Perspectives on Human-AI Interaction Applied to Health and Wellness Management: Between Milestones and Hurdles

Mohammed Tahri Sqalli, Dena Al-Thani, Marwa Qaraqe, and Luis Fernandez-Luque

Abstract Across the globe, the demand over a good quality healthcare is in the rise. Patients require rigorous treatments and thorough followups. Meanwhile, the advent of artificial intelligence has opened up various opportunities for healthcare providers to meet their patients' demands. With the use of artificial intelligence, data can be harnessed to provide digital guidance, design care management programs, as well as predict the upcoming health crisis. While artificial intelligence for managing patients' health and well-being may seem ready to be implemented, patients as well as health institutions still devote a preponderant importance to the clinician at the center of care. In this chapter, we explore the position of artificial intelligence in the management of health and well-being, where the human (patient) to human (clinician) interaction is key to its success. Yet, patients feel ready to get support from artificial intelligence. We first describe opportunities of how artificial intelligence is already used in the management of patients' health. We then describe the hurdles impeding the Human-AI interaction between the artificial intelligent health management systems and the user.

Keywords Human-AI interaction · Machine learning · Digital medicine · Health informatics

M. T. Sqalli (✉) · D. Al-Thani · M. Qaraqe · L. Fernandez-Luque
Hamad Bin Khalifa University, Qatar Foundation Division of Information Computing Technology College of Science and Engineering, Doha, Qatar
e-mail: mtahrisqalli@hbku.edu.qa

D. Al-Thani
e-mail: dalthani@hbku.edu.qa

M. Qaraqe
e-mail: mqaraqe@hbku.edu.qa

L. Fernandez-Luque
e-mail: lluque@hbku.edu.qa

M. Househ et al. (eds.), *Multiple Perspectives on Artificial Intelligence in Healthcare*, Lecture Notes in Bioengineering, https://doi.org/10.1007/978-3-030-67303-1_4

1 Introduction

The advancements in hardware as well as in machine learning (ML) have diversified the fields of application for artificial intelligence (AI) systems. Among the applications of these systems are in the medical field. This progress brought techniques for processing vast amounts of patients' generated data into several modalities. It has also allowed the conversion of multiple data streams collected by ubiquitous computing devices into unified feedback models. These models provide medical emergency insights, timely medical reminders, as well as accurate medical predictions (Koh and Tan 2005; Sqalli and Al-Thani 2019). The drive for improving medical interventions has thus pushed the movement of digitalizing health institutions through the adoption of these intelligent systems. AI systems are now a tool for supplementing clinicians' decision making, for providing customized and tailored health management plans, for predicting the next health crisis, and for designing personalized treatments using precision medicine (Chancellor et al. 2016).

However, with the prevalent adoption of machine learning into the medical context, these AI systems have also drawn attention to the social challenges they bring. These challenges range from how classification algorithms show bias or disadvantage a certain population group over another, or how the black-box aspect of these algorithms makes them difficult to be supervised by clinicians (Inkpen et al. 2019). Moreover, AI systems have also brought concerns among the research and medical community with regards to issues of discrimination, fairness and accountability (Koh and Tan 2005; Inkpen et al. 2019). To address these issues, machine learning engineers have emphasized on proposing mathematical insights to correct these social biases, and to improve the interpretability of the classifications algorithms (Dwork et al. 2012). This field of research by itself has witnessed an exponential growth in the past decade, as it is proven by several academic venues that address such topics. These venues include but are not limited to the ACM Fairness, Accountability, and Transparency (FAT*) conferences (Proceedings of the Conference on Fairness 2019; Inkpen et al. 2019), and other related workshops. Moreover, two of the United Nations (UN) agencies, mainly the Wolrd Health Orgamization (WHO) and the International Communication Unit (ITU), have pointed out the urgency of addressing those topics by establishing a focus group dedicated for Artificial Intelligence for Health (AI4H) in July, 2018 (Wiegand et al. 2019). Among the main goals of this group is to set the regulations for evaluating and benchmarking the ethics of forthcoming AI systems for health (Wiegand et al. 2019). Allowing these topics to be discussed sets the ground for an accountable and ethical deployment of artificial intelligence in the medical context.

In the health and wellness domain, a responsible deployment of artificial intelligence using mathematical insights for biases correction is not enough (Inkpen et al. 2019). The human responsibility is still critical, if not primary. In this context, artificial intelligence and machine learning systems serve as a helping tool or as an extension to the clinician decision making process (Inkpen et al. 2019). While these systems provide accurate predictions and insights, the final say goes back to the clinician who asses the indicators provided. Based on these indicators and other medical factors, the decision taken is the one that is foreseen to be the best for the well being of the patient.

Despite their accuracy, several machine learning systems suffer from being developed by engineers in isolation and without the inclusion of clinicians and patients (Inkpen et al. 2019). The human involvement in AI systems' conception, design, development and evaluation is essential to guarantee that the insights provided by these systems are meaningful, significant and actionable for clinicians. Moreover, these systems need to be developed in an understandable and context-aware manner for the medical community. The Human-AI interaction sub-field of Human-Computer Interaction focuses on these issues. Nevertheless, it still is unclear how future emerging trends of a swiftly developing AI may lead. Due to the novelty of the field, the human-AI interaction in the medical context is still emerging, especially with regards to technologies of decision support or expert systems being deployed and tested in-the-wild (Inkpen et al. 2019).

Moreover, it is essential to prevent unintended repercussions that these expert medical systems cause. The consequences vary between biases, data interpretation errors, privacy issues, accountability, loss of trust by medical practitioners, and irresponsible usage (Lazer et al. 2014). In addition, the decision-making process in the medical setting is subjective and contextual depending on a patient case by case basis. These two aspects of specificity are challenging to account for with the standard workflow of current machine learning models. Thus, there is an imminent need for artificial intelligence systems that account for sustainable, interactive, usable, context-aware and actionable features that lead towards an integrated human-AI interaction (Inkpen et al. 2019). The involvement of the patient or clinician in this ecosystem requires a human-centered approach, where the insights provided by these decision support systems are contextual. Enabling a context-aware AI model requires accounting for the different users' differences, demands, cultural contexts, aspirations and preferences (Olteanu et al. 2019).

The goal of this chapter is to investigate at what extent the human-AI interaction is being brought to the foreground during the design, development, and use of artificial intelligent systems in the management of health and wellness. Not much research has addressed this area of interest. This chapter is founded on the novel work of Amershi et al. (2019) proposing guidelines for incorporating Human-AI interaction in the design of health and wellness solutions. This work is the first to provide a multi-perspective analysis on how to use the guidelines of human-AI interaction proposed by Amershi et al. (2019) in the health and wellness management. This chapter is structured as followed. In the next two sections, we explain respectively the milestones crossed, as well as the hurdles impeding the human-AI interaction in the health and wellness. Table 1 summarizes these milestones achieved as well as the hurdles challenging the Human-AI Interaction between the patients and the AI systems that support them in managing their health and wellness.

Table 1 Milestones achieved and hurdles challenging the human-AI interaction in the management of patients' health and wellness

Milestones achieved	Challenging hurdles
1. Understandable, and explainable AI: Artificial intelligence is currently more understandable and explainable. It is now commercialized and democratized. It is also accessible for both clinicians and patients as a secondary diagnostic tool	**1. Artificial Intelligence Literacy**: The artificial intelligence literacy among clinicians is very limited, which prohibits their involvement in the design and building of machine learning systems adequate for the clinical setting
2. Documentation as an Integral Part of the Development Process: With the understandabilty of artificial intelligence in health and wellness management, providing documentation to the machine learning tools has witnessed a progressive leap	**2. Opaque Nature of Machine Learning Algorithms**: The black-box aspect of the inner neural network layers of a machine learning model is also a barrier to understandability among clinicians
3. Incorporating Both Artificial Intelligence and Human Intelligence: In the health and wellness sector, clinicians are still at the center of care. However, artificial intelligence is being used as a helping diagnostic tool	**3. The Design over Data versus Data over Design Paradigm Dilemma**: Accounting for an effective Human-AI interaction requires to consider the design of this interaction first before the nature of the data required. However, the training process in machine learning requires the opposite. This paradigm trade-off is a nuisance to an effective Human-AI interaction
4. The Birth of Human-AI Interaction: The digitalization of health institutions has directed the attention from human-computer interaction as a general field to the introduction of Human-AI interaction for health and wellness applications as a sub-field	**4. Control of Customized Functionalities for Niche User Segments**: There is a shift towards providing a customized interface design for each user of the medical system. Classical HCI evaluation metrics do not account for the multiplicity and fluidity of interfaces depending on each individual user
	5. Foreseeing the unforeseeable—Adapting to an Ever Changing Human-AI Interaction: Both the field of medicine and machine learning algorithm design are constantly evolving. So is the interaction between the clinician and the AI system. Foreseeing these changes and expecting them is both challenging and critical to maintain a meaningful human-AI interaction

2 Milestones

We list four milestones achieved in putting forward the human at the center of the human-AI interaction process.

2.1 Understandable, and Explainable AI

Artificial intelligence technology is now commercialized and democratized for the average user. Patients nowadays rely on AI-infused applications to manage their chronic conditions and monitor their health and wellness (Sqalli and Al-Thani 2019). Human-AI interaction experts crossed a milestone to transform AI from a deeply complex tool to a familiar and user-friendly one. Patients as well as clinicians are able to both effectively understand and explain the insights provided by the AI systems (2019). Human-AI interaction experts have also succeeded in bridging the chasm between the complexity of the neural networks for machine learning models and the simplicity of the interface enabling the patients and clinicians to easily use these AI capabilities (Adadi and Berrada, 2018).

2.2 Documentation as an Integral Part of the Development Process

Documentation in the medical field is of crucial importance for the safety of patients. It is the key to delivering the best error free care possible (Amira et al. 2019). Artificial intelligence for healthcare has also adopted that same mantra in order to meet the rigorous needs of the medical sector. Machine learning as well as HCI experts realize the importance of understanding how models and datasets are more usable when they are properly documented (Proceedings of the Conference on Fairness 2019). Moreover, health practitioners on the ground are advocating medical routines leading to well-documented datasets (Piwek et al. 2016; Inkpen et al. 2019).

2.3 Incorporating both Artificial Intelligence and Human Intelligence

The capabilities that both human intelligence and artificial intelligence offer are complementary to accomplish complex analytical tasks. While machine learning systems are effective tools to distill vast amounts of data into insights and patterns that might be invisible to clinicians. Human intelligence is effective at drawing meaningful context-relevant inferences from those patterns (Inkpen et al. 2019). Among the application of this fundamental idea is the combination of machine learning techniques along with multiscale modeling (Alber et al. 2019). Moreover, another example of the application of this concept is the use of augmented reality to initiate and improve the learning for children and adolescents with autism spectrum disorder Khowaja et al. (2020). This combination provides even more accurate predictive models. These models lead to uncovering insights about disease mechanisms, treatment strategies, and clinical decision making (Alber et al. 2019). Human-AI interaction therefore has crossed the milestone of setting the research design problems that are most suitable and are most relevant to the clinical context. Allowing both artificial intelligence and human intelligence to work in synergy guarantees the delivery of a more precise care management plan (Sqalli and Al-Thani 2019; Inkpen et al. 2019).

2.4 The Birth of Human-AI Interaction

The involvement of artificial intelligence in the field of human computer interaction has given birth to the human-AI interaction as a sub-field (Dove et al. 2017). The clinical setting is more and more referring to powerful machine learning algorithms, along with HCI tools to find solutions to complex diseases like cancer, genetic problems and heart problems (Turakhia et al. 2019). ML tools and HCI tools are essential in order to design analytical solutions tailored to the needs of health and wellness management (Dove et al. 2017). Both of these tools are used under the light of a translational perspective to contribute towards clinical development (Shah et al. 2019). This perspective of AI/ML—HCI has resulted in some successful outcomes in the field of cardiology (Turakhia et al. 2019), pattern recognition and segmentation techniques on medical images (Shah et al. 2019), tele-robitics care for the elderly (Sqalli et al. 2016), remote control for surgeries (Kurabe et al. 2016; Yamashita et al. 2016), and most generally health lifestyle data-driven applications using pervasive computing (Fernandez-Luque et al. 2019) among other applications.

3 Hurdles

We list five hurdles that challenge putting forward the human at the center of the human-AI interaction process.

3.1 Artificial Intelligence Literacy

The medical community suffers from artificial intelligence illiteracy (Dove et al. 2017; Yang et al. 2018). Although AI systems are progressively intruding the medical field, many patients and clinicians are still hesitant to involve those systems in their workflow (Inkpen et al. 2019; Yang et al. 2018). Dove et al. (2017) have explained how AI is currently viewed as “a magic wand” by clinicians due to their limited literacy. Lack of understanding of the current possibilities and limitations of artificial intelligence causes health practitioner users to have over-ambitions expectations from these system and algorithms (Dove et al. 2017). Limited literacy of AI therefore obscures the human integration that the field of HCI adopts. However, despite their limited AI literacy, clinicians use medical software systems that embed an aspect of AI in them (Amershi et al. 2019). Automated ECG interpretations (Turakhia et al. 2019), vital signs monitoring Piwek et al. (2016), and tele-medicine applications (Marvel et al. 2018) and others embed an important portion of artificial intelligence in them. Other health practitioners have blindly adopted those systems without much knowledge about their capabilities and inner functioning. Having little literacy about a certain technology does not prohibit using it under the premise that the clinician would use it cautiously. Human-AI interaction as a sub-field of HCI faces the challenge of designing intuitively those medical systems with the end-user, either as a patient or as a clinician, being uninvolved. Accounting for the end user when designing those systems breaks the barrier of illiteracy.

3.2 Opaque Nature of Machine Learning Algorithms

The black-box aspect of machine learning algorithms is another hurdle that impedes involving health practitioners in the design of medical systems. This is due mainly to a shift from an open-source software mentality to the ideology of privatization of data adopted by tech giants (Wilbanks and Topol 2016). The opaque nature of neural networks makes the task of dissecting the rules leading to the final model output difficult for clinicians. While in knowledge-based artificial intelligent systems data is represented in an understandable if-then rule knowledge-base, in neural networks, data is represented across a complex network. This representation makes the interpretability of the output impossible by novices (Adadi and Berrada, 2018). Moreover, potential anomalies hidden in the training data may cause biased or wrong output decisions (Pedreschi et al. 2019). Designing a medical-tailored machine learning model from the ground-up demands a participatory design approach. In this approach, both clinical expertise as well as the curation of a tailored machine learning model is required. By adopting this design approach, there is a potential for minimizing the biases and wrong medical interpretations. This leads to the conception of several AI development frameworks, whereby a plethora of algorithms, paradigms, as well as documentations stating the pros and cons of each framework are made available (Pedreschi et al. 2019). However, some of these frameworks according to Gillies et al. (2016) lack the transparency required for clinicians to understand the inner functioning of the algorithms. Moreover, adopting an existing AI development framework entails adopting its biases and flaws. This shapes how health practitioners interact with these systems. It also redirects their attention from the patient to addressing the biases of the used system (Pedreschi et al. 2019).

3.3 The Design over Data Versus Data over Design Paradigm Dilemma

Designing for an effective Human-AI interaction in the health domain stands at a crossroads between setting the priorities of the design process and the data analysis process. In the HCI human-centered design paradigm, designers aim to deduce insights and elucidate requirements for user needs (Fogg 2002; Norman 2002) before starting data collection, while in the data-centered design paradigm data scientists give the priority to the data. This creates tension with the design-first approach. The tension culminates when there is a need for identifying the pieces of data that are appropriate to the medical problem without any prior involvement of the end user. This tension leads to demanding more time for the design process, which then results in requiring more development time and more budget allocation (Yang et al. 2018). On the other end of the spectrum, in the data-centered design paradigm, machine learning models are trained using medical data that is already available, but without any specifications about the usefulness of the output for the clinician. This leads to an increase in the chances that the the output of the machine learning systems not fit the medical problem specifications.

3.4 Control over Customized Functionalities for Niche User Segments

Artificial intelligence has enabled the creation of customized sub-functionalities and behavior change modules within AI-infused health applications and platforms (Sqalli and Al-Thani 2019). Designers find the task of controlling the design workflow of each customized feature challenging (Inkpen et al. 2019). This abundance of features and functionalities creates a point of tension for Human-AI interaction experts. Personalized trends derived from patient data is becoming mainstream. Moreover, there is a potential that this personalization process will extend to be reflected on the design of the interface of those applications as well (Sqalli and Al-Thani 2019). Machine learning algorithms hold a potential to design drastically evolving personalized interfaces the same way they design personalized feedback for each patient user. While designers currently are the ones to decide on the end-design of an AI solution, there is an expectation that the data generated from the users is going to be the determinant of what interfaces users see on their devices. This creates hurdles for the standarization and approval of evaluation metrics for machine-learning generated interfaces. These metrics not only need to satisfy conventional HCI criteria, but also need to account for new Human-AI interaction criteria (Kirsch 2017).

3.5 Foreseeing the Unforeseeable—Adapting to an Ever Changing Human-AI Interaction

As machine learning models are progressively learning to adapt to the unexpectancies of patients' behavior, the human-AI interaction is becoming more and more blurred (Adadi and Berrada 2018). This therefore requires expert designers to think further ahead to mitigate the risks of a swiftly developing AI. Medical systems that incorporate autonomous learning face the challenge of quickly adapting to the changes of medical notions and patients' feedback (Adadi and Berrada 2018). Therefore, the role of human-AI interaction in this case is of essential importance to serve as a mediator between the clinician and the AI to overcome those challenges. While the traditional HCI evaluation standards like visibility, feedback, constraints, mapping, affordances, and consistency (Norman 2002) are still relevant in the design of a system's interface, they remain not enough to examine machine learning systems that are user-adaptive.

4 Conclusion

To conclude, the past decade has witnessed an increase in processing power. This increase has lead to the availability of artificial intelligence for mainstream audiences. The accessibility of AI has provided a promise for incorporation in the medical field. However, attention has been drawn to the societal hurdles associated with these intelligent systems, especially with regards to how machine learning algorithms show failure of accuracy compared to the clinicians' expected standards, or how they disadvantage a certain category of patients over another depending on the data fed for training. Moreover, another hurdle challenging AI/ML systems is their black-box aspect. The opacity of the inner functioning of neural networks composing certain algorithms makes the task of understandablity, explainability, and improvement difficult to the clinicians. This leads them to being more unaware about the possibilities and capabilities of what a machine learning system can offer. From a Human-AI interaction standpoint, light has been shed on specifying a precise role that the human, being either a patient or a clinician, plays in the interaction equation. The challenge lies in how the user should be at the same time controlling the AI system, as well as working in tandem with it to improve the decision outcomes that are best for the patient.

References

Adadi A, Berrada M (2018) Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). IEEE Access 6:52138–52160. https://doi.org/10.1109/access.2018.2870052

Alber M, Tepole AB, Cannon WR, De S, Dura-Bernal S, Garikipati K, Karniadakis G, Lytton WW, Perdikaris P, Petzold L, Kuhl E (2019) Integrating machine learning and multiscale modeling–perspectives, challenges, and opportunities in the biological, biomedical, and behavioral sciences. Nat Partner J Digit Med 2(1):1–11. https://doi.org/10.1038/s41746-019-0193-y

Amershi S, Inkpen K, Teevan J, Kikin-Gil R, Horvitz E, Weld D, Vorvoreanu M, Fourney A, Nushi B, Collisson P, Suh J, Iqbal S, Bennett PN (2019)Guidelines for human-AI interaction. In: Proceedings of the 2019 CHI conference on human factors in computing systems—CHI 19. ACM Press. [Online]. Available: https://doi.org/10.1145/3290605.3300233

Amira A, Agoulmine N, Bensaali F, Bermak A, Dimitrakopoulos G (2019) Special issue: empowering eHealth with smart internet of things (IoT) medical devices. J Sens Act Netw 8(2):33. https://doi.org/10.3390/jsan8020033

Chancellor S, Lin Z, Goodman EL, Zerwas S, Choudhury MD (2016) Quantifying and predicting mental illness severity in online pro-eating disorder communities. In: Proceedings of the 19th ACM conference on computer-supported cooperative work & social computing—CSCW 16. ACM Press. [Online]. Available: https://doi.org/10.1145/2818048.2819973

Dove G, Halskov K, Forlizzi J, Zimmerman J (2017) UX design innovation. In: Proceedings of the 2017 CHI conference on human factors in computing systems - CHI 17. ACM Press. [Online]. Available: https://doi.org/10.1145/3025453.3025739

Dwork C, Hardt M, Pitassi T, Reingold O, Zemel R (2012) Fairness through awareness. In: Proceedings of the 3rd innovations in theoretical computer science conference on—ITCS 12. ACM Press. [Online]. Available: https://doi.org/10.1145/2090236.2090255

Fernandez-Luque L, Aupetit M, Palotti J, Singh M, Fadlelbari A, Baggag A, Khowaja K, Al-Thani D (2019) Health lifestyle data-driven applications using pervasive computing. In: Big data, big challenges: a healthcare perspective. Springer International Publishing, pp 115–126. [Online]. Available: https://doi.org/10.1007/978-3-030-06109-8_10

Fogg BJ (2002) Persuasive technology: using computers to change what we think and do. Ubiquity 2002:2. [Online]. Available: https://doi.org/10.1145/764008.763957

Gillies M, Lee B, dAlessandro N, Tilmanne J, Kulesza T, Caramiaux B, Fiebrink R, Tanaka A, Garcia J, Bevilacqua F, Heloir A, Nunnari F, Mackay W, Amershi S (2016) Human-centred machine learning. In: Proceedings of the 2016 CHI conference extended abstracts on human factors in computing systems - CHI EA 16. ACM Press. [Online]. Available: https://doi.org/10.1145/2851581.2856492

In: Proceedings of the conference on fairness, accountability, and transparency, FAT* 2019, Atlanta, GA, USA, 29–31 Jan 2019. ACM. [Online]. Available: https://dl.acm.org/citation.cfm?id=3287588

Inkpen K, Chancellor S, Choudhury MD, Veale M, Baumer EPS (2019) Where is the human? In: Extended abstracts of the 2019 conference on human factors in computing systems CHI—EA 19. ACM Press. [Online]. Available: https://doi.org/10.1145/3290607.3299002

Khowaja K, Banire B, Al-Thani D, Sqalli MT, Aqle A, Shah A, Salim SS (2020) Augmented reality for learning of children and adolescents with autism spectrum disorder (asd): A systematic review. IEEE Access 8:78779–78807

Kirsch A (2017) Explain to whom? Putting the user in the center of explainable AI. In: Proceedings of the first international workshop on comprehensibility and explanation in AI and ML 2017 co-located with 16th international conference of the italian association for artificial intelligence (AI*IA 2017), Bari, Italy. [Online]. Available: https://hal.archives-ouvertes.fr/hal-01845135

Koh H, Tan G (2005) Data mining applications in healthcare. J Healthc Inf Manage JHIM 19:64–72

Kurabe K, Kato Y, Koike M, Jinno K, Yamashita K, Kito K, Sqalli MT, Tatsuno K (2016) A robot controller for power distribution line maintenance robot working by task-level command,, In:

2016 IEEE/SICE international symposium on system integration (SII). IEEE. [Online]. Available: https://doi.org/10.1109/sii.2016.7844038
Lazer D, Kennedy R, King G, Vespignani A (2014) The parable of google flu: traps in big data analysis. Science 343(6176):1203–1205. https://doi.org/10.1126/science.1248506
Marvel FA, Wang J, Martin SS (2018) Digital health innovation: a toolkit to navigate from concept to clinical testing. JMIR Cardio 2(1):e2. [Online]. Available: https://doi.org/10.2196/cardio.7586
Norman DA (2002) The design of everyday things. Basic Books Inc, New York, NY, USA
Olteanu A, Castillo C, Diaz F, Kıcıman E (2019) Social data: biases, methodological pitfalls, and ethical boundaries. Front Big Data 2. [Online]. Available: https://doi.org/10.3389/fdata.2019.00013
Pedreschi D, Giannotti F, Guidotti R, Monreale A, Ruggieri S, Turini F (2019) eaningful explanations of black box AI decision systems. In: Proceedings of the AAAI conference on artificial intelligence, vol 33, pp 9780–9784. [Online]. Available: https://doi.org/10.1609/aaai.v33i01.33019780
Piwek L, Ellis DA, Andrews S, Joinson A (2016) The rise of consumer health wearables: promises and barriers. PLOS Med 13(2):e1001953. https://doi.org/10.1371/journal.pmed.1001953
Shah P, Kendall F, Khozin S, Goosen R, Hu J, Laramie J, Ringel M, Schork N (2019) Artificial intelligence and machine learning in clinical development: a translational perspective. Nat Partner J Digit Med 2(1). https://doi.org/10.1038/s41746-019-0148-3
Sqalli MT, Al-Thani D (2019) AI-supported health coaching model for patients with chronic diseases. In: 2019 16th International symposium on wireless communication systems (ISWCS). IEEE [Online]. Available: https://doi.org/10.1109/ISWCS.2019.8877113
Sqalli MT, Tatsuno K, Kurabe K, Ando H, Obitsu H, Itakura R, Aoto T, Yoshino K (2016) Improvement of a tele-presence robot autonomous navigation using SLAM algorithm. In: 2016 International symposium on micro-nanomechatronics and human science (MHS). IEEE. [Online]. Available: https://doi.org/10.1109/mhs.2016.7824221
Turakhia MP, Desai M, Hedlin H, Rajmane A, Talati N, Ferris T, Desai S, Nag D, Patel M, Kowey P, Rumsfeld JS, Russo AM, Hills MT, Granger CB, Mahaffey KW, Perez MV (2019) Rationale and design of a large-scale, app-based study to identify cardiac arrhythmias using a smartwatch: the apple heart study. Am Heart J 207:66–75. https://doi.org/10.1016/j.ahj.2018.09.002
Wiegand T, Krishnamurthy R, Kuglitsch M, Lee N, Pujari S, Salathé M, Wenzel M, Xu S (2019) WHO and ITU establish benchmarking process for artificial intelligence in health. The Lancet 394(10192):9–11. https://doi.org/10.1016/s0140-6736(19)30762-7
Wilbanks JT, Topol EJ (2016) Stop the privatization of health data. Nat Int Weekly J Sci 535
Yamashita K, Kato Y, Kurabe K, Koike M, Jinno K, Kito K, Tatsuno K, Sqalli MT (2016) Remote operation of a robot for maintaining electric power distribution system using a joystick and a master arm as a human robot interface medium. In: 2016 International symposium on micro-nanomechatronics and human science (MHS). IEEE. [Online]. Available: https://doi.org/10.1109/mhs.2016.7824229
Yang Q, Scuito A, Zimmerman J, Forlizzi J, Steinfeld A (2018) Investigating how experienced UX designers effectively work with machine learning. In: Proceedings of the 2018 on designing interactive systems conference 2018 - DIS 18. ACM Press. [Online]. Available: https://doi.org/10.1145/3196709.3196730