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# Augmented Decision Making Model for Responsible Actors in Healthcare

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## ABSTRACT

The purpose of this paper is to understand if the use of artificial intelligence (AI)-based tools may enable augmented decision-making for responsible actors (Spohrer, 2021) in healthcare. The biggest challenge for AI in healthcare is its own full applicability in daily clinical practices, due to fragmented data and their poor quality, further complicated by the patients' reluctance to share them (Shinners et al., 2020) for privacy issues. The motivation of this work is to search for models and methodologies capable of overcoming these criticalities. In this sense, transparent AI deserves to be much more explored because it would enable augmented decisions (not just automated decisions) as they result from an effective HMI (Zhu et al., 2018). Then, this can also contribute to strengthening the patient's perception of the reliability and safety of the tool (de Fine Licht, 2020), by improving their trust in the healthcare operations (Das, 2020). A literature review has been carried out to propose a framework (Share-to-Care) to encourage a great acceptance by actors of new technologies in healthcare thanks to reasoned transparency. Methodologically, the 'theory synthesis' (Jaakkola, 2020) helped us in intending how to give back drivers and suggestions to researchers and practitioners in designing and using AI in healthcare. Findings concern transparent AI as leverage able to foster the spread of collaborative behaviors useful for augmented decision-making not only powered by technologies but mainly by humans.

**Keywords:** Transparency, Artificial intelligence (AI), Augmented decision-making, Healthcare management

## INTRODUCTION

AI aims to mimic human cognitive functions and allows the collection and analysis of large amounts of data (Jiang et al., 2017). For this reason, it is increasingly widespread in healthcare (Masucci et al., 2021), in activities such as anamnesis, diagnosis support, treatment planning, monitoring of the patient's condition (Reddy et al., 2019), offering clinicians the opportunity to tailor early interventions to each individual (Subramanian et al., 2020). AI can also help detect early disease risks as the system uses past and present information about health problems and can identify whether the patient is at risk of contracting a disease or not (Becker, 2019). Al could lead to greater empowerment of the patient (Polese and Carrubbo, 2016) and improve the bond of trust between doctor and patient. AI is expanding into areas previously only managed by human experts (Yu et al., 2018), but machines can only support and improve human roles (Barile et al., 2021).

 

However, many AI algorithms are difficult to understand or explain and actors fear mistakes in diagnosis and treatments (Davenport and Kalakota, 2019), with negative effects on actors' trust in AI systems (Das, 2020). Ensuring transparency, explainability and intelligibility in AI systems in healthcare is one of the six principles identified by the WHO (WHO, 2021) to understand how to provide health systems with high quality, fair and reliable decisions (de Fine Licht and de Fine Licht, 2020). The role played by transparency in making AI systems effective decision support systems is particularly interesting.

For this reason, this work tries to answer the following research question:

- **R.Q.:** is the use of AI-based tools sufficient to enable augmented decision-making processes for responsible health actors?

Following the 'theory synthesis' (Jaakkola, 2020) in intending how to give back drivers and suggestions to researchers and practitioners in such a way, for properly understanding the design and use of AI, in order to pursue win-win conditions for the benefit of all parties involved to co-create value (Polese et al., 2017), this conceptual paper starts with the description of the theoretical background. In the next section, the challenges posed by AI systems in healthcare are described to frame an augmented decision-making model based on AI. However, many doubts are relieved in terms of transparency so the co-design of AI systems for healthcare (Share-to-Care) is proposed as solution, to encourage a great acceptance of new technologies in healthcare thanks to reasoned transparency and to allow an augmented decision-making process through actors' capabilities co-elevation. In the last part, non-conclusive considerations are presented.

## THEORETICAL BACKGROUND

### Service Innovation and Data-Driven Decision-Making

Today innovation is increasingly associated with the function of encouraging companies in pursuing and maintaining their survival, through the achievement of a competitive advantage (Damanpour, 2010). Service innovation is achieved through a fruitful combination of technological elements, social relations, organizational adjustments and commercial interactions, based on a human-centered perspective (Yu and Sangiorgi, 2018). Service innovation occurs within networks (Vargo et al., 2015) when existing value propositions are modified through a process of integrating existing resources or by inventing new resources (Åkesson et al., 2016) and involves the creation, renewal and transformation of pre-existing knowledge. Innovation cannot be exclusively linked to the use of new technologies (Koskela-Huotari et al., 2016); they have the "task" of providing data. The use of data and technologies is closely linked to human behavior (Spohrer and Maglio, 2010). Innovation implies that through technologies responsible entities may improve themselves (Spohrer, 2021), and, as service systems are centered on people, it occurs when people, thanks to technologies, are able to optimize service systems operation (Maglio, 2015). Data-driven is a mindset that sees data as functional strategic resources for increasingly effective and timely decisions (Provost and Fawcett, 2013), rather than as mere outputs of intuitions and experiences (Polese et al., 2018), first in Healthcare (Capunzo et al., 2013; Carrubbo et al., 2013). Data-driven decision-making can improve the competitiveness of companies and enable them to pursue their marketing objectives (Troisi et al., 2020; Carrubbo et al., 2021). In the health sector, a complex context increasingly centered on the patient, the collection and analysis of patient data could allow doctors to intervene in an increasingly timely and precise manner (Sakr and Elgammal, 2016), with an overall improvement in general performance (McColl-Kennedy et al., 2012) and response times (Dautov et al., 2019). Data-driven decision-making involves the use of advanced analytics tools, such as artificial intelligence solutions and data management systems. The ability to acquire and analyze data in real-time thanks to the application of artificial intelligence algorithms allows companies to comply in a better way with companies' goals and initiatives (Brynjolfsson and McElheran, 2016).

## TOWARDS AN AUGMENTED DECISION-MAKING MODEL BASED ON AI SYSTEMS

### From Artificial Intelligence (AI) to Intelligence Augmentation (IA)

AI is the combination of software techniques and IT infrastructures, allowing performances comparable to human intelligence (Topol, 2019) and data-driven decision-making processes. AI is a widely debated topic in the literature: some believe that over time it can exceed human performance (Grace et al., 2018) and others suppose that Yulya, a humanoid, could win the Nobel Prize for medicine in 2036. AI researchers aim to understand how to make people wiser by enhancing their decision-making and skills, providing them with otherwise inaccessible information based on data (Zhou et al., 2021) thanks to AI systems. IA implies a mixture of AI technologies and people: through technologies, people may amplify their capabilities (Barile et al., 2018) and optimize their thought structure by improving their interpretative schemas (Barile et al., 2020). IA implies a perfect human-machine interaction in which machines do what they do best to help humans do what humans do best (thinking) (Zhou et al., 2021). IA can mitigate fears regarding the use of AI systems (Mohanty and Vyas, 2018). IA is intelligence that derives from a collaborative and effective human-machine interaction and integration; it allows systems to evolve into more intelligent and wiser configurations, based on rational and emotional components (Barile et al., 2021; Badr et al., 2021).

### From Automated Decision to Augmented Decision

There are doubts about the adequacy of the information released by the AI systems and fears in terms of privacy protection, reliability, accuracy and security of the tool (Lytras and Visvizi, 2021) that may invalidate its use by health professionals (Shinners et al., 2020) and patients (Reddy et al., 2020). It implies that the data available to health decision-makers are often partial, fragmented and unstructured, with doubts about their quality (de Fine Licht and de Fine Licht, 2020) and fears that the automated decision may be inadequate. Greater transparency about the functioning of such systems could lead to a more profitable collaborative relationship between the parties, stimulating an environment able to encourage phenomena of value co-creation (Mabillard et al., 2021). The augmented decision may be the solution: an automated decision enhanced by decision-makers' knowledge. The reasoned transparency can allow a decipherable and intelligible functioning of AI systems' black box (Wischmeyer, 2020). More understandable, user-friendly, usable, explainable and effective tools would favor decision-making processes more clear, reasoned and based on objective evidence. The augmented decision is not just an automated decision, which frightens and invalidates the use (or even only the correct use) of these tools by users, but it is enhanced and increased thanks to the reasoned transparency.

### From Data-Driven Decision-Making to Augmented Decision-Making

AI may allow a strengthened decision-making process (Raisch and Krakowski, 2021) based on an augmented decision-making process that implies a perfect human-machine interaction in which both two entities can exceed their limitations (Keding and Meissner, 2021). The augmented decision-making process, as understood in this work, is not only enhanced thanks to the use of new technologies that provide decision-makers with data and sophisticated calculation tools but is a decision-making process enabled and improved by the impact that new technologies can have on decision-makers' cognitive functions. The cognitive and deductive potential of the individual may be amplified thanks to good quality data and interpretative schemes (improved by technology) and information units (increased by technology) integrated with decision-makers' value categories (Barile et al. 2021). For this, it is necessary to understand how individuals in healthcare are willing to use AI and how to act to improve this acceptance degree.

## REASONED TRANSPARENCY FOR AUGMENTED DECISION-MAKING IN HEALTHCARE

Reasoned transparency would incentivize patients to release their data and enable healthcare professionals/decision-makers to make more reliable decisions. To pursue an augmented decision-making model, it is necessary to consider users' responsibility.

### "Share-to-Care": AI Systems Co-Design to Further a Great Acceptance of New Technologies in Healthcare

An augmented decision in healthcare is possible if doctors and support staff understand the decision support system used functioning and handle its results if necessary. Good quality and not fragmented data are issued by patients aware of being active parts of a process aimed to guarantee their well-being. This may be possible thanks to the implementation of peer-to-peer design and production platforms, where patients, specialists, designers and manufacturers can collaborate to maximize health activities and actors' learning and awareness. The involvement of all users may be useful to understand the problem. For this reason, new technology early adopters will have to help the designers to define the problem and to look for a solution (e.g. a new digital tool). This would contribute to the reasoned transparency that would mitigate patients' fears in terms of AI systems transparency. Felzmann et al. (2020) proposed the Transparency by Design model to support organizations in proposing transparent AI systems. The first phase, considered in this work, concerns the transparency in the design of AI systems; its indicators are the proactivity (technologies have to embody communities' values), integration (companies have to explain transparency measures and standards), and the focus on the audience, (decisions have to be accessible to people). These indicators have to prevent distrust and suspicion and to guarantee the public's perception of reliability. Bianchini et al. (2020), in a study carried out by the Department of Design of the Politecnico di Milano together with the pharmaceutical company Sanofi, propose the approach "Wear-to-Care" to design and materialize smart open-source wearables, DermAware, for atopic dermatitis patients, based on open and bottom-up innovation. The present study proposes to generalize the model proposed by Bianchini et al. (2020) to any other tool based on AI systems for any other patients' disease.

*Phase 1: Problematizing starting from patients and doctors' points of view*

This phase aims to understand patients' needs and behaviors, so the company has to search for a sample of patients and doctors through the databases of health facilities, to carry out interviews and favor the emergence of relevant factors for them. To give the research greater robustness, online questionnaires to citizens will also be administered to confirm or disavow what emerged from the interviews.

*Phase 2: Designing and prototyping a new product-service concept*

With the data analysis thus collected in the first phase, it may be possible to define the idea thanks to the joint definition of the problem to be solved. In this phase, there is the design of the tool, based on the specific medical needs, relevant categories that emerged from the previous investigation (phase 1) and the technical potential of the technology. The following step is the production of the prototype.

*Phase 3: Testing the prototype*

The last phase involves testing the prototype by the sample of doctors and patients interviewed in phase 1 to assess whether a revision is necessary for the prototype design phase or the new technological solution can be launched on the market.

The bottom-up design would allow to respect the functional dimension of the tool, (possible also with a top-down approach) but also to make the patient trigger the whole innovation process.

## Enabling Augmented Decision-Making Through Actors' Capabilities Co-Elevation and Upskilling

Share-to-Care may enable augmented decisions, but it's not sufficient the use new technologies, it's necessary that data used for decisions, provided by new technologies, are completed and reliable (R.Q.). The introduction of new co-designed technological solutions, which can be well accepted and effectively used by users/tools co-creators, may enhance the healthcare offer and may increase patient trust and confidence in AI systems. Thanks to Share-to-Care, actors become more responsible and a better version of themselves (Spohrer, 2021); their capabilities may co-evolve and upskill, which means that AI designers are perfectly capable of launching tools that are not meant to die in their introduction phase because patients are willing and able to use them and thus doctors may optimize the results of their decisions. The increased patients' knowledge about the tools with which health professionals develop diagnoses and treatments could improve their involvement and willingness to release resources (time, money, trust, data). The co-design of AI systems for healthcare would make the tool more understandable for users and more user-friendly (proactivity). From the interviews and questionnaires, it could be possible to understand patients' functional and social needs, useful to establish the standards on which the automated decision is based (integration). The bottom-up approach to innovation allows a better predisposition of patients to accept technologies, improves their skills, provides health decision-makers with data useful for a democratization of the decision, and makes the new technologies easier to use and more understandable for actors. The new technology can be customized according to users' expectations, needs and characteristics (focus on the audience). This also lets to more personalize health services and make them more precise and timely, thanks to qualitatively more reliable data thanks to a better degree of trust, confidence and knowledge of users, data-driven decision-making processes, based on augmented decisions, are possible.

## CONCLUDING REMARKS AND PRACTICAL IMPLICATIONS

This work suggests that the impact of AI systems in healthcare has to be treated with a multidisciplinary interpretation (medical, IT, management) and proposes an update in terms of augmented decision-making: new technologies can enhance people cognitive functions, thanks to an information flow which would otherwise be difficult to process, but this information flow have to derive from good quality data for which a good predisposition to release them and a good degree of technology acceptance by users are necessary. Following a phenomenological approach, "Share-to-Care" framework, for the co-design of AI systems deemed potentially acceptable by end-users, is proposed. The Share-to-Care framework proposes a user-centered approach to innovation in healthcare and it can have significant opportunities in terms of value co-creation. The main limitation of this work lies in its conceptual nature. A case study could be useful to validate the effectiveness of this insight and the framework proposed and to understand better if it's can be appropriate for each health context and each disease. for example, patients suffering from neurodegenerative diseases, may be patients not able to be active, in participating in their care, as well as in the co-design of tools that allow monitoring of their conditions. In this case, it should be understood which other actors should be considered and involved (for example their families) and how, the fact that they are not directly the patients, can affect their degree of acceptance of the technology and their predisposition to use it. These aspects have to be explored in further research. Furthermore, the main implication lies in the multidisciplinary approach used to design AI systems in healthcare, usually affected by transparency fears which may undermine the perceived quality of service thus supplied. An in-depth study of AI systems that can be well accepted by end-users, because clearer and more explainable, may be useful to support the decision-making process in healthcare.

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