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FACTORS AFFECTING THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN HEALTHCARE

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ABSTRACT

This paper investigates how clinicians perceive the usefulness and the ease of use of Artificial Intelligence (AI) in healthcare. The paper aims to understand whether AI solutions are perceived to have a positive impact on patient care and the clinician' work, and which factors affects the adoption of AI in healthcare. The paper draws upon key concepts of TAM (Technology Acceptance Model), adopting an exploratory approach. Semi-structured interviews with 22 clinicians from the NHS (the National Health System, in the United Kingdom) reveal that they perceive the usefulness of AI for healthcare (better efficiency, healthcare quality, and diagnostic accuracy). However, respondents point out factors which affect the way they perceive the ease of use of AI, such as the difficulty to integrate the technology within healthcare systems (low compatibility) and to understand the technology (high complexity), concerns with ethical issues, and the need to have intensive training on digital skills.

JEL: M100

KEYWORDS: Artificial Intelligence, Healthcare Systems, UK NHS, Technology Acceptance Model

INTRODUCTION

The diffusion of Artificial Intelligence (AI) across the many industries has been highlighted as one of the key pillars of the Fourth Industrial Revolution (Schwab, 2017). The expectation is that AI is going to affect most industries and professionals whose tasks may be automated totally or partially by intelligent technologies (McAfee and Brynjolfsson, 2017; Schwab, 2017). This research focuses on the healthcare sector, which is expected to be very affected by the diffusion of AI in the next years.

Industry and academic researchers have pointed the relevance of AI in the healthcare systems. In the United Kingdom, the Topol Review (2019) says AI is expected to transform the NHS (National Healthcare Services), bringing more efficiency, streamlining, and automating processes, improving diagnostic accuracy, and enabling the personalization of treatments. Intelligent technologies are substituting human expertise in areas that before were thought to be impossible or unlikely (OCDE, 2020; García et al., 2020; Topol Review, 2019; Yu et al., 2018; and Jiang et al., 2017). The interest on the impact of AI in the healthcare sector in the United Kingdom has increased substantially since the Topol Review (2019) has concluded that AI is a force for good in the improvement of patient care and service delivered. Following this call, this paper aims to investigate the perception of UK NHS clinicians about adopting AI solutions, answering the following two research questions:

To which extent UK NHS clinicians perceive the adoption of Artificial Intelligence in healthcare systems as a positive change to improve their own work and services for patients?

Which are the factors fostering and hindering the adoption of AI solutions in the UK NHS?

This paper is organized as follows. The second section introduces a literature review on AI applied to healthcare systems and a theoretical perspective which helps to investigate the research questions, based on TAM (Technology Acceptance Model) and the literature review on AI for healthcare. The third section introduces the data and methodology, based on semi-structured interviews, explaining the exploratory nature of the research. The fourth section presents results, reconnecting the discussion with the theory and previous research. The last section summarizes key findings and recommendations.

LITERATURE REVIEW

A literature review on the impact of AI in healthcare systems reveals that intelligent technologies perform some clinical tasks better, faster, and cheaper than highly trained experts in same functions. The association of big data related to healthcare and new AI techniques (machine learning and deep learning) have enabled automation in areas which were before restricted to human expertise (Yu et al., 2018). The applications of AI are expected to be useful in the virtual level, for instance, for better maintenance and understanding of patient records, diagnosis, and treatment, and in the physical level, for instance, with the use of robots in surgeries and intelligent prosthetics (Amisha et al., 2019).

Automated diagnoses, for instance, have allowed better allocation of resources to improve the quality of medical interventions (Panch et al., 2019; Topol Review, 2019). AI has huge potential for improving the quality and speed of imaging screening (e.g., cancer diagnosis), when the combination of human experts with automated pattern recognition improves the diagnosis (Rodriguez-Ruiz et al., 2018). In the long run, the association of big data with individual detailed records will enable AI to support the provision of personalized medicine (Dilsizian and Siegel., 2013).

AI can help healthcare professionals to free time for direct patient care (García et al., 2020). Scholars have also pointed out the relevance of AI for improving healthcare for societies with aging populations, when AI collects and analysis information from sensors (e.g., wearables) and transmit patient's information in real-time, providing care when and where it is needed (Yamada and Lopez, 2012; Topol Review, 2019). Similar reasoning is applied for AI solutions for chronically ill patients (Darwish and Hassanien, 2011).

However, to be successful, the introduction of AI should take into consideration broad aspects of healthcare systems, such as their social, economic, political, and commercial aspects (García et al., 2020; Panch et al., 2019). In the discussion of privacy, for instance, there are questions on how personal information is to be used and the degree to which data related to individuals is treated with the right level of security (OCDE, 2020; Vellido, 2019; Topol Review, 2019). The risk of data leakage increases when wireless technologies are used for data collection, for instance (Al Ameen et al., 2010).

Risks of low data quality or biases also affect the expectations about the use of AI in healthcare (García et al., 2020; OCDE, 2020). AI brings new expectations for quick and accurate diagnosis, which may increase the number of errors particularly because the increasing complexity of electronic health records may be overlooked (Dilsizian and Siegel., 2013). To reduce the error margin of AI applications for healthcare, it is recommended that the human experts check diagnosis and prescriptions; indeed, the results of AI solutions associated with human experts are the more accurate in the current state of technology development (Liew, 2018; Topol Review, 2019).

From a theoretical perspective, the literature review reveals a useful conceptual framework to explore the willingness of individuals for adopting new technology: the Technology Acceptance Model (TAM) (Davis, 1986). The model prescribes that the intention to adopt new technology depends on the way individuals perceive its usefulness (Perceived Usefulness – PU) and its ease of use (Perceived Ease of Use – PEOU) (Lee et al., 2003; Venkatesh et al., 2003). TAM has been used to understand all sorts of technology adoption, including innovations in the healthcare sector (Beldad and Hegner, 2017; Gagnon et al., 2012).

This research proposes to interpret the concepts of Perceived Usefulness and Perceived Ease of Use in accordance with seven constructs, which are framed in accordance with the relevance of topics in healthcare systems, as presented in Table 1 – the 7 Pillars of AI in Healthcare (7PAI) framework. The proposed 7PAI framework is based on TAM concepts of perceived usefulness and perceived ease of use and interpreted and complemented by the literature review on AI for healthcare systems.

Davis (1986) defines Perceived Usefulness as the extent to which an individual believes a technology would improve their job performance. This research investigates Perceived Usefulness through the constructs: (i) efficiency; (ii) healthcare quality; and (iii) diagnostic accuracy. Davis (1986) defines Perceived Ease of Use as the extent to which an individual expects that using a new technology will be free from effort. This research investigates Perceived Ease of Use through the constructs: (i) compatibility (how AI integrates with other systems); (ii) complexity (how difficulty is to understand AI solutions); (iii) training (required for adopting AI); and (iv) ethics (related to the use of AI). These seven constructs emerged from the literature on AI for healthcare (García et al., 2020; OCDE, 2020; Topol Review, 2019) and diffusion of innovation in healthcare settings (Dearing, 2010; Rogers, 2003).

Table 1: The 7 Pillars of AI in Healthcare (7PAI) Framework

Key Concepts	Constructs
Perceived Usefulness	Efficiency
	Healthcare quality
	Diagnostic accuracy
Perceived Ease of Use	Compatibility
	Complexity
	Training
	Ethics

Traditionally, TAM is a mathematical model used for test of hypotheses. This research though uses TAM conceptually only. As this research is exploratory in nature, it uses TAM key concepts – Perceived Usefulness and Perceived Ease of Use – to understand how clinicians perceive the usefulness and ease of use of AI solutions, aspects which affect their willingness to adopt such technologies.

DATA AND METHODOLOGY

This paper follows an interpretive perspective (Mason, 2002) to understand how UK NHS clinicians perceive the adoption of AI solutions in healthcare. The paper adopts an exploratory approach (Saunders, Lewis and Thornhill, 2009), considering the objective of understanding in depth the drivers and challenges for adopting AI solutions in the UK NHS. The paper is informed by theory (deductive approach), from the formulation of research questions to data coding and analysis, exploring a range of interpretations for each construct (Flick, 2002; Mason, 2002).

Primary data was obtained through semi-structured interviews (Flick, 2002; Pole and Lampard, 2002) with 22 UK NHS medical professionals (trauma surgeons, general practitioners, and medical educators). The sampling method has followed a purposive strategy (only clinicians capable of answering questions on AI solutions have been consulted) and convenience strategy (researchers have used their personal connections to get access to professionals) (Saunders, Lewis and Thornhill, 2009). The convenience strategy was instrumental to get access and time from health professionals in a year of pandemics (data was collected during June and July in the UK through online interviews).

The semi-structured interviews were based on the interview guide (open questions), focusing mainly on the proposed constructs presented in the 7PAI framework: Perceived Usefulness (efficiency, healthcare quality, and diagnostic accuracy); and Perceived Ease of Use (compatibility, complexity, training, and ethics). Interviews lasted 45-60 minutes. Respondents received the interview guide prior to meetings. Interviews were recorded with the consent of respondents and later transcribed and anonymized (Flick, 2002; Mason, 2002). Respondents have received a copy of their transcripts for approval, for improving research reliability (Silverman, 2006). The research validity emerges from the theory-driven formulation of questions, constructs, and coding systems, and the comparison and validation of findings with previous research and theory (Gray, 2016; Silverman, 2006). The coding was based on the 7PAI Framework, particularly looking for the concepts of Perceived Usefulness (efficiency, healthcare quality, and diagnostic accuracy), and Perceived Ease of Use (compatibility, complexity, training, and ethics).

RESULTS

This section presents the findings, following the structure of the 7PAI theoretical framework. First, it introduces results related to the Perceived Usefulness, considering the constructs efficiency, healthcare quality, and diagnostic accuracy. Second, it introduces the results related to Perceived Ease of Use, considering the constructs compatibility, complexity, training, and ethics.

Perceived Usefulness

The findings demonstrate that respondents have a positive perception of the usefulness of AI solutions for healthcare, confirming they expect AI to contribute to efficiency, healthcare quality, and diagnosis accuracy. Overall, the respondents have a positive view of the usefulness of AI solutions, with a few areas of concerns. These three aspects are discussed below.

In relation to *Efficiency*, respondents confirm their expectation that AI solutions improve efficiency in healthcare systems (90% of respondents). For instance, there is an expectation that AI may automate administrative tasks, streamlining health records across institutions (hospitals, trusts, GPs). In the frontline, AI solutions could automate the checking of vital signs and the administration of medication. Introducing AI to operate routine tasks would free time for health professionals to focus on patients (an aspect which is also relevant for the construct healthcare quality).

Covid-19 pandemics reinforced hopes that AI solutions will improve efficiency in GP settings. The expectation is that AI algorithms will be able to diagnose people remotely, avoiding the need to go physically to consultations. In addition, AI algorithms may indicate when a patient is more likely to need additional care. Respondents expect that AI solutions would reduce the number of patients in GPs, without affecting the quality of healthcare, freeing time for attending those patients who need most.

Some respondents (10%) are though cautious AI alone for diagnostic, arguing that critical decisions must be made by physicians. These respondents would recommend AI solutions for corroborating expert opinions, but not for substituting them. Respondents in this group highlight that some patients need empathy and compassion, pointing out that efficiency goals may not be a good idea in all settings. Contrasting both views, of those who are more positive about the impact of AI in efficiency and the others with a more cautious view, it emerges that there are issues of trust in the technology (thus the human expert must be there) and the limitations of technology when emotional intelligence is required (a topic which also emerge when discussion the healthcare quality). These may be barriers for scaling AI within the healthcare sector, as they limit the Perceived Usefulness of the solution.

The literature confirms these findings. AI-led automation could affect 35% of healthcare jobs, freeing time for professionals to direct care to patients (García et al., 2020) and increasing productivity (Pearson, 2017).

The Topol Review (2019) suggests AI is going to automate image recognition in radiology and pathology, freeing health professionals do deliver care. AI applications in the back office (e.g., scheduling and billing) could have an immediate impact in gaining efficiency (OCDE, 2020), as well as automating drug administration (Forlenza, 2019), and speeding up data processing (Ahuja, 2019; Amisha et al., 2019; Dilsizian and Siegel, 2013). However, it is also necessary to discuss AI principles and governance rules to increase trust in AI solutions (García et al., 2020; OCDE, 2020), keeping human experts on charge of decision making (Liew, 2018).

In relation to *Healthcare Quality,* there are two competing interpretations of the impact of AI solutions, both supported by previous research. The views demonstrate that practitioners are not yet clear about the place and scope for AI solutions, although the perceived positive impact is more pervasive (85%). On this fashion, some professionals expect that AI solutions are to improve the healthcare quality. For instance, the Babylon Health, an AI solution which uses NHS algorithms to provide rapid triage advice during the Covid-19 pandemics. This AI technology reduced the backlog in the first line of healthcare.

On the other hand, some respondents (15%) have a negative expectation that AI solutions are going to change the role of physicians, reducing the quality of patient care. For this group, the main concern is about decision making. Aware that AI algorithms are not yet perfect (if they are to be one day), and that AI algorithms are based on complex databases, these respondents believe human brains are still better prepared to match the domain knowledge with the needs of a patient. This negative interpretation is associated with the fear that AI solutions are going to be left alone to make decisions on diagnosis and treatments, which could increase the risk of mistakes for lacking human supervision.

The literature confirms both interpretations among healthcare professionals. Airon and Jhunjhunwala (2020) say that AI solutions may shift the healthcare system from the frontline of reaction to pre-emptive care, improving healthcare quality. Patients would be advised as earlier as the first warning indicators would point out the need for care, instead of later when health conditions have deteriorated (García et al., 2020; Topol Review, 2019). Healthcare systems could allow patients to be treated in clinics or their home, instead of hospitals, through using remote monitoring technology (Airon and Jhunjhunwala, 2020) and Natural Language Processing (García et al., 2020). Dilsizian and Siegel (2013) emphasise that AI may match big data with personalized data, reaching personalized medicine.

On the other hand, research links healthcare quality with human-centric emotional characteristics, such as empathy, experience, and instinct (Davenport and Kalakota, 2019). If the quality of healthcare is perceived by patients as being related to emotional interactions with professionals, AI solutions could not substitute humans in the frontline. There are also questions about the precision of AI decisions and the mechanisms to validate these decisions (García et al., 2020; OCDE, 2020; Topol Review, 2019).

In relation to *Diagnostic Accuracy*, respondents (75%) have high expectations that AI solutions are to improve the accuracy of diagnosis, although some others are more cautious about how much it can be improved. The more prevalent perception is that AI solutions are useful for improving detection, diagnosis and clinical decision making. For instance, in the Covid-19 pandemics, AI solutions were used for diagnosis. The consensus is that AI solutions should be used for supporting physicians, not for substituting professionals (similar idea expressed about healthcare quality). The question is whether AI solutions should be left alone for making decisions on diagnoses. When the matter is critical, respondents do not want to allow AI to make decisions alone. Their perspective is that in critical decisions, AI can be used to corroborate experts, instead of substituting them. The physician would keep the central role in diagnosing, with the benefit of having a second opinion (from AI).

The literature has examples in which AI algorithms are better and faster than humans in analyzing complex images for diagnosing diseases such as cancer (pattern recognition) (García et al., 2020; Dilsizian and

Siegel, 2013; Pearson, 2017; Watanabe et al., 2019). In the Covid-19 pandemics, AI solutions had a role to get accurate diagnosis (Mei et al., 2020). However, research also validates that better diagnostic accuracy is reached when AI solutions are combined with human expertise (Rodriguez-Ruiz et al., 2018; Watanabe et al., 2019). Dilsizian and Siegel (2013) concludes that if the system's recommendations are not validated by clinicians, a further scrutiny is necessary. AI cannot be left alone for making decisions on diagnosis and treatment (García et al., 2020; Liew, 2018).

<u>Perceived Ease of Use</u>

In this research, Perceived Ease of Use is assessed by investigating how respondents perceive the challenges for adopting AI solutions in the UK NHS healthcare system. The four constructs related to the concept are: compatibility, complexity, training, and ethics. These four aspects are discussed below.

In relation to *Compatibility*, respondents (95%) say that there are logistical challenges to integrate AI solutions to NHS technical platforms and processes, creating a compatibility problem for the adoption of AI. Respondents see obstacles in the level of *technical infrastructures* (either AI cannot be integrated, or it is difficult to integrate), *operations* (difficulties to integrate AI to current processes or to change processes to make integration possible), and *management structures* (lack of understanding on the role of AI vis-à-vis of professionals in information processing and decision making).

Respondents say that NHS technological platforms are fragmented, with a multiplicity of applications across trusts or units of delivery, which make the integration of new systems a coordination challenge. Operational practices vary significantly depending on the unit of delivery (hospitals, trusts, GPs etc.). There are still units which process documents and data manually, thus the difficulty in adopting AI solutions extensively at national level, which would benefit from gaining scale and access to data. It is more likely that the adoption of AI will follow the usual case-by-case approach.

The difficulty of adding new technological layers to NHS platforms is recognized by the literature (Topol Review, 2020). Castle-Clarke (2018) reports that data on diagnosis and treatments and administrative data on resources usage are not integrated in NHS systems. This lack of integration has been associated with poor service in primary social and healthcare services. AI cannot help much if information is not accessible in electronic and integrated format (García et al., 2020; OCDE, 2020). The Topol Review (2019) identifies the need to have better integration of data across the NHS for improving the outcomes of using AI. García et al. (2020) also discuss data integration, availability, and governance as success factors for the diffusion of AI in healthcare systems.

In relation to *Complexity*, the adoption of AI solutions depends on how healthcare professionals understand its complexity. The fact that AI is considered complex to be understood creates a barrier for its adoption, as professionals perceive the technology as not being easy to use. Respondents confirmed these concerns, with many perceiving AI solutions as having high technical complexities (50% of respondents), which are not understood either by healthcare professionals or by managers and directors in healthcare systems.

Despite recognizing AI complexities, other respondents (50%) consider that one does not need to understand the AI algorithm to perceive its advantage and ease of use. These respondents have a pragmatic approach about how to cope with AI complexity: they focus on the interface and results instead of on algorithms. However, the question remains: how may health professionals trust AI recommendations if they do not understand of the AI algorithm? In this line, these respondents question how it would be possible for the medical professional to explain a diagnosis or treatment recommendation done by AI solutions to patients if they are not able to understand how the algorithm works. In practice, patient groups could not accept AI diagnosis if they do not trust doctors are agreeing and understanding what should be done.

The literature confirms that the use of AI solutions for diagnosing may affect the level of trust between physicians and patients (La Rosa and Dank, 2018). When the AI solution reduces the relevance of doctors in the decision-making process, the impact is higher. The Topol Review (2019) acknowledges healthcare professionals face challenges to understand the AI complexity and suggest more training, for instance, to understand how AI can be used (see section below). García et al. (2020) highlights that a substantial number of healthcare professionals have never been involved in the development or deployment of AI technologies.

In relation to *Training*, it comes as no surprise that all respondents expect that AI adoption depends on extensive training for physicians. The perception of the complexity of the technology and the lack of understanding demonstrate that AI solutions are not easy to use without proper training. For respondents, training will make physicians more technologically savvy. Some suggest that medical teaching should incorporate training on AI solutions, enabling doctors to understand the actual potential of the technology. Only then it would be possible to scale up the adoption of AI in the NHS.

The literature confirms this interpretation. The Topol Review (2019) suggests the healthcare workforce must be trained to gain higher digital literacy. The report says that AI is to be used to augment the skills of the NHS workforce, which would require staff to understand data validity and accuracy. Those better trained would be able not only to identify the best AI solutions but also to champion their benefits to colleagues. Other reports reached same conclusions that healthcare professionals need better skills on AI machine learning and data science; however, they also acknowledge healthcare professionals are already under huge pressure to update their knowledge about their core medical practices and other digital skills (García et al., 2020; OCDE, 2020). Ho Park et al. (2019) suggest clinical training should prepare practitioners to be competent users of AI, but this requirement puts pressure on medical schools, as technology changes fast, making training obsolete quickly.

In relation to *Ethics,* respondents highlighted two main ethical concerns which may affect the adoption of AI solutions in healthcare settings, with divergent opinions on both. Concerns on ethics related to AI in healthcare are highlighted by 65% of respondents. There is a risk of AI having biases (depending on the data used by systems). Respondents are concerned that AI could make decisions based on factors such as race, gender, and socio-economic backgrounds, which would result in inequality of care at the point of delivery. Data privacy is also a matter of concern, as hackers may get access to systems.

The literature confirms that ethical concerns related to the risk of AI biases is an obstacle for the adoption of AI solutions in healthcare systems (OCDE, 2020; Reddy, 2019). Reddy (2019) highlights that algorithms may use data that has biases which are to affect the way AI make recommendations. OCDE (2020) emphasizes that AI models may reproduce mistakes, biases and stereotypes embedded in their databases. The literature confirms that patient's data and privacy are important considerations, as the risk of having AI systems hacked inhibits the adoption of AI solutions (Reddy, 2019; Price II and Cohen, 2019). The Topol Review (2019) emphasizes that healthcare professionals should be trained to understand the ethics in AI solutions to allow a better use of technology. The report highlights the relevance of having robust data governance, emphasizing not only the aspect of data privacy but also of data quality, as poor data is to conduct to poor AI-lead decision making.

CONCLUDING COMMENTS

This paper aims to understand whether AI solutions are perceived to have a positive impact on healthcare systems, and which factors foster and hinder the adoption of AI technologies in healthcare. To reach these objectives, this research proposes to answer two research questions:

To which extent UK NHS clinicians perceive the adoption of Artificial Intelligence in healthcare systems as a positive change to improve their own work and services for patients?

Which are the factors fostering and hindering the adoption of AI solutions in the UK NHS?

For answering these questions, this research has adopted an interpretive perspective. 22 NHS clinicians have been interviewed (semi-structured interviews), for collecting their opinion on the adoption of AI in healthcare systems. The interviews were transcribed and coded, using the proposed 7PAI conceptual framework. Results have been organized following the framework structure and compared with the literature review. The key findings are summarized below, by research question.

Question1: To which extent UK NHS clinicians perceive the adoption of Artificial Intelligence in healthcare systems as a positive change to improve their own work and services for patients?

Respondents confirm the adoption of AI in healthcare systems is perceived as a positive change, from the perspective of perceived usefulness. AI solutions are associated with improving efficiency, healthcare quality, and diagnostic accuracy. Respondents focused on the quality of services for patients, but there are also insights about the positive impact on their own work, such as the automation of routine and administrative tasks, freeing time for more sophisticated work and interaction with patients. Respondents emphasize the interaction between AI solutions and clinicians to provide better diagnosis and treatment, acknowledging that technology may improve the quality of their work. However, AI solutions should not be left alone: human experts should confirm AI recommendations.

Question 2: Which are the factors fostering and hindering the adoption of AI solutions in the UK NHS?

Overall, respondents emphasized the difficulties of adopting AI systems. Although the system is perceived as useful, there is not a similar perception in relation to the ease of use. Respondents say there are problems of compatibility to implement AI solutions across the NHS, because of the technical and operational fragmentation of its systems. The complexity of AI systems hinders the understanding of managers, clinicians, and patients, and compromises the trust between patients and doctors. It comes without a surprise that respondents identify extensive training as a way forward to overcome this difficulty in understanding AI solutions, although it is difficult to provide training in a faster moving field. Finally, respondents identify the ethical challenges which make AI solutions less easy to use, such as the risks of having data licking and biased algorithms making decisions on patients.

Considering these answers, this paper points out implications for managers and professionals. Although NHS clinicians identify the usefulness of the AI solutions, the actual adoption of AI will require more work on the grounds of making it to be perceived as easy to use. The NHS would need to invest in training and making technology available in a trial fashion to gain more adopters among clinicians. Particular attention is necessary for clinicians and patients to not lose trust in AI solutions, properly integrating technology with human-centered processes (clinicians to use systems instead of being substituted by systems) and patient-centered care (with clinicians interfacing the care with patients, not automated solutions). Considering these challenges, this research proposes that more training and phased projects which gradually embed AI solutions into NHS systems could be the best approaches to foster AI adoption. These approaches would allow clinicians and managers to better understand the technology, reducing the perceived complexity of systems. It would allow people to verify when AI solutions should be used, and how to integrate technology in their practice (enhancing compatibility). It also would allow a gradual evaluation of benefits and advantages of AI solutions, which would create a virtuous circle of more trained and informed professionals requiring and implementing more AI solutions, and training those colleagues who are adopting the technology later.

This paper has some limitations. The main limitation is the limited number of interviews (22), which could be improved. Additionally, the paper is grounded on the proposed 7PAI framework. With more data, other theories could be tried, and the framework could become more complete. Future research may investigate these findings in depth. The sample of 22 interviews can be expanded for getting a broader understanding of the phenomenon. There must be differences in relation to the current level of knowledge individuals have of AI solutions, which may have influenced responses. Also, the perspectives discussed in the paper are from UK NHS clinicians, who have the privilege of having plenty of resources in a developed country. The perspective may be different in regions which are poor of doctors and healthcare resources. This alternative perspective deserves further investigation.

REFERENCES

Ahuja, A.S. (2019) "The impact of artificial intelligence in medicine on the future role of the physician," *PeerJ*, vol. 7, p. e7702.

Airon, A. and A. Jhunjuhnwala (2020) "Employing AI to Improve Healthcare Delivery," *ORF Issue Brief*, Issue Number 385, July 2020. Observer Research Foundation.

Al Ameen, M. (2012) "Security and Privacy Issues in Wireless Sensor Networks for Healthcare Applications," *Journal of Medical Systems*, vol. 36, p. 93–101.

Amisha, P. Malik, M. Pathania and N.K. Rathaur (2019) "Overview of artificial intelligence in medicine," *Journal of Family Medicine and Primary Care*, vol. 8(7), p. 2328-2331.

Beldad, A.D. and S.M. Hegner (2017) "Expanding the Technology Acceptance Model with the Inclusion of Trust, Social Influence, and Health Valuation to Determine the Predictors of German Users' Willingness to Continue Using a Fitness App: A Structural Equation Modelling Approach," *International Journal of Human–Computer Interaction*, vol. 34(9), p. 882-893.

Castle-Clarke, S. (2018) "What will new technology mean for the NHS and its patients? Four big technological trends," The Health Foundation, The Institute for Fiscal Studies, The King's Fund, and The Nuffield Trust. Accessed on 15/08/2020: https://www.kingsfund.org.uk/sites/default/files/2018-06/NHS_at_70_what_will_new_technology_mean_for_the_NHS_0.pdf.

Darwish, A. and A.E. Hassanien (2011) "Wearable and implantable wireless sensor network solutions for healthcare monitoring," *Sensors* (Basel, Switzerland), vol. 11(6), p. 5561-95.

Davenport, T. and R. Kalakota (2019) "The potential for artificial intelligence in healthcare," *Future Healthcare Journal*, vol. 6(2), p. 94-98.

Davis, F. (1986) "A Technology Acceptance Model for Empirically Testing New End-User Information Systems," *MIT Sloane School of Management*. PhD thesis. Last accessed on 22/11/2020: https://dspace.mit.edu/handle/1721.1/15192

Dearing, J.W. (2010) "Applying Diffusion of Innovation Theory to Intervention Development," *Research on Social Work Practice*, vol. 19(5), p. 503-518.

Dilsizian, S.E and E.L. Siegel (2013) "Artificial Intelligence in Medicine and Cardiac Imaging: Harnessing Big Data and Advanced Computing to Provide Personalized Medical Diagnosis and Treatment," *Current Cardiology Reports*, vol. 16(1), p. 441.

Flick, U. (2002) An Introduction to Qualitative Research (2nd edition), Thousand Oaks; London; New Delhi: Sage Publications.

Forlenza, G.P. (2019) “Use of Artificial Intelligence to Improve Diabetes Outcomes in Patients Using Multiple Daily Injections Therapy,” *Diabetes Technology & Therapeutics*, vol. 21(S2). No page. Last accessed on 15/02/2021: https://www.liebertpub.com/doi/10.1089/dia.2019.0077

Gagnon, M.P., E. Orruño, J. Asua, A.B. Abdeljelil and J. Emparanzaet (2012) “Using a modified technology acceptance model to evaluate healthcare professionals' adoption of a new telemonitoring system,” *Telemedicine Journal and E-Health*, vol. 18(1), p. 54-9.

García, J.F., A. Spatharou, S. Hieronimus, J-P Beck and J. Jenkins (2020) “Transforming Healthcare with AI – The impact on the Workforce and Organisations,” *EIT Health and McKinsey & Company*. Last accessed on 22/11/2020: https://eithealth.eu/wp-content/uploads/2020/03/EIT-Health-and-McKinsey_Transforming-Healthcare-with-AI.pdf

Gray, D. E. (2016) Doing Research in the Business World. Los Angeles, London: Sage Publications.

Ho Park, S., K-H. Do, S. Kim, J.H. Park and Y-S. Lim (2019) “What should medical students know about artificial intelligence in medicine?” *Journal for Education Evaluation for Health Professions*, vol. 16, p. 18.

Jiang, F., Y. Jiang, H. Zhi, Y. Dong, H. Li, S. Ma, Y. Wang, Q. Dong, H. Shen and Y. Wang (2017) “Artificial intelligence in healthcare: past, present and future,” *Stroke and Vascular Neurology*, vol. 2(4), p. 230-243.

La Rosa, E. and D. Danks (2018) “Impacts on Trust of Healthcare AI”, *Proceeding of the 2018 AAAI/ACM Conference on AI, Ethics and Society*, December 2018, p. 210-215.

Lee, Y., K.A. Kozar and K.R.T. Larsen (2003) “The Technology Acceptance Model: Past, Present and Future,” *Communications of the Association for Information Systems*, vol. 12, Article 50 (no page number). Last accessed on 15/02/2021: https://aisel.aisnet.org/cais/vol12/iss1/50/

Liew, C. (2018) “The future of radiology augmented with Artificial Intelligence: a strategy for success,” *European Journal of Radiology*, vol. 102, p. 152–156.

Mason, J. (2002) Qualitative Researching (2nd ed.). London; Sage Publications.

McAfee, A. and E. Brynjolfsson (2017) Machine, Platform, Crowd: Harnessing Our Digital Future. New York, London: W.W. Norton and Company.

Mei, X., H-C. Lee […] and Y. Yang (2020) “Artificial intelligence–enabled rapid diagnosis of patients with COVID-19,” *Nature Medicine*, vol. 26, p. 1224-1228.

OCDE (2020) “Trustworthy AI in Health,” *Background paper for the G20 AI Dialogue, Digital Economy Task Force*. Saudi Arabia 1-2 April 2020. Last accessed on 22/11/2020: http://www.oecd.org/health/trustworthy-artificial-intelligence-in-health.pdf

Panch, T., H. Mattie and L.A. Celi (2019) “The ‘inconvenient truth’ about AI in healthcare,” *Digital Medicine*, vol. 2, article 77 (no page number). Last accessed on 15/02/2021: https://www.nature.com/articles/s41746-019-0155-4

Pearson, D. (2017) “Artificial Intelligence in radiology: the game-changer on everyone’s mind,” *Radiology Business*. Last Accessed on 22/11/2020:

https://www.radiologybusiness.com/topics/technology-management/artificial-intelligence-radiology-game-changer-everyones-mind

Pole, C and R. Lampard (2002) Practical Social Investigation- Qualitative and Quantitative Methods in Social Research. Harlow: Pearson Education.

Price II, W.N. and I.G. Cohen (2019) "Privacy in the age of medical big data." *Nature Medicine*, vol. 25(1), p. 37-43.

Reddy, S., S. Allan, S. Coghlan and P. Cooper (2020) "A governance model for the application of AI in health care," *Journal of the American Medical Informatics Association*, vol. 27(3), p. 1-7.

Rodriguez-Ruiz, A., E. Krupinski, J-J. Mordang, K. Schilling, S.H. Heywang-Kobrunner, I. Sechopoulos and R.M. Mann (2018) "Detection of Breast Cancer with Mammography: Effect of an Artificial Intelligence Support System," *Radiology*, vol. 290(2) (no page). Last accessed on 15th February 2021: https://pubs.rsna.org/doi/full/10.1148/radiol.2018181371

Rogers, E.M. (2003) Diffusion of Innovations. 5th ed. New York: Free Press.

Saunders, M., P. Lewis and A. Thornhill (2009) Research Methods for Business Students. 5th ed. Harlow: Pearson Education Limited.

Schwab, K. (2017) The Fourth Industrial Revolution. Geneva: World Economic Forum.

Silverman, D. (2006) Interpreting Qualitative Data – Methods for Analyzing Talk, Text and Interaction. London, Thousand Oaks, New Delhi: Sage Publications.

Topol Review (2019) Preparing the healthcare workforce to deliver the digital future. Last accessed on 13/08/2020: https://topol.hee.nhs.uk/wp-content/uploads/HEE-Topol-Review-2019.pdf

Venkatesh, V., M.G. Morris, G.B. Davis and F.D. Davis (2003) "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly*, vol. 27(3), p. 425-478.

Vellido, A. (2019) "Societal Issues Concerning the Application of Artificial Intelligence in Medicine," *Kidney Diseases*, vol. 5(1): p. 11-17.

Watanabe, A.T. (2019) "Improved Cancer Detection Using Artificial Intelligence: a Retrospective Evaluation of Missed Cancers on Mammography," *Journal of Digital Imaging*, vol. 32, p. 625-637.

Yamada, I. and G. Lopez (2012) "Wearable sensing systems for healthcare monitoring," *Symposium on VLSI technology*. Last accessed on 22/11/2020: https://ieeexplore.ieee.org/document/6242435

Yu, K.H., A.L. Beam and I.S. Kohane (2018) "Artificial Intelligence in healthcare," *Nature Biomedical Engineering*, vol. 2, p. 719-731.

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