagnostic wearable device such as an Apple Watch or Fitbit against non-wearable candidates. The findings were cross examined between the groups and the perceptions of these candidates were thematically analysed. Conclusions have been drawn which demonstrate differences in the understanding of AI from a diagnostic healthcare perspective both in a clinical setting from first diagnosis using AI instead of a doctor through to monitoring and detecting medical conditions in the form of wearable devices.

Key words:

Apple Watch, Artificial Intelligence, artificial neural networks, atrial fibrillation, Big Data, biosensors, biosensory wearables, cardiology, data protection, deep learning, diabetes, diagnostic healthcare regulatory concerns, diagnostic wearable devices, digital health, digital wearables, disease diagnostics, ethics, Fitbit, machine learning, movement disorder, neurology, Oura ring, privacy, regulatory concerns, smart health, trust

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List of Abbreviations

AF	Atrial Fibrillation
AI	Artificial Intelligence
ANN	Artificial Neural Networks
ASPECT	Alberta Stroke Program Early CT
ATT	Attitude Towards use
BD	Big Data
BMD	Biometric Monitoring Devices
CBT	Cognitive Behavioural Therapy
CDC	Centers for Disease Control and Prevention
CEO	Chief Executive Officer
CNN	Convolutional Neural Network
CT	Computerised Tomography
CTA	CT Angiogram
DL	Deep Learning
DNN	Deep Neural Networks
ECG	ElectroCardioGram
EU	European Union
FIR	Fourth Industrial Revolution
FDA	Food and Drug Administration
GAN	General Adversarial Network
GDP	Gross Domestic Product
GDPR	General Data Protection Regulation

GP	General Practitioner
HBM	Health Belief Model
HD	Huntington's Disease
IOMT	Internet Of Medical Things
IOT	Internet Of Things
LVO	Large Vessel Occlusion
ML	Machine Learning
MM	Mixed Methodology
MRI	Magnetic Resonance Imaging
MS	Multiple Sclerosis
NLP	Natural Language Processing
NWC	Non-Wearable Candidate
OECD	Organisation for Economic Cooperation and Development
PCC	Patient-Centred Care
PD	Parkinson's Disease
PEOU	Perceived Ease Of Use
PPE	Personal Protective Equipment
PPG	PhotoPlethysmoGram
PU	Perceived Usefulness
QUAL	Qualitative Research
QUAN	Quantitative Research
R&D	Research and Development
RT-PCR	Reverse Transcriptase-Polymerase Chain Reaction
SN	Subject Norm

SUDP	Sudden Expected Death in Epilepsy
TAM	Technology Acceptance Model
TENG	TriboElectric Nano Generator
WC	Wearable Candidate
WD	Wearable Device
WHO	World Health Organisation

1 INTRODUCTION

From the most basic provisions for rural areas to the most sophisticated technologies in advanced countries, healthcare is everywhere in the world. Healthcare is ever evolving. Indeed, there is an ongoing and urgent need to improve how diagnostics of patients' conditions are carried out, the speed of such diagnoses and, very importantly, the quality of the final diagnosis. Much literature suggests that digitalization has become omnipresent in the healthcare ecosystem. One of the driving forces for the digitalization of the healthcare environment is Artificial Intelligence (AI). In 2021, the market size for AI in global healthcare was valued at US$ 11.06 billion (Precedence_Research, 2022).

The evolutionary state of mathematical modelling and computer science was pioneered from the work of Alan Turning and led to the term "Artificial Intelligence" coined by Sir John McCarthy of Stanford University. AI has actually existed for many years and is not a simple novel development in computer science. The progression of AI and its diagnostic capabilities in today's modern world of AI innovation and improvement has been a turbulent ride for the data scientists and engineers who create it. Historically, a division of two AI camps evolved within the two main subsections of AI. Scientists and engineers aimed to outdo each other with their models and concepts. The Machine Learning (ML) and Artificial Neural Network (ANN) camp evolved within the data science community. Indeed, ethical and legal issues of AI when applied to patient uses in healthcare or the "black box phenomenon" across the medical professionals, are key issues. But to truly appreciate AI and its uses in healthcare diagnostics, readers must first understand what AI is, the principles behind AI, how these fundamentals relate to healthcare diagnostics and in what forms. Clarification of the term Artificial Intelligence is required and dividing the phrase into the adjective "artificial" and the noun "intelligence" gives a realistic understanding of the meaning of AI and the naming rationale.

AI is a branch of computer science in which combinations of mathematical algorithms (commands embedded in code) and rules are programmed with the goal of recreating human intelligence in the form of a machine. Hence the adjective "artificial". AI makes machines intelligent, enabling them to perform a combination of tasks just like a human, hence the noun "intelligence." AI is therefore referred to as the ability for a machine to reproduce human behaviour, regardless of the technology used to achieve it (Russell & Norvig, 2021, p. 10). Research in AI has focused predominantly on the components of intelligence: learning, reasoning, problem solving, perception and the use of language. More recently, Mbunge and colleagues delineate AI as "human-like intelligence embedded in intelligent machines or systems" (Mbunge et al., 2022, p. 3).

Widely recognised as the father of AI, Sir John McCarthy defined AI as "the science and engineering of making intelligent machines, especially intelligent computer programs while achieving goals and solving problems like humans"(McCarthy, 2012). Dr Kai Fu Lee, a prominent computer scientist in the field of AI and ex-president of Google China, provides the alternative more detailed definition that "artificial intelligence is the elucidation of the human learning process, the quantification of the human thinking process, the explication of human behaviour and the understanding of what makes intelligence possible" (Lee, 2018, p. 14): ultimately, a computer programme that is able to make intelligent decisions. Marvin Minsky, another founding father and pioneer of AI, the designer of the first visual scanner, says "a principal goal of the field of AI has long been to build a machine with humanlike common sense" (Minsky et al., 2004, p. 113). On the other hand, Professor Patrick Winston at MIT defines AI as "algorithms enabled by constraints, exposed by representations that support models targeted at loops that tie thinking, perception, and action together" (Winston, 2010).

Based on these definitions, all authors and pioneers in the field agree that AI is about intelligence demonstrated by machines as opposed to the natural intelligence demonstrated by humans. In AI, there is no solid definition of intelligence that does not depend on relating it to human intelligence. AI was created by *intelligent* humans with the ability to write and programme complex mathematical algorithms, the basis of the AI intelligence. The Oxford dictionary definition of intelligence is "the ability to learn, understand and think in a logical way about things; and the ability to do this well" (Oxford_Learner's_Dictionary, 2022). However, psychologists do not typify human intelligence to simply one distinctive trait, but a combination of many distinct abilities.

Research stemming back to the work of American philosopher John Dewey and his theory of the mind, consciousness and psychophysical, has played an important role in defining AI, especially so-called weak AI and strong AI (Flowers, 2019). Philosopher Hubert Dreyfus argued that computers, who have no body, no childhood, and no cultural practice, could not acquire intelligence at all (Dreyfus, 1972). Fjelland says "as long as computers do not grow up, belong to a culture, and act in the world, they will never acquire human-like intelligence" (Fjelland, 2020, p. 3). Plato's theory of knowledge was constructed on the idea of mathematics, in particular geometry. In the 1950's, mathematician Alan Turing posed the question "Can machines think" (Turing, 1950, p. 433)? Turing argued that, if the machine could successfully pretend to be human to a knowledgeable observer, then one certainly should consider it intelligent (Turing, 1950). Should Alan Turing pose the same question in today's modern, digitally advanced, technologically-dependant world, he would receive an affirmative answer. The negative doubting work of AI sceptics has, to some extent, become obsolete but new concerns have emerged from the ashes and shall be discussed later in this thesis

Over time, there have been *four* major eras or societies of how humans have worked and adapted to their surrounding environments. Now, in 2022, doctors are adapting to the use of AI diagnostic output and even AI-driven robotic surgery. Sarwar (2020) describe these societal evolutions and explain that the world is currently in Industry 4.0, also called the Fourth Industrial Revolution (FIR). The FIR is reflected in the adoption of AI methods which have revolutionised human activities, healthcare being a prime example. AI and Big Data (BD: large datasets defined through velocity, variety, variability, volume and veracity; (De Mauro et al., 2016)) have fast become the cornerstone in medical research and global healthcare. However, Morris (2019) say that insufficient attention has been paid to monitoring and analysing the current and expected outcomes of the FIR in healthcare. While AI healthcare advancements continue to prevail, a commentary from McClelland mentions that the technology-driven societal changes we are experiencing with AI and automation always engender concern and fear (McClelland, 2020). Etim (2019) discusses that, by 2030, intelligent agents and robots could replace as much as 30% of the world's current human labour, while Gartner Insights claim that "there is no doubt that successful application of AI can unlock new opportunities and help achieve business goals" (Gartner, 2020). Dr Kai Fu Lee describes AI as "job-eating technology " (Lee, 2018, p. 13) which is understandable, given the outperforming of humans that AI has proven to be capable of. Gruetzemacher and Whittlestone (2022) describe the dramatic progress of AI, especially in recent years and particularly with the transformative capabilities of DL and how it has revolutionised the healthcare industry.

ML is a subsection of AI and is generally considered as a family of algorithms that allows computers to learn patterns from provided data (Sidey-Gibbons & Sidey-Gibbons, 2019). ML algorithms syntax data, learn from these data, and make informed decisions based on what they have previously learned and what they have been trained on (Frühwirt & Duckworth, 2019). Through increasing use in recent years, ML is making healthcare diagnostics smarter by acting like a second pair of eyes. In breast cancer diagnostics, for example, ML can detect patterns of certain diseases within patient electronic healthcare records and inform clinicians of any anomalies (Ahsan et al., 2022). Diagnostic results, obtained when using ML, are more accurate, faster to obtain, and predictably suggestive. Unlike the human brain , ML techniques do not reach a threshold of exhaustion, do not panic or burn out and have no information-retaining limits. ML systems are often described as "rule-based", "symbolic systems" or even " expert systems" because they perform based on input rules to make the system think and learn for the patterns. They identify themselves within the input training data, eventually making a decision - an output. In healthcare diagnostics, medical imaging such as Computerised Tomography (CT) scans and Magnetic Resonance Imaging (MRI) function purely on ML techniques and examples of this will be discussed in Section 2.0.

A formal definition of ML has been provided by Tom Mitchel: *"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E."* (Mitchell, 1997, p. 2). Because ML "learns" how to get progressively better at a task, without having been specifically programmed for that task (Frühwirt & Duckworth, 2019), it has been revolutionary in disease diagnostics through the analytical capabilities and predictions. Most ML approaches fall into two main categories: supervised learning and unsupervised learning (Shlobin et al., 2022). Supervised ML uses labelled datasets to train algorithms, classify data and predict outcomes accurately. Unsupervised ML does not require labelled data, but aims to identify hidden patterns present in the data and is often used in data exploration and novel hypothesis generation (Sidey-Gibbons & Sidey-Gibbons, 2019).

Deep Learning (DL), also widely referred as Deep Neural Networks (DNN) (Shamshirband et al., 2021), is an advanced subfield of ML involving more sophisticated algorithms or opinions embedded in code and inspired by the cognition functions of the human brain. DL is the ability of DNN to learn complex representations from data at each layer of an ANN, mimicking learning in the brain by abstraction (Penuel & Statler, 2011). Shamshirband et al. (2021, p. 2) describe DL as: "DL architecture can be simply defined as an ANN with two or more hidden layers aiming at enhancing the prediction accuracy". DL has become a major interest in healthcare and especially in disease diagnostics. DL means computers learn from experience and understand the world in terms of a hierarchy of concepts (Krittanawong et al., 2017).

Recent research has explored the level of bias when using DL systems, and the subsequent impacts on society. As DL has no theoretical limitation as to what it can do, the more data DL systems access means the more computation DL gives, yielding a better, more precise outcome with improved predictability and accuracy. DL has been described as a ground-breaking approach to AI that has "turbocharged the cognitive capabilities of machines" (Lee, 2018, p. 12). Gruetzemacher and Whittlestone (2022) describe the dramatic progress of AI, especially in recent years and particularly with the transformative capabilities of DL and how it has revolutionised the healthcare industry. DL has become a major interest in healthcare, replacing the original ML in some medical specialities. Patients are being diagnosed by DL systems and predictions about their future prognosis are being carried out by a machine, not from the experience of a trained doctor or a team of specialists. Important DL predictions begin with a lot of data. DL harvests these data and ultimately profits from them, but "creativity is a fundamental feature of human intelligence that is an inescapable challenge for AI" (Boden, 1998).

Through implementation of AI, the global health industry has gained valuable and variable insights at great speed, enabling lifesaving predictions and better decision support through both structured and non-structured data. AI has enabled technology, through the abundance of BD, to take the leap from being passive in nature to being more generative, providing solutions for problems and overcoming its human components. AI has introduced a paradigm shift in healthcare (Yu et al., 2018) and the AI revolution is building momentum in healthcare (Yang et al., 2022). Shamshirband et al. (2021) claim this emerging technique has demonstrated tremendous potential in tackling challenging problems. Robots are also being explored for treatment, by empowering precision surgery, rehabilitation, or targeted drug delivery (Awad et al., 2021).

The healthcare sector has long been an early adopter of (and has benefited greatly from) technology, which has become apparent from the number of registered AI patents in healthcare combined with the increase in patient-centred self-monitoring devices, such as digital wearables. AI, through ML, DL and Natural Language Programming (NLP), has enabled better prediction of illnesses and treatments. For example, in 2021 zzapp Malaria, a company that uses AI to fight malaria, won the grand prize in one of the most difficult tech competitions to date (zzapp, 2022). From the joint award of XPrize and IBM Watson, the winner's technology will allow a humanitarian approach to eliminate the countries still plagued by malaria. The power of AI enables zzapp to identify malaria hotspots and optimize interventions for maximum impact in the form of a mobile app.

Improving the clinical diagnostic process is a quality priority (Adler-Milstein et al., 2021). With this in mind, AI diagnostic tools are being used for analysis of many histopathological, congenital and progressive illnesses. Several clinical diagnostic areas will be discussed later in Section 2.0 as key examples of AI applications in healthcare. AI has improved healthcare both in disease diagnostics and disease monitoring but also from an administration and scalability perspective, that is, the ability to perform many more diagnoses and evaluations in any given time. The need for speed, reactivity, proactivity, precision, analytical capability and accuracy in real time have now become more obvious to healthcare professionals and stakeholders (Ćwiklicki et al., 2020) and AI is allowing these achievements. Even back in 1999, Myers and Berry (1999) suggested that AI would be incorporated into general workflow process systems to improve better reactive control, scheduling, and planning with improved knowledge and insights and faster outcomes and answers. Now, while the revolutionary promise of AI in healthcare has been widely documented, with wayfinding applications across a broad range of therapy areas, recent work published by Gozes et al. (2020) discusses how AI applications have been used even to reduce the workload of healthcare workers. Additionally, in 2019 the World Health Organisation signalled AI would be an important technology to manage the COVID-19 pandemic crisis and would become the most important non-medical intervention to mankind (Cave et al., 2021). From forecasting health risks within populations to detecting heath care gaps, whilst also bridging them, there is no doubt that AI in healthcare is not just a nice-to-have, it's a need-to-have.

Deployment of technology in the medical field with the corresponding ethical issues is always controversial. In 2019, the Organisation for Economic Cooperation and Development (OECD) established AI Principles which promote use of AI that is innovative and trustworthy and that respects human rights and democratic values (OECD, 2019). Global healthcare has been in turmoil since the impact of COVID-19. Economies and investments have crumbled, inflation has increased, and countries have a dwindling GDP, yet 47% of AI investments remain unchanged and 30% of organizations plan to increase such investment (Goasduff, 2020). Especially in 2022, global healthcare organizations, pharmaceutical companies and medical device companies have urgently needed to maximise the technologies and capabilities of AI, not only to save lives but to improve operational performance.

Ultimately, AI is poised to change healthcare and signs of endorsement and encouragement are evident from global healthcare bodies, the World Health Organisation (WHO) in particular. AI systems need to be transparent and validated for safety. They need to be ethical, unbiased, trustworthy and transparent, with all data generation, data handling and data storage in line with, for example, European Union (EU) General Data Protection Regulation (GDPR). The responsible adoption of AI in healthcare must benefit patients and populations (Panel for the Future of Science and Technology, 2022). Through implementation of AI, especially during the past years of the pandemic, the global health industry has gained valuable and variable insights at great speed, enabling lifesaving predictions and better decision support through both structured and non-structured data.

Other considerations and concerns must be acknowledged when discussing AI in healthcare, despite the positives of using AI models. Elements of bias have also been suggested. To summarise, Sundar Pichai, the Chief Executive of Google, interviewed by Professor Klaus Schwab in 2018 at the World Economic Forum in Davos, said "*AI is one of the most profound things we're working on … as humanity. It's more profound than fire or electricity or any of the bigger things we have worked on. It has tremendous positive sides to it, but, you know it has real negative consequences, [too]*" (World_Economic_Forum, 2018).

Wearable technology is an electronic technology which is incorporated into accessories that can be directly worn on the body and which contain sensor technologies (Tehrani & Andrew, 2014). In terms of market size, it has been estimated that, by 2022, wearable device revenues would reach US$ 73 billion (Laricchia, 2022). Up until 2018, a year before the COVID-19 pandemic started, Silvera-Tawil et al. (2020) reported on a Web of Science search, supported by the Derwent World Patent Index, which returned over a million documents for sensor-based patents between 2013 and 2018.

Patients are wearing portable sensory devices not only in clinical settings but moreso now across the general population. Tracking daily steps, monitoring sleep patterns or even calorie intake, wearable devices, for example as smart watches, can measure pulse rates. Algorithms use pulse wave data to detect clinical diseases such as Atrial Fibrillation (AF) and atrial flutter. Some wearable devices have been designed to monitor and alleviate, for example, certain neurological disorders (Vinny et al., 2021) and examples of this will be discussed in greater detail in Section 2.0, the Literature Review. With the increase in wearable technology such as the Apple Watch, Fitbit (also a wearable in the form of a watch), and more recently, the Oura ring, people are in general beginning to pay more attention to their overall health (Li et al., 2016).

As an example of how wearables and AI combine in disease diagnostics, the diagnosis of Sudden Unexplained Death in Epilepsy (SUDEP) is highly relevant. SUDEP is the number two cause of years of potential life lost out of all the neurological diseases and kills someone every seven to nine minutes in the United States (US). The US Food and Drug Administration (FDA) approved Empatica Embrace in 2018 as the first smart watch using AI to detect convulsive seizure associated with SUDEP (Empatica, 2018). Empatica Embrace has already been accredited with saving life very early on after approval .

Medical wearable textiles are also currently in development. Ultimately, wearables can be used for early disease diagnosis and disease monitoring: early diagnosis is often a path to life saving. In some countries, smart wearable devices have collected health-related data for early COVID- 19 screening and diagnosis (Krishnamurthi et al., 2021). Aside from being fashionable, wearable devices, such as wearer's rings and wrist bands, have the potential to fuel AI methods with a wide range of valuable patient health data (Nahavandi et al., 2022). AI is powered by BD, core assets to the FIR in healthcare (Park & Bae, 2022).

To date, most extant studies about healthcare wearables have focused on the technical perspective. This is mainly because these modern-day technologies, such as the digital wearable devices, combined with the Internet Of Things (IOT) (and now more recently introduced the Internet of Medical Things (IoMT)) are driving the transition from traditional healthcare to a smarter healthcare system. Patients can take back certain elements of control through improved Patient Centred Care (PCC): they are able to monitor their own biostatistics rather than relying on an overworked doctor in a society where it is becoming more and more difficult to easily see, or get access to, a first-line doctor, the General Practitioner. Whilst there is much social encouragement to become healthier and be more aware of certain clinical symptoms of our bodies, digital wearables are empowering individuals to take control with the old phrase *prevention is better than a cure* in mind. From better elements of self-care routines, better sleep, better diet, better hydration and less sugar, biosensory wearables are certainly making an important contribution.

While there appears to be many benefits of wearable devices and the applications associated with them, there have been suggestions that such wearable diagnostic devices could have opposing effects and lead to the consequence of diagnostic wearables perhaps causing a level of increased anxiety, especially if there is misinterpretation of result readings, or even data anomalies. It could be assumed that there is a likelihood, when using wearable diagnostic devices, of inducing a certain level of psychological stress.

Research questions

The aim of this thesis has been to investigate how AI has revolutionised healthcare, especially in certain areas of disease diagnostics, and how these areas can be linked to digital wearables, allowing the patient to control, monitor and track their health and disease progression. Through the technological advancements of AI and the speed of digital disruption in healthcare, the so-called FIR is paving the way for greater things, yet also yielding concern. The ongoing development of digital wearables, the speed of AI development, the size of corporate investment between tech and pharma and tech and governments is enabling a transformation in global heath economies. However, while empirical studies are in abundancy about AI diagnostic performance, there is a huge scarcity, as will be described in Section 2.0, from the patient perspective of the use of AI and healthcare diagnostics. This study aims to bridge this gap and pave the way for future research around the world of the patient, not just those who financial profit for AI.

More formally, the following research questions will be answered in the thesis:

RQ 1 What do patients think of AI in healthcare diagnostics?

RQ 2 What factors are driving patients to adopt digital diagnostic wearables to monitor their own health, and why?

RQ 3 What factors are hindering people to adopt the use of wearables diagnostic devices and what are the main concerns as to why they have not adopted these technologies?

RQ 4 How do patients personally feel about being diagnosed by AI rather than a doctor?

RQ 5 What are the frequent applications of AI in wearable devices and what would people want to see in the future?

The purpose of next Section 2.0 is to illuminate the knowledge that exists relating to the focus of the present thesis, and to highlight deficiencies and clear gaps in knowledge. Considerable knowledge and insight have been identified using many examples, paying particular attention to how AI has become revolutionary in diagnostic healthcare and eventually how it has been transferred to the general consumer as a wearable device.

2 LITERATURE REVIEW

To answer the research questions (see Section 1, p.8), database searches were performed using ProQuest, Medline, PubMed, Web of Science and Scopus. The purpose of this literature review was to identify new, up to date empirical research that highlighted how AI is being used in healthcare diagnostics. Across this literature review looking at disease diagnostics and healthcare, there was evidently a clear gap about the patient perspective of AI in healthcare diagnostics. The transition of the diagnostic capabilities of AI in a hospital setting was then examined, looking at how these capabilities were transferred to different forms of commercially wearable devices. Many of the areas discussed are currently being researched and prototypes are being created through the emergence of big tech, big pharma and venture capital companies all collaboratively working together to make AI diagnostics more available in the form of these wearable devices. The present literature review provided insights into two main diagnostic worlds: the diagnostic capabilities in hospital and the diagnostic performance of wearable devices, naturally addressing other concerns (such as ethics and privacy) that were identified.

Whilst accepting the possibility of a considerable amount of recently published research on such a prominent topic, the search process was first split into disease categories, for cardiology, neurology, COVID-19 and mental health, and then work relating to wearable devices. Boolean operators were used to identify the most recent current research. Then a second scoping search was carried out for AI, trust and ethics in healthcare.

The following search terms were used across the electronic databases previously mentioned:

- AI OR Artificial Intelligence AND disease diagnostics
- AI AND OR Artificial Intelligence AND cardiology
- AI AND OR Artificial Intelligence AND healthcare
- AI AND OR Artificial Intelligence AND COVID-19
- AI OR Artificial Intelligence AND Smart Health
- AI AND ML AND DL AND disease diagnostics
- AI OR Artificial Intelligence AND medical ethics
- AI AND OR Artificial Intelligence AND trust
- AI AND Artificial Intelligence AND Wearable Devices
- Wearable devices AND disease diagnostics OR failure
- Wearable devices AND disease monitoring
- AI AND medical AND perception
- AI AND Artificial Intelligence AND Success OR Failure AND healthcare

Eventually, a manual thematic screening was performed across over 830 abstracts from which the most pertinent articles appropriate to the present investigation were selected, based on content, relevance and recency. It was important to look at more recent literature due to the rapid speed at which developments in the area were progressing and the number of publications which dealt with AI in healthcare and AI and digital wearables.

At the end, over 500 abstracts were read thoroughly, and the relevant papers were selected for review, which was performed solely by the author of this thesis. The papers were analysed narratively by employing the principles of thematic analysis. Cardiology and AI generated the most results around the disease area of AF, not only within the diagnostic section search. Searches for AI AND trust and AI AND ethics produced high numbers of hits with recent publication dates.

In order to evaluate the performance of AI-driven devices and diagnostic capabilities and in order to benchmark the literature findings, the terminologies of Sensitivity and Specificity were employed, which are accepted as good measurements of performance, although not without issues (Trevethan, 2017). Essentially, sensitivity is the ability of the test to detect true positives and specificity the ability to detect true negatives: the higher these values, the better the performance of a diagnostic test or device, for example. In this literature review, these values will be used to report on AI-driven diagnostic test performance, for comparative purposes

Furthermore, through understanding how AI is defined in terms of its clinical diagnostic performance, this is also transferable into the wearable device market to manufacture and test those that have been developed for a clinical purpose and how they can be manufactured for the general market. Apps are being created all the time for all sorts of health condition diagnoses. Despite not being officially defined by the FDA as “medical devices“, they must show some demonstrable accuracy in their performance: wearable devices with diagnostic applications therefore need to be tested. For example, Fitbit test their cardiology device performance against the gold standard ECG. The reproducibility is measured by the so-called repeatability coefficient: the lower the coefficient value, the better the result. Additionally, Apple worked in conjunction with the American Heart Foundation to ensure the reliability and accuracy of their own ECG functions, while creating the application. The literature review will demonstrate in what areas the diagnostic capabilities of AI have outperformed doctors, highlighting suggested extinctions of certain medical professionals such as radiologists, dermatologists, pathologists and similar.

While the performance of AI has been captured and discussed in many publications identified, only one paper pays reference to the patient perspectives of AI in healthcare diagnostics. A demonstrable reluctance of acceptance of AI within the medical field has been highlighted and this thesis provides insights as to why. Transitioning into the wearable device diagnostic capabilities, this research aims to really explore how and why patients accept wearable devices, how they feel about their own experienced diagnostic results and what is their understanding of AI. This broad topic has been streamlined to focus on the fundamental issues of eight months’ worth of research. Patients are not central to any of these investigations, their input is scarce.

2.1 Literature review framework

The present literature review was carried out on a collection of subjects closely relating to the research topic, following the outputs from the searches using the criteria elaborated above in Section 2.1. The overall structure of the literature review is presented in Figure 1, for clarity. Under the main subject of the literature review, AI in Healthcare Diagnostics, the literature from ten focused individual subjects was reviewed in detail, using the search terms described above. These were considered to be the main subjects where AI had been applied in medicine following review of the literature from the searches carried out. In addition, several more specific subjects were also reviewed in more detail, as these were found to be the most important areas of medicine where AI had been utilized both in depth and in detail.

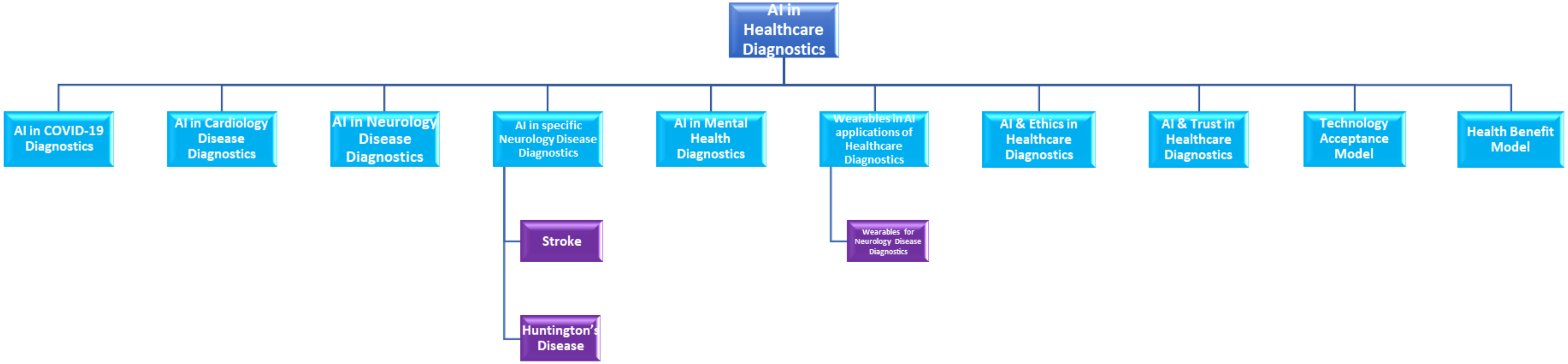

FIGURE 1 OVERALL STRUCTURE OF THE LITERATURE REVIEW CARRIED OUT FOR THE PRESENT THESIS

2.2 Artificial Intelligence Applications in Healthcare Diagnostics

Publications in the medical world are often isolated and insulated from each other, therefore comparisons across methodologies remain specific to the therapy area in question and, more often than not, data analyses are non-interchangeable. While this thesis can be deemed somewhat medical, due to the insights into specific therapeutic areas where AI has been implemented with proven successes, by combining with the more qualitative studies of the digital wearable section, ethics, trust and privacy, this thesis elucidates the connection between AI, disease diagnostics and wearable devices and explores the realistic adaptation so far of digital health diagnostics.

Like many of the articles reviewed in this literature review , Lai et al. (2020) use a qualitative research approach, in this case to investigate the French population perceptions and attitudes of AI in healthcare. These authors give a clear definition of what AI is and how its limitless powers hold the promise to revolutionise patient care within the French healthcare system. Only now in France, like Poland (as discussed by Ćwiklicki et al. (2020)), referred to later) is the healthcare community beginning to understand the benefits of incorporating AI tools into the French healthcare system. Yet there is still a lot of scepticism amongst the doctors and the French regulatory authorities. Unlike other countries, France has been a lot slower in adopting AI in healthcare, which was evident from their survey findings (Lai et al., 2020). Concerns of using AI included the deskilling of healthcare professionals and eventual elimination of certain groups of healthcare specialities especially in the roles of radiologist, pathologist and dermatologist, due to AI diagnostic outperformance and high diagnostic accuracy. Another main identified concern the researchers found was the belief that incorporating AI into patient care would lead to concerns about data sharing and privacy (Lai et al., 2020).

While this work of Lai and colleagues focuses only on the French population, they only interviewed 40 healthcare stakeholders. This is only a small number of interviewees given they adapted a grounded theory approach and there was no mention how these 40 stakeholders were decided upon. One potential strength of this research is that the authors included different speciality doctors, something of a rarity within the literature. A strength of this cross speciality is insight included from those roles that could potentially become obsolete, possibly the reason for the suspicion and negativity from these groups of doctors. Lai et al. (2020) give a nicely summarised overview about general perceptions and, in particular, how healthcare professionals perceive AI in their current medical practice, together with influencing factors of adoption of AI. The researchers identify and define possible barriers to entry at stakeholder level and cross reference their findings of medical versus non-medical stakeholders, giving a broad difference in opinions. However, ethical, legal and data privacy concerns remained central and consistent within all groups of interviewees and contributed to the doubt around AI adoption in the French healthcare system. This type of research was the first of its kind in France and performed between 2017 and 2018. Positive findings were included. The authors concluded, like the work of Myers and Berry (1999), that AI incorporation and adoption was a possible way to eliminate certain healthcare burdens which, in turn, could reduce departmental cost, improve workflow and produce fast results and less administration. An important weakness of the study is that there was only one representative of the patient group, compared to 39 healthcare stakeholders, some with vested financial interests in the topic (Lai et al., 2020). With this bias of stakeholder selection, the findings were not representative of the patient population.

However, a major concern from all interviewed stakeholders was with assigned responsibility. There was no clarity or agreement on who should be responsible or culpable should there be an issue such as misdiagnosis, positive or negative. Liability and accountability issues were not were not resolved nor concluded in this research. Additional other concerns focused on BD (Lai et al., 2020). Data usage, data storage and data discrimination, for example by third parties, leading to misuse and discrimination, were raised. Concerns about the access and use of medical driven AI were seen as a challenge, with cyber security a concern. Stakeholders agreed that better legislation and clear frameworks were required around the type of data and data volume, and explanatory patient consent was needed. Transparency of systems was required. To conform to European GDPR was simply not enough (Lai et al., 2020).

Lai et al. (2020) state AI tools are not being embraced as quickly as their production and physicians were actually unsure of how the AI tools generated the diagnostic conclusions (the "black box phenomenon"). While doctors believe the abilities of AI tools are overestimated, others have seen the capabilities of AI in diagnostic medicine. Yet, contrary to popular belief and AI hype, doctors stated that they do not always use these tools in real practice. Such a statement sits well with the work of Ćwiklicki et al. (2020)on healthcare acceptance models, whose research states that AI will never be truly accepted or integrated in healthcare without the cooperation of healthcare professionals, who need to understand how AI-generated its results due to the opacity of the AI itself. Furthermore, regulatory frameworks and public interested bodies need to be involved. Both Lai et al. (2020) and Ćwiklicki et al. (2020) came to the same conclusion.

The qualitative findings of Lai et al. (2020) were cross referenced by the authors with other similar studies performed in China, Australia and UK, and the authors state that similar findings were made, yet they did not present which specific findings. This would have been a great opportunity to quantitatively compare and contrast the different variables across countries and demographics, because, naturally, the attitudes and willingness to accept AI tend to be higher in the countries that develop the most AI systems. France is not necessarily renowned as an AI pioneer, so comparing the countries mentioned in the research would have been a good approach and would have provided more insight. However as this was an exploratory investigation, perhaps now in 2022 a new comparative study will be produced.

Ćwiklicki et al. (2020) used a narrative literature review for their research. Similar to the work of Lai et al. (2020), they identified many similarities between the reasons for AI adoption and AI concerns, or hindering barriers within the healthcare system of Poland. Both groups of authors appear to generate the same conclusion, but Ćwiklicki et al. (2020) present a more robust publication with better insights because of the mixed methodology approach. While both groups touch on similar findings, there are also no distinct differences between the results or conclusions. Ćwiklicki et al. (2020) begin with an explorative qualitative analysis. Then, as part of the mixed methodology approach, the authors evaluate the concordance of the experts' agreement and opinions using a non-parametric statistical approach. They evaluate the concordance of opinions by calculating Kendall's W (Kendall's coefficient of concordance, giving a full picture of similarity variables) (Field, 2014). They highlight key determinants required of the healthcare system's adaptive capacity to respond to the outcomes of the FIR. Even in 2020, when the paper was published, a conclusion was made that the FIR in the Polish healthcare sector appeared still in its infancy as there seemed to be a lack of technological adaptiveness.

In this context of healthcare, Ćwiklicki et al. (2020) refer to adaptiveness as the capability in response to change, driven by technological innovation, and how such changes can and will alter different aspect of healthcare. Interesting to note, this paper was received in October 2019, pre the COVID-19 pandemic so it could be assumed that now, in 2022, the Polish healthcare system was forced to adopt AI and set aside their concerns discussed in this paper since all global healthcare needed to adapt to change and rapidly improve their adaptiveness per capita to introduce and accept AI diagnostic advancements. While defining the health care system and its stakeholders, they did not include patients which is ironic in creating a healthcare patient framework! Ćwiklicki et al. (2020) describe how it is necessary to decompose the "healthcare system´ and reduce any attitudinal boundaries between human and machine, and debunk any AI myths. The authors touch on wearable devices, implantable technologies and biotechnologies as a slight reference to AI adaptation.

In looking at AI in healthcare in general, not for any specific country or discipline, Yu et al. (2018) give a historical overview from the 1970s and the so-called first-generation AI, which relied on medical expert knowledge and input. The authors present a very clear, structured paper. These researchers examined the different types of true AI and their uses in biomedical applications (Yu et al., 2018). With a key focus on future challenges and very similar to the findings of Bertalan Mesko who says "there is no doubt now that digital health is becoming the new norm" (Mesko, 2021, p. 100234), Yu et al. (2018) investigate the economic, legal and social challenges, giving a synopsis of the progression of different types of true AI and how their implications have improved translational medicine and biomedical research. Touching on the data hungry, DL algorithms, comparing supervised ML to unsupervised ML, Yu et al. (2018) present why it has become widely accepted through the question of *how* the renaissance of AI has revolutionised medicine, exactly like Mesko (2021, p. 100234) who says "envision healthcare to be seamless:

that the process from diagnosing the symptoms to monitoring the process is error free. We see the first steps in this direction through advanced AI systems in diagnosis or in medical-level at-home devices". The advancement of ML and its subsets has improved the speed of diagnostic performance and accuracy of diagnosis, clarity of diagnostic imaging differentiation and general patient-centred care and, combined with the wearable device, healthcare treatments could become preventative.

As the authors delve into the technicalities of each "subset of AI" and how it has become a tool of reliance, Yu et al. (2018) highlight how ML has allowed better decision making and medical diagnosis in dermatology, ophthalmology, radiology, and pathology. Like many publications, Yu et al. (2018) explain how AI has superseded humans in the diagnostic capabilities in areas of medicine, defining the branches of AI and the types of algorithms used in the various medical fields. Referencing dermatology, again like other publications, the research team also concurred with the literature, reinforcing that AI outperforms dermatologists. Also, the use of AI in ophthalmology has been so successful that Google have implemented a shared platform in India to speed up the screening of diabetic retinopathy patients, one of the first areas of diagnostics using AI.

Yu et al. (2018) describe how routine monitoring devices, used in intensive care, generate extremely large amounts of data and represent a real opportunity for AI alert systems. Yu et al. (2018) also highlight that AI in healthcare will enhance the speed of diagnostic decisions, especially in patients with life-threatening conditions. Finally, the authors discuss that AI will not necessarily improve physician fatigue though could, to some extent, allow physicians to focus on high priority patients. Ultimately, for evolution of AI to be truly successful in healthcare, the perception of physicians needs to change: doctor and machine need to coevolve, complimenting each other.

In this literature review, there has been an identified scarcity in comparisons between different countries. Therefore, different demographics and cultures have not been directly compared for their similarities, or differences, with regard to AI in healthcare. The AI capabilities may vary from country to country due to differences in technology acceptance, frameworks and adaptive capabilities, and financial resources for implementation. Human adoption of AI is as equally important, and doctors need to accept and use AI in order for it to be a worldwide success.

2.3 Artificial Intelligence Applications in COVID-19 Disease Diagnostics

Global healthcare has been in turmoil since the impact of COVID-19. Economies and investments have crumbled, inflation has increased and countries have a dwindling Gross Domestic Product (GDP), yet 47% of AI investments remain unchanged and 30% of organizations plan to increase such investment (Goasduff, 2020). Especially in 2022, global healthcare organizations, pharmaceutical companies and medical device companies have been in urgent need to maximise the technologies and capabilities of AI, not only to save lives but to improve operational performance.

With the unprecedented pace of efforts required to tackle COVID-19, scientists alone could not achieve what was necessary. Even the WHO stated that AI will play an important role tackling the pandemic. Global healthcare was at its worst in terms of pressure: lack of staff due to illness and burnout (Morgantini et al., 2020). A global shortage of Personal Protective Equipment (PPE) (Saran et al., 2020). High hospital occupancy led to a shortage of beds, ventilators were in short supply and in some countries being shared between patients. Healthcare workers could not analyse and diagnose test results as fast (Beitler et al., 2020). Doctors had not seen a so-called "COVID-19 lung" and the COVID-19 effects were poorly understood (Melms et al., 2021). The physiological effects of COVID-19 on other organs including the heart, kidneys and liver were identified and preliminary data suggested that COVID-19 had reduced access to solid organ transplantation (Aubert et al., 2021). Everything appeared to be falling apart due to this novel, ubiquitous virus. It was a totally new experience for global healthcare though now, in 2022, many lessons have been learned and presented in the pandemic recap paper of Coccolini et al. (2021). At the beginning of the pandemic there were no benchmarks or clinical treatment protocols. Much in healthcare appeared to be based on both speculation and assumption. The COVID-19 pandemic has transformed the global health community's acceptance and use of digital health technologies (Coccolini et al., 2021). AI has played a vital role in the fight against COVID-19 and this Section includes a review of literature that discusses how AI, in the form of ML and DL, has been a key driving force in the fight against COVID-19.

As seen from the literature which investigates the diagnostic capabilities of AI in healthcare, and the factors which drive patients to accept this technology or not in their day to day lives (in the form of wearable devices), it has been the incorporation of AI that has facilitated many aspects of healthcare improvement and speedy diagnosis during the pandemic. ML and DL technologies and tools have led to a better understanding of the virus through rapid genomic sequencing (Metsky et al., 2020). ML and DL have also accelerated medical research on drug discovery while predicting patient outcomes. In addition, rapid diagnosis of medical imagery has been a key role of AI in these dark times (S. Huang et al., 2021). Not only from a diagnostic capability, AI has been the driving force regarding virus containment (Council_of_Europe, 2022). AI has enabled augmented mobile heath application data, where smart devices like watches, mobile phones, cameras and a range of wearables can be employed for diagnosis, contact tracing and efficient statistic/health monitoring in COVID-19 (Maghdid et al., 2020). AI has, from an epidemiological perspective, analysed the varying symptoms across populations (Raza, 2020).

AI tools have allowed identification of viral similarities and their prevalence between infected patients and various underlying health issues, enabling fast conclusions and flagging of defined high-risk groups within populations (Shachar et al., 2020). Rapid contact tracing has been the cornerstone of effective public health response in the face of global infectious disease outbreaks. Using BD analytics in AI driven data surveillance, for example digital QR codes, individual travel history and movements have been "tracked and traced" (Lin & Hou, 2020). During track and trace, AI algorithms process data and display a colour-coded, real-time health status of the destinations in attempts to prevent further spread and to control the virus, using geolocation data. Track and trace, through AI and BD, can generate an automatic text initiating self-isolation and warning people they have been exposed. As a powerful tool against COVID-19, AI technologies are widely used in combating this pandemic (J. Chen et al., 2020).

Through a combination of integrated scientific knowledge and the speed of digital technologies and interventions, AI has provided early diagnosis of clinical cases during COVID-19. AI, in the form of DL, has proven to be efficient at differentiating COVID-19 from other forms of pneumonia during chest CT assessments, giving highly accurate radiological diagnosis (Bai et al., 2020). AI has, from an epidemiological perspective, analysed the varying symptoms across populations and has identified the prevalence of similarities between infected patients and various underlying health issues, enabling conclusions to be made, especially in flagging high risk group patients. Furthermore, Bai et al. (2020) discuss that AI augmentation has improved radiologists' performance in distinguishing COVID-19 from pneumonia of other origin, yielding higher measures of accuracy, sensitivity and specificity.

Genomics is mainly used to analyse the origin of the virus SARS-CoV-2, in vaccine development, and for Reverse Transcriptase-Polymerase Chain Reaction (RT-PCR) detection (probably the main detection method, which identifies parts of the viral genome) (J. Chen et al., 2020). Various diagnostic AI algorithms have been applied to compare the sequences, gene fragments, and mutations in the RNA of the virus (Demirci & Adan, 2020). Like many authors, (Metsky et al., 2020) give an insight into the benefits of ML models in genetic genomic sequencing. Discussing how ML models were developed and applied to analyse the genetic sequence in lateral flow tests, Metsky et al. (2020) present assay designs and experimental tool kits driven by ML and genetic sequencing (predicating pathogenicity), highlighting strain diversity, which is valuable knowledge to ongoing disease monitoring and surveillance. Initially, the high number of case outbreaks had been overwhelming in terms of diagnostic testing and sequencing and the close relationship of SARS-CoV-2 and other subspecies of the virus itself could lead to so-called false positives. Implementation of AI has reduced such anomalies, providing better insights.

With the numerous symptoms in which COVID-19 presents itself, the true damage lies within the human body. Multiple organs, not just the lung, have been affected to an extent that was not expected. Without the analytical and identifiable capabilities of the use of AI in medical imaging, such findings would have been impossible to diagnose, and the predictability of recovery impossible without medical imaging. The work of Gozes and colleagues (Gozes et al., 2020) explores medical imaging. The authors used an automated DL image analysis system to examine CT images of patients from Chinese disease-infected areas. Further studies were also carried out on US patients, although more limited in scope. Their system analysed the images at two distinct levels, examining both lung nodules and specific lung regions of interest. The system was pre-trained on over a million images, followed by fine tuning using cases from several Chinese hospitals. Ultimately, when comparing positive Chinese patients with uninfected US control patients, the system achieved a sensitivity of 98.2% and specificity of 92.2% indicating the importance of using AI diagnostic systems in the pandemic.

Again, on the subject of AI applications in medical imaging, Greenspan and colleagues (Greenspan et al., 2020) have provided an important and wide-ranging review position paper on the use of AI system solutions for COVID-19 imaging. They focused on three areas: early disease detection; management of diagnosis in a hospital setting; and patient-specific models that require combinations of CT imaging with clinical data. They highlighted important issues, for example relating to the considerable variability in use of chest CT in different countries, with China using the technique routinely for diagnosis, but the US opting more for chest X-rays.

Using AI for detection and diagnosis, Greenspan et al. (2020) cite the work of Gozes et al. (2020) as demonstrating how different diagnostic techniques may be merged to give improved results for the patient. Using the "Corona-score" developed by Gozes et al. (2020), they show how the evolution of COVID-19 infection may be monitored in hospitalised patients and how additional, highly detailed, patient data may be extracted and used for care. They discuss the example of Denmark, where chest X-rays are routinely taken for COVID-19 patients. They combine these data with other clinical data using a model and prediction of outcome for patient management in terms of, for example, requirement for a ventilator or transfer to an intensive care unit. Greenspan et al. (2020) also discuss the use of free apps as part of the control of the COVID-19 pandemic, describing how the pandemic has shown the ability of DNN to enable the development of end-to-end products. Their criteria for implementation of the apps into the general population are: high throughput; portable; reusable; sensitive; and private. Work based on use of chest X-ray repositories is discussed.

Finally, Greenspan et al. (2020) discuss the issues relating to the many COVID-19 diagnostic studies that need access to high quality data and how these data are not standardised but fragmented, leading to issues related to the quality of the studies which use the data. Ethical and legal issues may also play a role. These issues are being addressed with some urgency by, for example, the call to create a pan-European data set including imaging. Standardisation of data collection, with unambiguous assignment of values, is key. Examples of data sets and their access in Europe, Denmark and the UK are discussed (Greenspan et al., 2020).In agreement with the work of Gozes et al. (2020), these authors also conclude that many issues, especially in the early stages of COVID-19 detection and imagery, require attention, and the critical role of imaging in diagnosis. Greenspan et al. (2020) give their final views: "we need to prove the strengths, build the models and make sure that the steps forward are such that we can continue and expand the use of AI, particularly *just in time* AI" (Greenspan et al., 2020, p. 10), and "there are many possibilities and promising directions, yet the unknown looms larger than the known" (Greenspan et al., 2020, p. 10).

Some applications can also diagnose cough samples in telemedicine through AI and audio recognition (Imran et al., 2020). Scientists at MIT have even created diagnostic face masks embedded with tiny sensors that can detect COVID-19 in 90 minutes (Makin, 2021). AI will most definitely play a vital role in providing a more predictive global healthcare economy, especially since the economic shocks of COVID-19.

To battle a virus requires a vaccine, but while some governments (for example, Sweden) preferred to strive for herd immunity, many governments particularly in the EU and USA had vaccine development at the forefront of their objectives. Creating a COVID-19 vaccine for big pharma meant not only global recognition as the first to market developer, but also a huge cash injection and increased company share value. However, fast development and execution would not have been possible without the incorporation of AI models. AI has been used to screen existing drug trial candidates for COVID-19 by analysing the interaction between protein targets and existing antibody detection, making the clinical trial criteria for patient inclusion more accurate, with less bias and carrying this out much faster than before. Ong and colleagues (Ong et al., 2020) predicted possible vaccine candidates using the Vaxign-ML reverse vaccinology ML platform that relied on supervised classification models, while Zhou and colleagues went against the ML approach of Ong et al. (2020) for the same purpose and used the DL ANN algorithms for drug repurposing (Zhou et al., 2020), combining gene-expression and drug interaction databases. Randhawa and colleagues (Randhawa et al., 2020) devised a method by applying ML to identified genomic signatures for fast and accurate classification of available SARS-CoV-2 genomes. All these studies compare different subfields of AI, in the form of ML and DL. What is comparable, though, is that despite the model selections ,the results of the DL and ML diagnostic capabilities were equally as good as each other, despite the battle between the ML camp and DL camp (mentioned in the introduction of this thesis). However, despite all of the above findings Mak and Pichika (2019) aren't as positive.

Mak and Pichika (2019) discuss the use of AI for discovery, development and, ultimately, commercialisation of new drugs in the pharma industry in order to improve patient care and treatment. This is a subject area that has been discussed and debated in healthcare over decades. Mak and Pichika (2019) have considered how AI can assist in the drug discovery process itself, pharmaceutical R&D and the potential for partnerships between big pharma and drug discovery companies. While accepting the positives of using AI in drug development these authors discuss more negative expectations than other authors. They note that no drug coming from an AI-development background has yet been approved for clinical use (Mak & Pichika, 2019). The use of ML and also DL for drug discovery is considered, with the ability of neural networks to adapt and learn from huge amounts of data potentially leading to drug discovery, repurposing of existing drugs and even personalised treatments based on genetic data mining (Mak & Pichika, 2019).

Finding new drugs is, by far, the most difficult part of drug development. There are estimated to be a potential 10^{60} candidate molecules which could be available (Mak & Pichika, 2019).

Continuing the use of AI applications in the field of drug discovery, in an extensive review, Harrer and colleagues (Harrer et al., 2019), from IBM and MIT, consider the use of AI within one area of drug development, namely the application of AI in clinical trial design. Clinical trials are a key and critical aspect that occupy much time and cost in the drug development cycle. No new pharma product can enter the commercial world without successful trials that have been carried out to gain regulatory approvals. More than 50% of development costs are used in these trials, in particular the later, large Phase III trials, yet a 32% failure rate occurs at this stage due to patient recruitment problems (Harrer et al., 2019).

Harrer and colleagues (Harrer et al., 2019) identify several aspects of clinical trials in which AI can play an important role for improvement of their efficiency and effectiveness. These include AI intervention to assess suitability of the population to be included; eligibility, empowerment, and motivation at recruitment; and adherence to the trial protocols, detection of the endpoints and retention at the patient monitoring stage. Although perhaps obvious, Harrer et al. (2019) emphasise that recruitment of the correct patients is a massive investment that can only be realised with the successful completion of a trial, hence aspects such as protocol adherence are so key and the contributions that AI can make to help this are of great value. Considerations of wearable (cognitive) sensors and video monitoring to continuously collect patient data, independent of the patient, are important. In particular, monitoring of patients in neurological trials is especially challenging due to the nature of the conditions that patients experience, such as epileptic fits – that is, highly individual conditions (Harrer et al., 2019). These authors also emphasise the challenges related to the use of the available data, both in terms of accessibility and different formats that exist (Harrer et al., 2019). Again, legal issues exist particularly with the advent of regulation such as the EU GDPR. The authors conclude by posing a number of questions that must be answered in relation to AI use in clinical trial design, similarly posed by Mak and Pichika (2019). Even though offering real advantages, the AI systems they have considered and described must mature before their more general inclusion into healthcare and life sciences applications occurs.

It is important to mention that, even though AI has provided effortless insights and assistance in many arenas during the COVID-19 pandemic, from a wearable's perspective, even to this date close to three years after the pandemic, the incorporation of sensory wearables is still in the embryonic phase. There is little concrete literature, other than suggested hypothetical ideas where AI has been used in the form of a diagnostic wearable during these times, unlike in other therapy areas.

2.4 Artificial Intelligence Applications in Cardiology Disease Diagnostics

Cardiology, the study of disorders of the heart and cardiovascular (blood vessel) system, is a major branch of medicine. The early report of Dassen and colleagues (Dassen et al., 1988) discusses the history of AI use in cardiology, actually starting in the early 1970s, giving a long history to this particular application area. As a consequence, the use of AI-developed diagnosis of, for example, cardiac abnormalities has received much attention. Manlhiot and colleagues (Manlhiot et al., 2022; Table 1) and Van den Eynde et al (Van den Eynde et al., 2022; Table 1) have listed examples of typical current and successful applications of AI in cardiology.

Searches carried out using the basic search terms *artificial intelligence* and *cardiology* in the PubMed database, up until June 2022, identified nearly 200 publications which have studied this application area. It is recognised that this basic search may have not identified all relevant literature. For example, if *ML* or *Machine Learning* is used instead of AI as a search term, or if *cardiovascular* is used instead of cardiology, the number of publications in PubMed multiplies. If the search dates are extended, then almost 4500 citations appear between 2010 and 2020 (Stultz, 2022). Nevertheless, this basic search is highly informative. In 2022 until June, there are 44 citations alone in the basic search, a fifth of those identified, emphasising the current trend to incorporation of AI into cardiology at a fast pace. Given this recent-day focus, this literature review section will concentrate on the 2022 basic search publications in order to demonstrate the relevance and importance of AI in cardiology diagnostics today.

Within the publications identified for 2022 up until June, eight (more than one per month) are general reviews and three are editorials, all considering AI applications and their status in cardiology (Bohm & Jajcay, 2022; D'Ascenzo, 2022; Itchhaporia, 2022; Kodera et al., 2022; Krajcer, 2022; Langlais et al., 2022; Manlhiot et al., 2022; Nakamura & Sasano, 2022; Schuuring et al., 2022; Stultz, 2022; Van den Eynde et al., 2022). The publications of Kodera et al. (2022) and Nakamura and Sasano (2022) are from a special edition of the Journal of Cardiology, focused on AI in Cardiology (February, 2022). However, as mentioned by Stultz (2022, p. 42), “no review can capture the full breadth of work in this area”.

The editorial by D'Ascenzo (2022) introduces a special edition of the journal Minerva Cardiology and Angiology, covering AI and cardiology: the few publications included in this edition are not reviewed here as they add no additional information over that included in the other 2022 reviews. The editorial of Stultz refers to and criticises the paper by Itchhaporia (2022) along the theme “all models are wrong but some are useful”, a somewhat pessimistic viewpoint emphasising that, in his opinion, when data can be described by powerful features (relating to a set of clinical characteristics highly correlated with an outcome), DL is unlikely to bring any additional benefits over traditional methods. Stultz (2022) emphasises that the quality of the model depends on the quality of the underlying dataset.

The 2022 reviews identified are, in all cases, repetitive in part. They all include standard descriptions and discussions of AI, ML and DL, often with diagrams to demonstrate the relationship of these in practice. The reviews are mostly general and discuss not just the applications of AI in cardiology (briefly, for the most part) but also the issues and pitfalls, which are echoed in each review. Challenges include: integrating data into the clinical workflow; interpreting and understanding ML models; identifying AI-based misdiagnoses; and addressing and resolving social, legal, and regulatory issues that may arise (Krajcer, 2022). These latter include ethical issues, discussed in a later section of this literature review. Also, bias of the data and robustness of the models (as their application across a wide variety of input data) are important issues that must be addressed, including institution-specific bias (Manlhiot et al., 2022; Nakamura & Sasano, 2022). Even the best models can be limited by the quality and magnitude of the input data (Bohm & Jajcay, 2022). The reviews universally conclude that AI/ML in cardiology has substantial promise, great interest with a large amount of work and resources dedicated: there have been undeniable successes that are already having an impact on patient care (Manlhiot et al., 2022). The future looks very much as though AI in cardiology will play a very important role but will not replace the clinician (Itchhaporia, 2022; Kodera et al., 2022).

The review of Langlais et al. (2022) from Canada is a good example of the type of review published in 2022. This review looks at novel and key uses of AI in cardiology, mapping out the current applications, limitations and future directions (Langlais et al., 2022). The authors review different ML categories (supervised, unsupervised, semi-supervised and reinforcement learning) and discuss the various cardiac diagnostics that have been developed in these different cases (Langlais et al., 2022). A comprehensive review of the different AI technology limitations is included, notably concerning bias and trust, recurring AI themes addressed by many authors in the review articles. The authors present strategies to address these limitations (Langlais et al., 2022).

Importantly, Langlais et al. (2022) consider the integration of AI models into clinical practice. Generation and cleaning of data, developing and testing algorithms with clinicians, external validation and, eventually, incorporation into clinical trials to test the algorithms should all be considered. Guidelines are needed for incorporation of AI into clinical practice and, because practices and the population subject to AI are constantly evolving, AI strategies must be updated. An automatically adaptive ML approach could be used, with clinician input to correct predictions and update algorithms. This would all improve the models with time but could also bring issues, such as over-specialisation of the model or data imbalance (effectively, bias).

Within the reviews examined, one aspect is conspicuous by its absence. None discuss the role of the patient or the patients’ view about the use of AI with respect to their diagnosis. Often, the subject of patient care or improvements to this which can be offered by AI are mentioned, but not the actual involvement of the patient in any way. Krajcer (2022) mentions in passing that some clinicians are using virtual reality systems to plan procedures or educate patients about various treatments, but this is not fully dealing with patient acceptance or their views about use of the technology. This finding is surprising since, ultimately, patient acceptance is key if the technology is to be fully implemented. To employ AI fully in cardiac diagnostics, explanations must surely be provided to the patient by the clinician, which also assumes that the clinician understands exactly how the AI is functioning. This may be a key issue alone (Stultz, 2022).

In addition to the general reviews covering AI in cardiology, multiple publications in 2022 examine the use of AI in specific cardiological diagnostic techniques, for example; cardiovascular imaging (Lauzier et al., 2022; Patel & Makaryus, 2022; Sanchez-Martinez et al., 2021; Stultz, 2022); cardiac MRI (Alandejani et al., 2022; Fotaki et al., 2021); nuclear cardiology (Miller et al., 2022; Otaki et al., 2022; Slomka, 2022); invasive angiography (Molenaar et al., 2022); and even audio techniques for detection of heart abnormalities (Voigt et al., 2022). The detection, prediction and management of specific cardiological diseases, such as AF have also been reviewed (Isaksen et al., 2022). The majority of these applications involve imagery of different types.

Certain other individual publications are worth highlighting to demonstrate the detailed application of AI in cardiac disease diagnostics. For example, reporting on a very large study at the Mayo Clinic in USA, Attia and colleagues (Attia et al., 2019) used a Convolutional Neural Network (CNN) to train and implement AF diagnosis in patients receiving a standard 12- lead ElectroCardioGram (ECG). From over 180,000 patients with nearly 650,000 ECGs, they demonstrated a high degree of result sensitivity (79.0%) and specificity (79.5%) from single ECGs examined after implementation of the system. These results increased to 82.3% sensitivity and 83.4% specificity when all ECGs taken during the first 31 days before the starting index ECG were included, improving the model's accuracy. Their findings make an important contribution to patient care and AF detection.

Kodera et al. (2022), citing the work of Diller et al. (2020), discuss an unusual application of AI in cardiac diagnostics that should be mentioned, namely the use of Generative Adversarial Networks (GAN) for the creation of artificial (fake) heart MRI images by a DL algorithm. These images were based on actual cardiac MRI data from 303 patients with known specific heart defects. Some 100,000 artificial images were generated. Of these, 200 original and 200 artificial images were presented in random pairs to human clinicians, both expert and non-expert in cardiology imaging (Kodera et al., 2022). All of the artificial images were labelled as "anatomically plausible", in other words accurate representations of hearts with the defects (Diller et al., 2020). Of importance, the artificial images had no data anonymity or privacy issues, enabling free sharing between institutions. The authors demonstrated their utility in training other network models using a sub-set of 100 images: when compared to actual cardiac data, the results obtained were very similar, less than 1% (Diller et al., 2020).

Several cardiac diagnostics can now be easily carried out using wearables. Although the consumer can nowadays simply purchase wearables that contain the ability to detect, for example, heart issues such as AF, large studies based on hospital or point-of-care environments are still being undertaken. To note, Manlhiot and colleagues (Manlhiot et al., 2022), citing work back to 2015, report that the deployment of smart devices detecting AF led to concerns with overdiagnosis, unnecessary testing after false positive readings, and over-detection of non-pathologic forms of diseases that would otherwise not have caused complications or have required treatment. Several years later, these views are not likely to be representative of the current situation, given the approval of such wearables as the Apple Watch by the United States FDA for cardiac diagnostics.

Dagher and colleagues (Dagher et al., 2020), from Tulane School of Medicine in the USA, have reviewed the position and future of wearables, notably in the field of cardiology. They describe the technology as empowering, with wearables literally “flooding” consumers. In particular, their use in AF detection is particularly useful, with ML and AI playing key roles in optimising performance.

Dagher and colleagues (Dagher et al., 2020) discuss the continuous improvements occurring in wearable technology related to, for example, measurement of heart beats and heart rate, leading to the detection of abnormalities. The technology and improvements are discussed in detail in relation to clinical studies, for example, such as the Apple Heart Study, one of the largest wearable studies to date. However, when applied to measurement of blood pressure, the results are nowhere near as accurate. The coupling of the technology with, for example, an accelerometer measurement helps mitigate movement and noise effects on the cardiac results obtained. The ultimate goal is to incorporate data recording, analysis and intervention into a single device (Dagher et al., 2020).

The authors discuss the clinical aspects of AF in some detail and their results and possible link of AF to, for example, sleep apnoea (Dagher et al., 2020). How wearables may “slot-in” to different situations is considered. Unfortunately, these details appear later in the publication and, to the reader, are out of order: they should have appeared earlier in the article, to set the clinical scenes. Their conclusion is that it is a question of when, not if, wearables become part of an individual’s healthcare (Dagher et al., 2020).

This publication was a useful review on the status of wearables, with brief summaries of studies performed to date. Unfortunately, the organisation of the content is not helpful to the reader and jumps between different scenarios. Also one important and key finding is that here Dagher et al. (2020), like the work of Quinn et al. (2022) actually begin to consider the patient as the end user, something not readily identified in other publications reviewed across the research of this thesis. Quinn et al. (2022) agree with Dagher et al. (2020) that ML, when applied to the healthcare domain in all aspects, fails to meet the needs for transparency that both the clinician and end user, the patient, ultimately require.

2.5 Artificial Intelligence Applications in Neurology Disease Diagnostics

Imagine an individual who is suffering with a debilitating motor degenerate disease that affects not only quality of life but also mental cognition. Being unable to perform daily habitual functions like getting out of bed, a visit to the bathroom, playing with children, walking to the shops with the dog or even holding a pen. Being motor impaired has more of an impact on patients' lives than some realise. This next section will address a number of neurological disease where AI has added value and played a major role in disease detection and disease prognosis, where AI has outperformed some of the best teams of Neurologists and, ultimately, raising concerns whether or not neurology could become completely dependent on AI in the future. Neurology concerns the study and treatment of disorders of the nervous system (Highland_Hospital, 2022). As such, the subject area is vast and covers many different sub-disciplines. Within these disciplines, the study of movement disorders, due to a wide range of medical conditions, is key and lends itself to the use of AI for, in particular, various forms of motion detection which can be used for patient diagnosis (Vinny et al., 2021).

The work of Vinny et al. (2021) is a reference publication for the use of AI in neurology, in general. Vinny et al. (2021) discuss how the various methods of AI promise to revolutionize the standard neurology practices, used and established over many years, in unimaginable ways. The authors demonstrate, outline and highlight the types of algorithms, from ML (supervised and unsupervised), DL, CNN and ANN, and how each model has made an important difference to medicine through their analytical differentiation and predictive capabilities of certain diseases (Vinny et al., 2021). AI has led to preventative lifesaving treatments because of rapid intervention by medical teams following the speed of early disease detection. The authors give comprehensive insight to their findings describing how speed, together with the analytical precision, specificity and sensitivity of AI, has outshone humans in assessment of certain neurological conditions.

Time is of the essence when it comes to a stroke. Brain deterioration occurs every 15 mins after the initial onset of an intercranial haemorrhage or infarction (brain bleed or obstruction causing tissue death) and could eventually lead to permanent disability and brain damage. The typical window for thrombolysis treatment is normally 4.5 hrs and early medical intervention is essential (Vinny et al., 2021). The same authors define the advantages of a trained AI ML model for quantifying the ASPECT scores (Alberta Stroke Program Early CT, which is a measurement grading of ischemic - reduction in blood supply - changes in hyperacute ischemic stroke) from CT scans of acute stroke patients. Their work is also supported by the work of Beitler et al. (2020) who reference the improvements of CT using DL, not just ML. The authors record how this model has achieved 91.8% specificity. Using an AI system to detect stroke patterns from non-contrast CT scans of the head, coupled with an alert system to healthcare workers, Barreira et al. (2018) showed that this AI system can save, on average, 52 minutes before an emergency stroke intervention team is required: catching every 15 minutes is key. Not only can AI-driven CT scans quickly assess the amount of functional brain tissue, these AI scans can also pinpoint which areas of the cerebrum will be affected the most, with time. AI CT, communicating via mobile apps and wearable devices, can sound the emergency alarm well before a radiologist. AI stroke software has proven tested high accuracy, sensitivity and specificity, outperforming a team of neurologists because the efficiency of an AI system will progressively improve (if not even surpass) human reasoning when making a clinical judgment to reach final diagnosis, faster and more accurately (Vishnu & Vinny, 2019). Furthermore, in a treatment area once deemed impossible, novel AI software tested at the Stanford stroke centre, the most prolific centre of research in the US, has broken research and development boundaries in stroke patients, where an endovascular intervention, once deemed impossible to manage, has now been made possible due to AI in disease diagnostics and healthcare (Kay, 2020). AI has allowed key advances in the diagnosis of intracerebral haemorrhage and has been able to predict both the potentiality and the prognosis of coma using new AI imaging techniques. Also, at the Stanford research centre, scientists have trained algorithms to read chest X-rays (Stanford_-AIMI_Center, 2022). The algorithm not only outperformed the radiologists but was able to detect 14 different pathologies. AI is able to ascertain, through CT imagery, how certain diseases will progress, improving better patient care and improved monitoring expectation, and allowing a more specific and bespoke personal treatment plan.

Multiple Sclerosis (MS) is a neurodegenerative disease classified by clinical symptoms and not underlying pathological mechanisms. Vinny et al. (2021) describe that disease activity, progression and relapse activity have always been proven difficult to predict and have posed many clinical dilemmas. However, they discuss the use of an unsupervised ML algorithm to analyse MRI images of MS patients, whereas much reference has been made to a more supervised approach in the earlier days of training ML algorithms in medical imagery. Therefore, this is important because the use of an unsupervised learning approach also shows the progression of the ML algorithms, now capable to diagnose and analyse more independently with less human interference. In this complex therapy area, the incorporation of ML models and AI models has defined and categorised new disease subtypes of MS. ML models, through data driven progression patterns, can predict patient groups who will have the highest rate of disease and disability progression and speed of deterioration, which is impossible to accurately predict by man alone. Using AI to define new subtypes of MS has accelerated medical research in this field and broadened clinician understanding because a prolonged or misdiagnosis of MS may lead to a diminished and poor prognosis (J. Huang et al., 2021).

In dementia and other neurodegenerative diseases, again heavily dependent on the results of a CT scan, AI has successful and proven diagnostic accuracy and has also proven successful in the discrimination between Alzheimer's Disease and Vascular Dementia, two quite different diseases. Training data sets for this differentiation using AI models were congruent with post-mortem findings. Again, this is another example of how AI accuracy, predictability and diagnostic performance has exceeded the "gold standard" of human expertise.

Parkinson's Disease (PD) manifests over time and physically presents as tremors, rigidity, bradykinesia, postural instability or even lack of facial expression. PD is difficult to detect at the early stages and very expensive. Vinny et al. (2021) discuss AI as another diagnostic option away from the traditional PET scan normally used. DL models have generated a test accuracy of 80% using a neuromelanin signal in MRI imaging data. The algorithm also discriminates PD from atypical Parkinsonian syndromes with only 85.7% accuracy, yet still better than a team of trained neurologists and imagery experts. ML has the potential to displace the work of radiologists as neuroimaging converted to digitized image data sets, when fed into these, will soon deliver an accuracy exceeding that of the trained human eye due to their algorithmic ability to work with thousands of fed data points, giving it a predictive and diagnostic advantage (Semigran et al., 2016).

ML techniques have been used for many years in medical imagery especially in epilepsy and seizure detection. Vinny et al. (2021) discuss how ML algorithms have given up to 98% accuracy against control assessments. AI medical imagery can also classify epileptic subtypes. An ANN has been used across three epilepsy centres but only showed a sensitivity of 73.7%, yet specificity of 90.0%. These results were not ideal regarding sensitivity. However, a support vector machine algorithm was able to distinguish patients with so called active epilepsy against those in remission (seizure-free for 12 months) across MRI imagery. DL algorithms were able to detect seizure onset with an accuracy of 99.6%, a sensitivity of 99.72%, a specificity of 99.60%, a false alarm rate of 0.004 per hour and a prediction time of 1 hour prior to the seizure onset, which is exceptional diagnostic performance (Vinny et al., 2021).

Although Vinny et al. (2021) present the benefits of AI in disease diagnostics, they also discuss the issues surrounding use and adoption of the technology. For example, trust issues between both patient and clinician are challenging. As discussed in the European Commission White Paper (European_Commission, 2020) and Frühwirt and Duckworth (2019), there needs to be a perceptual shift. Imposing strong regulatory frameworks will always be a problem. Old-guard neurologists often cite the reason to stay with traditional clinical methods as "the risk of getting misled in a sea of incidental findings" (Vinny et al., 2021, p. 276). This sentiment also concurs with other publication reviews identified as part of the work for this thesis.

Human experts are considered the gold standard in neurology diagnoses. Researchers have aimed to develop AI that is, in principle, identical to human intelligence – so-called Strong AI (Fjelland, 2020). Clinicians do not actually understand how the algorithms come to their conclusions or predictions (the "black box phenomenon"), a topic that is mentioned in the work of many authors including Quinn et al. (2022), who discuss the need for a clear solution of transparency for the clinician. Salahuddin et al. (2022) state that efforts are being made to explore interpretability methods for understanding the inherent black-box nature of the DL algorithms for clinicians. Lai et al. (2020) suggest that the “black box phenomenon” could prevent the doctor from providing clear information to his patient, depending on the degree of the tool’s independence in the final result. AI models and their performance are heavily dependent on an abundance of training data. Vinny et al. (2021, p. 280) state that, even though AI performance metrics seem “too good to be true”, there will always be an element of human bias. Errors should be expected: both patient misdiagnosis or erroneous treatment decisions could have serious legal, ethical and cost ramifications. Patient safety should never be compromised!

The work of Pedersen et al. (2020) goes into further detail about how AI can support clinical decision making in neurology. The authors are clear on one major point: AI has the power to transform healthcare to a system where machines and humans work together to provide better patient treatments.

2.6 Artificial Intelligence in Specific Neurological Disease Diagnostics

In order to more specifically show how AI has had a major impact in the diagnosis of neurological diseases, literature that considers AI applications in the examples of Stroke and Huntington’s Disease has been assessed in more detail.

2.6.1 Stroke

According to the World Stroke Organization Global Stroke Fact Sheet, 2022 (Feigin et al., 2022), there are globally over 12 million new stroke patients each year, all types, with deaths at 85 per 100,000 population. Stroke is the second leading cause of disability and death worldwide (Saini et al., 2021). The disease therefore represents a major burden on health systems everywhere. Any improvement in the diagnosis and management of stroke patients, through technology such as AI and wearables to monitor symptoms, will be a major help to the health systems and to patient care (Mbunge et al., 2022). Tran et al. (2019) discuss how technology should be integrated in care processes to avoid any negative impact on patient care, unnecessary burdens or added stress and intrusion to their lives.

The evolutionary importance of AI to the diagnosis and treatment of stroke is illustrated by a simple literature search of PubMed. Using the search terms “artificial intelligence” and “stroke” in either the Title or Abstract, PubMed gives almost 300 hits, stretching back to 1994. Here, a selection of research studies is reviewed as examples of the type of more recent literature that is available on the subject.

A lengthy study by Abedi et al. (2021) gives good insight into the use of AI in cerebrovascular disease, a combination of two diseases ranging from heart attack to stroke. This paper gives a commentary on all types of cerebrovascular events found using very specific medical key words and focuses on the recent developments of AI applications in this disease area, identifying gaps and suggesting areas of improvement (Abedi et al., 2021). The authors look at how AI has been implemented through many AI-enabled applications across the four stages of patient care management, including patient pre-diagnosis; acute imaging and triage; secondary prevention post-diagnosis modelling; and finally, rehabilitation post-diagnostic modelling. Additionally, the authors look at AI in the overall application of the health system from improvement of workflow, as a clinical decision support system model and how AI can be applied to innovative clinical trials. The authors state that the use of AI can improve health disparity and address implicit bias (Abedi et al., 2021).

The study of Abedi et al. (2021) ultimately reviews 44 selected cardiovascular records and 29 cerebrovascular studies. Across both disease areas, the researchers found that ML techniques gave an improved predication of cardiovascular risk in patients with and without explicit risk factors. DL models have been used to estimate the risk of stroke in AF patients. They found that ML is valuable in offering patient care and can identify gaps in medical care management while also being successful in better predicting existing ischemia and distinguishing that from subclinical coronary stenosis. Again, supporting the work of Vinny et al. (2021), Abedi et al. (2021) also state that AI, in particular ML, can give early detection of ischemic stroke differentiating from subclinical coronary stenosis. Abedi et al. (2021) again report, as Vinny et al. (2021), that time of clinical intervention is key.

Abedi et al. (2021) report that, from the timely diagnostics of ML through to the DL tools using large amounts of data, giving improved prediction and diagnostic ability, and through triage and personalized treatment plans, studies on the use of ML in assisting with rehabilitation have been limited. Out of all the research reviewed, the authors were only able to find one study where ML has been proven to predict activities in daily living activities of post-stroke patients, referencing a possible area of future investigation (Abedi et al., 2021). The researchers conclude that "ultimately, the future of healthcare is an organic blend of technology, innovation, and human connection" (Abedi et al., 2021, p. 30).

One specific, major type of stroke is termed Large-Vessel Occlusion (LVO), essentially the blocking of blood circulation in areas of the brain. LVO accounts for about 30% of stroke cases with an incidence of 24 per 100,000 people, but gives a 4.5-fold increase in mortality compared to other stroke types (Shlobin et al., 2022). These authors carry out a large-scale, systematic review of the application of AI to LVO stroke. From over 11,500 publications identified from their searches, Shlobin et al. (2022) selected and assessed 40 according to their criteria. Some 25% were international studies. The authors were especially interested in applications of AI in patient triage, diagnosis, patient selection and outcome prediction (Shlobin et al., 2022).

For triage, Shlobin et al. (2022) identify five studies that used ML for improved rapid, automated evaluation of stroke patients during pre-hospital transport of patients, meaning that the patients were taken directly to a stroke intervention centre and seen quickly, giving an improved patient outcome and ultimately saving their lives. This was a key benefit of LVO diagnosis using AI-models incorporating different types of CT imaging. Shlobin et al. (2022) found that ML had been used by some studies to diagnose the type and severity of stroke. Only two studies dealt with patient selection using ML, meaning that the algorithm was able to identify patients eligible for treatments. Finally, what can be concluded from their study is that by using ML in triage, diagnostics and patient selection, there are clearly proven benefits and advantages (Shlobin et al., 2022). However, as this research was only done for one type of stroke patients for outcome prediction, eleven studies used ML to predict the outcomes of mechanical thrombectomy (MT: the minimally invasive removal of a clot from an artery). The authors conclude that the application of AI in the areas of their review remain at an investigational stage, with most of the literature in fact focused on diagnosis (Shlobin et al., 2022).

Considering in more detail the area of stroke diagnosis, the work of Fasen and colleagues (Fasen et al., 2022) focuses more specifically on the evaluation of AI software (StrokeViewer) in the diagnosis of circulatory brain occlusions and in comparison with manual reading of CT Angiographs (CTA: a CT scan employing an injected contrast dye for visualisation). StrokeViewer employs a combination of computer vision and DL-based algorithms: limited training and validation data sets were used. Manual assessments by two neuroradiologists were applied. From a review of 474 patients by Fasen et al. (2022), 75 were found to have an occlusion according to the standard used. Sensitivity of the AI software was 77.3%, little different from the manual method at 78.7%. Also, the software detected 40/42 and 18/33 of two different positions of occlusions, but the software version employed had not been trained for certain type of occlusions. More importantly, 8/16 occlusions, missed by manual reading, were identified. However, the specificity of StrokeViewer (the ability to detect true negative results) was 88.5%, lower than the 100% from manual reading. The authors report that these results were similar to other works reported in the field. In highlighting several potential limitations of their study – including, for example, manual evaluations by a number of different radiologists (which they consider more real-world) instead of a fixed group - the authors concluded that “the current AI software cannot replace radiologists and senior radiology residents” (Fasen et al., 2022, p. 1581).

In contrast to the study of Fasen et al. (2022), Gunda et al. (2022) report on the implementation of AI-decision software (e-Stroke Suite: for non-contrast CT and CTA assessment) for acute stroke management in a large stroke primary care centre. They evaluate the impact of the automated analysis on the rates of both thrombolysis (using clot-dissolving drugs) or MT in periods firstly without the automation and then, in the same period of the following year, after automation had been introduced. No other changes in patient care were introduced during these periods.

Almost 400 patients from each 7-month period of the years, before and after, were included. The results were striking. After introduction of automation, 56.9% more patients were treated for thrombolysis: no other treatment trends were identified. Feedback from the clinicians using the new system indicated increased confidence and speed of image interpretation with improved local decision making. Although limited as an observational study, the work of Gunda et al. (2022) supports the concept that AI-decision making in clinical practice can have positive benefits.

2.6.2 Huntington’s Disease

Huntington's Disease (HD) is a condition that stops parts of the brain working properly over time. The disease is inherited and gradually worse over time. The condition is usually fatal after a period of up to 20 years. Apart from memory loss and personality changes, HD is characterised by movement disorders.

In order to investigate and understand more the progression of HD, scientists at McGill University trained an AI-algorithm to monitor blood samples and post-mortem brain tissue (Iturria-Medina et al., 2020; Ray, 2020) through gene expression patterns. Key correlations were identified between gene expression in the brain samples using AI than years of human research and investigation. The algorithm strongly predicted the severity of the condition, clinical deterioration and conversion to advanced disease states.

Tortelli et al. (2021) report a systematic review of the use of wearable/portable digital sensors for HD. Because HD is a combination of both motor and non-motor features, that can be both heterogeneous and vary over time in the patient, there is great potential for the use of such devices. The classic, normally applied scale for disease assessment cannot capture the rapid variability of the symptoms, which would be detectable using such sensors and on a longer-term basis. Thirty publications were included in the final analysis (Tortelli et al., 2021). Six included patients with other neurological diseases, but with the majority focused on clear HD symptoms and comparing HD patients with healthy volunteers. Monitoring duration was from a few minutes in a clinic to eight weeks in patient’s homes (Tortelli et al., 2021).

Accelerometers were the most used sensors, trending from mono- to tri-lateral versions in later work. Only one study used a flexi-force sensing resistor. Two studies used no sensor, instead applying an app on smartphone or tablet. Of interest, technology advances allowed the sensors to become lighter, smaller, flexible and dynamic with higher frequency sampling and larger memories (Tortelli et al., 2021). Trends were towards easier-to-wear and more comfortable devices, going from larger to adhesive/wristwatch types. The disease characteristics investigated in the literature included both voluntary and involuntary movements, a range of sleep-related conditions, balance and walking/gait characteristics or more general movement activities during a day.

An important conclusion of the review was that wearable/portable sensors have been of limited value in understanding the natural history of HD or in better defining HD characteristics (Tortelli et al., 2021). A range of agreements with the current assessment standard were identified, from strong agreement (gait measurements) to poor agreement (sleep activities). However, in certain cases, the sensors were able to distinguish between HD patients and controls with regard to involuntary movements during sleep or sleep efficiency. The most investigated trait was gait/walking ability. In the home, the sensors detected greater variability in the motor measurements than in controlled clinical settings (Tortelli et al., 2021).

The authors highlight areas of concern, including the lack of validation and standardization of devices, making cross-study comparisons difficult (Tortelli et al., 2021). Analysis of the large amounts of data is a completely open field. Also, patient selection bias in studies using wearables/portables must be taken into account with respect to, for example, gender, education and the role of relatives. Finally, several unmet needs are discussed, but these are translated across from Parkinson's disease assessments.

This review provided an interesting and comprehensive oversight of the subject from a highly respected, world class institute in London (Tortelli et al., 2021). The use of wearables/portables is, without doubt, of great interest and promise in biomarker assessment for HD and other disease areas (Farahani et al., 2018; Tian et al., 2019; Tran et al., 2019). What is important, however, is the acceptance of the patient to uses such diagnostic devices.

2.7 Artificial Intelligence Applications in Mental Health Diagnostics

According to the WHO, in 2019 mental health disorders affected at least 1 billion people worldwide, though these are only the ones known (World_Health_Organisation, 2022b). Many people suffer in silence. But this number affected is changing. The US Centers for Disease Control and Prevention (CDC) reported that 40.9% of the American population, and particularly those in marginalized communities, have experienced at least one diagnosable mental health condition in the first year of the COVID-19 pandemic (Czeisler et al., 2020).

Chung et al. (2020) give an in-detail overview of the problems and the challenges that have arisen from the speed of the evolution of healthcare data, with a focus on mental healthcare. In any healthcare system, use of the available data is essential to improve not only the healthcare system itself, but to improve the diagnosis of patients who rely on these services. Chung et al. (2020) report that, with the abundance of availability in healthcare data, better informed decisions can be made. Within the focus on mental health, a complex clinical area, the abundance of generated data has caused problems due to its complexity. However, visual stimulants driven by AI can play an important role in data analysis of mental health data and better present the findings (Chung et al., 2020). On the sensitive topic of mental health and the use of AI in healthcare combined, the authors used a description of using AI in healthcare and mental healthcare diagnostics which differs tremendously in the type of AI use and the AI models (Chung et al., 2020). AI is a very broad topic but generally takes the form in mental health diagnostics in the form of chatbots.

While acknowledgements of dispute for the use of chatbots in mental health applications due to ethical reasons is accepted, chatbots have also been a proven help, especially in patients with social anxiety (Brown & Halpern, 2021; Damij & Bhattacharya, 2022; Fitzpatrick et al., 2017; Ward, 2021). Furthermore, VR and AR are increasingly of interest in mental health treatment for patients who have demonstrable signs of post-traumatic stress, recreating the traumatic scenes better than the trained voices of a psychiatrist (Eshuis et al., 2021). Patients with schizophrenia have been introduced to Avatar therapy via mobile applications such as Replika, an AI driven chatbot to help patients faster than they could be seem by a doctor using the sophistication of algorithms. Pham et al. (2022) have touched on this alongside the mobile application whereby the patient can have open and to some extent vulnerable conversations with an Avatar without fear of judgement.

Schizophrenia is a serious mental illness that affects how people think. It is estimated that over 24 million people worldwide have schizophrenia while less than a third of these cases currently receiving treatment or additional supportive care (World_Health_Organisation, 2022a). Two main symptoms of schizophrenia include visual and auditory hallucinations. Imagine patients being constantly tortured through the power of their mind, the delusions and cognitive impairment which affect their lives so much that they cannot project any form of speech, so they drool, they are isolated normally alone, and in some cases not only do they cause extreme harm to themselves, but to innocent bystanders too. Whilst medication is readily available, for those who have been clinically diagnosed by a doctor, AI is bringing another of approach of both diagnosing the illness and helping patients to adapt to normal day to day life. Garety et al. (2021) have researched AI in the form of Avatar therapy. This therapy, using intelligent algorithms, has enabled patients to address the daily persecutory voice hallucinations (Garety et al., 2021). Patients have been able to gradually learn how to take control and address these torturous events in a fixed number of sessions, a huge benefit being that they are given an element of patient-centred control in a comfortable setting without having to wait months to see a mental health specialist.

The present literature review identified that COVID-19 played a major impact on people's mental health (Akay, 2022; Lewis et al., 2022; Samji et al., 2022; Usher et al., 2020; Vindegaard & Benros, 2020). From a diagnostic perspective, the use of AI, especially in the form of chatbots, should be an integral part of a mental healthcare plan because evidently there is a global shortage of mental health specialists. Schroeder and Schroeder (2018) say that AI chatbots in mental health are better suited to patients who are already enrolled in some level of psychotherapy.

While chatbots are the key focus for offering assistance to mental health patients, Pham et al. (2022) discuss Woebot (Woebot_Health, 2022). This is an automated, conversational application available through Facebook Messenger or mobile apps which can monitor symptoms and episodes of anxiety. Woebot offers behavioural health solutions that are personable and actionable, providing a faster tool for mental health and a form of Cognitive Behavioural Therapy (CBT) normally provided by a therapist (with a very long waiting list).

Some might agree that mental health assistance in the form of AI chatbots, Avatars and similar are important for those patients who cannot see a doctor, are already medicated and are to some extent less vulnerable of self-harm and harm to others. Yet there is opposition to the use of AI in mental health due to ethical concerns. Furthermore, other concerns rest within certain social and digital barriers with different age groups and racial populations. Brown and Halpern (2021) have looked at the ethical consequences of using a chatbot with mental health patients having to rely on self-advocacy to move to the next stage of help, while touching on the implicit bias that can be demonstrated using AI interfaces. However, they make the case for humans as first line mental health providers, not chatbots (Brown & Halpern, 2021).

Chatbots are being used as conversational agents and have proven abilities, able to conduct treatment for mental health patients using CBT (Abd-Alrazaq et al., 2019). They are helping patients (who are socially compromised) to develop coping tactics and enhanced social skills (Abd-Alrazaq et al., 2019). But with this AI-led technology comes many concerns. The work of Brown and Halpern (2021) concludes that three fundamental requirements, when treating patients with mental health, are overlooked when using chatbots as a first-line treatment option. These three fundamentals are the ethical demands of both fairness and justice, and patient respect. While the scope of the mental illness umbrella is huge, problems could be a nightmare if a schizophrenic decided one day he is ok when really he is not, kills someone and then has life imprisonment because he was never seen physically by a doctor who can notice the physical symptoms and who can identify the human emotional stress and triggers that a chatbot cannot. Mbunge et al. (2022) also reported this in their work. AI lacks human-like emotion and this needs to be addressed especially when using AI in mental health treatment. However, AI will need to have a different twist, a different approach perhaps, depending on the type of mental health condition. You cannot compare chronic anxiety with schizophrenia.

Envisage patients suffering with mental health issues and treatment steps relied on a chatbot, not taking into consideration the fluctuation of moods or self-esteem across the month. The work of Adikari et al. (2022) reports that AI chatbots lack emotion and any level of sentient capabilities. Rightly so, this could be a dangerous liaison with very strong ethical ramifications. Like with the work of Brown and Halpern (2021) and the areas of concern that AI developed chatbots cannot replace the extremely human interaction in pursuit of inclusive mental healthcare, Adikari et al. (2022) take their research a step further. These authors claim the non-clinical needs of patient mental health are being overlooked (Adikari et al., 2022). It is with this in mind that the researchers adapt emotional transition models representing different emotional behaviours of patients in order to improve Patient Centred Care (PCC) using AI and chatbots (Adikari et al., 2022). With a focus on PCC, chatbots can improve emotional stress and depression and can provide emotional support in a number of patient groups and therapy areas. While wearables and autonomous sensory equipment are already being used to assess and help patients, chatbots can be trained to be an empathetic interface between patients and the healthcare professional (Adikari et al., 2022). The researchers' algorithmic adjustments showed that, while being empirically tested and validated on Canadian cancer patients, the chatbot was successful as a conversational agent using natural language and real-life engaging dialog. They concluded that chatbot use in healthcare can be customised and aligned to any clinical setting or clinical protocols (Adikari et al., 2022).

Brown and Halpern (2021) seem a little more dubious. Citing the work of Moreno and colleagues (Moreno et al., 2020) these authors believe that mental health AI alternatives will only be viable "once we work out which forms of virtual services actually translate to quality care and health equity". Meanwhile Miner et al. (2020) state that, if chatbots are able to represent appropriate voices through collaborative inputs, they could one day be able to provide short term basic mental health support.

Finally, a recent article published in the Wall Street Journal (Ward, 2021) discusses whether AI can replace human therapists. The WSJ interviewed two workers in the field over a range of subjects and helped to give perspective on the current issues of today for AI in healthcare diagnostics, including application of chatbots. One view was that it is hard to imagine human therapists being replaced by chatbots. While this is not a peer reviewed article, Brown and Halpern (2021) also refer to the article in their own work. Despite all the suggested positive outcomes that, to some extent, have been backed by real life evidence and not just by conceptual frameworks (as in other fields of AI in healthcare), it is true chatbots cannot either partake in verbal cues or demonstrate clinical empathy because they are unable to attune themselves to both the clinical and emotional needs of patients. The role of the human interface-acting therapist in mental health care diagnostics is therefore still vital.

2.8 The Application and Use of Wearables in Artificial Intelligence Applications for Healthcare Diagnostics

One of the major, ultimate endpoints for the use of AI in healthcare diagnostics is the incorporation of the technology into items that the patient can use, known as wearables. Over the period 2014-2018, the use of wearables has quadrupled in the US to 33% (Safavi & Kalis, 2020). By 2022, it is estimated that 67 million people in the US will be using wearables (Wurmser, 2019). Various surveys have shown strong positive responses to future use of such devices, including in the elderly.

There has been a major emphasis on wearables in the last years, with the emergence of technologies such as the Apple Watch and Fitbit wearables that have been licensed by regulatory authorities for the diagnosis of clinical conditions, such as AF. Fitbit wearable devices, recently bought by Google, have been mentioned in over 1,000 publications from a simple PubMed literature search for the device name. These devices are gaining traction as possibly the leading cost-effective consumer wearable, while offering the same capabilities as the Apple Watch. This section of the literature review examines the literature dealing with the patient use of wearables in more detail, citing examples of the available information.

AI was created by man and in numerous areas of healthcare, under the so-called FIR, AI now has the proven ability to outshine its creators. Many examples of this ability have been discussed throughout the present literature review. Regardless of the speed and frequency of publications per month regarding all the AI benefits, there are very few publications that actually focus on the patient and patient views. Patients are the epicentre of digital wearable success.

Tian et al. (2019) describe smart healthcare as a way of making healthcare more efficient and insightful through the incorporation of various technologies, including AI. The authors analysed the impact of these technologies on PCC and propose solutions for improvement and patient integration (Tian et al., 2019). Narrating how the disruptive emergence of smart healthcare technologies has improved disease prevention, disease diagnostics, and healthcare management, these have also encouraged a more convenient yet personalised form of healthcare and better patient self-management. Smart health has grown from IBMs coined concept of a smart planet (Martin et al., 2010), a world in which the IOT plays a pivotal role.

Smart health is defined by Tian et al. (2019) as a health system that is driven by wearable devices, IOT, or mobile devices transmitting sensory information and connecting people and their information across a number of sources in the healthcare ecosystem. The authors say smart health can promote interactions in all fields of healthcare, while Gong et al. (2013), cited by Tian et al. (2019), describe it as a higher stage of information construction in the medical field. AI underpins all advancements in healthcare (Tian et al., 2019). As discussed already within this present literature review, many examples have been provided as to how and why AI is now essential in healthcare and Tian et al. (2019) reinforce that smart health, driven by the different forms of AI, is the future. Farahani et al. (2018) state that smart healthcare could possibly make personalized medical services ubiquitous.

Despite the positivity around the topic of smart health, whereby patients can monitor their own health conditions through numerous AI wearable sensory applications and devices, Tian et al. (2019) say that concerns have been raised regarding both a lack of guidelines and guidance and the absence of realism behind future development goals. Furthermore, there appears to be a lack of uniform standards around data integrity with wearable devices and their platform integration. One emerging question in this research field is how these data are stored and how will they be used in the future. From a patient perspective, there is always the issue of privacy concerns: actual technology usability and patient security reassurance is crucial. Legislation and regulatory frameworks are required and must include joint efforts from doctors, health institutions, and technology companies and, more importantly, patients. Tian et al. (2019)recognise the importance of patient inclusion, though many publications focus mainly on the key players in healthcare to the exclusion of patients.

Tran et al. (2019), like Tian et al. (2019), examine the current state of wearable Biometric Monitoring Devices (BMDs) and AI. These technologies present themselves in many forms and are capable of remotely monitoring patient status and management, measuring and analysing patient data in real time, which is a key feature of any diagnostic health monitoring wearable (Tran et al., 2019). These researchers carried out two experiments together and aimed to investigate how chronic patients, across an array of illnesses within the French population, feel and how they perceive incorporating wearable devices into routine treatments or care (Tran et al., 2019). The authors assess and analyse patient perception of AI-driven tools. The rationale behind such a study coincides with similar findings across the present literature review. The literature on patients' views of the use of BMDs and AI in healthcare is scarce and relies mainly on context-specific studies which are not a true reflection on how the patient truly feels. Nor do the studies reflect patient readiness and willingness to uses these interventions. Hence, why this study provided interesting insights (Tran et al., 2019).

Tran et al. (2019) demonstrate that the most popular areas of patient readiness to integrate AI biosensory wearable devices into their care were mole and skin screening for cancer detection and AI biosensors to predict chronic disease flare ups. Chatbots were also of interest as a fast way to help patients determine the urgency of their problems, a sensitive subject again discussed earlier in the mental health review in Section 2.7. Ultimately, about 80% of participants were ready for the use of technology in their care state, but only a small proportion were willing to use AI without any human input or control. Surprisingly, the researchers found no association between patient demographics, clinical characteristics, and their willingness to integrate BDM and AI. They wanted any medical recommendations to remain a "human task" and preferred AI and BMD to act more as a complementary adjunct and not as a replacement for their clinician.

It has to be mentioned that the Tran et al. (2019) study focuses on the French population. Other research expanded this research stream to other populations. For example, the work of Ćwiklicki et al. (2020), which looked at a Polish population of patients, also touches on patient perceptions. It could be assumed that the patient perception of integration of BMD and AI in healthcare would be demographic specific. However, authors including Ćwiklicki et al. (2020), Tran et al. (2019) and even Li et al. (2015) identify no specific association between patient demographics and their readiness to adopt BMD and AI based tools in their care pathway. While running two investigations, simultaneously documenting patient perception of BMD and AI in healthcare, 50% thought that it was an opportunity while 11 % deemed AI in healthcare a danger (Tran et al., 2019). Human centred interventions remain important. Some 35% of patients refused to integrate at least one BMD and AI tool into their care (Tran et al., 2019). These authors conclude that AI should help the clinicians to predict outcomes but ultimately it is the human task of recommendations by the clinicians which should remain central to healthcare practice (Tran et al., 2019). Apart from the accepted flaws of this study, what was important is that there is a need for more patient perception research.

Li and colleagues (Li et al., 2015), from the medical university of Taipei, investigate embracing the era of wearable medical devices. Whilst this paper is seven years old, and accepting the speed of technological evolution, these researchers discuss testing the performance accuracy that medical grade devices must endure and pass to enter the medical market in order to create an autonomous health system (Li et al., 2015). Identifying key markets and customer groups, the team propose the type of wearables that were to come, including bracelets and watches, though no mention of rings (such as the Oura ring). To note, the Oura ring was not available when their work was carried out, but has received attention by other authors since (Mason et al., 2022). They say that wearable gadgets not claiming to diagnose or treat diseases, do not require, for example, FDA approval (Li et al., 2015). The authors state that people who wear devices are already health conscious but the people who need these devices (at the time of publication) do not actually wear them! In comparison to the more recent work of Tian et al. (2019), there is now a fast development and evolution of all sorts of wearable devices. Of importance, patients who need them are actually wearing them. There appears to be an increased willingness to try the technology from a clinician level, but again very few publications on patient willingness to incorporate these devices and technology into their own treatment plan.

This seems interesting, since several diseases require continuous monitoring and treatment. For instance, diabetes is a global concern often referred to as the silent pandemic and has a huge impact on peoples' lives. With the correct medication and adapting lifestyle changes, the disease can be controlled and contained, thereby preventing premature death. The global diabetes prevalence in 20- 79 year olds in 2021 was estimated to be 10.5% (536.6 million people), rising to 12.2% (783.2 million) in 2045 (IDF, 2021). Diabetes itself is classified as Type 1, Type 2 (which is diet and lifestyle related), gestational diabetes and prediabetes (which is border-line diabetic and more common than we think). The work of Yoon et al. (2022) is pertinent to producing a diabetes wearable, something also which CEO Tim Cooke himself of Apple Inc is currently trialling as an Apple AI-driven glucose detector wearable prototype. These authors developed a new hybrid wearable in the form of a skin patch (Yoon et al., 2022). The researchers show how wearables have advanced, from the previously mentioned work of Li et al. (2015), from wrist bands to bracelets to biosensor patches. Unlike most biosensor patches, the sophisticated design proposed by Yoon et al. (2022) is able to measure different bio- and chemical physiologies. Currently, most wearable bio-sensory patches can only measure the performance of one physiological measurement at a time. The patch developed by Yoon et al. (2022) monitors sweat glucose levels and acts as an ECG together, integrating both temperature and pH monitors. Research by Lee and Shin (2021) reported that precise calibration of the pH and temperature for enzyme-based diabetes sensors is essential. A fully integrated hybrid patch provides advanced glycaemic control ideal for the management of diabetes and cardio disease combined.

It has been noticed during this literature review that many studies around the incorporation of biometric, sensory, and physiological wearables have been performed by Chinese researchers. While readings from Kai Fu Lee state China is the copycat capital of the world (Lee, 2018), from the present literature review, China seems very innovative in diversifying development in healthcare digital wearable development.

Ai et al. (2021) from China explain how the emerging field of flexible bio-mechatronic wearables, namely sensors, actuators and robots, will play an important role in future physical rehabilitation systems as part of an intelligent healthcare society. Also, this was identified in the Tran et al. (2019) paper. Patients are happy to wear biosensory clothing to guide physical therapy rather than through visits to a physiotherapist. Ai et al. (2021) aim to address the challenges of rehabilitation using IOT, accelerometers and wearable sensors (Ai et al., 2021). From robotic assistance rehabilitation in stroke patients through to kinetic wearables for disabled people, these systems appear to have a better outcome than human physiotherapists during rehabilitation programmes and so called telerehabilitation. These researchers describe and demonstrate how smart health wearables have brought convenience to the lives of many patients and assisted healthcare. However, data confidentiality and data privacy are, as stated by many authors, still a major concern (Ai et al., 2021).

Again on the subject of smart wearables but specifically related to cardiac diseases, Chen et al. (2020) present their findings on the use of smart wristbands equipped with AF algorithms as a health management tool. While there has been an increase in self-management health devices, the most popular areas of diagnostics remain in the field of cardiology. There has been a plethora of cardiac-related publications, in particular around the disease areas of AF. Authors such as Nemati et al. (2016) and Wasserlauf et al. (2019) examine both wearable technology and smart watch performance in AF diagnosis and monitoring. While Chen et al. (2020) discuss the possible benefits of wearable devices in AF detection, they also highlight issues that need to be addressed and which are not considered by Nemati et al. (2016) and Wasserlauf et al. (2019). Some wrist bands are only equipped with what is called PhotoPlethysmoGram (PPG) sensors. According to Chen et al. (2020), that is not enough to truly identify atrial heart activity. An ECG is required for a true AF diagnosis and the authors investigate the effect of smart wrist bands that contain both functions (PPG and an ECG) using an AF identifying algorithm. They hypothesise that a dual combination would provide better sensitivity, specificity and accuracy than one function alone. Chen et al. (2020) gained a “satisfactory” result when combining both ECG and PPG.

Meanwhile on the high street and available to all, without a prescription or referral, Apple are continually improving and adding to their health tracking applications in the Apple Watch, to the extent that researchers at Stanford University in 2021 were investigating the benefits of the Apple Watch as a health monitoring tool (Hackett, 2021). Because this study was funded by Apple, one might assume there was an element of bias here, yet other work from independent researchers, as described in the cardiology literature review Section 2.5, and who were not sponsored by Apple, also found similar results. From heart monitoring and sleep tracking to the ability to check blood oxygen levels, Apple are continually developing their programmes to encourage a healthier lifestyle, giving consumers the ultimate power to take control of their health tracking without a clinician. Only recently, an Apple Watch was able to detect a user’s thyroid problem through its biosensor AI capability before the doctor identified the problem months later (Owen, 2022). Additionally, there are reported incidents where the Apple Watch has alerted users of sleep apnoea and asymptomatic AF, leading to a patient needing a pacemaker, a topic previously discussed in the cardiology literature review in Section 2.5.

2.8.1 Use of Wearables for Neurological Disease Diagnostics

The area of neurology disease diagnostics using wearables is so important that a separate section of review was considered warranted. Because of the effects of movement disorders and similar neurological conditions on patients, diagnosis and monitoring of these conditions using a range of wearable sensor technologies, coupled with AI-led data interpretation, has become important. Different technologies are reviewed here, together with specific examples of the impact of AI-driven wearables on certain neurological conditions.

An early study by Manupibul et al. (2014) presents the development of a smart insole system for plantar (foot sole) pressure measurement to study body balance. The authors discuss the complexity of balance and the measurement systems available at that time. Development of both the hardware and software is presented but, unfortunately, very little data are included, making performance assessment almost impossible for the reader. This is an important weakness of their work unlike that of Matsumoto and Takano (2016) whose research is more advanced despite being only two years later. These authors have embraced wearable technology applications, incorporating them with the smartphone. Again, focusing on the importance of body posture, Matsumoto and Takano (2016) present early work on the development and implementation of a posture detection system using wearable sensors on the wrist, ankle and in the foot sole. At that early time, two smartphones and one tablet were required for data accumulation, so capturing real time data was constant. The authors presented the analysis of three motions using their system, but the data were preliminary only. However, this was a good foundation for further research to create motion sensory algorithms which have now, six years later in 2022, proven to be effective in helping and monitoring patients not only with postural stability issues, but with neurological disorders, too. When humans age they become less stable on their feet and while some authors refer to elderly falls as geriatric syndrome affecting mortality, morbidity, and institutionalization (Rafanelli et al., 2022). Not all falls are explainable. But it is not just the elderly who trip and fall. Some people have undiagnosed vertigo or ear issues which affects the balance too: some have more undiagnosed serious conditions like a brain tumour or bone cancer, which affects their stability.

With this in mind, Li and colleagues (Li et al., 2018) describe the development of a pair of wearable shoes fused with range sensor arrays for the home monitoring gait parameters of importance to patients susceptible to falls. Their sensors measured five gait parameters of peak pressure, stance ratio, stride length, walking velocity and step time-variability. Their system was validated against a reference method by volunteers walking both normally and with abnormal gait parameters. Overall, their technology calculated the gait parameters in close correlation with the reference method for both the normal and abnormal gait parameter, meaning that primary end point findings were met and that the wearable sensory shoes would be of advantage to patients with postural and balance issues (Li et al., 2018). However, compared to the more recent work of Hong et al. (2022), these authors really focus on AI and the IOT again indicating the incorporation and technological advancement in a short space of time of AI in healthcare diagnostics. A practical example of a postural monitoring wearable that used AI for data interpretation and diagnostics is the work of Hong et al. (2022). These authors discuss the advancements and development of a framework to contribute to postural recognition issues globally. They propose an AI-driven IOT solution using both online and offline wearables able to capture all types of motion. Whilst recommending their two complementary DL algorithms to this AI IOT online/offline approach, Hong et al. (2022) discuss how their own development has outstanding proven tested accuracy, and infinite reliability and performance against current postural devices - a strong statement when only 20 candidates were used. From digital helmets monitoring head trajections, to vision-based fall monitors that identify blind spots, they also touch on the more advanced applications of the smartphone (Hong et al., 2022). The past work of Rakhman et al. (2014), eight years before, is comparable in that they proposed a smartphone-based accelerometer and gyroscope to build a fall detection system, but that study showed poor accuracy. Hong et al. (2022) adapt the original concept and improve on the work of Rakhman et al. (2014). Through the contribution of smart phone application data, using different algorithms, six new postural recognitions could be classified and incorporated into the newer postural recognition wearable devices, a major breakthrough and indication how smart phones and wearable devices have unlocked possibilities in disease monitoring.

While posture recognition systems have been challenging, Hong et al. (2022) describe the technological postural assessment developments. Their work gives insights to current communicative wearable sensory devices and the AI models used. The authors examined related work which has paved the ground for their own improved developments, especially that of

Matsumoto and Takano (2016), whose multiple sensory detection system relied heavily on Bluetooth and had low reliability. Referencing Manupibul et al. (2014), the authors also suggest ways to improve the device. The work of Li et al. (2018) is conceptually good, but Hong et al. (2022) suggest again low accuracy in fall prediction. Recognising posture issues is a challenge as daily posture in life activities can be misjudged and is the reason why the authors believe both online and offline wearable devices are essential to understand postural analysis and fall prediction and detection (Hong et al., 2022).

Hong et al. (2022) are methodical in their approach to analyse different types of postures and sensors in order to create their own algorithms and device. From a patient compliance perspective, which is important in the creation of any digital wearable either in the shoe or on the body, these researchers investigate wearable convenience and comfort (Hong et al., 2022). Because posture involves different movements, data capture must be real and true for everyday life. Because efficient fall detection systems also require wireless networks, Hong et al. (2022) wanted to create the perfect online/offline, cutting edge, algorithmic device collecting multiple data points with self-learned adaptivity. Their outcomes proved successful.

In considering more complex devices for neurological applications, Gupta et al. (2022) discuss the rise in interest and the development of flexible artificial sensory systems that can emulate actual human biological sensory perception, transmitted via sensory wearables. The authors discuss the adaptation and advancements of TriboElectric NanoGenerator (TENG) based devices that can harvest energy as they go. The research proposes suggestions to create mechanoreceptor and biological sensory wearables. While discussing brain-inspired computing and innovative intelligent "innovative neuromorphic devices" (Gupta et al., 2022, p. 4), the authors highlight important AI technological advantages in the development of DL neural networks. AI sensory perception systems are of global appeal in medicine. Such sensory input systems include motion, tactile, visual and auditory. The authors believe that the development of AI-driven sensory wearable systems, replicating afferent neural transmission (relaying sensory information from sensory receptors to regions of the brain), can lead to important advancements in human–computer interaction models and wearable devices (Gupta et al., 2022).

AI skin inspired mechanoreceptors can drive encoded synaptic pressure to stimulate neural transmission responses. Gupta et al. (2022) report that incorporation of a voltage system means such devices can generate their own power supply. Of importance is the use of AI in pain and nociception (the process by which noxious stimulation is communicated through the peripheral and central nervous system). For nociception, the researchers fabricated a multilayer electric dermic and neuromorphic sensory interface able to emulate a real-life sensory perception.

Overall, this paper discusses the development of artificial neural sensory technologies and sensory perception using types of AI models, but mainly DL (Gupta et al., 2022). The short paper explains how AI is rapidly contributing to this field of medicine and biotechnological research and nicely sets the scene for consideration of the research from Petrini et al. (2019).

Additional studies relating to sensory technology systems are shown by the work of Petrini et al. (2019) studying sensory feedback for leg amputees. Petrini et al. (2019) discuss the fact that conventional leg prostheses do not convey sensory information about motion sensory stimuli because there is no afferent neural propagation to the brain. The advancement in AI driven sensory perception systems could possibly reduce the frustration of phantom limb pain in amputees which is due to the lack of neurological feedback to the brain from the missing leg. The impact of such biomechanical advancements, combined with accompanying AI advancements especially DNN, are what have been driving Dr Art Kuo, Professor of Kinesiology at the University of Calgary, to develop smart prosthetics in order to allow lower limb amputees greater mobility - especially on uneven ground (University_of_Calgary, 2022). AI wearable sensors have been able to assess balance in older adults. AI sensory wearables are also being used to identify and find ways to improve walking efficiency, motor control and co-ordination in both post-stroke and neurodegenerative patients. Giving a review of the advancements of wearable portable devices, Petrini et al. (2019), along with the work of Nahavandi et al. (2022), agree that it is the collection of multidimensional data during everyday functions that enables predictions to be made and how the exact pathway of deterioration and care can be decided and recognised.

Parkinson's truly is a terrible disease. There is no cure and every part of daily life is affected. The advancement in AI sensory intelligent perception systems and neuromorphic devices has recently been a major breakthrough for Parkinson's patients. A state-of-the-art wearable watch, the PKG Watch, from the digital technology company Global Kinetics, relays information to neurologists through the power of AI. The wearable has the ability to collect multiple data points and gives a fast and proven reliable indication about the patient's condition (PKG_Care, 2002). Information collected by the PKG Watch informs the doctor about daily movements and difficulties from decreased motion speed with tremor detection, allowing for a better medication assessment and possible additional treatment interventions such as physiotherapy, to prevent further decline of the patient. From April 2022, NHS England provided Parkinson's patients these life changing sensory smart watches to monitor their disease remotely (NHS_England, 2022). As the non-motor symptoms begin to be recorded digitally, they will also help doctors track the disease and improve the patients' condition.

2.9 Artificial Intelligence and Ethics in Healthcare Diagnostics

The growth of AI in healthcare diagnostics is continually progressing yet, as seen across much of the literature, several ethical challenges are becoming clear. An ethical AI is referred to as the computational process of evaluating and choosing among alternatives in a manner that is consistent with societal, ethical and legal requirements (Dignum, 2021). While incorporating AI in healthcare, ethics and morals come into question. Who is in control? Who is responsible? Is the information correct?

Shen et al. (2019) give a systematic review addressing the ethics of AI versus clinicians in disease diagnosis. Wiltfang et al. (2021) look at AI in personalised diagnostic therapy for Alzheimer's and the ethical implications and Biller-Andorno et al. (2022) address the ethical uses of AI in the process of patient resuscitation. Pharma companies, hospitals and other organisations, such as medical imaging laboratories, are now recruiting "ethicists of AI" (Saheb et al., 2021, p. 2). Google has fostered ethical principles for the use of AI (Google, 2022) and in 2021 the WHO released their dossier on Ethics and Governance of Artificial Intelligence for Health (World_Health_Organisation, 2021). When incorporating AI in healthcare, biomedical ethics must be considered, consisting of four pillars: beneficence, non-maleficence, autonomy, and justice (Gillon, 1994). AI medical ethical frameworks must ultimately consider and comply with many ethical codes because at the forefront of any medical and healthcare intervention is simply *Primum non nocere - First, do no harm*. This needs to be carried from medical ethics into the domain of computational bioethics (Bali et al., 2019).

Across many of the ethical research papers read and reviewed as part of this thesis research, it has been noticed that many authors who are researching AI and medical ethics are mainly from legal backgrounds or from science and technology. There appears to be a lack of multidisciplinary authors involved in the work reported in the publications, in particular clinicians. This next section will address several ethical concerns of AI in healthcare.

Saheb et al. (2021) identify issues across several therapy areas. Concerns are identified and categorised as the following: ethics of relationship, medico legal concerns, ethics of robots, ethics of ambient intelligence, patients' rights, physicians' rights and ethics of predictive analytics (Saheb et al., 2021). The authors construct a research map and provided a framework of robust guidelines to include multi-disciplinary stakeholders and policy makers when reviewing and deciding on AI in medical ethics (Saheb et al., 2021). Given that the intelligence of AI in healthcare can perform multiple tasks and AI has demonstrably proven diagnostic capabilities, aiding and assisting clinicians in many areas, the authors acknowledge that, if left unchecked, any autonomous AI system may lead to "catastrophes against humanity" with potentially unintended consequences (Saheb et al., 2021, p. 1). The authors focus on the accountability, liability, and culpability of AI in many different healthcare settings because even doctors want to know who is ethically responsible if a mistake is made (Saheb et al., 2021). They mention ethical concerns of companion robots for elderly or mentally ill patients as a "smart solution " (Saheb et al., 2021, p. 5) but decide that AI medical interventions in psychiatry lacked sufficient healthcare training. Questioning the ethically responsible person in medical imagery of breast cancer, chronic disease, and ischemic stroke, the authors aim to address ethical concerns (Saheb et al., 2021). They base their conclusions on their own literature research using "artificial intelligence" and "AI" in their key word search, to narrow the focus of their study (Saheb et al., 2021). This is an important point, because the researchers wanted to investigate both virtual and physical ethics of AI: to use the search words DL and ML would generate not only thousands of results, but would be epistemological and could potentially be an unrealistic review.

Clinical competence, medical education, and ethics around using, storing and sharing the abundance of clinical BD were addressed as areas of concern by (Saheb et al., 2021). "Data is the new oil" (Bhageshpur, 2019) and AI systems, not matter in what capacity, depend on data to be successful. Saheb et al. (2021) state that clinicians are faced with numerous ethical dilemmas posed by AI with a particular focus on bias and error, which is well documented. The authors identified 12 main ethical themes of concern to the healthcare industry and acknowledge the fact that it is important to have professionals with diverse disciplines who can comprehend the ethical problems involved with AI in healthcare, not only lawyers and tech specialist (Saheb et al., 2021).

Ashok et al. (2022) perform a systematic literature review of 59 papers published around ethical frameworks of AI across many industries, including healthcare. Unlike Saheb et al. (2021), who identified 12 ethical themes to consider, these authors identify 14 digital ethics implications for the use of AI in seven archetypes mainly focusing on a framework consisting of physical, cognitive, information and governance (Ashok et al., 2022). The authors, like many when considering ethical concerns and AI, find that despite AI validation, there is still a high level of propagating bias and stereotyping (Ashok et al., 2022). This is particularly a concern in healthcare when it comes to social demographics and patient treatment and care. There are many AI diagnostic predictions and inexplicable autonomous decisions. While there is an urgent need for a global healthcare ethical community, especially within the EU, it must be remembered that the ethical code or ethics of one industry may not be applicable to the ethical standards of another (Ashok et al., 2022).

Ethics is about considering the potential harms and benefits of an action in a principled way, so is it ethical to propose isolation of potentially infected patients who are already vulnerable, mentally unstable, and alone when they fall into the DL-deciphered COVID-19 high risk group or are required to self-isolate? It could be assumed that putting pressure on individuals with mental health issues could have a major unfortunate consequence. In a very large study published in the renowned and highly credible medical journal the Lancet, Pirkis et al. (2022) sought suicide data from vital statistics systems and real-time suicide surveillance systems during four months of the COVID-19 pandemic. The authors found an increase in suicide numbers during this period compared to pre pandemic surveillance. Patients need to know more about the use of their healthcare data, a requirement which is also nicely represented by the ongoing discussion of data privacy issues in the field of healthcare.

Indeed, another common thread of concern hindering patient adoption of AI in healthcare diagnostics is data privacy and data protection. The public need to know how and why their data will be used for the greater good, especially for medical purposes. They need to be reassured in order to improve their perception of algorithms being a more trustworthy handler of their data than operations run by humans, where security breaches are much higher and privacy infringements readily occur. Misuse and data harvesting, whereby personal data are sold on by a company, is also a worry. Now, an emerging technology suggested on the Gartner Hype Cycle, "Algorithmic Trust Models" (Gartner, 2020), is being developed to ensure better privacy and security of data, protecting not only the source of BD assets but also individual identity. Regarding trust and ethics, there are many concerns around the trust and use of healthcare data going to insurers who then increase healthcare premiums with these off-the-radar insights, leading to patients who cannot afford treatment and healthcare insurance, again something that can be deemed highly unethical.

In a complex and comprehensive mapping review (essentially, based on questions and dealing with themes), Morley and colleagues (Morley et al., 2020) examine many aspects of ethics and AI. Their stated goal was "to inform policymakers, regulators and developers of what they must consider if they are to enable health and care systems to capitalise on the dual advantage of ethical AI (Morley et al., 2020, p. 1), maximising the potential use of AI whilst proactively avoiding any potential ethical harm of the technology. These goal(s) translated into their research question as "how can the primary ethical risks presented by AI-health be categorised, and what issues must policymakers, regulators and developers consider in order to be ethically mindful?" (Morley et al., 2020, p. 1).

Morley et al. (2020) view AI as a co-operative "accessory" to healthcare, complementing rather than replacing clinicians. A proactive approach on ethics is needed in order to implement AI use: the ethical principles in healthcare are established but are much less clear for AI processes and there is some urgency to correct this situation.

Morley et al. (2020) is too detailed and complex to review and summarise here but serves as a reference work on the subject. Ultimately, while covering a wide range of topics, they examined several (themes) in more detail in order to promote detailed discussions of parts of the issue, rather than the whole subject (Morley et al., 2020). One important identified limitation of their work was a lack of focus on specific AI-use cases. However, they provided an overview on the already identified ethical issues (Morley et al., 2020): they may have missed certain new issues not yet reported in the peer-reviewed literature, but appearing on pre-print servers. Of course, expanding their literature search criteria and looking at case studies would have helped to correct such limitations.

On the specific case of ethical trust and robot assisted surgery, Sullins (2014)asks the question whether more or less trust should be placed in the technology. As an example, the da Vinci robotic system, first approved by FDA in 2000, has become a key tool in certain surgeries, being involved in 87% of prostate operations in the US by the date of publication (Sullins, 2014). Since then, the manufacturers Intuitive Surgical have built a family of systems with over 7 million operations carried out across several different surgical areas (Intuitive_Surgical, 2022).

Because of safety issues raised by the technology, Sullins (2014) considered what the appropriate level of trust that patients, surgeons and hospital administrators should place in the device: ensuring that the technology is not being "over-hyped" is key. Because of the special professionalism and situation associated with surgery in general, whether the new technology is side-lining conventional surgery improvements must be considered. Ethical trust – in particular, the trust a patient must have in the surgeon – is key. The legal rights of patients must also be factored in.

Sullins (2014) considers a number of important subjects, such as the motivations for innovation, informed consent, conflicts of interest (a robotic system cannot be designed without the input of surgeons, which may make the surgeons less critical of the systems when developed) and “roboethics”, identifying the most ethical ways to integrate robotics into aspects of life. How the technologies may change the surgery profession is considered. Sullins conclusion is straightforward – cautious optimism, whilst acknowledging the future ethical challenges that technology brings (such as robotic enhancements to humans) will be important (Sullins, 2014).

On the same theme of AI and robotic surgery, O’Sullivan and colleagues (O'Sullivan et al., 2019) also review the legal, regulatory and ethical frameworks and standards for this specific use. Again, this review is detailed and comprehensive, with a 57-point, paragraph-by-paragraph summary to help the reader. This could be considered an update on the subject examined earlier by Sullins (2014). As Morley et al. (2020), the authors view the future situation as robots learning routine tasks which are then supervised by a surgeon – the “co-operation” accessory of robotic systems to healthcare (O'Sullivan et al., 2019). Whilst developing such state-of-the-art robotic systems is one challenge, obtaining acceptance and approval for their use are completely different issues. Providing expert assistance to the human, in a co-operative way rather than full autonomy, may be a good solution. Morley et al. (2020) liken the situation to autonomous driving, and the standard developed by the Society of Automotive Engineers; but only up to Level 2 of the standard (hands-off but driver monitoring continuously, prepared to intervene) is permitted in Europe. No such attempt to develop a standard for automated surgical systems currently exists, but the arrival of fully autonomous systems for surgery is well into the future anyway, in their opinion (Morley et al., 2020). They observe that their use in, for example, military situations will be less ethically and legally stringent and, to some extent, mistakes in those situations are highly likely anyway. However, even in certain civilian circumstances, for example power outages, the ability of a system to become fully autonomous would be an advantage – but who is responsible for the actions of a robotic system then? Where does the responsibility chain begin and end?

O'Sullivan and colleagues (O'Sullivan et al., 2019) consider the issues of safety and security, especially cyber-attacks and security of updates to robotic systems. They perhaps state the obvious – that any form of cyber-attack during surgery would be unacceptable – but prevention of this requires consideration of many factors. If a known vulnerability exists but there is no update (called a patch) for this, something more than update management is required, perhaps through system security certification (O'Sullivan et al., 2019). Given that no standards exist for surgical robots, ways to assess their performance must be developed and O'Sullivan and colleagues (O'Sullivan et al., 2019) question how to test software-driven autonomous robot surgeons. Working on animals or other training systems, for example, is not the same as working on humans.

The authors examine responsibility in detail, defining three aspects to consider: Accountability (the capacity of a system to give an explanation for its actions); Liability (at present and legally, a robot cannot be liable for its actions); and Culpability (relating to punishment - but a robot cannot be punished) (O'Sullivan et al., 2019). To note: when a robot learns new things, it does so within the framework set by the designers and each robot is physically designed for certain tasks. Unpredictability therefore indicates the existence of dangerous defects. In their opinion, ethical questions vary according to the autonomy of the robot, increasing as the autonomy increases (O'Sullivan et al., 2019). Despite the benefits of robot-assisted surgery, there are several practical and hence ethical issues that arise, which patients should understand as part of the consent process. The authors question whether, for example, a complex system like the da Vinci should be considered a robot or just simply a manipulator. While there seems to be great interest around the physical aspect of using AI, especially in robotic surgery, other therapy areas must also be considered.

Privacy and security are not the same! While privacy includes, for example, the right to be left alone and not to be disturbed by other people, when people talk about privacy concerns around AI and data they are often referring unknowingly to security. Security is described as the state of being free from danger or threat though: improving security might not necessarily secure privacy (Google_Cloud, 2022).

Industries and governments globally have had to convince the public that they will use AI and BD responsibly. Issues concerning responsibility, data management, data storage, data usage, data security and, ultimately, data ownership are continually being discussed. The recent focus on ethical AI has arisen from increasing concern over its unintended negative impacts. As mentioned previously and based on the findings of this research project, AI can make independent and automatic decisions but from a healthcare perspective, many questions have arisen, such as who ultimately will be benefiting from these autonomous decisions. Who will be held accountable should mistakes or misjudgements be made, be it either with suggestive healthcare treatment paths or prognosis for suffering patients where medics could possibly suspend their own clinical judgement in favour of ML outcomes? All of this still remains unanswered, hence the need again for frameworks and transparency.

The availability and use of very large datasets has been an important advantage in training and establishing AI models in order to improve patient care and diagnostic and surgical performance. However, this is only one of the areas that is causing concern regarding privacy, security and the ethical uses of AI in healthcare. BD is pertinent to the success of AI and with this in mind, concerns around privacy, trust, data storage and, to an extent, non-consensual data exploitation, are causing patient concerns. The next section therefore explores literature around AI and trust in healthcare.

Deployed AI technology in the medical field brings together great legal and biomedical minds, often arguing with the data scientists who created the algorithms in question. In 2019, the OECD established AI Principles which promote use of AI that is innovative and trustworthy and that respects human rights and democratic values (OECD, 2019). OECD set standards for AI that are practical and flexible enough to stand the test of time. Especially during COVID-19 times, conspiracy theorists have revelled in the enjoyment of installing public angst and scaremongering. Many ethical concerns have been raised regarding public trust and the use of AI and individual personal data.

2.10 Artificial Intelligence and Trust in Healthcare Diagnostics

People are increasingly exposed to applications that embed AI algorithms. In fact, there is a general belief that people trust any AI-based product or service without question (Sharan & Romano, 2020). Healthcare is a domain with unique ethical, legal, and regulatory challenges as decisions can have immediate impact on the well-being or life of people (Ahmad et al., 2018). There should be no room for error or mistakes when peoples' lives and wellbeing are at stake.

Trust can be intrinsically formed or stem from extrinsic sources such as reputation, or other positive or negative factors. The propensity to trust can be understood as a personality trait (Rotter, 1967). Trust could be described as a psychological mechanism to deal with the uncertainty between what is known and unknown (Rotter, 1967). While there are many definitions of the meaning of trust, understanding the trust dynamics between AI and humans, particularly in the field of healthcare, is crucial to understand how and why AI is fully accepted and adopted as a diagnostic tool. Having already addressed earlier that doctors do not really understand how AI produces what it does, it could be assumed that, because of this lack in understanding, the doctor does not trust the AI result. The aim of this part of the literature review is to identify areas of concern regarding AI and trust. When designing any AI medical system, it is critical to consider who will use it. Trust is crucial to the success of any personal or professional relationship and could also be extended to that of technology.

In a clinical setting, patients receive diagnoses verbally from their doctors. The trust of patients has an important role in the doctor–patient relationship (Yang & Chen, 2018). However, more often than not, especially in today's technologically advanced healthcare economy and as seen across the reviewed literature, many of the diagnostic outcomes and prognosis predictions that clinicians use to inform the patient, especially in the fields of medical imagery, pathology and cardiology, are generated by AI because AI is playing a more central role in healthcare. Every day there is news of a new algorithm revolutionising healthcare (Topol, 2019). Being informed of a critical disease or illness that could progressively be life-threatening or have major life-changing implications such as impeding independence, and quality of life would be devastating to anyone. Naturally, people would seek a second opinion in the times of such devastating news.

When it comes to advice, people often listen to friends, family and people they trust. This will be investigated in the research of this thesis, discussed in Section 3. Logg, Minson and Moore (Logg et al., 2019) conduct experiments comparing people's adherence to advice, when they thought it was coming from an algorithm, with when they thought it was coming from a person. These authors wanted to demonstrate the appreciation of advice generated by algorithms versus what the participants believed was a human. Participants completed tasks in which they made quantitative judgements and received advice (Logg et al., 2019). Interestingly, the authors state that "lay people were more reliant on advice when they thought it was coming from an algorithm" than other human specialists (Logg et al., 2019, p. 90).

The subject of trust and technology has been heavily investigated, especially with respect to AI systems. Lee and See (2004) believe that there is a difference between interpersonal trust and trust in technical systems. Technical systems may lack intentionality, which is profoundly relevant to honesty and benevolence (Lee & See, 2004). Because AI systems produce highly complex outcomes and, in some cases, the solution or result is unfamiliar to the end user, especially clinicians, it is questionable as to the level of trust clinicians actually have in AI. Yet trust in AI models must be established as intelligent systems become a commodity in a world of increasing digitisation (Andras et al., 2018), especially in healthcare. Trust in technology, explicitly, is the belief that the system will do what it is expected to do (Li et al., 2008).

While there are many key challenges and influencing factors between trust, AI and healthcare including clinicians and, more importantly, patients, it is the perception of the user that ultimately controls the uptake of such technologies. Many publications point to inappropriate trust as the reason for under- or over-relying on AI (Dzindolet et al., 2003; Hoffman et al., 2013; Lee & See, 2004; Parasuraman & Riley, 1997; Siau & Wang, 2018; Zhang et al., 2020). But in healthcare, despite all the AI sophistication and funding, it is the patient whose life is at risk.

Chong et al. (2022) investigate AI trustworthiness, stating that humans accept or reject AI suggestions when they should not because their trust for the AI does not match AI's trustworthiness. Holzinger et al. (2022) discuss how robust AI solutions must be able to cope with data imprecision, missing and incorrect information, and explain both the result - and the process of how it was obtained - to a medical expert. The topic of explaining to the expert, in this case the clinician, is a recurrent theme across much literature, again relating to the black box phenomenon. Holzinger et al. (2022)report how the EU is desperate for experts who understand AI ethics and medicine due to the complexity of this topic. Meanwhile these authors discuss how using conceptual knowledge as a guide for reality can help to develop more explainable and less biased ML models (Holzinger et al., 2022). With a view to bridge the gap between research and practical implications, Holzinger et al. (2022) aim to create an explainable AI framework. Their work also supports the work of Durán (2021), who also try to justify and explain the need for a coherent conceptual systematic framework as to how AI generates its results, because certain outcomes have been causing concern among physicians. Durán (2021) focuses on the limitations of AI in healthcare, in particular the lack of understanding from the doctor. In a world where “first do no harm” comes top of the clinician’s role, this must be quite daunting. Durán (2021) investigates the topic of scientifically explainable AI, which literally means being able to explain the AI output to the doctor, and concludes that there needs to be an understanding and a traceable path dependency to increase trust within the physician group of users and: like the work of Holzinger et al. (2022), an explainable framework. Bridging this knowledge gap in medical AI could eventually bridge the gap between algorithm and physician and therefore one could assume a better uptake and improved trust.

Another dimension of trust is privacy. Patient privacy and confidentiality issues have hindered the uptake of medical AI in a practical setting. There is increased difficulty to collect patient data, with additional restrictions on data sharing and uses due to ethical implications (Chiruvella & Guddati, 2021).

Markus et al. (2021) address the lack of transparency as one of the major barriers that limit the uptake of AI implementation and that adoption in clinical practice is still limited. Like other researchers cited previously, they also investigate how, by creating a framework of explainable AI, better interpretability of results could improve trust in line with the European goal of creating trustworthy AI. Durán (2021), Holzinger et al. (2022) and Markus et al. (2021) all believe explaining AI will overcome trust issues at the clinician level so that adoption in clinical practice is improved. Markus et al. (2021) believe that trustworthy AI should fulfil three necessary conditions: AI systems should be lawful, ethical and robust. When using AI, interoperability and fidelity are necessary in order to reach explainability. Quite simply, interpretability of an explanation shows how understandable that information is for a human. Meanwhile, fidelity of an explanation expresses how true or accurate that explanation describes AI model behaviour to the task in question: for example, generating the predictions of a stroke, heart attack, or seizure, areas where AI has made accurate diagnoses. The recent work of the European Institute of Technology and Innovation also details that explaining AI will drive adoption and increase uptake with a promising future (European_Institute_of_Innovation_and_Technology, 2020).

Salahuddin et al. (2022) discuss the transparency of DNN in medical imaging. Despite medical imaging being one of the first areas where diagnostic medicine has embraced AI imagery classifiers, and providing outstanding results, according to Salahuddin et al. (2022) there are still concerns regarding transparency, trust and acceptance impeded by the lack of understanding, highlighting that overcoming this is an essential clinical, legal and ethical requirement.

Finally, Asan et al. (2020) present their findings on AI and human trust in healthcare, with a focus on clinicians. However, as already mentioned, despite the abundance of research into AI trust in healthcare, there is very little research on what the patient thinks. It could be assumed that the characteristics and fundamentals of trust in AI in healthcare would vary greatly between the clinician and the patient, though there is little evidence to compare and contrast this assumption directly. While the work of Asan et al. (2020) describes how AI has the ability to translate the uncertainty and complexity in data into actionable — though imperfect — clinical decisions or suggestions, transforming healthcare practices, they focus specifically on factors that can improve clinician trust of the AI outcome in the clinical decision-making process. While AI can improve and enhance the clinical decision-making process, but because AI systems lack “common sense”, it is important to combine the intuitiveness of medical experts with the speed and accuracy of AI to create the perfect architectural collaboration between man and machine (Asan et al., 2020). However, their own research found that *maximizing the user’s trust* does not necessarily yield the best decisions from human-AI collaboration.

2.11 Theoretical considerations - Why do individuals adopt and accept technological innovation?

In order to interpret the research results of this investigation, the fundament basics and theories linked to the acceptance of technology and diagnostic healthcare must be considered. This next Section will introduce and address two related theories in the background of this thesis. It is important to understand healthcare professionals’ motivators and any influencing factors that drive them to accept AI-driven healthcare diagnostics. It is also equally important to understand the end user, the patient who is ultimately the consumer. Two models will be reviewed and considered while investigating the impact of AI in health care diagnostics, transferring these technologies to the patient in the form of wearable diagnostic devices.

2.11.1 The Technology Acceptance Model

The Technology Acceptance Model (TAM), developed by Davis (1985) is a model that addressees any user’s acceptance of technology. Although TAM has previously been used to investigate doctor acceptance of “technology” in healthcare, research is still limited which considers the true acceptance of AI by doctors in healthcare diagnostics and even less in relation to the patient. Much of the research reviewed for the present work has referred to the black box phenomenon, shorthand for models that are sufficiently complex but are not straightforwardly interpretable to humans, and why doctors do not want to adopt AI in clinical practice.

2.11.1.1 TAM 1

Only a hand full of publications refer to the TAM in the context, concluding that the abstinence or reluctance to use AI in healthcare diagnostics is not necessarily fitting with the original Davis model. A representation of TAM is presented in Figure 2.

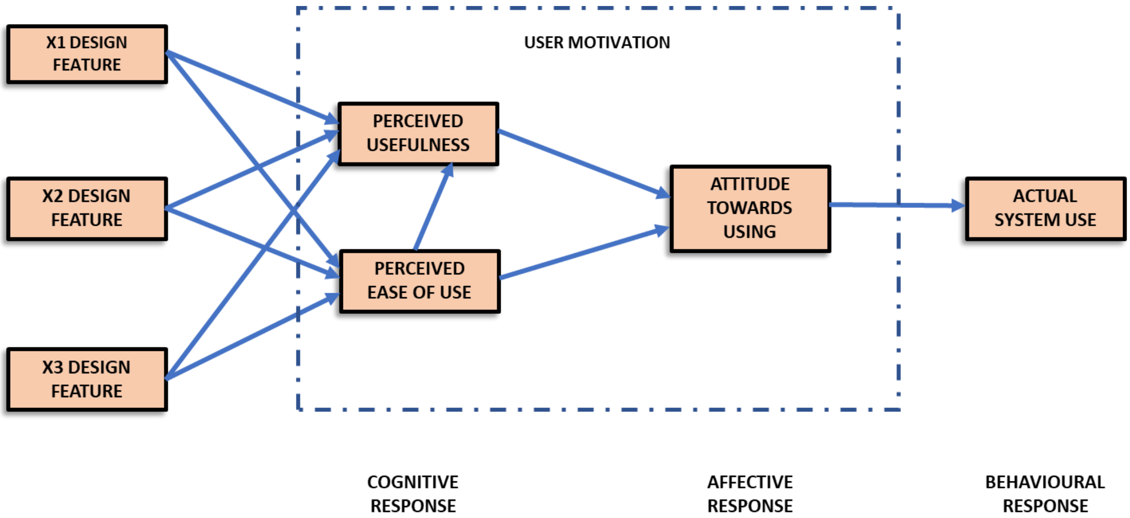

FIGURE 2 TECHNOLOGY ACCEPTANCE MODEL (TAM) ORIGINAL VERSION, BASED ON DAVIS (1985)

TAM is based on the theory of reasoned action and has translocated across all industries where technology adoption is essential. Originally, two factors that determine whether technology (in this case AI in healthcare) is either accepted or rejected were initially identified in Davis' work (Davis, 1989), namely Perceived Usefulness (PU) and Perceived Ease Of Use (PEOU).

- *Perceived usefulness* (PU) – This was defined by Fred Davis as "the degree to which a person believes that using a particular system would enhance their job performance" (Davis, 1989, p. 320). This means whether or not someone perceives technology to be useful for what they want to do.
- *Perceived ease-of-use* (PEOU) – Davis defined this as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). If the technology is easy to use, then the barriers are conquered. If it's not easy to use and the interface is complicated, no one has a positive attitude towards it.

External variables, such as social influence, are also important factors to determine the attitude of people. When these things are in place, people will have the attitude and intention to use the technology. However, the perception may change, depending on age and gender, because everyone is different

In 2003, Lee and colleagues described Davis' TAM as "the most influential and commonly employed theory for describing an individual's acceptance of information systems" (Lee et al., 2003, p. 752). However, with time the original TAM has been revised due to criticism and societal influencing behavioural changes. The TAM model has further developed into an analytical simplification of how functionality and interface characteristics relate to technology adoption decisions (Melas et al., 2011).

Based on the definition of PU in TAM, and in line with the interviews carried out for the present thesis, this corresponds to how useful is a wearable diagnostic device to each individual interviewed and why. The other determinant in the model, PEOU, defined as the degree of being able to use a technology without making effort (Davis, 1989), was again another identification question in the interview survey carried out. The original TAM showed that "perceived ease of use is hypothesized to have a direct effect on perceived usefulness" (Davis, 1985, p. 26). Naturally, if technology is easy to use, there is an increased chance that more people will adopt it. Technology acceptance and use is determined by Behavioural Intention (BI). BI, in turn, is affected by Attitude Toward use (ATT), as well as the direct and indirect effects of PEOU and PU. Both PEOU and PU jointly affect ATT, whilst PEOU has a direct impact on PU, argue Davis, Holden & Karsh and Yarbrough & Smith (Davis, 1989; Holden & Karsh, 2010; Yarbrough & Smith, 2007).

Criticism of the original 1989 TAM lead to complementary changes to improve the model and TAM2 was born (Venkatesh & Davis, 2000).

2.11.1.2 TAM 2

TAM 2 an updated extension of TAM in which the component ATT has been removed and replaced with a new variable, Subject Norm (SN). SN was added to harness any social influence of technology acceptance that drives individuals to use it. TAM 2 is presented in Figure 3 below.

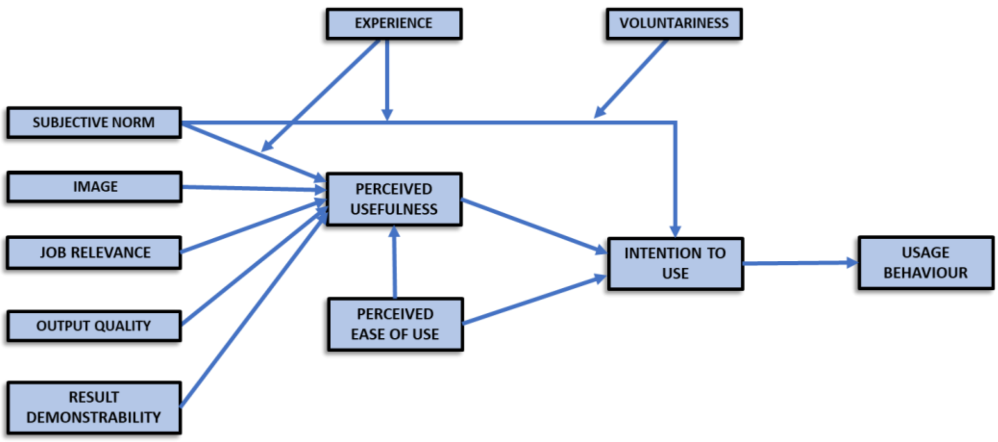

FIGURE 3 TECHNOLOGY ACCEPTANCE MODEL VERSION 2 (TAM2), BASED ON VENKATESH AND DAVIS (2000)

In 2011, Melas and colleagues (Melas et al., 2011) challenged the original TAM and the newer updated TAM2 model in healthcare due to the lack of research and empirical data in this area.

The authors say that TAM could still be further enhanced for TAM in healthcare and opportunities still existed for improvement of this useful theoretical tool, especially adding additional external variables (Melas et al., 2011). However, their work is contrary to the work of Bhattacherjee & Hikmet, Holden & Karsh and Yarbrough & Smith (Bhattacherjee & Hikmet, 2007; Holden & Karsh, 2010; Yarbrough & Smith, 2007) as these authors say that TAM and TAM 2 provide evidence and qualitative insights with respect to the use of technology in healthcare. Holden and Karsh (2010) performed an analysis of publications considering TAM in healthcare and found that TAM research was inconsistent and small convenient samples were being used. They reported important heterogeneity among the studies in terms of sample characteristics and technologies studied and therefore no real conclusion was possible, ultimately supporting the work of (Melas et al., 2011).

2.11.1.3 TAM 3

The extended TAM 2 includes PU, in which there are social influence processes as well as cognitive instrumental processes (Venkatesh & Davis, 2000). However, Venkatesh and Bala (2008) developed a model of the determinants of PU and PEOU to give TAM 3. Figure 4 below shows the representation of TAM 3 as proposed by these authors.

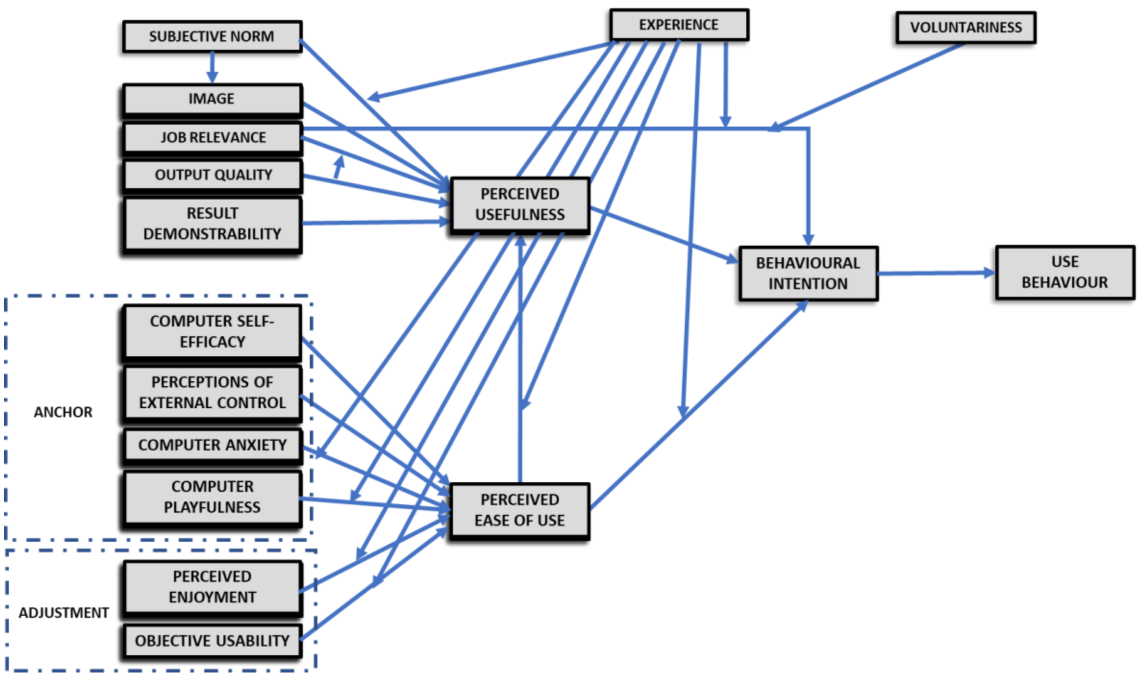

FIGURE 4 TECHNOLOGY ACCEPTANCE MODEL VERSION 3 (TAM 3), BASED ON VENKATESH AND BALA (2008)

Venkatesh and Bala (2008) argued that individuals will form early perceptions of the PEOU of a system based on several so-called “anchors”, factors which are related to general beliefs of an individual regarding computers and computer use. The anchors suggested by Venkatesh and

Bala (2008) are computer self-efficacy, perceptions of external control (or facilitating conditions), computer anxiety, and computer playfulness. All of these factors can also be transferred to considerations of the use of a wearable device by a patient for healthcare diagnostics.

2.11.2 The Health Belief Model

The Health Belief Model (HBM) was developed in the 1950s by social scientists in the US public health laboratories The model focuses on individual beliefs about health conditions and precursors to individual health-related behaviours with a view to understanding why people fail to adopt disease prevention strategies or even test for early disease detection (Hochbaum et al., 1952). Addressing two components of behaviour, the HBM directs focus towards health-related behaviours whereby individuals have a desire to avoid illness or, conversely, get better. The HBM is a theory that a particular health action, if taken, will prevent or cure a disease. Naturally, any life changing course of action depends both on patient perception and any barriers that might hinder the course.

The HBM is composed of six constructs all of which can be linked to this present investigation, as shown in Figure 5 below (Janz & Becker, 1984):

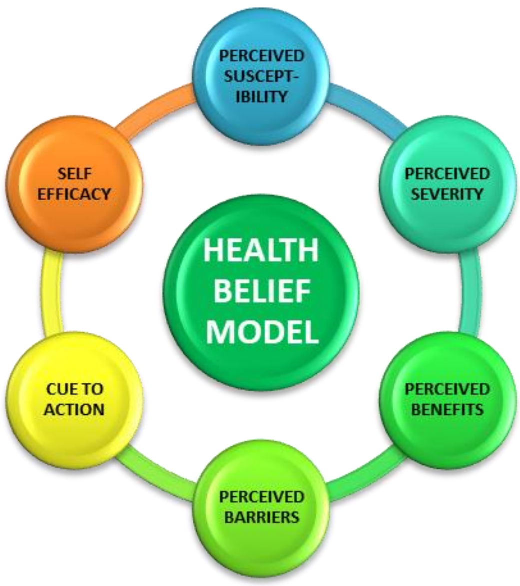

FIGURE 5 THE HEALTH BELIEF MODEL. BASED ON JANZ AND BECKER (1984)

1. **Perceived susceptibility** refers to a person's subjective perception of the risk of acquiring an illness or disease. For example, in the case of the present research, if interview candidates have a predisposed genetic susceptibility like Parkinson's or Huntington's disease, or genetic psychiatric mental health issues, how would they feel about wearing a diagnostic device to predetermine their overall health in real time and track deterioration over time, if not treated?

2. **Perceived severity** identifies a person's feelings of how serious their illness or disease is and how in this case does it transfer to a wearable diagnostic device. How do patients consider the medical consequences of their actions for example using a wearable device or not?

3. **Perceived benefits or perception of the effectiveness** of various actions. In the case of the present research, there could ideally be a perceived benefit to wearing a diagnostic device which allows patients to take a course of action.

4. **Perceived barriers** in the context of the present investigation, could be assumed to be linked to the ease of use of the wearable device, again in alignment with the TAM theory of PEOU and PU. The cost of the device could also be a barrier, especially if the interviewees have been advised to buy their own.

5. **Cue to action** is normally referenced as any stimulus needed to trigger some form of decision-making process and accept a recommended health action. In the case of the present investigation, the stimulus could be the suggestion/recommendation from a doctor to purchase a wearable diagnostic device, or even the extremity of suffering the physical symptoms of a heart attack, which could actually be anxiety related. Furthermore, a stimulus could be classed as a family member who has a chronic disease.

6. **Self-efficacy** refers to the level of a person's confidence in his or her ability to successfully perform a behaviour. For example, can people interpret the results of their wearable devices and take action if their wearable devices notify them.

Janz and Becker (1984) critically reviewed the model some ten years after first introduction, concluding that "perceived barriers" proved to be the most powerful of the HBM dimensions across the various study designs and behaviours that they considered assessed, and which had been published in the previous decade. While important overall, "perceived susceptibility" was a stronger contributor to understanding any type of preventative health behaviours (Janz & Becker, 1984). While the HBM is more descriptive than explanatory, it does have a number of limitations (LaMorte, 2019). However, the HBM is perfectly positioned to the core of the present thesis, in combination with the TAM, to address what lengths people will go to in order to improve their health in the form of AI digital diagnostic wearables, and what steps they are actually prepared to take.

There is very little research on the HBM and wearable diagnostic devices, hence the present research which will be discussed in the next Section 3.

2.12 Conclusions from the literature review

Having reviewed an abundance of literature around the use of AI in healthcare diagnostics and its link to certain digital wearables, it is without doubt that AI has revolutionised the healthcare industry in many ways. With proven predictive specificity and sensitivity, increased diagnostic speed and adjunct effect of reducing clinician workload, AI in the modern era of digital healthcare has many positives, whilst yielding almost endless possibilities and opportunities.

What has become apparent throughout this literature review is the fact that, despite AI and its subsets of ML and DL, human input is still required in many fields of healthcare, but full automation is something not too distant in the future in certain clinical fields. Granted, as this empirical research review has proven, yet despite evident examples of AI benefits, there are many perceived barriers of technology adoption. These perceived barriers are causing widespread negativity and concern, thereby preventing the technological uptake. Whilst there are many references to clinician perception, the black box phenomenon and the true transparency of AI systems, there is a lack of empirical findings regarding patient perception.

Issues exist around clinicians explaining the true reasons to patients about their diagnoses and how patients feel about disclosing their personal heath data. Also, additional issues deal with what patients understand about AI and its use in making often life-changing decisions about their futures. The patient is ultimately the end user who will have to make and live with those life changes, accept a prognosis, or even spend their life with the incorporation of a wearable technology device through personal preference or medical necessity. Questions have been identified about what is patient resistance and scepticism toward AI-based medical interventions, and how patients perceive their usefulness. Misinformation about AI may lead to a lack of trust among some patients or, in some cases, both constant self-monitoring using a wearable and constantly checking your health performance could lead to increased anxiety. In accordance with this research gap, the present work aims to address the actual perception of the patients towards AI in healthcare diagnostics.

3 METHODOLOGY

3.1 Introduction

This section outlines the methodology used for the present research investigation and will cover the qualitative research principles used and the rationale behind this method of choice. The design of the interviewee survey, in line with the theoretical underpin discussed in Section 2, will be introduced as to how it can bridge an identified gap in the research, especially if replicated on a larger number of interviewees. Additionally, this section will also introduce the proposed data analysis techniques, transitioning into a detailed presentation of results and findings in the next section.

3.2 Selection of methodology

A qualitative research method was adopted to explore and understand patient perceptions of AI in healthcare diagnostics. This format of research allowed a flexible report to be written honouring an inductive style, as suggested by Creswell (2014), on a subject with very little extant literature. Using this method, the opinions and perception of patients can be collected openly, explored and inductively built on, allowing findings to bridge gaps and pave the way for future research.

While a qualitative research method seems to denote an unstructured interview (for example, Mason, 1996), the present research design was based on a semi-structured interview. A semi-structured research design was a suitable inductive approach to link secondary research literature theoretical findings, through the work of Davis (1985) on the TAM and Hochbaum et al. (1952) on the HBM. Using a semi-structured interview allows the interviewer to keep an open mind of what can emerge (Bryman, 2012). As this research is a new topic, a qualitative interview was chosen because it is exploratory in nature, investigating a new theme where there is little information. Additionally, the little research found, relating to the opinions of the doctor and the uses of AI in healthcare diagnostics, used qualitative exploratory research. Therefore, it seemed fitting to also adopt this approach. Clarke and Jack (1998) define qualitative research as a way of describing an event in its context which is useful for investigating complex, new or relatively unexplored areas.

An interview guide composed of semi-structured, open-ended questions was approved by Modul University Vienna's Institutional Review Board (IRB) and all potential participants received a letter of consent from the researcher. This way, all interviewed candidates were considered equally informed about the survey researchers' questions and the survey purpose, giving permission for the interview to be recorded. To maximise the feeling of privacy and security, the participants' names and details were not recorded. The surveys were anonymous using only their ages and gender as identifiers. The interviewees' physical appearance was not recorded, only the audio of the interview, on a video call using either Face Time or WhatsApp. The audio was simultaneously transcribed using the dictate function of Microsoft Word. Any corrections were made after the interview and the transcribed data were cleaned, removing dead noise in preparation for coding. Candidates were reassured that, upon completion of data analysis, all individual audio files and transcripts were to be deleted.

3.3 Research instrument

The research was divided into two separate surveys. The two surveys were designed to capture a cross section of answers and insights to identify similarities of differences and concerns between two heterogeneous groups. Survey One was for Wearable Candidates (WC) and Survey Two was for Non-Wearable Candidates (NWC)(see survey templates included as Appendices 3 & 4). Despite identifying two independent sets of candidate criteria, wearable versus non-wearable, both surveys opened with identical exploratory questions regarding AI and the interviewees' understanding of what AI was. This inductive approach tried to gain deeper meaning and construction to the survey and its findings about the interviewees' understanding of AI in diagnostic healthcare applications (which then became transferable into wearable devices). However, the body of the wearable survey versus non-wearable survey differed in questions because the research would be redundant if non-wearable users were asked about "their" wearable device (which of course did not exist). Therefore, the questions in the two surveys were different in order for the researcher to gain a deeper understanding into non-wearable users' thoughts, motives and rationales for not embarking on the journey of wearable diagnostic healthcare devices. The last section of both surveys contained the same questions regarding data privacy and data protection, with a view to identifying any concerns that may be linked to the literature review section of the present thesis dealing with ethics, security, and privacy.

In summary, the following interview characteristics were accounted for:

- Completion time of approximately 45 minutes
- Topics derived from a combination of the research questions and findings from the literature review
- Discussion guidelines adapted to the answers provided in the questionnaire, semi-structured, casual and discussion-based interview style
- 18 participants were interviewed across the course of three consecutive days

3.4 Pilot test

A pilot test was carried out on five people with ages ranging from 35-57 years. The responses received and progress of each interview in this pilot allowed questions that were deemed too direct or intrusive to be changed in both language and terminology, with the intention to make the interview more simplified. Terminologies and question wording needed to be translatable to all participants, irrelevant of their background or technical understanding. The survey needed to flow and feel natural in the structure, so probing questions were composed using a ladder effect. Some pilot participants found the initial questions too intrusive and/or too direct and therefore these questions were removed or altered. Pilot test questions took approximately 45 minutes to answer and were conducted in English.

3.5 Sampling procedures

Survey researchers attempt to estimate the properties of an entire population by observing or asking questions of only a select subset of individuals drawn from that population (Krippendorff, 2018). For the purpose of this qualitative research investigation, a snowball sampling approach was used (Simkus, 2022) with a view to theoretically triangulate data linked to both the main research question, in line with the reviewed gap in literature across Section 2. Snowball sampling is a non-probability sampling technique where existing study subjects recruit future subjects from among their acquaintances (Sharma, 2017). This came about in the survey when participants recommended friends suffering with, for example, AF, Type 1 diabetes, sleep disorders and chronic anxiety, all of whom actively used diagnostic wearable devices to monitor their conditions. Underlying all snowball sampling is the idea of intertextuality, the notion that units of text are connected, that they form actual or virtual networks within natural boundaries (Krippendorff, 2018). Snowball sampling ends when it reaches natural boundaries, such as the complete literature on a subject (Bryman, 2012).

3.6 Data analysis

The findings and results of the analyses are presented in the form of word clouds and word network maps. A mixture of software has been used to perform this analysis with Excel and Atlasi.ti.

Before the analyses were carried out, all of the interview data collected were initially cleaned because MS Dictate was used for the transcription (all dictation errors had been corrected for dialect misunderstandings). For the purpose of the results analysis thematic analysis was conducted using guidelines of Braun and Clarke (2006).

Following these guidelines key steps were adhered to:

- Data familiarity
- Initial coding
- Grouping of initial codes
- Review of code groups and identification of themes
- Review of themes and association of transcript quotations with codes
- Rearranging themes and write up

Data familiarity was done by reading and rereading of the data transcripts. Following data familiarity, initial codes were identified and listed. Coding meant giving the words of the participant a summative label in preparation to group the data. The initially identified codes were grouped twice based on similarities and differences. The grouped codes were again reviewed contextually, and certain themes were identified.

After coding and theming each question, case classifications were created in Excel and ATLAS.ti. Other than the grouped themes, the data were also processed to create word clouds and word lists to see the most frequently used words and their association to each identified theme. AI, doctor, device, capability, datum, diagnosis, accuracy, concern, opinion and health remained the top listed words that meant the discussions during interviews were highly relevant to the subject and helped establish the infrastructure to patient concerns and perceptions of AI in diagnostic healthcare.

3.7 Collection of sensitive information

In this study, personal health topics were discussed with some patients. Some candidates suffer with atrial fibrillation, type-one diabetes, chronic anxiety or alternatively mentioned family members who also have existing heath conditions. Therefore, with this in mind, particular attention was paid to the work of Tourangeau and Smith (1996), which described methods of collecting sensitive patient information. The interview guide was also prepared based on the guidance of Bryman (2012) and included a mix of different question types such as introducing, follow-up, probing, specifying, direct, indirect, structuring, and interpreting questions, along with silence (Kvale, 1996).

4 RESULTS AND DISCUSSION

The Results and Discussion section reports the analyses of the collected data in detail, following the context of the literature review and the research questions posed.

For the six main themes (the five plus an extra identified theme in the NWC results, reported below), 209 initial codes were identified which were grouped based on thematic similarities and differences. From this and further familiarity of the data, 46 sub-themes were identified. Here. a sub theme has been defined as a theme within a theme, so a topic which is recurrent within a group of themes. These subthemes were then categorised into five main themes to address the research questions shown in Section 1, p.7.

The software package ATLAS.ti was used to generate visual information through the network concept map ability of the software. The networks between codes allow conceptualization of the data by connecting sets of related elements (so words and quotations) together to create a word network map. Using the network concept in ATLAS.ti, a visual interpretation across the group of results can be seen.

On Figure 6 below, like in all the others that will be presented in this next chapter of results, the following interpretations of the information can be made:

- A dot, the origin of an arrow, shows a unidirectional relationship to the adjoining box with an arrow the end of the line
- An arrow on both ends of a line between two boxes, shows a two-way relationship, so how one variable impacts the other
- Line thickness is auto generated via ATLAS.ti and depends on the type of relationship between phrases linking the concepts.

The central "code", as seen in these diagrams, is the main theme central to the network and is called a Parent Code.

4.1 Findings for Wearable Candidates

From the data analyses, five main themes were identified in the WC category results. Aggregate themes include the following:

- Awareness of AI in Healthcare
- Benefits of AI-Based Healthcare
- Factors Contributing to Adoption of AI-Based Healthcare
- AI Diagnostic Wearable Devices and Applications
- Barriers to Adoption of AI-Based Healthcare

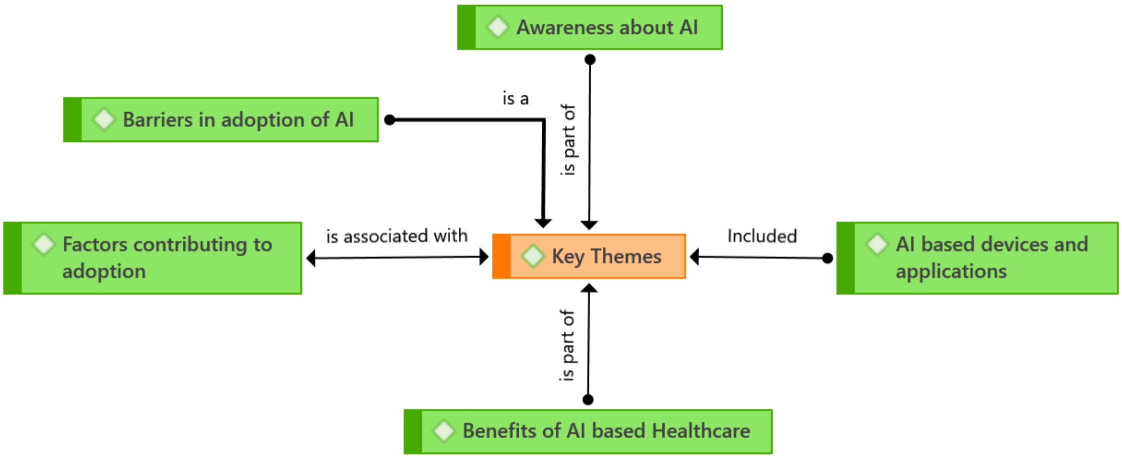

FIGURE 6 RELATIONSHIPS BETWEEN THE MAIN THEMES IDENTIFIED FOR THE WC

Figure 6 above shows the relationships between these five main themes that were obtained from the WC data analyses carried out. The results obtained under each of these themes are discussed here, in separate sections.

4.1.1 WC Theme One: Awareness of AI in Healthcare

The codes and themes were directly derived from the different quotations and transcripts of the WC. The first question in the survey was about AI. All candidates were asked as a foundation question "*In your own words, please describe what you think AI is*". Further exploratory probing questions were then asked regarding AI in disease diagnostics and healthcare. In line with the interview questionnaire and the candidate answers, the codes below in Table 1 were created:

Codes	Sub-themes	Main Theme
AI mimics human behavior	AI concepts	Awareness of AI in Healthcare
Preprogramed algorithm		
Blind acceptance of privacy policy		
Information about data protection	Awareness about the privacy policy	
Computerized Intelligence		
No fear of data sharing		
Unread privacy policy		
Less known AI in hospitals	Knowledge about AI	
Peer influence		
Understanding about AI		
Access to information and AI procedures	Perception about AI	
Concerns about AI		
Gradual trend to acceptance of AI		
Gradual trust building in AI		
Importance of AI		
Impression of AI		
No difference by device		
No experience with AI		
People Need conclusive information		
Risk of error		
Trust in AI-based devices		
Trust in AI-based devices		
Desired knowledge about AI	Required knowledge about AI	

TABLE 1 SUB-THEMES AND CODES FOR WC THEME ONE: AWARENESS OF AI IN HEALTHCARE

Other than the themes, the data were also processed to create word lists and, subsequently, word clouds in order to see the most prominent words used in the text and their association with each theme. The word cloud below in Figure 7 was generated for WC Theme One and gives a visual indication of findings related to the topic of AI in healthcare diagnostics.

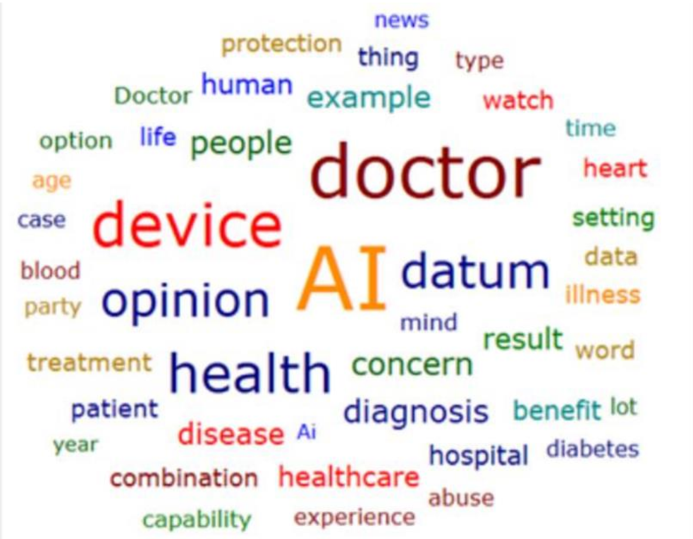

FIGURE 7 WORD CLOUD REPRESENTING WC INTERVIEW THEMES FOR WC THEME ONE: AWARENESS OF AI IN HEALTHCARE

Some of the main respondent words generated in this word cloud were AI, doctor, capability, device, opinion, health, and datum, indicating that the questions were on the right track to answer the research questions and bridge the gap in current literature.

The WC gave varied views about the concept and their own understanding about what AI is. An extraction of the different vocabulary within this theme can be seen below and derived the different statements provided by the candidates and their AI awareness.

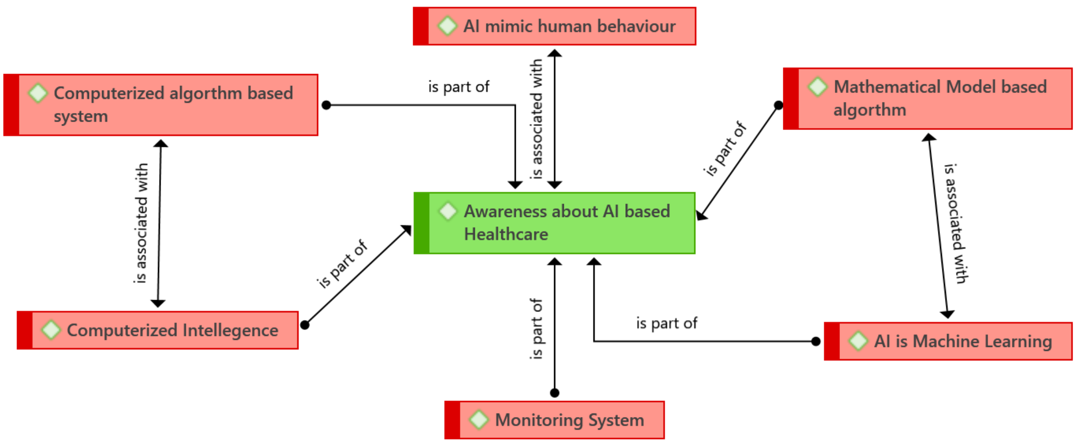

FIGURE 8 RELATIONSHIP BETWEEN THE WC THEME ONE: AWARENESS OF AI IN HEALTHCARE AND THE IDENTIFIED THEMES, SHOWN AS A NETWORK MAP

Figure 8 above represents a network map showing the most common findings among the WC with regard to their awareness about AI in healthcare. This diagram shows the articulation of phrases and associations what WC believe AI in healthcare is, based on their current understanding and awareness. The double arrowed line between Computerized algorithm-based systems and Computerized Intelligence shows a two-way relationship, how one drives and compliments the other. Also, Mathematical Modelling and AI is Machine Learning are complementary to each other, as depicted by the double arrows on the line.

The WC produced a more educated answer than the NWC using certain words and correct terminologies while discussing and explaining AI. Three WC precisely explained what AI is and how it works. Additional answer quotations are given in Table 2 below:

“AI is using machine learning and a lot of data to reach to the conclusions that human cannot do”
“AI is the computers and devices which will take over the human activity and act like humans”
“It is the computerised intelligence that learns from behaviours and predicts outcomes based on the data it receives”
“AI is mathematical model-based algorithm able to give ideas and predictions based on training data and experience, but it can be bias in some cases“
“AI is clever computer software in the form of avatars and robots virtual and augmented reality”
“AI mimics human behaviour because of the software behind algorithms behind it”

TABLE 2 QUOTATIONS FROM WC FOR WC THEME ONE: AWARENESS OF AI IN HEALTHCARE

Within the WC, there was a clear understanding about AI and its concepts in healthcare, primarily because many WC are using a wearable device for health purposes. Some candidates are using these devices to monitor their own conditions, such as diabetes type 1, AF and chronic anxiety. For other WC, these devices were not being used necessarily for a specific condition, but also for health purposes in general. Many of the WC were monitoring their personal statistics such as blood pressure, sleep patterns, daily movements, calories burnt versus consumed, and as an indirect way of monitoring weight gain and exercise performance, ultimately trying to prevent, for example, diabetes. This fits with the HBM in line with disease prevention.

The concept of AI awareness and, to some extent, the data required for the mathematical algorithm training, was also reflected in the participants answers to privacy, data sharing, data trust data concerns and the level of bias AI could demonstrate, though WC had no major surprising concerns. In fact, WC were more relaxed about the use of their private data generated from AI wearable devices especially for research purposes and/or technology performance improvements. Furthermore, WC understand the data from their device and perceived it as useful. They like the design features how their data was displayed, describing it as ”easy to interpret” and “useful”. Data produced by their devices allowed them to make the relevant health adoption changes, for example relax, move, meditate, walk more, and so on. WC have a positive attitude toward their wearable device and said they were ”very useful” and would recommend them to others. Not only do these answers mirror the theoretical underpin of this research, capturing the work of Davis (1985) reflected in the TAM, but WC usage behaviour also reinforced the work of Melas et al. (2011) and the improved TAM2. WC voluntarily check their diagnostic statistics, some people up to three times per day. WC voluntarily use it to make health changes and not just wait for notifications based on their results. They take control and all candidates said they acted accordingly, which gives them a positive sense of control and accountability to improve their health. Some candidates, like the AF, chronic anxiety and diabetic patients, are reliant on their WD. WC directed their focus about the use of AI in healthcare in the form of wearable devices and their desires to avoid illness or improve their condition, just like the HBM hypothesis (Janz & Becker, 1984).

Nobody within the WC owned an Oura ring, candidates use an Apple Watch, Fitbit or Garmin watch. Apple Watches are used more in candidates who monitor their sport performance such as resting pulse. Fitbit is the main device used for diagnostic purposes for AF and anxiety patients, though the ECG capabilities of the Apple Watch were also recommended.

Despite the existing knowledge that WC demonstrated, they all agreed that with the increased use of AI in day life, which they believed has been accelerated due to the COVID-19 pandemic, there still seemed to be a gap in knowledge of the true capabilities of AI especially in disease diagnostics in a clinical setting. WC also mentioned that it was the sophistication of AI, combined with the best scientists, that enabled the fast production of the COVID-19 vaccine. This information was naturally propagated across news channels in the UK at the time, so there was some understanding about AI in vaccine creation within the WC group. Additionally, WC referred to “track and trace” notifications often received during the pandemic. While describing track and trace, WC referred to the word “geotagging” (the correct way to describe such a track and trace function). Many NWC called track and trace “spying“, another example of the different descriptive uses of AI and its capabilities between the groups. WC did not understand how AI was able to alert them of COVID-19 contact and the need for isolation, but believed it was a positive use of AI technology, especially in the earlier days of COVID-19 when the virus was still not fully understood.

Regarding the topic of WD, both the diabetic WC and AF WC gave lengthy discussions and examples of how their WD actually saved their lives. The diabetic WC discussed how his watch has, through alert notification, prevented him slipping into a hypoglycemic coma on two separate occasions. Meanwhile the AF candidate, who is wearing a device purely for cardiology reasons, also received a lifesaving notification from his wearable device regarding a big drop in his blood pressure, which meant immediate hospital admission and 24-hour monitoring. This ability of wearable devices, especially in cardiology, is heavily reported in the Section 2 literature review from patients who have both symptomatic and asymptomatic AF. For this class of patients, their wearable devices had become “a necessary way of life”.

Discussions with the WC about their current applications involved trying to find out how diagnostic capabilities of their device made them feel. Compared to the NWC, who could only make hypothetical suggestions and assumptions, mainly related to increased anxiety and obsessive behaviours, this was also noted in the WC, mainly by the candidates heavily focused on exercise and achieving a “personal best” regarding training performance. What was surprising was that the WC previously mentioned, who wore these devices for true diagnosed medical reasons, were particularly “obsessed” with checking their statistics every few hours, perhaps like a sporting candidate, because these wearable devices for AF and diabetes had simply been lifesaving.

4.1.2 WC Theme Two: Benefits of AI-Based Healthcare

Users of AI-based WD mentioned several benefits about their device ranging from exercise monitoring to life saving. This next section codes and sub-themes are mentioned in Table 3 below that reflect the benefits mentioned by users:

Codes	Sub-themes	Main Theme
Taking AI suggested actions	Action on device recommendations	Benefits of AI-Based Healthcare
Frequency of monitoring AI based results	AI based monitoring of health indicators	
Health monitoring by AI		
Advantages of AI, fast diagnosis	Benefits of AI	
Motivation from AI results		
Precise and correct result from AI		
Setting routine by AI based devices		
Benefits of AI based devices	Benefits of AI based devices	
Consulting Doctor as second option	Combined Healthcare service	
Consulting Doctor as second option		
Easy health update through AI	Health related outcome of AI	

TABLE 3 SUB-THEMES AND CODES FOR WC THEME TWO: BENEFITS OF AI-BASED HEALTHCARE

As previously discussed, all of the WC believe there is a benefit in having a WD. However, due to the lack of true understanding behind the AI capability, all of the WC did not fully know how and why their device could perform true diagnostic functions without a blood test. This brings us to this next section about WC opinions with respect to being primarily diagnosed by AI versus a doctor.

WCs had proof and many examples where their device had provided accurate tracking and alerts in line with their physical symptoms. For example, one wearable candidate suffered with chronic anxiety so much so that, before seeking the appropriate help, she was unable to leave the house due to panic attacks and was diagnosed with border line agoraphobia (fear of leaving the house or a safe environment). This WC wore a Fitbit and gave examples of how the diagnostic capability of the device mirrors that of the physical symptoms she has when she begins to feel anxious. For example, when this WC began to feel anxious, her statistics displayed on the watch would indicate an increase in pulse rate, a clear sign of anxiety. Her Fitbit sleep application would also detect breakthrough awakening patterns during her time asleep, showing every time that an interruption of REM occurred. Due to the capabilities of the Fitbit AI diagnostics, she was alerted when to take her medication or even when to meditate. Granted, when possible, she took the advice of her Fitbit alerts for time to stop, take a break and, as she described it, “recharge and calm down”.

Many WC believe it is a human right to know how their results are generated, especially if AI is involved. Working through the diagnostic questions, WC were asked about their thoughts and opinions about being primarily diagnosed by AI only, a doctor or a team of doctors, or a doctor who was using the assistance of AI. All WC preferred to be diagnosed by doctors assisted with AI. It could be assumed that, because the WC already accept AI capabilities through their own subjective experience and personal examples, they are more open minded to the further capabilities and the “limitless power it holds”, as stated in the literature many times. WC said doctors have practical knowledge and have an emotional side, AI does not and AI is only as good as the data it is trained with. WC said AI and a doctor diagnostic combination would give the best of both worlds because doctors do make mistakes.

Additional AI benefits were identified as faster results, reduced waiting time for diagnosis, improved treatment plans and treatment options, real time data capture, improved diagnostic accuracy and less mistakes due to human error. WC believe that AI could be more precise and, in some circumstances, could be more trusted than a doctor. All WC at some stage in their lives had had either an MRI scan or a CT. They never questioned the results, which implied that they ultimately trusted their results. WC had strong opinions on how AI in a clinical setting can really improve the healthcare systems. Also, they believe that WD are best as a monitoring tool but can diagnose unidentified conditions.

The network map below seen below in Figure 9 shows how the WC linked the benefits of AI to certain areas of healthcare improvement. AI diagnostic benefits included reduced waiting times to see a doctor, and precise and correct diagnosis.

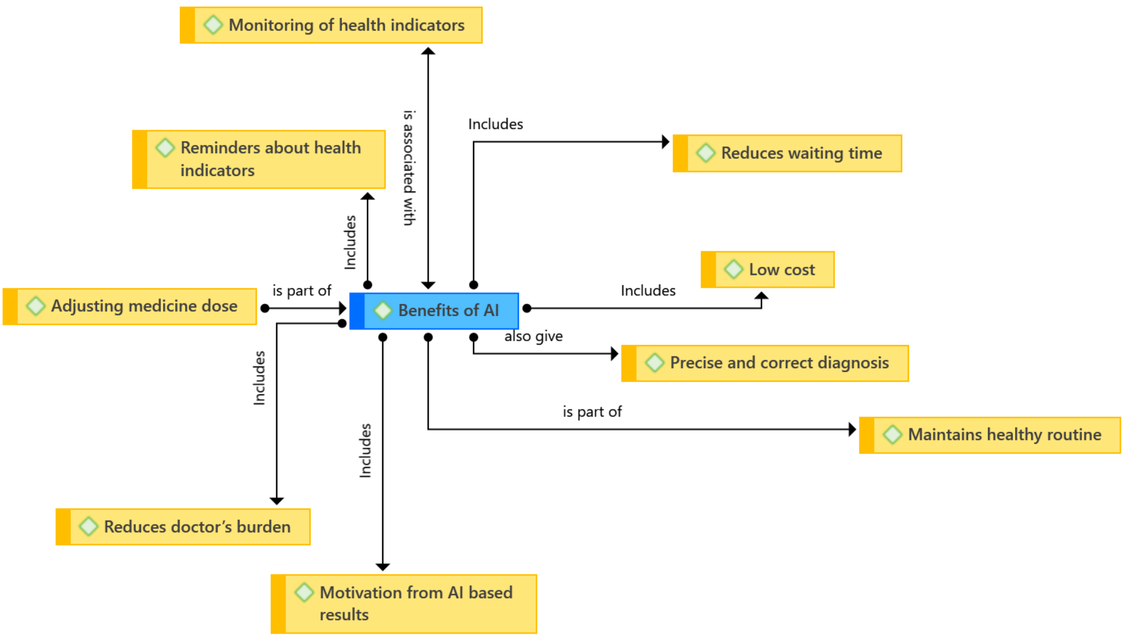

FIGURE 9 RELATIONSHIP BETWEEN THE WC THEME TWO: BENEFITS OF AI-BASED HEALTHCARE AND THE IDENTIFIED SUB-THEMES, SHOWN AS A NETWORK MAP

This network map shows that monitoring of health indicators and benefits of AI are linked with a double arrow showing a two-way relationship: monitoring health indicators captures more data to benefit AI and benefits of AI mean capturing more diagnostic data.

4.1.3 WC Theme Three: Factors Contributing to Adoption of AI-Based Healthcare

The factors which convince people to use AI-based WD are closely linked with the benefits discussed in the above section for WC Theme Two. However, due to the importance and number of times mentioned, there was an overlap in themes, therefore there is some repetition, but the subject is discussed separately here due to the important role in advocating the AI-based healthcare devices.

The following sub-themes and codes in Table 4 were identified through the coding process. Sub-themes derived from the main theme were linked in the findings through inductively exploring the initial answers.

Codes	Sub-themes	Main Theme
Efficiency of AI	Benefits of AI	Factors Contributing to AI Adoption
Combination of human factor and AI	Combined healthcare services	
Combinational of AI and human factor	Combined Healthcare Services	
Evolution of AI	Combined healthcare services	
Human factor as second option		
Impressive evolution of AI		
Desire to see improved AI results	Perception about AI	
Following recommended actions	Response to recommendations	
AI as first choice	Trust in AI	
AI to rectify mistakes	Combined Healthcare service	
Combination of AI and human factor	Combined Healthcare service	

TABLE 4 SUB-THEMES AND CODES FOR WC THEME THREE: FACTORS CONTRIBUTING TO ADOPTION OF AI-BASED HEALTHCARE

Getting an appointment with a doctor in the UK is renowned to be difficult. Just to see a GP can take six weeks and waiting for test results is a daunting, worrying and unpleasant experience. Therefore, when WC referred to AI acting as an assistance to doctors, the main important suggestion was in the form of a triage service. This has already been highlighted in the literature by Abedi et al. (2021) and Shlobin et al. (2022), especially when deciding if immediate medical attention is required. However, this has been ethically challenged, especially as mental health triage and strongly disputed by Ward (2021) and Adikari et al. (2022). AI proved a favourable option for a chance of reduced waiting times and all candidates agreed that AI would mean faster results and time to prepare for the sad inevitable, should their condition be terminal. For a second opinion, therefore, a combination of both is a preference as mentioned by the participants. Other positive AI beliefs are represented in the quotes from WC shown below in Table 5.

“AI learns and improves its results and needs data to learn more and produce improved results. This could be global data not just what is in the doctor’s head”
“AI is constantly developing and knowing more about healthcare and also updates the knowledge of users regarding their health conditions, treatments and precautions”
“Expectation to get more accurate diagnostic by AI based devices because of global health data sharing policies”
“The patient or users are offered a list of options to improve their health conditions because AI has more insights than a team of doctors”
“AI is preferred if the doctors are subjective and have biases, but the AI will not be biased”
“In case of mistake by human specialist the AI will be consulted”
“The money and time investment in AI based devices for healthcare is less than the cost of doctors and clinical services so AI could be a cheaper more efficient way of treating populations “

TABLE 5 QUOTATIONS FROM WC FOR WC THEME THREE: FACTORS CONTRIBUTING TO ADOPTION OF AI-BASED HEALTHCARE

4.1.4 WC Theme Four: AI Diagnostic Wearable Devices and Applications

AI-based devices are the mediums or agents which provide services to the users in the form of notifications, information and statistics and visuals. The types of diagnostic wearables, combine with their applications’ functional capabilities, are discussed in this section.

FIGURE 10 WORD CLOUD OF DESCRIPTION AND PREFERENCES IN HEALTHCARE DIAGNOSTICS FOR WEARABLE CANDIDATES IN WC THEME FOUR: AI DIAGNOSTIC WEARABLE DEVICES AND APPLICATIONS

The word cloud shown above in Figure 10 gives the descriptions provided by WC for preferences in healthcare diagnostics under this Theme Four.

From a Technology Acceptance perspective, also mentioned as a theoretical underpin of these investigations (see Section 2.11.1, p.53), the following mentions came to light as to why WC used their devices other than for the diagnostic capabilities. The uses were more to do with the device functionality, PEOU and the PU. Additionally, despite the current applications, WC all suggested several applications they would like to have for diagnostic reasons. What was interesting is that all WC women wanted some type of hormone diagnostic biosensory capability, and a subdermal vitamin D sensory function. This is understandable when recent studies have revealed that women of a certain age require vitamin D as a key supplement while going through any perimenopausal and hormone changes. This is a reasonable answer for women of that age. This topic was also referred to by women in the NWC group, as discussed in the NWC results Section 4.2.1, p.80.

All WC were interested in any type of neurological diagnosis as well as a hydration biosensor to monitor their levels of hydration. Further findings are as follows:

- Apple Watch is used by majority of the wearable candidates.

- Apple Watch is used but not for diagnostic purposes. In some cases, the most popular diagnostic tool in cardiology was Fitbit.
- Devices are easy to use and have perceived usefulness because they update automatically.
- Additional applications that would be of interest for future diagnostic capabilities would include hormone level, ketone level, hydration, vision scan and neurological detection for tremor analysis to predict early PD.

Few of the users stated that they do not use devices for current illness or health condition monitoring, but they would if their doctor recommended it. WC expected to receive a WD free from the health service if their condition was serious. They agreed with the NHS provision of PKG watches for Parkinson's patients as mentioned in the literature review. WC users trust devices and believe they are a good idea: everyone should use one because they can diagnose.

4.1.5 WC Theme Five: Barriers to Adoption of AI-Based Healthcare

While WC did not display many barriers to adoption (they all owned a wearable, so this was to be expected). They did, however, make suggestions and raise concerns for others while answering the questions. The word cloud in Figure 11 below is an indication of some of the common themes that were addressed in this section, specifically relating to trust and privacy.

FIGURE 11 WORD CLOUD OF TRUST AND PRIVACY FOR WC IN WC THEME FIVE: BARRIERS TO ADOPTION OF AI-BASED HEALTHCARE

The main concern central within the WC group on the Barriers Theme was the provision of their device data being sold to third parties. WC also believed that there should be more honesty if a diagnosis has been purely determined by AI in a clinical setting. Additionally, doctors should be more understanding if a patient visits them based on health concerns generated by their wearable device.

The codes and sub-themes addressing the subject of Barriers to Adoption of AI-Based Healthcare are shown in Table 6 below.

Codes	**Sub-themes**	**Main Theme**
Trust in AI based results	AI based monitoring of health	Barriers to Adoption of AI Based Healthcare
Blind acceptance of terms and conditions	Awareness about data privacy	
Information about data protection		
Trust in data protection		
Data sharing is offensive	Concerns about data privacy	
Not happy with premium reduction		
Not happy with premium reduction		
Privacy breach by companies		
Believes in data protection	Concerns about data protection	
Concerned about sharing and selling of data		
Concerns about data monitoring		
Concerns about data monitoring		
Concerns about data usage		
Data sharing worries		
Not willing to share data		
Not willing to share data with insurance company		
Not willing to share data with insurance company		
Objection on companies to sell and share data		
Absence of diagnostic app	Demand of AI	
No device recommendations		
Absence of emotions in AI	Emotional Factors	
Absence of emotions in AI		
Choosing second opinion		

Codes	Sub-themes	Main Theme
Doctor as first priority		
Partial trust in device		
Reason to choose second opinion		
Reason to take second opinion		
Reason to trust doctors		
Trust in blood test		
Trust in doctors		
Trust in doctors	Influence of doctors	
AI program limitations	Limitations of AI	
Not following recommendations	Response to device recommendations	
No actions	Response to recommendations	
View on taking actions	Response to recommendations	

TABLE 6 SUB-THEMES AND CODES FOR WC THEME FIVE: BARRIERS TO ADOPTION OF AI-BASED HEALTHCARE

All WC had no issues about data storage, or trusting the data generated by AI in either a hospital setting, or via their wearable device. WC admitted that they do not know or read all the terms and conditions of their applications and never worry about privacy. However, the question regarding sharing of data with third parties such as insurers raised a varied discussion. The main outcome across all candidates bar one was the identification of insurance discrimination, the ability of health insurers to use the data and discriminate in the premiums offered to patients, and increased premiums depending on what data were collected and shared from their wearable device. Not only was discrimination an issue, WC believed (due to personal experience with insurers already) that these so-called third parties (the WC) would then be spammed by marketing companies via push notifications that could not be silenced or rejected. WC would not conform to sharing their data with insurers as they deemed them untrustworthy. They concluded that if sharing data with third parties became a term and condition of any wearable diagnostic function, they would not accept the application, irrelevant if it could save their life or monitor their condition.

4.2 Findings for Non-Wearable Candidates

The major difference between the themes from WC and NWC is that the WC have personal subjective experience of using a Wearable Device (WD) with diagnostic functions and health monitoring apps. NWC do not have their subjective experience to share. However, the NWC candidates who participated in this research investigation have shared what they believe and understand about AI in diagnostic health and wearable diagnostic devices through reading , and listening to other sources, not exactly tangibly subjective like the WC. But in spite of this, this next section will provide some valuable insights and slowly contribute to building the bridge in the identified gap in literature on patient perceptions of AI in diagnostic healthcare and diagnostic wearable devices.

To understand the reasons why NWC choose not to have a WD, several different questions were asked of NWC, as seen in the NWC survey in Appendix 4 compared to that for WC (included in Appendix 3). The same five themes were identified and addressed for NWC, as for the WC. However, an additional theme, AI-Based Healthcare Adoption Trends, was added due to the difference in questions. Analysis of results across these five common themes, for both WC and NWC, varied.

The following are the themes identified from the data analyses for the NWC:

- Awareness of AI in Healthcare
- Benefits of AI-Based Healthcare
- Factors Contributing to Adoption of AI-Based Healthcare
- AI-Based Healthcare Gadgets
- Barriers to Adoption of AI-Based Healthcare
- AI-Based Healthcare Adoption Trends

4.2.1 NWC Theme One: Awareness of AI in Healthcare

Initially when asked to describe AI in their own words, NWC had some information and understanding about AI though not as clear cut as the WC in their own description of AI, which was the opening question of both surveys. NWC related their knowledge and understanding about AI diagnostic wearables to reading news sources and listening to friends who own wearable diagnostic devices, mainly in the form of Apple Watch, Garmin or Amazon Watch. Friends of NWC actively used these devices for diagnostic and health purposes. Most of the NWC could not eloquently explain what AI was compared to the more intelligent descriptive answers from the WC group, though they did mention some aspects related to software and computers. In Table 7 below, the following codes and sub-themes derived from the transcripts representative of NWC and their understanding about AI and associated devices were created. In each of them, sub-themes evolved through probing questions.

Codes	Sub-themes	Main Theme
Understanding about AI	Knowledge about AI	Awareness about AI in Healthcare
Concept of wearable devices	Knowledge about wearables	
Concept of AI diagnostic APPS and reliability, accuracy	Knowledge of AI wearable functions	
Lack of AI understanding about AI	Lack of information about AI	
Appreciation of AI based diagnosis	Perception about AI	
Impression about AI	Perception about AI	
Impression about AI based diagnosis	Perception about AI	
Desired knowledge about AI	Required knowledge about AI	
Desired knowledge about AI	Required knowledge about AI	
Desire for evidence-based diagnosis	Required Knowledge about AI	
Desired knowledge about AI trustworthiness and reliability	Required knowledge about AI	

TABLE 7 SUB-THEMES AND CODES FOR NWC THEME ONE: AWARENESS OF AI IN HEALTHCARE

A few key statements shared by the NWC about the concept and utilization of AI, based on their current knowledge and understanding, plus any experience, are summarised in Table 8 below as follows:

"AI is intelligence and surveillance that is done by machines and used in all walks of life"
"It means artificial intelligence that spies on you"
"It's in Apple Watches and Fitbits to tell you to do more exercise if you have high BP"
"AI is robots and machines that can behave like humans and do tasks like humans"
"AI is in my Alexa it recognises my voice and answers questions, Amazon use AI"
" A wearable device is a watch ring armband that gives sleep information and body statistics"
"AI works on pre-programed criteria for particular matters"

TABLE 8 QUOTATIONS FROM NWC FOR NWC THEME ONE: AWARENESS OF AI IN HEALTHCARE

From a diagnostic perspective of AI in a clinical setting, NWC were very sceptical about the abilities of AI to perform diagnostic tasks. They were not aware that, despite all having had an MRI or CT at some stage in their life, these medical imaging systems perform through the incorporation of AI. NWC expressed many concerns and doubts about how AI is capable of performing diagnostic capabilities, especially in the form of a watch or ring. They were also not fully aware of the extent in which AI is used in a clinical setting in disease diagnostics, for example dementia detection and stroke predictions. Some NWC asked if the doctors understand and trust AI results. Despite multiple references within the literature review regarding doctors' lack of AI understanding and the opacity of AI systems (Ćwiklicki et al., 2020; Lai et al., 2020; Quinn et al., 2022), this was not highlighted to the candidates.

Regarding this first NWC theme about Awareness of AI in Healthcare, this enumerates the various ways participants would also like to see AI employed in a clinical setting. Some NWC asked would doctors use and trust the outcome of AI diagnostics on their own family members and if so, why. NWC wanted to know more about AI as the interview evolved and there was a change in the level of interest regarding the diagnostic performance capability of AI in healthcare. NWC posed many hypothetical situations where AI could be used for diagnostic purposes on themselves, especially the ladies of the group who all expressed an interest in some form of hormone diagnosis in the form of a WD.

NWC agreed that AI in healthcare could possibly be a useful tool to assist doctors, as suggested by the work of Shlobin et al. (2022). Their questioning and thought expansion increased as the interviews proceeded and questions or statements ranged from, for example, how does AI works, how does it make decisions and gives advice. NWC began to wonder and ask who was involved in writing the AI software and what medical involvement from doctors did this AI diagnostic software include. Doubting that there were no medical professionals giving input, NWC asked how can AI be correct at diagnosing if it was not written by doctors. The concept of training data and machine training was misunderstood even once the interviewer had explained what AI actually was in a break script after Question 1 (see Appendix 1).

Having finally digested the information from the researcher on what AI is and how it can be used in diagnostic healthcare, participants began to open their mind. NWC stated they would want to see the evidence of diagnostic excellence, trends and percentage of success and failure in a clinical setting if AI was being used to diagnose themselves, all of which appeared to be hindering factors for NWC to truly accept diagnostic AI. Also, NWC touched on the subject of liability and culpability in their answers like in the work of O'Sullivan et al. (2019) and Saheb et al. (2021). Hypothetical situations were discussed and insights and sub-themes for analysis were beginning to emerge within this group, contributing to the primary end point of the research gap and the purpose of this thesis.

Conceptually, the ideas shared by NWC about AI were somehow relevant and reasonably similar across the group. Vocabulary similarities and use of correct terminologies describing AI were missing when compared to the WC, which could be due to the initial lack of interest or understanding of AI in general. NWC did not seem favourable to adopt a diagnostic WD, because "they didn't need it" but they were all unaware that the diagnostic functions of WD were driven by AI. NWC believed that nothing can be truly concluded without blood tests, so the NWC believed that WD and AI could not identify any undiagnosed health condition, questioning how reliable AI is in both a clinical setting and through its incorporation into WD.

As the interview proceeded, more subthemes within each theme and bilateral questions emerged. The researcher wanted to find out why NWC did not have a WD, what were the barriers to adoption and hindering factors, and this was addressed later on in another theme.

NWC wanted to know how AI decisions differ from or reflect the diagnosis of doctors and if AI is truly reliable. NWC expressed the desire to know if the AI diagnosis is better than the doctors' diagnosis, moreso than the WC in this theme. Regarding the theme and referring to the code identifier *concepts* of *knowledgeable devices and concepts of diagnostic application* in the above Table 7, NWC were able to provide good examples based on people they know where the diagnostic capabilities in the form of a WD were being used. It was actually through three NWC and adoption of snowball sampling that this researcher was able to interview four candidates, all of whom were diagnosed by AI and are currently wearing a diagnostic wearable in the form of an Apple Watch, Fitbit or Garmin: these case studies are mentioned in the previous section and refer to the AF, diabetic and chronic anxiety patients. The most important items are how reliable AI is, followed by how AI works and then how AI diagnosis differs from doctors.

4.2.2 NWC Theme Two: Benefits of AI-Based Healthcare

The following codes were generated using a thematic analysis across the interview transcription dialogue to identify any benefits that the NWC could suggest for the use of AI in healthcare

Codes	Sub-themes	Main Theme
Functional domains of AI based health monitoring	Health benefits of AI	Benefits of AI-Based Healthcare
Benefits of AI diagnostics	Health related outcome of AI better treatment	
Benefits of AI in drug discovery	New drugs precision	
Benefits of AI speed	Health related outcome of AI fast results	
Benefits of reduced doctor burden faster times	Early detection fast treatment	

TABLE 9 SUB-THEMES AND CODES FOR NWC THEME TWO: BENEFITS OF AI-BASED HEALTHCARE

The benefits of AI described by the NWC and in order of significance were early disease detection and better treatments (for example, for cancer). NWC stated that if AI was reliable, accurate and trustworthy, then maybe there would be faster and earlier detection of cancer, and better treatment plans. Some NWC stated that they would like to know if they were prone to dementia or PD, but then questioned the reliability of AI in these disease areas. What was important for the NWC was the fact that they had all given personal examples of a prolonged waiting time to see their doctor. NWC said that if AI could reduce waiting times that would be a benefit, though this was geared more through assistive administration with AI, not direct triage diagnostics. If more AI functions could improve the UK National Health Service, they would accept this.

4.2.3 NWC Theme Three: Factors Contributing to Adoption of AI-Based Healthcare

This next section looks at the opinions and perceptions of NWC and what is important about AI in healthcare diagnostics.

FIGURE 12 WORD CLOUD FOR TERMS USED BY NWC IN THEME THREE: FACTORS CONTRIBUTING TO ADOPTION OF AI-BASED HEALTHCARE

A word cloud describing the terms seen in this theme is shown here in Figure 12.

Key codes are listed below in Table 10, together with identified sub-themes. Of interest here is that NWC to some extent would be happy to be diagnosed by AI in a hospital setting, but only if there was the support of a doctor. Like many who are diagnosed with bad news regarding their health, a second opinion for confirmation is always desired. Here, this section addresses the thoughts of second opinions from an initial AI diagnosis versus a doctor, or a combined diagnosis of man and machine.

Codes	**Sub-themes**	**Main Theme**
Choosing doctors as second option	Acceptance of AI based healthcare	Factor Contributing to AI Adoption
Efficiency of AI diagnostics	Benefits of AI	
Advantages of AI diagnostic	Benefits of AI	
Combination of doctor and AI	Combined healthcare services, more accurate cross case evidence	
Combination	Reassurance of doctor approval	
Trust in doctors	Experts and specialists	
AI as second option	Combined experiences	
Reason to choose doctors	Learned experience	

Codes	Sub-themes	Main Theme
Reasons to choose doctors and AI combined	Evolution of combined health service	
Recommendations of doctor's matter	Positive views on AI	
Doctors trust in AI	Accuracy error	
Trust in AI primary diagnosis	Proven efficacy doctors trust in AI output	
Trust in AI treatment suggestions	New drugs and treatment options	
Recommendations of doctor's matter	Based on experience with AI non bias	

TABLE 10 SUB-THEMES AND CODES FOR NWC THEME THREE: FACTORS CONTRIBUTING TO ADOPTION OF AI-BASED HEALTHCARE

When asking NWC what they thought and how they felt about being initially diagnosed by AI versus a doctor, they were not very positive. NWC all preferred to be diagnosed by a doctor or a team of doctors, and definitely not AI. One surprising finding was that the majority of NWC would happily accept the results of AI diagnosis combined with a doctor's diagnosis for a best-case scenario, again mentioning that doctors make mistakes, too. Across the questions in this theme, the need for the human interface was apparent. NWC had more trust in doctors themselves because of the many years doctors train and learn. Also, doctors have a hands-on approach and can refer to their colleagues' expertise and advice. while some of the NWC had the attitude that "the doctor is always right". This was despite three candidates presenting stories of individuals they knew who were misdiagnosed by their doctor based on the symptoms they demonstrated: within six months, two of the individuals died, and one had a mastectomy through human diagnostic error. Mesko (2021) mentions in his work that AI in diagnostic healthcare has shown to be error free, reinforced in the work of Vinny et al. (2021). If given bad news, all NWC candidates would always seek a second opinion whether a diagnosis was from AI or a doctor. However, an evolving question which was asking would you seek a second opinion if AI diagnostics suggested "all clear" lead to uncertainties and several "I don't know answers" or, alternatively, "probably" and "definitely". This again further reinforced the NWC lack of trust in AI diagnostics compared to a doctor. Ultimately, NWC would prefer doctors for second opinion diagnosis.

4.2.4 NWC Theme Four: AI-Based Healthcare Gadget Wearables

The purpose of this section was to identify why and what were the hindering factors preventing the NWC adopting WD and other devices such as Oura rings, bracelets and similar. In this discussion participants mostly mentioned the reasons and conditions responsible for absence of

WD. Most important of all the reasons for not using a WD was the involvement of doctors or the good health of an individual. Both these factors help to avoid investment in AI based healthcare devices. A majority of NWC shared that doctors never advised them to wear a device or use any application. Additional statements made were:

- Never advised by doctor to wear a device
- Due to absence of health issues, no need is ever felt to wear an AI-based device

Also, probing questions were asked to see in what situation would they purchase a WD for health diagnostic purposes. The sub-themes and codes created for analysis are shown in Table 11 below:

Codes	Sub-themes	Main Themes
Description of device, brand	Diagnostic function and willingness to use	Accepting AI wearable device
No recommendations about device	Absence of Devic	AI-Based Healthcare Gadgets and wearables
Reasons to not to use devices	Healthy and no conditions	
Concerns of Device	Reliability, privacy data security	
Concept of wearable devices	Wearables type and preference	
Reasons to use future devices	Easy to use, cost efficiency, useful, reliable	
AI purchase based on doctor recommendation	If chronic illness that need monitoring	

TABLE 11 SUB-THEMES AND CODES FOR NWC THEME FOUR: AI-BASED HEALTHCARE GADGET WEARABLES

Some statements made by NWC under this theme are shown below in Table 12.

"I'm healthy anyway so I don't need a wearable device"
"If I had a serious illness like heart disease and was advised to get one I would"
"If my doctor told me I needed one I would expect it to be provided by the National Health Service
"I would have one if it could detect hormones as I'm perimenopausal"

TABLE 12 QUOTATIONS FROM NWC FOR NWC THEME FOUR: AI-BASED HEALTHCARE GADGET WEARABLES

The word cloud shown below in Figure 13 relates to Theme Four AI-Based Healthcare Gadget Wearables.

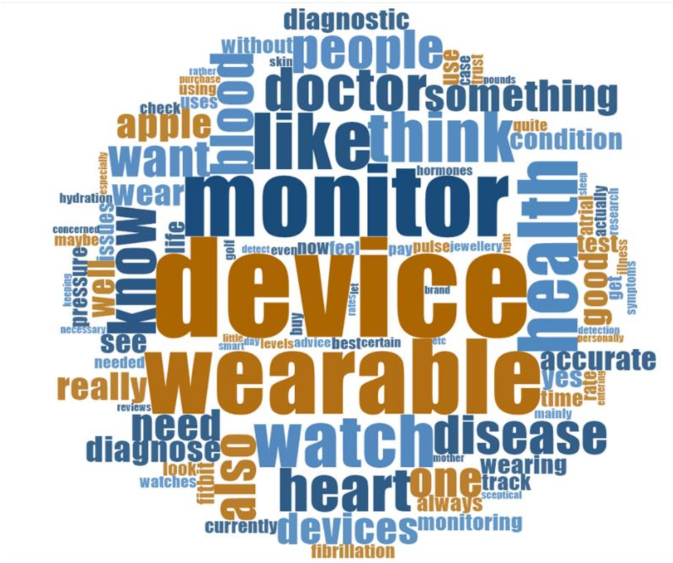

FIGURE 13 WORD CLOUD OF HEALTH AND WEARABLE DEVICES FOR NWC

Figure 14 below shows how NWC perceive WDs in their physical form and how they also perceive what diagnostic capabilities they currently perform. Notice that only three diagnostic capabilities were mentioned by the NWC: blood pressure monitoring, blood sugar monitoring and sleep related applications. There was no mention of additional diagnostic capabilities of WDs, clearly due to the gap in knowledge. However, NWC were all aware of the exercise function to calculate steps and burn calories. Weight loss seemed to be a common trait among the ladies of the group. The Apple Watch was mentioned by the NWC and there was little reference to Fitbit (unlike in the WC interviews).

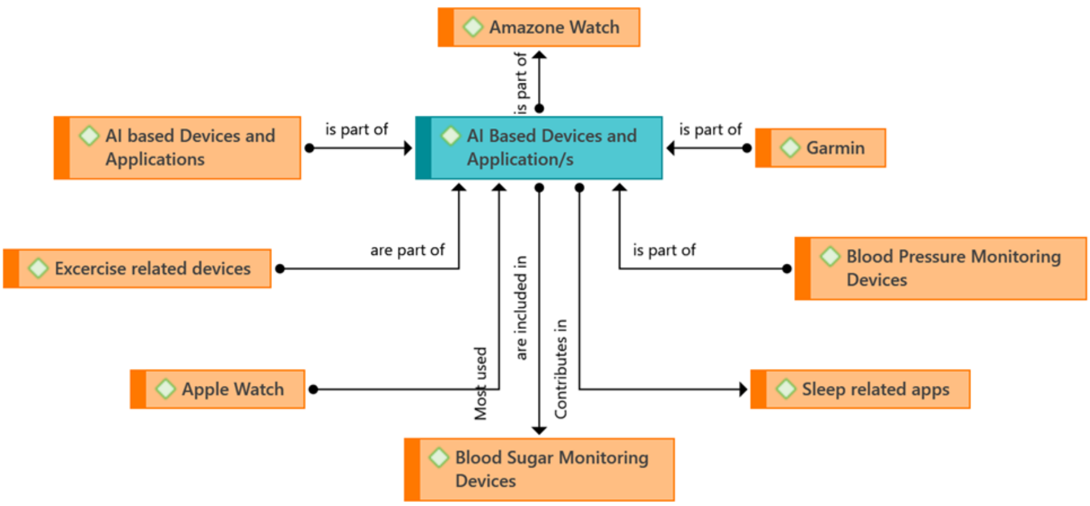

FIGURE 14 HOW NWC PERCEIVE HEALTHCARE DIAGNOSTIC GADGETS UNDER THEME FOUR: AI-BASED HEALTHCARE GADGET WEARABLES

One topic that was mentioned in this broad question was heart conditions. Many NWC would purchase one, if their doctor recommended a WD, and if there was proven evidence to support the device monitoring the condition. This is in line with the "cue to action" construct of the HBM (Janz & Becker, 1984). Female NWC mainly said they would purchase one only if they had a life-threatening illness or serious condition, even when they feel sceptical about WD. This fits with the "perceived severity" construct of the HBM (Janz & Becker, 1984).

4.2.5 NWC Theme Five: Barriers to Adoption of AI-Based Healthcare

Perceived barriers to adoption of AI-based devices and applications for NWC are more than those shared by the WC. They may be the reasons why NWC are not using any device or applications. The sub-themes and codes can be seen in Table 13 below.

Codes	Sub-themes	Main Theme
Concerns about AI	Concerns about AI diagnostic reliability, trust-worthiness	Barriers to Adoption of AI Based Healthcare
Information about data protection	Data protection awareness, abuse of data, sharing data, discrimination	
Concerned about the use of shared data	Fear of cyber-attacks third party discrimination	
Concerns about AI	Discrimination	
Trust in Doctors	Doctors influenced by Ai	
Reasons to avoid data sharing	Factors to behind data privacy	
Concerns about data protection	Data privacy hacking security	
Concerns about data sharing and utilization	Privacy concerns	
Less time to see AI based results	Reason to avoid AI based devices	
Human factor includes empathy AI does not	Emotion , understanding sympathy trust compassion	

TABLE 13 SUB-THEMES AND CODES FOR NWC RELATING TO NWC THEME FIVE: BARRIERS TO ADOPTION OF AI-BASED HEALTHCARE

The most important barriers of adoption for NWC included the role of the doctor and people's trust in the human factor more than a machine. Personal data collection generated from AI WDs and safety issues around data handling were also mentioned. NWC believed they had not enough true understanding about why their data from WDs is kept. They believed there was lack of appropriate information and knowledge. The value and relief in a human touch is also a reason to avoid use of AI-based healthcare services. NWC believed that, ultimately, any data generated from a WD would be used in target marketing and all candidates openly admitted to the fact that they never read any terms and conditions regarding data privacy. NWC did not want to use a WD because they felt they did not need one: main barriers for adoption were based around trust and data security. They believed that their data was private and personal.

NWC were dubious about how reliable the WDs were, which stemmed back to the trustworthiness of the AI used in them. Naturally, there was an element of interest, but the acceptance of a WD was not only based on the element of trust, but also its perceived usefulness and ease of use (as described in the TAM model by Davis (1985)). Many NWC said they were “not techy” and if they were to purchase a device, mainly through recommendation of the doctor, they would want it to be easy to use and understandable. As mentioned in the previous NWC Theme Four, which somewhat overlapped in the elements of themes and sub-themes of this Theme Five, it can be concluded that the NWC really do have more trust in the human element, be it in the form of a hospital diagnosis direct from a doctor - yet being total unaware of how their results were generated anyway. As found across the literature review, AI in hospitals is used more than people realise. NWC always wanted to see a doctor and clearly relied on the expertise and knowledge of doctors and not machines. NWC believed that disease detection requires a blood test. One candidate quoted “the blood never lies”. All NWC agreed that WD could not diagnose any disease or condition firstly, yet they could be used as monitoring tools especially regarding high or low blood pressure.

The use of AI and any endorsement appeared to also be a barrier of adoption to accept AI in diagnostics. Some NWC believed that doctors will be targeted to push AI in the future. These candidates made reference to waiting time targets, surgery and departmental budget targets and company sponsorship and cash endorsements (a common occurrence in the pharmaceutical world).

Referring to WD, many NWC referenced the fact that they believed these devices could be detrimental to one’s mental health, which is also suggested in the literature review. NWC thought that WDs could instigate obsessive tendencies, over checking personal stats: waiting and worrying about a health alert or notification could lead to anxiety and stress.

FIGURE 15 WORD CLOUD RELATING TO THE BARRIERS TO ADOPTION OF AI-BASED HEALTHCARE FOR NWC

The word cloud shown above shows clearly that "data" is the primary concern and hence a major barrier to adoption of AI-Based Figure 16 below highlights the relationships between the Barriers to Adoption of AI-Based Healthcare for NWC.

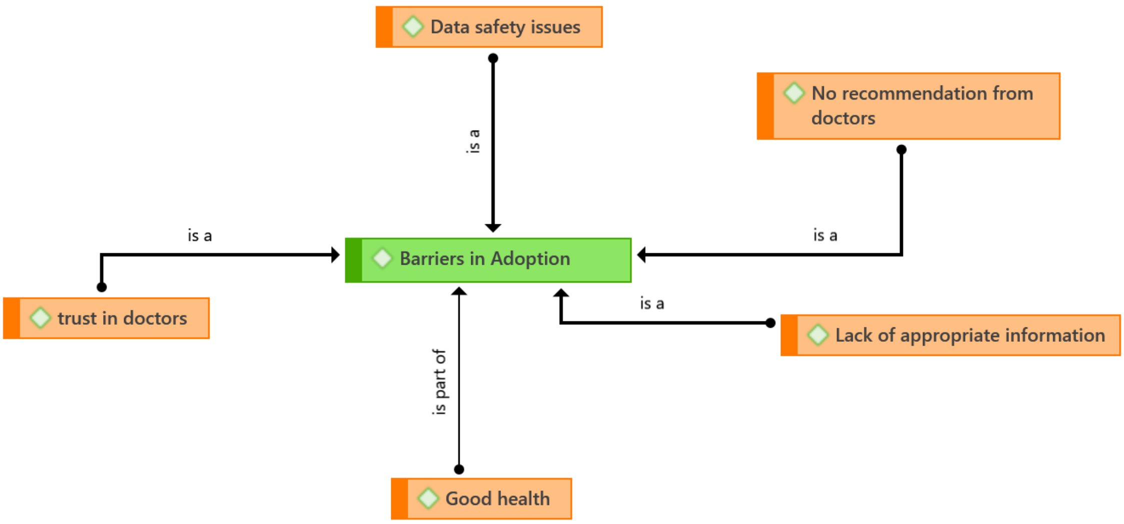

FIGURE 16 HOW NWC PERCEIVE THE BARRIERS TO ADOPTION OF AI-BASED HEALTHCARE UNDER THEME FIVE: BARRIERS TO ADOPTION OF AI-BASED HEALTHCARE

The above figure represents how the conceptual findings within the data of NWC show a very strong relationship between barriers to adoption and the hindering factors that the NWC associated with wearable devices. People who believed they had good health was a clear barrier to WD adoption, because they thought they didn't need a WD. NWC have a lack of information on how the AI WD work, so this was recognised as a barrier to adoption. Naturally, data safety issues prevented people from wanting a WD. Other words associated with barriers to adoption within the NWC can be seen in the word cloud of Figure 15 above.

4.2.6 NWC Theme Six: AI-Based Healthcare Adoption Trends

The sub-themes and codes for NWC Theme Six: AI-Based Healthcare Adoption Trends are shown below in Table 14.

Codes	Sub-themes	Main Themes
Use of shared data in medical research	Contribution to society	AI-Based Healthcare Adoption Trends
Factors affecting payment decisions	Decision on health-related payment for AI	
Recommendations of wearable devices by doctor	Demand of AI based healthcare	
Worried about cybercrime due to data sharing	Fear of cyber attacks	
Factors affecting payment decision	Health related investment in AI	
Factors affecting payment decision		
Factors affecting payment decisions		
Factors affecting payment decisions		
Willingness to pay		
Willingness to pay		
Willingness to pay for device		
Willingness to pay for devices		
Willingness to pay		
Factors affecting payment decisions	Health related payment in AI	
Functional domains of healthcare monitoring by AI	Outcome of health-related investment in AI	

TABLE 14 SUB-THEMES AND CODES FOR NWC THEME SIX: AI-BASED HEALTHCARE ADOPTION TRENDS

This theme is based on the willingness to invest in AI-based healthcare services when individuals are convinced of the capability of AI to monitor and safeguard personal health. All the participants expressed willingness to invest some amount to buy AI-based healthcare applications if they were advised by their doctor. All candidates agreed there was no price on health, however they all concurred that if a doctor advises a patient to wear a WD, it should be given free. What was important to these candidates and again in TAM (Davis, 1985) was the ease of use of these wearable devices. NWC wanted easy, clear WD that updated automatically, gave clear simple results and were “non techy”.

4.3 Conclusion

The research across both groups of candidates gave valuable insights to answer the posed research questions. Many differences in opinion were recognised between both WC and NWC and how they perceive the uses of AI in healthcare diagnostics from a clinical setting to a wearable device. WC answers evidently displayed that they are very comfortable around the use of their data and data storage, they have no issues with data privacy and data protection, whereas the NWC expressed many concerns contrary to the WC. From a theoretical underpinning, both WC and NWC demonstrated in their answers examples which conform to various aspects of the TAM and HBM. While differences remain across the groups, what was interesting is that both WC and NWC actually desired the same fundamental diagnostic functions in the future. Both groups of candidates expressed what they believed would be helpful future applications, including neurological detection and hormone level diagnostics, mainly in the ladies. Applications used to measure vitamin D levels and hydration were also the main interest. Furthermore, a key similarity is that despite the acceptance of AI, data storage data usage in diagnostic health in the WC compared to NWC, all candidates collectively were against the uses of their private health data, generated by AI, being sold to third parties. Similar concerns revolved around data abuse, data discrimination and marketing spamming.

The next section will provide a final summary and conclusions of the complete work carried out in this thesis, including an assessment of limitations together with future research directions that could be carried out.

5 CONCLUSION

5.1 Summary of findings and conclusion

For the purpose of this thesis, over 830 articles have been reviewed. Not only is there a rising increase in the use of AI in healthcare, but research of AI and its true capabilities has expanded into nearly all areas of medicine. From a practical sense, AI is currently being incorporated into the global healthcare infrastructure to support administrative tasks and reduce workloads of the doctor and other healthcare stakeholders. But this thesis has provided a true reflection of how the FIR, through the adoption of AI, is revolutionising human activities and healthcare diagnostics from a clinical setting to allowing patients to take control of their own health using AI-driven diagnostic wearables.

Patients are taking back certain elements of control through PCC: they are able to monitor their own biostatistics through diagnostic wearables in the form of WD such as the Apple Watch, Fitbit, and Garmin watch, which has been addressed in the findings of the interviews for the WC. Other WC are using these WD functions to monitor sleep patterns, anxiety levels and accepting notifications prompting a cue to action. Li et al. (2015) say people are in general beginning to pay more attention to their overall health rather than relying on an overworked doctor in a society where it is becoming more and more difficult to easily see, or get access to one, another evolving outcome of this thesis.

While there is much literature around diseases and AI, learnings from this research were fruitful and a depth of valuable information has been gathered. Sadly, the scarcity in the lack of information around patient perception and the use of AI in healthcare diagnostics is greatly missing, despite there being many references to “stakeholders” and “stakeholder findings”. Patients are actually also healthcare stakeholders. A focal point of AI in healthcare diagnostics and an ultimate position is the incorporation of the AI technology into WD, though there has been no true reference to what the patients actually think about this: many of the published studies reference conceptual theories and prototypes for certain severe illnesses. However, global big tech are capitalising on their resources and science to make applications better and more specific to other diseases, as part of home healthcare. By the end of 2022, it is estimated that 67 million people in the US alone will be using WD for heart monitors, pain monitors, for movement disorders and fall sensory devices for the elderly (Wurmser, 2019). The speed of diagnostic application innovation is attracting a lot of interest.

Given the rising demand for healthcare, especially since the COVID-19 pandemic, combined with increased illness in an aging society and an obvious lack of human resources, the use of AI-based diagnostic devices could really help patients, compensating for limited human resources and lack of access to a doctor. This would help to monitor patients’ health in a cost-efficient way. Tian et al. (2019)raise concerns about the lack of knowledge and guidance around the use of AI in healthcare diagnostics, and so did the participants in the NWC research group of this thesis research. Markus et al. (2021) address the overall lack of transparency as one of the major barriers that limit the uptake of AI implementation, and this was also suggested in the results of this thesis research. NWC were reluctant to adopt AI because there was no transparency regarding healthcare data and what it is used for, compared to WC who were not so concerned. This thesis research has focused on the neglected area of consumer perspective and, in line with the TAM and HBM, addressed factors that prompt acceptance and usage of AI and diagnostic wearable technologies.

Having presented the research findings in depth in the previous section, this section will provide a summary of the main findings in relation to the posed research questions included in Section 1. As all the data were collectively and thematically aggregated, the below word cloud in Figure 17 presents the amalgamation of common words used across both the interviews of WC and NWC. The previous sections have already demonstrated word clouds with individual relevance to the results and questions of each group. This word cloud below provides a collective overview and captures the language used throughout the whole of the interview transcripts.

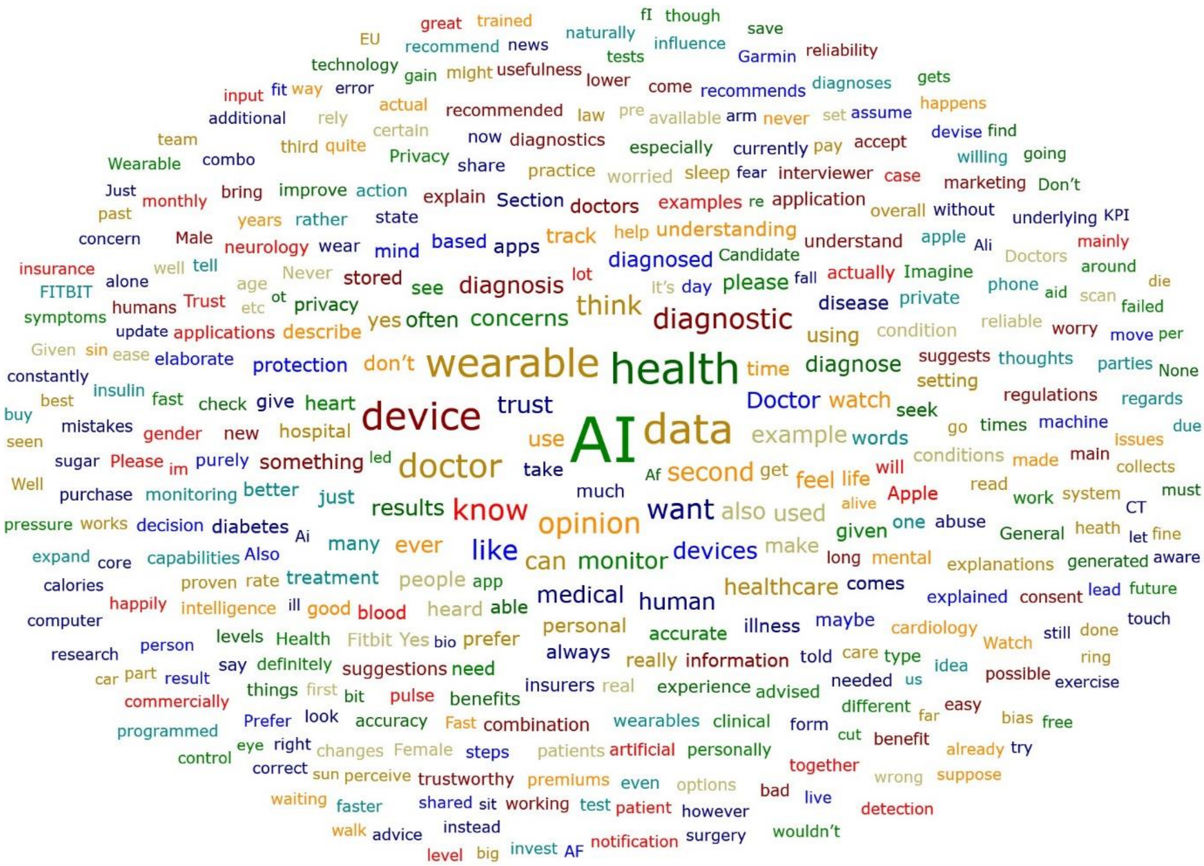

FIGURE 17 WORD CLOUD REPRESENTING AMALGAMATION OF COMMON WORDS USED BY BOTH WC AND NWC IN THE SURVEYS

RQ 1 What do patients think of AI in healthcare diagnostics?

Collectively, there is an apparent mixture of opinions and thoughts between WC and NWC regarding AI in healthcare diagnostics. Understandings about AI and its diagnostic capabilities, from a clinical setting through to the functionality of AI driven WD, varied between the two groups. The overall outcome was that WC think much more positively about the use of AI in healthcare diagnostics, from both clinical settings to WD. The positive attitudes of WC were reflected in their answers and suggestions of how AI could improve healthcare, from monitoring illnesses and conditions to improving patient care, speed of diagnostics and even suggesting new and improved targeted treatment plans. WC were encouraged by their WD and were happy that AI applications had proven to be accurate in line with their sporting performance, achieving personal bests through to the monitoring diseases like in AF, diabetes and chronic anxiety. WC acknowledged the *benefits and or effectivenes*s of AI especially in their WD, in turn acknowledging construct three of the HBM. In line with construct five of the HBM, WC accepted the *cue to action* stimulus of their devices to make changes or act accordingly, and demonstrated construct six of the HBM *self-efficacy, ability to interpret and understand their results.* While many WC did not have an active illness, they believed that AI through their devices could help them prevent illness of certain forms, for example diabetes or stress-related anxiety. WC believed that AI is certainly the future of healthcare if used in synergy with doctors and that more doctors should not dismiss the proven accuracy of certain WD, for example Fitbit and Apple Watch, whose testing has provided a high level of sensitivity and specificity compared to the gold standard benchmarks such as ECG. WC said that doctors should encourage self-health monitoring and accept the results patients present to them, generated by their WD, especially if their physical symptoms reflect the results of their WD: for example, increased blood pressure and fast pulse, manifested in the physical form of chest and arm pains. WC did not believe that AI will become fully automated in healthcare and that human input will remain central to adoption. NWC exuded concern, doubt and reluctance to accept the full capabilities of AI in healthcare diagnostics, reinforced by the constant questioning of trust, reliability, accuracy and truth. NWC, at this time of their lives, did not have a WD, nor were they aware of the true diagnostic capabilities of AI in diagnostic healthcare. They were shocked as to what extent and in which diseases AI plays a central role.

RQ 2 What factors are driving patients to adopt digital diagnostic wearables to monitor their own health, and why?

WC were already health conscious; their attitude was more of prevention that cure. WC all said that, due to the influx of various WD within an ever-increasing tech market, WD are a commodity that should be used. WC were not concerned about the price, but more interested in the new upcoming diagnostic functions. However, NWC would only adopt WD if it was free, suggested by their doctor and if they had a debilitating serious disease reflected in construct one of the HBM *perceived susceptibility*. Most of the NWC said wearing a diagnostic device to predetermine their overall health in real time and track deterioration would be of benefit. Meanwhile, other NWC preferred not to know hence would not wear a diagnostic WD because they believed they would only be spending their days living in fear of a WD alert or alarm.

What was surprising was that the NWC group were not particularly health focused. Candidates had a dismissive attitude to monitoring their health to improve self-care, because they were asymptomatic of all illness and diseases. While the NWC mainly consisted of ladies of a perimenopausal age, a driving factor for consideration to adopt a WD was definitely hormone diagnostics. Furthermore, NWC would accept a WD based on doctor recommendations and wanted easy to use , simple devices if they were necessary, nothing too fancy compared to the sophisticated AI desires of the WC, who were clearly mentally invested in their WD.

RQ 3 What factors are hindering people to adopt the use of wearables diagnostic devices and what are the main concerns as to why they have not adopted these technologies?

This question specifically relates to the NWC. From a lack of awareness and understanding about AI, through to issues concerning trust, data security, data privacy, abuse of data and reliability of AI , these can be concluded as the main hindering factors preventing adoption of a WD in the NWC group. Hindering factors were not really from a price point perspective, because despite all NWC wanting a free WD based on recommendations of a doctor, should they have a chronic condition, although NWC were actually prepared to buy a WD as there "should not be a price limit on one's health". What was obvious in this analysis was that NWC, to some extent really relied on and trusted what their doctors told them and could not act independently based on their own to buy a WD. Factors identified by most NWC that could influence them were referral and reviews, trustworthiness, the capability of the device, ease of use, and brand name.

RQ 4 How do patients personally feel about being diagnosed by AI rather than a doctor?

Despite the plethora of mixed opinions and thoughts across both groups regarding AI and its perceived strengths and weaknesses, concerns, threats and pitfalls, a very surprising reveal occurred with a focus to this research question. Separating the level of knowledge and understanding between the groups, **ALL** candidates that were interviewed wanted to be diagnosed by a doctor and not AI. The trust of patients has an important role in the doctor–patient relationship (Yang & Chen, 2018) and all candidates demonstrated trust in doctors. This research question was split across primary AI diagnosis versus primary doctor diagnosis, compared with a combination using doctor and AI (or simply just a team of medical specialists). NWC were happy to have a combination diagnostic like the work of Morley et al. (2020) view AI as a co-operative "accessory" to healthcare, complementing rather than replacing clinicians. Health problems are not easy to treat without some element of human emotions. AI does not express human emotion, like the work of Mbunge et al. (2022) suggests. Improved patient satisfaction is linked with patient counselling as well. AI-based devices are emotionless; they can give certain health monitoring results efficiently, but cannot give a feeling that a doctor's words and touch can give to the patients. These devices are not able to respond to the pain feelings, expressions, sign language, and other related inputs. It is a big challenge, which can only be done by the doctors, so simple AI diagnostic alone is not as personal.

RQ 5 What are the frequent applications of AI in wearable devices and what would people want to see in the future?

The type of diagnostic applications was the same in the WC group: every subject was using a WD in the form of an Apple Watch, Fitbit or Garmin: nobody used Oura rings. All candidates had exactly the same diagnostic capabilities incorporated into their devices, except the diabetic patient who has a bespoke item of AI-driven technology actually linked to an internal implant in his pancreas and which was sending real time data alerts to the hospital. However, despite the differences in the WC and NWC and their opinions, the responses to this research question were very interesting. Putting aside the dismissive and doubting attitudes of the NWC to AI in healthcare diagnostics, when asked what applications would they like to see in the future that would encourage them to adopt AI WD, or increase your uses of diagnostic devices, both groups gave mirror answers. All candidates wanted to see the following diagnostic capabilities:

- Neurological diagnostic functions to detect PD, dementia or other neurological illnesses associated with age
- Hydration detection though biosensory function to encourage people to drink more water
- Ketone secretion for those who followed a low carbohydrate diet to prevent diabetes, where the level of ketones can be detected in the skin not from urinating daily on a ketone test
- Vitamin D diagnosis, because all candidates had been diagnosed with vitamin D deficiency especially the ladies, and surprisingly all the men too
- Hormone diagnostic applications were a desire, as previously mentioned in the other sections
- Thermometer to detect fever and illness (this was suggested mainly because of COVID-19)
- Retinol diagnostics
- Sleep apnoea

Overall, this research investigation met all the constructs of the theoretical underpinning of the TAM and HBM models and bridged an important gap in research. In conclusion, AI in healthcare diagnostics is not only a nice to have it will soon become a need to have.

5.2 Limitations of present research

This research investigation provided some valuable insights into the patient perspective across two defined group of candidates, NWC and WC. Despite gaining an abundance of information, the research itself did have some limitations. The researcher was not included in this study due to following interview guidelines and to reduce bias.

Firstly, the sample size of interviewees included only 17 candidates. For this thesis 17 seemed reasonable for qualitative purposes to identify a new exploratory gap through deductive literature findings. However, due to the small sample size, it meant that, in line with qualitative research guidelines, to cross compare the cases of NWC and WC, between ages, and genders for each topic was not possible. It would have been better to have over 30 candidates though this was not possible, therefore a cross-case analysis of comparisons could not be made. Secondly, a snowball sampling method was carried out because it fitted the purpose of the investigation and was a perfect way to recruit candidates through a network approach, which turned out well to interview real candidates with AF, Diabetes type 1 and chronic anxiety in the WC analysis. Snowball sampling is a non-probabilistic approach, meaning that not every candidate in a true population has an equal probability of being selected. Because snowball sampling is not a random selection of samples compared to other methods, unlike a probability sampling it is difficult to make generalizations as it is not a true representation of the population being studied. While this was a qualitative research study to bridge a gap in literature about the patient perspective and the use of AI in diagnostic health care, future ideas and further research methods evolved inductively while writing this thesis.

5.3 Future research

Having formed a foundation already through the exploratory inductive interviews' research, any future research based on this topic should use a different approach to fill the void mentioned above in the limitations section. Firstly, future work should incorporate a Mixed Methodology (MM) approach, combining elements of Qualitative (QUAL) and Quantitative (QUAN) viewpoints and research techniques. Larger sample sizes should be used and a different sampling method selected; for example, simple random sampling, stratified sampling or other probabilistic methods. A MM would permit a more complete and synergistic utilization of any larger sets of data findings than either a separate QUAN or QUAL research design, based on the outcome and findings of this thesis. Using a future MM approach, data collection analysis and inference techniques will give a broader purpose of breath, depth, understanding and corroboration across the variables identified in the QUAL part of a design. Ultimately, MM research is about heightened knowledge and validity. A MM will give multiple validities (Johnson & Christensen, 2016). Furthermore, with reference to Greene (2007), a MM will allow capture of more data to triangulate. The credibility of using a MM could enhance the integrity of existing qualitative findings from this thesis, building on cases to improve the adaptation and understanding of AI in global healthcare. Finally, as this research was conducted with UK-based citizens only further research could include an investigation into cultural differences in a larger and even international group.

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APPENDICES

Appendix 1: Information sheet

Qualitative Analysis Briefing Document for Research Questions

This is a market research questionnaire to investigate peoples understanding of Artificial Intelligence and its uses in diagnostic healthcare. This research will also examine peoples' understanding of AI and how it is used in their commercially available wearable devices such as FITBIT, Apple watches and so on. What diagnostic applications do they have and why used them? This is a confidential survey for marketing purposes. All interviews will be recorded, transcribed and all answers will be anonymous.

The following questions will be addressed and all relevant additional key findings will be used to create further sub questions, reflected in the results.

Research Q 1 What do patients think of AI in healthcare diagnostics?

Q 1.1 What do people think AI is sub question finding

Research Q2 What factors are driving patients to adopt digital diagnostic wearables to monitor their own health and why**?**

Research Q3 What factors are hindering people to avoid the use of wearable diagnostic devices and

Q 3.1 What are the main concerns why they have not adopted these technologies?

Research Q 4 How do they feel about being diagnosed by AI compared to a human/Doctor**?**

The following statement was read to the candidates when they needed some more understanding after they had answered Question 1, describing AI in their own words AI for more clarification

Artificial Intelligence is all around us taking shape in many forms that most people are unaware of. Artificial Intelligence is often referred to as AI. AI is the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions. AI may also be applied to any machine that shows behaviours associated with a human mind, such as learning and problem-solving. AI has become central to ever-changing and evolving healthcare, improving the diagnostic capabilities for diseases, predicting disease progression, and even being used to suggest treatment plans. AI is also taking an important role in surgery to train doctors and perform intricate operations, and sometimes replacing humans. AI is included in the health diagnostic and monitoring capabilities of digital wearables. Digital wearable devices come in the form of watches, rings, arm bands, sensory clothing or even as inserts in the soles of shoes for people with stability and postural issues. They collect your data, monitor your biometrics, and suggest improvements to improve your health.

Appendix 2: Consent form

MODUL UNIVERSITY
PRIVATE UNIVERSITY VIENNA

Re: Informed Consent Letter

Dear ________________________________

I am currently a student at Modul Private University Vienna and I am completing my research in the fulfilment of an MBA.

This research is to investigate what people think about the use of artificial intelligence in healthcare diagnostics and in the form of a wearable device that can monitor health statistics and biometrics.

Your participation is voluntary, and you can withdraw at any time without penalty.

With your permission the interview will be recorded. The recordings will be transcribed, and all findings will be presented anonymously using only your gender and age, no names will be used. All data once presented to the end reader in a report format will be deleted not to be reused again. If you have any concerns, please feel free to reach out to my supervisor or myself. Our details are provided below.

Researcher name:

Emma Miller

Email: 61902990@modul.ac.at

Research Supervisor:

Professor Marion Garaus

Email: marion.garaus@modul.ac.at

Signature of participant: ________________________________

Date: ________________

Appendix 3: Interview Questionnaire - Wearable Candidates

Wearable Candidate Questionnaire

General information

What is your gender Male/ Female /Transgender/Prefer not to say

Please state your age

Section 1 Background

1. **In your own words please describe what you think AI is?**
2. **How often have you heard the words "AI or AI results" in a hospital or medical practice?**
3. **Having explained what AI is (*further explanations were given by the interviewer as diagnostic examples for example in cardiology, neurology, diabetes, mental health) and from your understanding of AI, would you prefer to be diagnosed by a doctor or by something using AI?**
4. **Why?**
5. **What would you like to know more about when AI is used in a clinical setting to diagnose your health conditions?**
6. **Why?**
7. **Imagine you have an illness and you have been diagnosed by a doctor, but you want a second opinion. Would you also seek a second opinion if your diagnosis was made purely from AI?**
8. **Why?**
9. **Would you want an AI second opinion or a combo of AI and human?**
10. **What benefits do you think AI would have in diagnostic healthcare?**
11. **What concerns do you have?**

Section 2 Health and wearables

1. **How would you describe what a wearable device is and what comes to mind?**
2. **Have you ever been advised by your doctor to track your own heath with a wearable device?**
3. **If yes, which wearable devices have been recommended to you and why?**
4. **Do you have a wearable device that you are currently using to track your health? If yes which one?**
5. **What health or diagnostic apps do you have**?
6. **Why do you have these apps?**
7. **How often do you check them or rely on them?**
8. **How do you perceive ease of use and usefulness of your wearable device?**
9. **Do you trust your device? Why - please expand and give an example if possible?**
10. **How often does your device recommend and make health diagnostic suggestions or changes and please give example**?
11. **What action do you take action when it recommends suggestions**?
12. **How does your wearable device make you feel with regards to your health?**
13. **What are your thoughts of wearable devices being able to diagnose and track your own medical conditions and why?**
14. **What additional diagnostic apps do you want to diagnose your health?**

Section 3. Trust and Privacy

1. **Have you ever heard of the data protection regulations or would you like me to explain them?**
2. **What is your understanding of data protection where your health care data is stored: please elaborate**?
3. **How often do you read the data privacy laws in your wearable apps and device? If not, why not?**
4. **How do you feel that AI is core to all your devices and collects your data?**
5. **What would you like to know about how your stored health data?**
6. **Have you ever worried about abuse of your personal health data and why?**
7. **How would you feel if your private wearable device data were given to insurers to lower your monthly health premiums?**
8. **Why?**
9. **What are your main trust and privacy concerns about AI in healthcare diagnostics in the form of wearable devices?**

Appendix 4: Interview Questionnaire - Non-Wearable Candidates

Non-Wearable Candidate Questionnaire

General information

What is your gender Male/ Female /Transgender/Prefer not to say

Please state your age

Section 1. Background

1. **In your own words please describe what you think AI is?**
2. **How often have you heard the words "AI or AI results" in a hospital or medical practice?**
3. **Having explained what AI is (*further explanations were given by the interviewer as diagnostic examples for example in cardiology, neurology, diabetes, mental health) and from your own understanding of AI: in a hospital or surgery setting , would you prefer to be diagnosed by a doctor or by something using AI and why?**
4. **What would you like to know more about if AI is used in a clinical setting for your diagnosis?**
5. **Imagine you have an illness and you have been diagnosed by a doctor but you want a second opinion. Would you also seek a second opinion if your diagnosis was purely from AI and why?**
6. **Would you want an AI second opinion or a combination of AI and human working together OR just a human and why?**
7. **What benefits do you think AI would have in diagnostic healthcare?**
8. **What concerns would you have and why?**
9. **Given the diagnostic capabilities of AI how do you feel if AI were to suggest treatment options to patients instead of a doctor based on his or hers own personal experience?**
10. **If a doctor has an opinion and AI has an opinion, who would you trust more and why?**

Section 2. Health and wearables

1. **How would you describe a wearable device and what comes to mind?**
2. **Have you ever been advised by your doctor to track your own health with a commercially available wearable device?**
3. **Why do you NOT have a wearable device?**
4. **How would you feel if your doctor told you that you needed to invest in your own wearable device to monitor your health?**
5. **How much would you be willing to pay for your own wearable device if it could improve your overall health and monitor your disease and diagnose yourself ?**
6. **What would influence your decision and why?**
7. **Do you know many people with a wearable device to monitor their health and if so what for?**
8. **What are your thoughts of wearable devices being able to diagnose an unknown underlying medical condition?**
9. **What diagnostic applications do you think would bring a benefit to you if you were to purchase a wearable diagnostic device in the future and why?**

Section 3. Trust and Privacy

1. **Have you ever heard of the data protection regulations or would you like me to explain them?**
2. **What is your understanding of data protection when it comes to your personal healthcare data: please elaborate?**
3. **What type of concerns if any WOULD you have about your health data generated from a wearable device?**
4. **Why do you or do you not have these concerns?**
5. **Have you ever worried about abuse of your personal health data and why?**
6. **Would you happily share your health wearable data with consent to third parties such as insurers?**