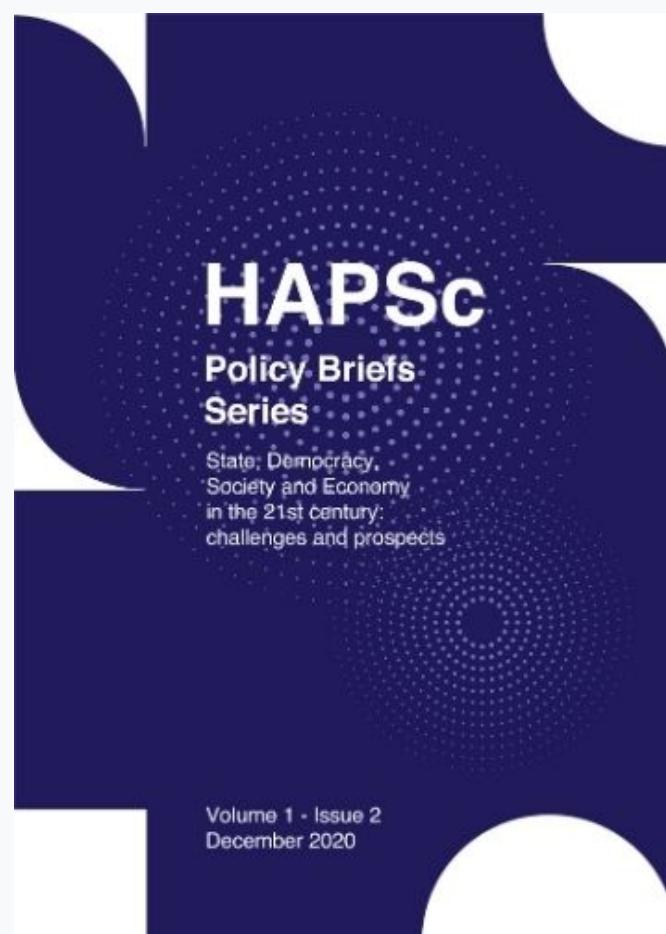


HAPSc Policy Briefs Series

Vol 1, No 2 (2020)

HAPSc Policy Briefs Series



AI and Big Data: A New Paradigm for Decision Making in Healthcare

Iris - Panagiota Efthymiou, Athanassios Vozikis, Symeon Sidiropoulos, Dimitrios Kritas

doi: [10.12681/hapscpbs.26490](https://doi.org/10.12681/hapscpbs.26490)

Copyright © 2020, Iris - Panagiota Efthymiou, Athanassios Vozikis, Symeon Sidiropoulos, Dimitrios Kritas



This work is licensed under a [Creative Commons Attribution 4.0](https://creativecommons.org/licenses/by/4.0/).

To cite this article:

Efthymiou, I. .-. P., Vozikis, A., Sidiropoulos, S., & Kritas, D. (2020). AI and Big Data: A New Paradigm for Decision Making in Healthcare. *HAPSc Policy Briefs Series*, 1(2), 138–145. <https://doi.org/10.12681/hapscpbs.26490>

AI and Big Data: A New Paradigm for Decision Making in Healthcare¹

Iris - Panagiota Efthymiou², Athanassios Vozikis³, Symeon Sidiropoulos⁴, Dimitrios Kritas⁵

Abstract

The latest developments in artificial intelligence (AI)—a general-purpose technology impacting many industries — have been based on advancements in machine learning, which is recast as a quality-adjusted decline in forecasting ratio. The influence of Policy on AI and big data has impacted two key magnitudes which are known as diffusion and consequences. And these must be focused primarily on the context of AI and big data. First, in addition to the policies on subsidies and intellectual property (IP) that will affect the propagation of AI in ways close to their effect on other technologies, three policy categories — privacy, exchange, and liability — may have a specific impact on the diffusion of AI. The first step in the prohibition process is to identify the shortcomings of current hospital procedures, why we need acute care AI, and eventually how the direction of patient decision-making will shift with the introduction of AI-based research. The second step is to establish a plan to shift the direction of medical education in order to enable physicians to retain control of AI. Medical research would need to rely less on threshold decision-making and more on the prediction, interpretation, and pathophysiological context of contextual time cycles. This should be an early part of a medical student's education, and this is what their hospital aid (AI) ought to do. Effective contact between human and artificial intelligence includes a shared pattern of focused knowledge base. Human-to-human contact protection in hospitals should lead this professional transformation process.

Keywords: AI; decision making; Big data; healthcare; HRM; Human Resources Management.

Introduction

Big data and decision making in healthcare

In the modern and interconnected world, decision-making has turned out to be a dynamic and increasingly uncertain process, depending on reliable knowledge. This makes it impossible for

¹ To cite this paper in APA style: Efthymiou, I. P., Vozikis, A., Sidiropoulos, S. and Kritas, D. (2020). AI and Big Data: A New Paradigm for Decision Making in Healthcare. *HAPSc Policy Briefs Series*, 1(2): 138-145. DOI: 10.12681/hapscpbs.26490

² Iris - Panagiota Efthymiou is Board Member and President of the Interdisciplinary Committee, of the Hellenic Association of Political Scientists (HAPSc), Scientific Associate at the Laboratory of Health Economics and Management University of Piraeus, Board Member of Womanitee, HAPSc: Athens, Greece.

³ Athanassios Vozikis is Associate Professor at the University of Piraeus and Director of the Laboratory of Health Economics and Management (LabHEM) of the University of Piraeus, Greece.

⁴ Symeon Sidiropoulos is Political Scientist, President of the Hellenic Association of Political Scientists (HAPSc), Scientific Associate at Laboratory of Health Economics and Management (LabHEM) of the University of Piraeus.

⁵ Dimitrios Kritas is PhD candidate, University of Crete. He is also Deputy President of the Hellenic Association of Political Scientists, Field Manager of the Public Policy and Administration Research Laboratory, University of Crete, Scientific Associate of the Laboratory of Health Economics and Management (LabHEM) of the University of Piraeus and Researcher of the Center for Political Research and Documentation (KEPET) of the University of Crete, Greece.

healthcare organizations (HCOs) and Human Resources Management (HRMs) to respond effectively to the complexities of a particular situation. HCOs are seeking to revise their systems, reconsider their procedures, and enhance related market processes. Analytics are resources that can aid in the decision-making process of companies, suggests that businesses have to be successfully adopted. Analytics solutions are in a position to make a better decision with more accuracy. These organizations have easier and simpler access to crucial information on operations and procedures and to ensure that the priorities are being fulfilled. Organizations identify Key Performance Indicators (KPIs) and are strategic instruments for the review of key HRM objectives (Sousa et al. 2019).

The rising volume of data in the healthcare system has implemented large-scale data strategies necessary in order to increase the quality of healthcare delivery. Despite the incorporation of massive data analysis techniques and platforms into current data management architectures for healthcare systems, these architectures pose challenges in mitigating emergencies. Big data analytics allows large-scale aggregation of data sets, support for human capital decisions, and cost-effectiveness measurement of healthcare organizations. Therefore, the decision-making process focused on Big Data Analytics in Healthcare Organizations, to define key Big Data Analytics that can help decision-making by healthcare leaders and to propose several solutions to increase productivity along the Healthcare Value Chain (El Aboudi & Benhlima, 2018).

The present state of acute care decision making

A computer scientist reviewing the existing threshold-based hospital protocols to design patient management algorithms could easily infer that automation of acute care diagnostics and treatment would be easy to enforce. The explanation for this is that the latest hospital guidelines are based on 20th-century decision-making and are usually very clear. However, experienced physicians know that these basic procedures are not representative of the true degree of acute care quality; Lynn and Curry 2011). Randomized controlled trials (RCTs) that use the threshold rules implemented in-hospital procedures as universal guidelines for the whole population are subject to pronounced heterogeneous clinical effects (HTE) (Ching et al. 2018; Kent, Steyerberg, and Klaveren 2018). Such studies offer proof of the overall drug impact on the population under evaluation as a whole, but not whether the medication used in the RCT would be helpful or detrimental to the patient receiving immediate care. It follows logically, therefore, that no procedure, no matter how well endorsed by RCT, can be implemented without professional monitoring by either a person or an AI to protect patients from injury. Physicians and nurses should provide guidance consequently the procedural decision-making

process is straightforward enough that, with their own knowledge, they should adjust the diagnosis and care received in real-time (Lynn 2019).

AI and its role in medical diagnostic analysis decisions

One concern with acute care use of AI that may not be immediately evident to those with little knowledge of the medical environment is the general gap between the decision and the results of the decision. It is also not apparent if a treatment decision was incorrect with a patient's condition until several days after complications, rehabilitation delay, or deterioration happened. (Arora et al. 2005; Graham et al. 2013). In medical treatment, where the wisdom of the decision is often not readily clear, the clinician in charge of the case can not necessarily wait in confidence to see the results. However, the clinician wants to be able to see the decision-making process itself in fine contextual detail and in real-time and ensure that it corresponds to the nuances and comorbidities of the immediate patient under consideration. Here it can be clearly observed that the need for a new emphasis on medical education because bedside clarification of AI is not helpful if the practitioner is not qualified to be able to read the RTP identified by the AI (Lynn 2019).

The implementation of AI brings new communication challenges to a dynamic hospital environment that is already associated with a high error rate. This is valid as though the machine is a diagnostician and is currently providing care to a person who is about to undergo medication. Guidelines for hand-offs including AI should be prioritised to ensure that they are available as AI is introduced into patient treatment. In comparison, the probability of a possible delay between decision and outcome is likely to be more apparent when a Black Box AI-managed patient fails to recover. The clinician may like to know whether he or she has made an error in AI-based diagnostics or treatment decisions, or both (Graham et al. 2013; Lynn 2019).

Clinical dependency and Artificial intelligence

The second issue that can evolve over time in the acute care setting is intellectual reliance on AI, especially AI, which lacks comprehensive communication skills. If the perceived desire to study advanced pathophysiology diminishes, so does the expertise of the practitioner or nurse. This is the actual state of autonomous driving, where the efficiency of AI must also be measured and monitored by a human being in real-time. With the advent of AI, basic diagnosis and treatment-based threshold guidelines will be replaced by AI-based guidelines that will be even more complicated and will require RTP analysis. However, if proper action is not taken soon, the impact of AI on medical education has the potential to trigger a much deeper reduction (Lysaght et al. 2019).

AI algorithms and applications are being built to support clinical decision-making and/or public health policy development. This AI algorithms usually use computerised predictive analysis algorithms to sort, arrange, and look for trends in broad data sets from different sources, and offer a probability overview so healthcare providers can make faster, better and knowledgeable choices (Efthymiou et al., 2020). Clinical Decision Support Systems (CDSS) are equipped with rule-based systems, fuzzy logic, artificial neural networks, Bayesian networks, as well as general machine learning techniques. CDSS with learning algorithms is currently under development to support physicians in their decision-making based on previous successful diagnosis, treatment, and prognosis. Implementers can include hospitals and healthcare providers who integrate AI-assisted CDSS into the implementation of healthcare services, as well as academics who gather data feedback into the CDSS and assess the effectiveness of AI-algorithms. Organizations and/or individuals may be the developers and implementers of such systems (Lysaght et al. 2019).

AI help in decision making of emerging antibiotic resistance scenario

Antibiotic resistance is an evolving global problem. Responsible decision-making involves the incorporation of large and deep knowledge. Artificial intelligence systems may help decision-making at several levels but developing them requires a consistent co-development strategy to ensure that they are implemented upon deployment. Optimal decision-making in healthcare is also informed by the boundaries of rationality. In specific, how does AI aid in contexts where the idea of free choice has the added difficulty of weighing long-term individual and social risk as well as potential short-term benefits? AI to maximize antibiotic treatment antibiotic therapy, whether suitable or incorrect, is a regulator of antimicrobial resistance. Antimicrobial resistance is a dynamic social and biological threat that represents many of the problems (Mercer et al. 2016). The decision to administer an antibiotic influence, not just the particular patient, but both the human microbiota and community as a whole by the introduction of drug-resistant species. Decision-making during infection control is a complex and sometimes contradictory process (Charani et al. 2011). Another difficulty in the area of infection is the need to provide decision support not only on human causes, but also on bacteria, the antibiotic used in the sense of clinical polypharmacy, the development of tolerance, the symbiotic microbiome, and the broader ecosystem. However, lessons need to be drawn from the existing challenges in encouraging the use of therapeutic decision-making methods. The development of AI systems in the area of infection is still in its infancy. There is currently little thought about how these possible adverse effects of artificial intelligence can be managed and how programmers can react to them when they are detected. Present media attention to the use of artificial intelligence has drawn

some strong views on health welfare. From the patient view, confidence in computer-driven healthcare decisions is inconsistent. In a recent study analyzing public trust in computer-driven decisions, people indicated that while computer-based decision-making had possible benefits in enhancing the precision, engagement, and supervision of medical professionals, it remained important (Rawson et al. 2018). Participants also stated that it is focused on the understanding that human behavior can not merely be based on facts but must rather consider the social and cultural context in which the decision is taken. For antibiotic prescribing, many prospective end-users are currently unsure about how decision-making support can be applied, particularly where the mechanism may move towards a more social viewpoint than that of the client, which is frequently the case where decisions are taken to treat infections. Many of these issues will be overcome by the participation of healthcare practitioners, patients, and professions in the early implementation of such resources. AI architecture promotes participatory methods since, in effect, it seeks to replicate the capabilities of human intelligence. However, although the co-design of the framework to enhance the architecture and performance dimensions is essential, this might not be enough. Co-design would also answer issues and aim to encourage more clarity in the way the decisions made by the framework have been developed and are used to improve human decision-making. Examples such as this illustrate that while AI can certainly improve our capacity to promote decision-making in healthcare, humanization of outcomes is also needed to contextualize knowledge to the user. Decades of lessons from software implementation and human and corporate behavioral studies suggest that co-designing systems can not only encourage improved acceptance of treatments but also facilitate openness in the technological framework that makes up the AI networks used in medicine. This adequately encourages AI experts to be able to clarify and involve the end-user, not only in terms of the optimum configuration of the application and functions but also in terms of the architecture and preparation of the AI system and the possible adverse effects to use in a manner that is accessible to everyone. This would also encourage the fostering of specialist participation in the creation and shaping of systems to ensure that AI is internally, geographically, and contextually important while being alert to changing global epidemiology (Rawson et al. 2019).

AI and Decision-Making Capacity

Decision-making capability consists of the ability to grasp the facts relevant to a decision, to consider its importance, to think about the risks and advantages of the various courses of action, and to express the decisions taken. While philosophers use words such as "understand," "appreciate" and "lie" in

several contexts, this concept is widely understood by the medical community (Griss and Appelbaum 1998; Lepping, Stanly, and Turner 2015).

Incapacity is not a small problem: statistics indicate that more than one-third of elderly and mental hospital inpatients lack decision-making ability. However, in one report, health care practitioners have not been able to recognise incapacity in 42% of cases. When physicians successfully classify patients lacking decision-making capability, data indicate that they frequently struggle to meet incapacity (Janz et al. 2004).

Making life-and-death decisions for injured people takes a tremendous toll on physicians, as reports show a correlation between end-of-life decision-making and occupational health care burnout. However, including family members or patient surrogates in the decision-making process is no panacea. Surrogates interpret patients' desires poorly in about one-third of cases, usually imposing their own expectations on the patient concerned. In comparison, often surrogates undergo additional discomfort and mental health issues, with consequences that often linger for years (Marks and Arkes 2008; Wendler and Rid 2011). One solution to this issue is the Advance Directive or Advance Treatment Plan. Ethical and functional problems with these methods have been addressed elsewhere; for this purpose, it is considered that only patients who have not expressed an advance choice for their treatment. Every day, patients lacking decision-making capability are subject to examinations and procedures that they may not have agreed to. Indeed, needless audits and procedures are not only ethically questionable, but they can also put excessive economic pressure on already-stretched health care systems. Lamanna et al propose that just as AI algorithms allow online retailers to predict which goods the consumer is most likely to purchase or which films they are most likely to experience, so AI may be harnessed to predict which health care decisions the patient will make (Lamanna and Byrne 2018).

AI and its crucial link with public sector opinion

The gradual use of AI in a variety of sectors has been seen in recent years. AI currently not only focuses on robotics but also reaches beyond it, for example, artificial intelligence developments in health care and medicine. Latest examples from other sectors include those that concentrate on AI technologies in the public sector and concentrate on emerging artificial intelligence methods for deep conflict resolution and humanitarian response to conflict resolution, consultation, lobbying, mediation, peacekeeping, crisis management, and other critical humanitarian processes. In addition, Iris et al have investigated the impact of AI-mediated communication on attribution and trust, and among their key observations in the context of current responses and interactions as carried out by

Google and other firms. It is now believed that modern technological advancements, such as the Internet, social networks, and computer technology, are not only part of our everyday lives, but are also part of our governments. The author also discussed the involvement of AI in politics and related issues. And the tried to answer the very important question regarding the European Union's use of AI for optimization of power in line with sociopolitical nature and some international agreements as well ("Artificial Intelligence Ai in Politics Should Political Ai Be Controlled" 2020).

Conclusion

The implementation of artificial intelligence to the bedside has the ability to dramatically alter the conventional position of the physician and nurse. In the future, physicians will track the time cycle study and actions reached by the AI to ensure that the patients under their supervision remain protected from the new, twenty-first century hazards of statistical insignificance and heterogeneous treatment results. However, this ensures that acute care AI programmes have extensive details about the conditions affecting the decisions taken by the AI. To ensure that physicians are able to perform the role of AI supervision, policy leaders can rapidly plan by changing the emphasis of medical education from twentieth-century threshold decision making to twenty-first-century time pattern recognition. In the field of healthcare, a vast amount of data is produced from various medical sources, including, for example, biological images, laboratory test results, doctor's written notes, and health status criteria that allow for real-time patient health tracking. In addition to the enormous amount and variety, data on health care travel at a high level. As a result, big data methods provide enormous prospects for efficiency in healthcare systems. The promise of broad data methods in healthcare studies has drawn the interest of many researchers. Latest advances in big data for health informatics and their role in combating disease detection are discussed, for example, the detection of diagnostics and the treatment of multiple diseases.

References

Arora, V., J. Johnson, D. Lovinger, H. J. Humphrey, and D. O. Meltzer. (2005). Communication Failures in Patient Sign-out and Suggestions for Improvement: A Critical Incident Analysis. *Quality & Safety in Health Care*, 14 (6): 401–407.

Artificial Intelligence Ai in Politics Should Political Ai Be Controlled" International Journal of Innovative Science and Research Technology (n.d). Available at: <https://ijisrt.com/artificial-intelligence-ai-in-politics-should-political-ai-be-controlled>. (Accessed: 19/09/2020).

Charani, E., Edwards, R., Sevdalis, N., Alexandrou, B., Sibley, E., Mullett, D., Franklin, B. D. and Holmes, A. (2011). Behavior Change Strategies to Influence Antimicrobial Prescribing in Acute Care: A Systematic Review. *Clinical Infectious Diseases: An Official Publication of the Infectious Diseases Society of America* 53 (7): 651–62.

Ching, T., Himmelstein, D., Beaulieu-Jones, B. et al. (2018). Opportunities and Obstacles for Deep Learning in Biology and Medicine. *Journal of The Royal Society Interface*, 15 (141): 1-47.

Efthymiou I. P., Efthymiou - Egleton Th. W., Sidiropoulos S. (2020). Artificial Intelligence (AI) in Politics: Should Political AI be Controlled?. *International Journal of Innovative Science and Research Technology*, 5(2): 49-51.

Efthymiou, I., Sidiropoulos, S., Kritas, D., Rapti, P., Vozikis, A. and Souliotis, K. (2020). AI transforming Healthcare Management during Covid-19 pandemic. *HAPSc Policy Briefs Series*, 1(1): 130-138.

El Aboudi, N., and Benhlima, L. (2018). Big Data Management for Healthcare Systems: Architecture, Requirements, and Implementation. *Advances in Bioinformatics*, 2018: 1-10.

Graham, K.L., Marcantonio, E.R., Huang, G.C. et al. (2013). Effect of a Systems Intervention on the Quality and Safety of Patient Handoffs in an Internal Medicine Residency Program. *J GEN INTERN MED*, 28(8): 986–993.

Grisso, T. and Appelbaum, P. (1998). *Assessing Competence to Consent to Treatment: A Guide for Physicians and Other Health Professionals*. New York: Oxford University Press.

Janz, N., Wren P., Copeland L. et al. (2004). Patient-Physician Concordance: Preferences, Perceptions, and Factors Influencing the Breast Cancer Surgical Decision. *Journal of Clinical Oncology: Official Journal of the American Society of Clinical Oncology*, 22 (15): 3091– 3098.

Kent, D. M, Steyerberg, E., van Klaveren, D. (2018). Personalized evidence based medicine: predictive approaches to heterogeneous treatment effects. *BMJ (Clinical Research ed.)*, 363:k4245.

Lamanna, C., and Byrne, L. (2018). Should Artificial Intelligence Augment Medical Decision Making? The Case for an Autonomy Algorithm. *AMA Journal of Ethics*, 20 (9): 902–910.

Lepping, P., Thushara S., and Turner, J. (2015). Systematic Review on the Prevalence of Lack of Capacity in Medical and Psychiatric Settings. *Clinical Medicine*, 15 (4): 337–43.

Lynn, L. A. (2019). Artificial Intelligence Systems for Complex Decision-Making in Acute Care Medicine: A Review. *Patient Safety in Surgery*, 13 (1): 1-8.

Lynn, L. A. and Curry, J. P. (2011). Patterns of Unexpected In-Hospital Deaths: A Root Cause Analysis. *Patient Safety in Surgery*, 5 (1): 3.

Lysaght, T., Yeefen, L. H., Xafis, V. and Ngiam, K. Y. (2019). AI-Assisted Decision-Making in Healthcare. *Asian Bioethics Review*, 11 (3): 299–314.

Marks, M. A. Z., and Hal, R. A. (2008). Patient and Surrogate Disagreement in End-of-Life Decisions: Can Surrogates Accurately Predict Patients' Preferences?. *Medical Decision Making: An International Journal of the Society for Medical Decision Making*, 28 (4): 524–531.

Mercer, K., Li, M., Giangregorio, L., et. al. (2016). Behavior Change Techniques Present in Wearable Activity Trackers: A Critical Analysis. *JMIR Mhealth Uhealth*, 4: e40

Rawson, T. M., O'Hare, D., Herrero, P., et al. (2018). Delivering Precision Antimicrobial Therapy through Closed-Loop Control Systems. *Journal of Antimicrobial Chemotherapy*, 73 (4): 835 –843.

Rawson, M. T., Ahmad, R. Toumazou, C., Georgiou, P and Holmes, A. H. (2019). Artificial Intelligence Can Improve Decision-Making in Infection Management. *Nature Human Behaviour*, 3 (6): 543–545.

Sousa, M. J., Pesqueira A. M., et. al. (2019). Decision-Making Based on Big Data Analytics for People Management in Healthcare Organizations. *Journal of Medical Systems*, 43 (9): 290.

Wendler, D. and Rid. A. (2011). Systematic Review: The Effect on Surrogates of Making Treatment Decisions for Others. *Annals of Internal Medicine*, 154 (5): 336–346.