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Investigating the Barriers to Physician Adoption of an Artificial Intelligence-Based Decision Support System in Emergency Care: An Interpretative Qualitative Study

Cécile PETITGAND,[a,b,1] Aude MOTULSKY[a,c], Jean-Louis DENIS[a,c], and Catherine RÉGIS[b,a]

[a] *Research Center, Centre hospitalier de l'Université de Montréal, Montreal, Canada*
[b] *Faculty of Law, Université de Montréal, Montreal, Canada*
[c] *Department of Management, Evaluation and Health Policy, Université de Montréal, Montreal, Canada*

Abstract. The development of artificial intelligence (AI) systems to support diagnostic decision-making is rapidly expanding in health care. However, important challenges remain in executing algorithmic systems at the frontlines of clinical practice. Hence, most often, these systems have not been trained with local data nor do they fit with context-specific patterns of care. This research examines the implementation of an AI-based decision support system (DSS) in the emergency department of a large Academic Health Center (AHC) in Canada, focusing specifically on the question of end-user adoption. Based in an interpretative perspective, the study analyzes the perceptions of healthcare managers, AI developers, physicians and nurses on the DSS, so as to make sense of the main barriers to its adoption by emergency physicians. The study points to the importance of considering interconnections between technical, human and organizational factors to better grasp the unique challenges raised by AI systems in health care. It further emphasizes the need to investigate actors' perceptions of AI in order to develop strategies to adequately test and adapt AI systems, and ensure that they meet the needs of health professionals and patients. This research is particularly relevant at a time when considerable investments are being made to develop and deploy AI-based systems in health care. Empirically probing the conditions under which AI-based systems can effectively be integrated into processes and workflow is essential for maximizing the benefits these investments can bring to the organization and delivery of care.

Keywords. artificial intelligence, decision support system, emergency care, adoption

1. Introduction

The development of artificial intelligence (AI)-based systems to support clinical decision-making in health care is currently undergoing rapid expansion. AI, broadly

[1] Corresponding Author, Cécile Petitgand, Email: cecile.petitgand@umontreal.ca.

defined as the imitation of human cognition by a machine [1], is expected to enable better surveillance, detection and diagnosis of illnesses, as well as uncover novel treatments to spur precision medicine [2-4]. AI systems have already proven more effective than dermatologists at diagnosing skin cancer [5], and experts believe they will outperform medical specialists in surgery by 2050 [6]. As a result, health care is often presented as one of the most propitious domains in the upcoming "AI revolution" [7][8]. Yet, despite the enthusiasm around AI's capacity to increase the quality, safety and efficiency of care, important challenges remain in executing algorithmic systems at the frontlines of clinical practice. Hence, most often, these systems have not been trained with local data, nor do they fit with context-specific patterns of care [1][9][10].

The present research aims to explore some of these challenges by analyzing the implementation process of an AI-based decision support system (DSS) in the emergency department of a large Academic Health Center (AHC) in Canada. Research to date has identified several hurdles facing the deployment of AI systems in health care. These relate mainly to technical issues (e.g. lack of quality data sets to train algorithms; non-interoperable information platforms) and ethical/legal considerations (e.g. concerns about data privacy, algorithm opacity and patient safety; lack of ethical and legal frameworks to provide safeguards against inappropriate use) [11-14]. Research gaps remain in understanding how these barriers interrelate with human and organizational factors to drive and influence implementation.

This article adopts an interpretative perspective [15] to analyze the implementation of an AI-based DSS in an emergency department (ED), focusing on actors' representations of the system. We explore how health managers, AI developers, physicians and nurses perceive the AI-based DSS and interpret the interrelated technical, human and organizational barriers that lead to its ineffective adoption in the AHC.

2. Methodology

2.1. Study site and AI system

The study site is one of the largest AHCs in Canada, located in the province of Québec. In November 2018, an AI-based DSS was tested for implementation as a pilot project in the AHC's ED. The DSS is a diagnostic technology based on a deep-learning algorithm using clinical data and evidence-based results from the scientific literature. For patients visiting the ED, the DSS presents as a questionnaire that is answered on a mobile tablet. First, the patient is asked about the purpose of their visit to the ED. A Natural Language Processing engine then analyzes the text written by the patient to identify the chief complaint (e.g. skin rash, abdominal pain, etc.).

The patient is then asked a series of questions based on the chief complaint, with each question adapted to the previous response. The main objective is to identify red flags and signs of serious conditions. At the end, the DSS outputs a medical history that is printed by nurses or clerks and presented to the physician prior to their encounter with the patient. According to the DSS developers, who are also emergency physicians at the AHC, the medical history is meant to optimize patient questioning and diagnostic decision-making by providing physicians with information about the history of the presenting complaint, pertinent positives and negatives, past medical/surgical/family history, and social history.

2.2. Data collection and analysis strategies

An in-depth case study was performed at the ED, triangulating data collection methods and sources in an ethnographic approach to make sense of actors' perceptions of the DSS implementation process. A snowball technique was used to recruit participants and 20 semi-structured interviews were conducted: first with the DSS developers (5) and AHC managers (5), and then with emergency physicians (7) and nurses (3). Complementing the interviews (which were recorded and transcribed), informal conversations with nurses and clerks took place, as well as non-participant observations of meetings with managers, designers, physicians and nurses (10 in total), and of DSS utilization in context (15 hours). Field notes allowed observed situations to be contextualized, and preliminary elements of analysis to be identified. Finally, multiple secondary documents were gathered to better grasp actors’ interpretations and trace the DSS implementation history; these included emails sent to physicians, documents prepared by AHC managers and developers, as well as different versions of the DSS-generated medical history. For data analysis, a description of the implementation process was first completed using a narrative strategy [16] that highlighted key timelines and activities. Then, using all collected data, thematic content analysis was performed with NVivo 12 software (QSR International) to identify, categorize and refine the main barriers to physician adoption of the DSS. [17]

3. Findings

Our analysis of the implementation process revealed several barriers identified by research participants that limited the DSS integration into clinical processes and workflow, and eventually drove several physicians towards non-adoption. These barriers related to three types of issue.

3.1. Availability

First, trials were conducted with patients to test whether they could complete the DSS questionnaire. Following adjustments to improve the intelligibility of the questionnaire, AHC managers and DSS developers jointly decided that only a subsection of patients would be asked to complete the questionnaire: English- or French-speaking outpatients who did not present any mental deficiency, visual handicap or alcohol/drug intoxication symptoms. This considerably limited the number of medical histories generated by the DSS.

Moreover, the lack of interoperability between the DSS and the AHC clinical information systems (Electronic Patient Record and Emergency Information System) meant that medical histories had to be printed and handed to physicians in paper form. These tasks were assigned to nurses and clerks who were already overworked with their regular obligations. As a result, medical histories were often not printed and thus were not provided to physicians. According to the DSS developers, this was the main factor limiting physician adoption of the medical history. Developers argued that physicians did not have enough opportunities to read medical histories and learn how to integrate them into their clinical practice. However, according to nurses, this did not really explain why physicians were not becoming "early AI adopters":

> Every time it doesn't work, they say it's because nurses didn't print the history, or didn't direct them [patients] to the tablet, or because... "Wait a minute, you, [developers], what have you done to change our processes? What have you done to improve the medical history? What have you done to innovate?"[...] Since, it's something to help physicians, they need to play their part. (Nurse 2)

3.2. Usability

Some nurses were convinced that physicians were not using the medical histories because they had difficulty understanding patient information reported by the DSS. This was, in fact, a major barrier reported by several physicians. The physicians interviewed considered that the AI-based system was good at reporting simple complaints (a localized pain, a broken leg, etc.) but very poor at making sense of multi-complaint conditions (pain throughout the body, pain related to severe pre-existing conditions, etc.). This was a major concern, as most patients coming to the ED presented with the latter profile:

> The history shows a multitude of symptoms to which the patient responded 'Yes, I have this'. But is it relevant? Is it active? Is it related to the current complaint? Afterwards, you need to disentangle all this. (Physician 4)

This type of feedback was directly reported to the DSS developers during focus groups. In response, adjustments were made to the design of the medical history to better classify patient information and simulate the clinical reasoning of physicians (presentation of pre-existing conditions, chief complaint, etc.). However, adoption rates did not increase significantly. Implementation data collected by the DSS developers showed that the proportion of annotated medical histories remained almost the same (around 30%) before and after these adjustments.

3.3. Perceived usefulness

At the start of implementation, several physicians were positively disposed toward using an AI-based DSS to enhance their diagnostic practice. However, some reported having discovered "errors" in the medical histories. In particular, two physicians reported that reading the medical history led them down the wrong diagnostic path. Had they not questioned the patient again, they would have made a serious clinical error:

> But, you know, there are times when it completely took me down the wrong path... Not often... But it happened and it should not happen. It's like, me... I have zero tolerance. It's a tool that's supposed to help us... not at the price of losing a patient... But to miss something, something huge, you know... So that's... It didn't happen often. But it happened, so it cooled my enthusiasm. (Physician 6)

Perceptions of DSS-induced errors were shared among physicians, and this led some to develop a persistently sceptical attitude towards the usefulness of the DSS. The AI system was thus viewed as introducing a real risk into clinical practice that was capable of causing harm to patients. This is a perception that tends to increase clinician resistance to health information systems.

4. Discussion and implications

This in-depth case study shows how the combination of availability, usability and perceived usefulness can contribute to physician distrust of an AI-based DSS. The study further points to the importance of empirically probing the interconnections between technical, human and organizational factors to make sense of barriers that limit the implementation of AI-based systems in health care. However, these interconnections are rarely taken into account by researchers working on the deployment of AI-based technologies in clinical environments [4][9].

Moreover, the research emphasizes the need to consider the unique challenges raised by AI integration into clinical processes and workflow [10]. As shown in this study, actors' perceptions of a technology influence their actions towards it, be they related to adoption or resistance. For this reason, it is essential that managers responsible for implementation deal with specific assumptions and expectations regarding AI systems. Since these can generate negative perceptions (e.g. distrust in the effectiveness of automated decision making), that can hinder testing and adaptation, it is necessary to develop systematic learning processes based on user feedback to ensure that AI systems are implemented effectively.

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