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Building Trust in Artificial Intelligence: Findings from Healthcare Organization

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Abstract

Artificial intelligence (AI) is commonly applied to the diagnostic process, thus developing a treatment protocol, personalized medicine, and patient care. Second-order cognitive processes are utilized by physicians to control their reasoning while evaluating AI advice. Inadequate diagnostic decisions often result from deficiencies in the use of metacognitions both related to decision-makers' reasoning (self-monitoring) and the AI-based system (system monitoring). Physicians will then fall for decisions based on beliefs as opposed to real data or seek out inappropriate superficial information. Inappropriate diagnostic decisions are, therefore, linked to a lack of trust in AI. This article aims to understand how trust in AI is built among hospital practitioners. A 20-month ethnographic study was conducted in a medical research center wherein hospital practitioners daily apply AI for their medical processes. This research work demonstrates that trust around AI is built through cognition and emotion. Factors like peer validation or social imagination play an important role in AI for creating trust.

Keywords

Artificial Intelligence, Cognitive Trust, Emotional Trust, Healthcare, Ethnography.

Introduction

The use of artificial intelligence (AI) in healthcare is becoming increasingly important. It is defined as using algorithms and software to approach human cognition to analyze complex medical data. The main objective of AI applications in healthcare is to address the relationships between treatments and patients' state of health. AI plays a major role in diagnostic process for treatment protocol development, in personalized medicine as well as in patient care.

Interest in the applied healthcare AI industry is paramount. Big tech companies including Google, IBM and startups like Welltok and Ayasdi have developed AI algorithms for healthcare applications (Solanki et al., 2019). Medical institutions such as The Mayo Clinic, Memorial Sloan Kettering Cancer Center, and Massachusetts General Hospital have also established service-related AI algorithms (Li et al., 2019). The Radiological Society of North America Conference has mainly focused its research work on AI applied for imaging. Likewise, radiology field has become greatly attractive for AI. The AI ability to interpret imaging results facilitate physicians to detect a subtle image variation or information accidentally missed by a clinician.

However, AI is not as seamless (Fazal et al., 2018), and it generates less predictable errors compared to rule-based systems (Liberati et al., 2017). Many researchers work to improve AI technologies and debate their societal implications are emerging (Jiang et al., 2017; Cheng et al. 2016; Shen et al. 2019). Surprisingly, substantial effort is still lacking to understand how hospital practitioners' trust in AI is built. This is of great importance as AI advice influences physicians' decision-making process (Burton et al.2020; Jussupow et al., 2021). A study by Jussupow et al. (2021) of 80 physicians diagnosed cases of patients with an AI-based system. It showed that physicians use second-order cognitive processes to monitor and control their reasoning while evaluating AI advice. These cognitive processes determine whether physicians can take full advantage of AI. Specifically, non-suitable diagnostic decisions more usually arise from deficiencies in the usage of metacognitions for decision makers' reasoning (self-monitoring) and AI-based system (system monitoring). As a result, doctors do not make decisions given real data. They rather refer to their own beliefs or search for inappropriate superficial information.

The study of Jussupow et al. (2021) offers a first perspective on the metacognitive mechanisms that decision-makers use to evaluate system advice. However, it does not provide any understanding on how trust in AI is built among hospital practitioners. The objective is herein to fill this gap in the literature. The question that arises is how trust in AI is built among Physicians?

Conceptual Background

Firstly, a theoretical framework for the use of AI in the health sector will be defined. Likewise, it is relevant to review the notion of trust and how to deal with AI. This theoretical framework will help to determine the gap in the literature to clearly define the research question.

Use of Artificial Intelligence in Healthcare

AI is the core of many fields such as law, industry, commerce, or transport to innovate faster than ever. It is defined as a machine's ability to perform cognitive functions that it is associated with human minds, such as perceiving, reasoning, learning, and problem-solving (Rai et al., 2019).

The most dynamic discipline eager to benefit from AI is healthcare, mainly because it increases learning capacity and provides a decision support system at scales that transform the healthcare future (Noorbakhsh-Sabet et al., 2019). The increasing availability of healthcare data and the rapid development of big data analytic methods have made possible AI applications in healthcare (Jiang et al., 2017). Noorbakhsh-Sabet et al. (2019) have described the different applications of AI in this specific field: it includes clinical applications (such as disease prediction and diagnosis or treatment effectiveness and outcome prediction), translational application (for drug discovery and repurposing or clinical trial and in silico clinical trials) and public health relevance (epidemic outbreak prediction). All of these applications were recently made possible thanks to machine learning (ML) methods, including deep learning methods (Jiang et al., 2017; Noorbakhsh-Sabet, 2019).

ML is the computer's behavior adaptation to a situation based on the data to which they are exposed (Glikson and Woolley, 2020). AI utilizes large datasets to identify interaction patterns among variables by constructing algorithms. By learning the own associations of patients' data, AI allows computers to make predictions. The predictions agree according to the situations of each patient. However, this training process can introduce unintended bias via data characteristics, algorithm, or data-algorithm interaction (Danks and London, 2017).

Deep learning is a subset of ML. Using multiple layers of artificial neuronal networks, deep learning mimics the human brain's operations and generates automated predictions from training datasets. The goal is to estimate the weights through input and outcome data to minimize the average error between the outcome and their predictions (Goodfellow, 2016). One of the perspectives of deep learning techniques is the replacement of certain supervised tasks by algorithmic models of unsupervised learning. For example, recent research at Massachusetts General Hospital has just shown how the use of artificial neuronal networks could ultimately transform the management of anesthesia during medical operations (Schamberg et al., 2020).

These potential applications of AI in the field of health care empower enhancement of the decision-making for hospital practitioners and, consequently, the quality of care for patients. And yet, AI needs to be used to show its potential. Including AI technology in clinical practice creates new challenges. Although AI systems have reached high levels of accuracy, they are not immune to errors since they are mainly based on statistical data patterns rather than explicit human expertise. These mistakes have been described by Jussupow et al. (2021).

For instance, AI-based systems can display racist and sexist decision schemes because of distortions in training data (Kirkpatrick 2016). Identifying incorrect assessments of AI systems is also inherently difficult due to their technological properties. Another example is the application of AI systems in radiology. They rely on deep learning algorithms to offer diagnostic advice based on imaging data, thus less obvious and seamless in comparison with the logic of traditional rule-based systems (Jiang et al. 2017). They provide solely the results of their analysis, while the reasoning remains a black box (Fazal et al. 2018). Physicians are unable to follow AI advice without scrutiny and therefore they do not benefit from AI potential. If physicians cannot trust the accuracy of AI advice, how can they have enough confidence to use it? The way hospital practitioners build their trust in AI remains an open question.

Trust in artificial intelligence

Trust is a complex notion, that many different sciences try to explain. It can be emphasized as the elementary virtue of all social life. It allows anticipation of actions and reactions between human beings in a world of uncertainty and interdependence (Cook, 2001). Through this socialization process, trust reduces this uncertainty. By doing so, trust becomes an intermediate state between knowing and not knowing (Littlewood, 2007), creating a link between risk and acceptance of this risk.

Trust is a fragile concept because its essence is about the willingness to be vulnerable to another person's actions (Hengstler 2016; Paul and McDaniel, 2004). The construction of trust rests on several steps (Bönke, 2012). First, there is an advance trust based on trust propensity. This is also named the initial trust (McKnight et al., 2002). This advanced trust will generate natural interactions. The more interactions they are between the different stakeholders, the more the trust will strengthen itself. Second, trust needs a strong belief in both others' competence and integrity. If a disappointment occurs, trust will be tainted, and damages could be insurmountable. To avoid this unfortunate situation, interactions must fulfill expectations. Finally, trust needs an acceptable tolerance of the degree of mistakes that could emerge from these interactions.

Trust is a non-natural notion developed in participatory management (Heckscher, 1995; Stern and Coleman, 2015). It has imposed itself as a control and structure mechanism to consider employees' autonomy and multiplication of interactions. Legendre et al. (2012) made attempts to explain the trust relationship between health professionals and patients. They highlighted in critical situations the unfeasibility for health professionals and patients to translate, the private thoughts of respondents, thus leading to a gap between people's written and oral content in a semi-directive interview.

Nowadays, it seems obvious and necessary that interactions between AI and healthcare professionals will be increasingly growing and even more rapidly. An analogy between human beings' interactions and AI can be made. If we define AI as an actor, trust is necessary to connect users and AI. In the absence of trust, there will be no use of AI since no structuring control mechanism will reassure about the AI results. As social trust has a global impact on how members of society trade, communicate, and how consumers accept new technologies or industries (Fen et al., 2018), trust in technology can fulfill this building role as trust in the human element might transfer to trust in technology. Trust in technology is defined as "*a belief that certain technology can perform as intended in the situation where negative results are possible*" (McKnight et al., 2011)

The interest of AI and information technology (IT) in creating trust is already studied (Bönke, 2012). The authors suggested that IT systems could help recognize risks in relationships and support efforts to maintain them. Initial trust in new technologies is quite significant because perceptions of risk must be overcome to create a willingness to use the technologies (McKnight et al., 2002, Hengstler 2016). Hengstler et al. (2016) drew an analogy from human social interaction to understand the trust relationship between humans and automation. This interaction seems to be mediated by three components: predictability (anticipation), dependability (consistency), and faith (support). They concluded that cognitive compatibility, trialability, usability, operational security, and data security are decisive factors promoting the performance dimension of trust in technology. AI technology is only truly effective when it takes over some degree of control from the user (Hengstler et al., 2016; Jussupow et al., 2021), but a delegation of control cannot counterbalance flawed technology (Liberati et al., 2017; Fazal et al., 2018).

Other authors have defined different predictors of the building of trust in technologies: experience, understandability, and observability (Rogers, 2010). Understand machine's motives thanks to seamless algorithms and functional logic is a *sine qua none* condition to strengthen the trust (Lee and See, 2004). Castro et al. (2017) used Natural Language Processing (NLP) to classify the regular patients and those with cerebral, thus reaching respectively 95% and 86% accuracy rates on the training and validation samples. As a result, an accurate users' understanding on AI expectations and allowance being made for a degree of error is achieved. Cha et al. (2022) primary focused on three players to define trust in technology: providers, the platform company, and users. Counterparty recognition is a vital factor that can reduce uncertainty when users experience technology.

In information systems, trust is defined through trust beliefs, i.e. the cognitive beliefs of the fiduciary resulting from the fiduciary attribution process. The concept of trust beliefs is articulated with cognitive trust (McKnight et al., 2002). It is the theoretical perspective to view trust as the rational choice of a fiduciary. The choice is motivated by a conscious calculation of the benefits. In the absence of emotional trust, cognitive trust is however insufficient to assess whether or not trust will ultimately influence human decision making (Komiak and Benbasat, 2006). In our empirical study, we consider trust as a construct of both cognitive and emotional trust. Two forms of trust are defined in the literature: cognitive and affective trust (e.g., McAllister, 1995). Cognitive trust refers to the rational evaluation for evaluating the trustworthiness of the exchange between the other party based on the knowledge and information regarding its ability, professionalism, and reliability (McAllister, 1995; Schaubroeck et al., 2011). Affective trust refers to the emotional bonds or connections between the party and exchange relationship that are grounded in the care and concern that it demonstrates.

Many scientific studies to improve AI technologies and debate their societal implications are published in the literature (Jiang et al., 2017; Cheng et al. 2016; Shen et al. 2019). Surprisingly, minimum effort up to now has been devoted for understanding the building relationship of hospital practitioners' trust in AI. This is quite relevant as AI advice influences physicians' decision-making process (Burton et al.2020; Jussupow et al., 2021). Jussupow et al. (2021) conducted experiments with 80 physicians diagnosed cases of patients with an AI-based system. They elicit five decision-making patterns and develop a process model of medical diagnosis decision augmentation with AI advice. As a result, physicians either fall for decisions based on beliefs rather than real data or search for inappropriate superficial information. This study offers a first perspective on the metacognitive mechanisms that decision-makers use to evaluate system advice but does not understand how trust in AI is built among hospital practitioners.

Research Methodology

A 20-month ethnographic research was undertaking within Amiens-Picardy University Hospital, a French academic hospital. This study aims to understand how hospital staff, especially pharmacists, build their trust in AI. The proposed approach for collecting and analyzing data is addressed in the below section.

Data Collection

An ethnographic study based on participant observation, and semi-structured interviews, was launched between February 2020 and October 2021 within the University Health Research Center at the Amiens-Picardie hospital. This Research Center hosts several units dedicated to applied medical research, such as the Functional Neurosciences and Pathologies Laboratory for the simplification of care for complex patients. Most of the research units test medical processes based on AI.

The initial project idea arose from the original use of AI for a doctoral thesis in pharmacology. The subject is supported by the Physio-pathological Mechanisms and Consequences of Cardiovascular Calcifications research unit. The objective is to mobilize AI for the identification of drugs potentially contributing to acute renal failure. The learning algorithm uses data in open databases, such as the world pharmacovigilance database of the World Health Organization, VigiBase, or the program for the medicalization of information systems (PMSI). A Ph.D. student in pharmacology, with a double course in management, was recruited to carry out the ethnographic study started in February 2020.

The Ph.D. student conducted participant observations as a member of the Physio-pathological Mechanisms and Consequences of Cardiovascular Calcifications research unit. An AI-based solution was used for the research. Observations showed that same AI-based solution was utilized by co-workers. Those investigations were then extended to other research units at the university health center. Several AI-assisted devices were utilized by researchers at the center, such as robots for surgery. Therefore, this research encompasses the AI use in its two forms of incarnation: virtual agent and physical robot (Glikson and Woolley, 2020)

Several notes were taken following observations and feedback for the period February 2020 to October 2021. Eighteen semi-structured interviews were conducted with quite a few hospital practitioner-researchers from the health research center. Each interview lasted between 1 and 1.5 hours. The interviewees were all originally trained as pharmacists, whereas they have different backgrounds as hospital practitioners including general practitioners, rheumatologists, and also researchers in cardiovascular disease or toxicology. More specifically, two interviewees had managerial administrative responsibilities. The age range of those interviewed varies between 26 and 59 years, with an average age of 33 years.

Data Analysis

The research question had emerged following several weeks of observation of practices related to the adoption of AI in the health research center. An abductive approach was hence chosen to analyze the data set: note-taking following participant observation and interview transcripts. The reluctance and criticism submitted by hospital practitioners concerning technologies that seem to meet the expected functionalities have led to open questions regarding the trust placed in AI. The reluctance towards AI is a definite effect. Confidence in AI is a likely cause of this reluctance. Back and forth attention were paid to the literature review and the field investigation to strengthen our approach.

A thematic analysis through iterative two-round manual coding was performed to examine the data (Saldaña, 2021). For the first time, two coders activated transcriptions to achieve open coding. This first coding aims to identify first-order concepts, thus highlighting of formal abstraction such as risk, familiarity, or reproducibility. These concepts were compared with the literature to assess their robustness for research arguments validation. Subsequently, a second-order code was produced to identify the emerging themes by grouping the concepts of the first coding. It is a second-degree abstraction. These second-rate themes have been used to understand building the confidence of hospital practitioners.

Discussion

The Physio-pathological Mechanisms and Consequences of Cardiovascular Calcifications research unit called on a local startup specializing in automatic medical language processing. The proposed AI solution allows to structure drug information. It also streamlines retrievable drug information through an ergonomic search engine facilitating healthcare professionals' work. The user will make a request to the drug data base to instantly obtain the most relevant extracts and answers. Note the name of the solution "PS".

The "PS" solution was utilized by the doctoral student in pharmacology for several months to carry out research on acute renal failure. Although the solution provided promising outcomes, the entire research unit team remained reluctant and expressed doubts about the relevance of the results.

Reluctance towards AI was also confirmed given the observations made in other research units using different AI-assisted tools at the hospital center. The other units apply, for example, intelligent robots for surgery or dolls that can simulate heat exchange for a newborn baby. No tool malfunction was reported. Nevertheless, misdiagnoses are sometimes reported due to shortcomings in usage related to the AI-based system.

It is well-known that physicians use second-order cognitive processes to monitor and control their reasoning while evaluating AI advice (Jussupow et al., 2021). As a result, physicians fall into the trap of making decisions based on beliefs rather than real data or seeking out inappropriate superficial information. To better understand these beliefs, this study focused on both the emotional and cognitive trust placed by healthcare professionals in AI. The analysis of observations and interviews with healthcare professionals revealed several factors influencing trust in AI and its results, which revolve around these two notions of trust. The various factors are associated with–these two notions sometimes either in common or in parallel.

Cognitive trust

Trust in AI appears to have one of its sources in cognitive trust: a rational, constructed, and explicit trust. When healthcare professionals were asked what builds trust between human beings, the notion of proof came up regularly.

"*Strong track records are needed to trust someone, for example, if I know the person has never lied to me. If this is a new person, nothing will put me at ease. You have to prove yourself.*" (P1)

The proof is here defined by the connotation of worth but is not sufficient to establish cognitive confidence. It is also assumed that a clear and precise argument is necessary. The proof seems to have two dimensions: evidence in action, demonstrating one's worth, and inaction to show one's knowledge. This duality of proof would be involved in the strength of cognitive trust. When healthcare professionals were asked about trust in AI, the analogy of human beings with trust can also be drawn to that with respect to AI. A need for a persuasive speech emerges.

"*It is necessary that the person has a minimum of knowledge [to be trusted], that the answer is constructed and supported by knowledge*." (P5)

Interviews identified several factors feeding this cognitive trust in AI in the healthcare field: peer review, AI assimilation, and expectations for a medical process.

Peer Review

A recurrent theme across healthcare professionals' answers involving cognitive trust was the necessity for peer review. Collective activity of researchers in their field, who critically judge AI and repeatedly use it, assures the perceived quality of AI (and its results) and its usefulness. Peer review ensures the integrity of the AI. Scientific communities trust peer review to uphold shared values of rigor, ethics, originality, and analysis and rely on it to establish shared knowledge. Therefore, peer review in its essence represents evidence and builds cognitive trust in AI:

"*The effect of notoriety will help me to trust AI. If someone well-known talks about it, I will trust him. Recognition of the tool by my peers would increase my trust*." (P3)

Peer evaluation also allows having a network of professionals who have already tested this AI-based tool. The assurance of contacting someone who has already used AI seems to fuel trust in this AI technology.

"*In front of a new device, I'm already going to contact the designers and then try to see if other people have already used it, for example my colleagues, or if there are publications on it, or a frequently asked question… Contact these people to see problems that they could have met*." (P11).

AI assimilation

Peer use of AI alone is not sufficient to explain cognitive trust. Assimilating AI implies familiarity or repeated use by the healthcare professional to be required. This process of assimilation is necessary to both learn and understand AI, regain control over this unbalanced relationship, and ultimately trust AI.

AI assimilation seems to require four steps. Understanding is the first step to trust AI:

"*Before using AI, I have to know beforehand how it's going to be, how it was built, how it has trained to recognize. Without knowing or understanding, on things as complicated as AI with machine learning,* *deep learning etc., I think I wouldn't use it. If it's too opaque, incomprehensible, that I can't see how the machine was tuned or get the suppliers, I'm not going to trust*.” (P4)

To profit efficiently from AI, it is necessary to understand it and to deepen its use. Understanding is only possible after training. The possibility of being trained to use such AI would be a founding element to build cognitive trust.

“*There is clear importance to training. If you consider AI as a tool, you have to be well trained to use it and for it to be easy to use, so this is essential*.” (P1)

Also, control seems to integrate understanding. The relationship of trust resides in the delegation of control to others. Taking back control allows to counterbalance this relationship and to ensure that all processes are integrated.

“*If AI only processes data that I give it, I will have trust in these data. [...] At the beginning, I wish I could stop it [AI] every now and then to check on what it is doing*.” (P15)

The second step is the first use, followed by repeated uses. AI assimilation needs a positive first use to consolidate cognitive trust. The success of the first one conditions next uses. This action is nevertheless nebulous because the stage of comprehension is often not completed. In the absence of a clear understanding, the ease of use will be more complex to acquire. If the first use is the glue of cognitive confidence, later uses are the walls that keep it strong.

“*The first impression, you don't do it twice. It's hard to come back if the experience is really negative [...] One positive experience is not enough. Trust is not binary. I have a positive experience so I'm starting to trust. The more positive experiences I have the more this trust "credit" will increase and therefore I will be more receptive*.” (P2)

The fourth step is error handling. It appears that hospital practitioners want to understand AI imperfections and react accordingly. Faced with a situation of failure, healthcare professionals do not find themselves in front of the unknown. This assurance is considered in the assimilation of AI. Understand error depends on everyone's propensity to accept the margin of mistake inherent in any technology. It is assumed that healthcare professionals readily accept this notion, mainly because they face this problem in the context of medical research. Accepting the risk of having an inconclusive result is part of the research process.

“*I don't think it's [AI] 100% efficient and software developers can't promise that anyway. So there is always a margin of error that we are willing to accept when using the tool*.” (P11)

Tolerance for margin error depends on peer review. If the assimilation of margin of error was already firmly established by peers, an increase in this margin during the use of IA by healthcare professionals would not be accepted and cognitive confidence would consequently suffer. The side-effects of the error also influence the understanding healthcare professionals will have towards the mistake. Scope of AI therefore comes into play. In healthcare, error is detrimental, and risk must be minimized. Tolerance for error is hence reduced and cognitive confidence is closely linked to it.

AI as a medical process

AI is considered as a medical process by healthcare professionals. Cognitive trust is reinforced if expectations relative to any medical tool are met. Expectations of a medical process are anticipated and focused on two key concepts: reproducibility and transparency. Reproducibility is one of the necessary conditions to include the observations made during this experiment in the process of perpetual improvement of scientific knowledge:

“*I find it [AI] to be a reliable tool. For example, in pathology, scores depend on the human, who is doing the analysis. AI is trained to tell whether cell is tumor or not, and since it is a computer that interprets and not a human being, non-reproducibility bias is completely removed*.” (P9)

The transparency concept evoked by hospital practitioners refers to the possibility of auditing the source codes of AI:

"*This is not a black box, no one can hide things in it. Transparency provides confidence in the quality of AI. I am a supporter of free software [...] Access to the source code is a precondition for this*." (P2)

Emotional trust

Trust in AI granted by hospital practitioners is also fueled by emotionality. Two concepts that determine this emotional trust were identified in this study: the personality trait and the social imaginary.

Personality trait

Personality is the set of behaviors that make up the individuality of a person. It gives an account of what qualifies the individual: permanence and continuity of the modes of action and reaction, originality, and specificity of his way of being. APA Dictionary of Psychology defines personality trait as "*relatively stable, consistent, and enduring internal characteristic that is inferred from a pattern of behaviors, attitudes, feelings, and habits in the individual*". For instance, one of the people questioned self-describes as a misanthrope, whereas as a perfectionist for another person. These are personality traits.

Emotional confidence finds one of its sources in the personality trait. The personality trait, or the character - term used by our interviewers - is a concept that often comes up to explain the reluctance or acceptance of AI by healthcare professionals:

"*Given my nature, I probably wouldn't be very comfortable ... At first, I wish I could stop [AI] every now and then to check on what she is doing*." (P12)

It seems that the openness of healthcare professionals to AI depends on their personality trait. The personality trait manifests itself through perceived personalization. It is not something rational but specific to everyone. Although not necessarily in line with the use of AI, personal experiences, such as risk aversion or relationship with those around them, shape the receptivity of healthcare professionals to AI. This finding supports that personality is determined by social learning and cognitive learning.

Social imaginary

The concept of social imagination is extensively reviewed in sociology, philosophy, or media studies. It is defined as "*the creative and symbolic dimension of the social world, the dimension through which human beings create their ways of living together and their ways of representing their collective life*" (Thompson, 2020). Social imagination is determined through media cultures such as films and novels. It appears that the collective imagination about AI has been built through science fiction films and novels. The representation of AI through films or books came up often in the interviews:

"*I'm a big fan of science fiction, I've read Asimov, I've seen Terminator, I know Skynet very well who isn't the first AI to want to kill humans in literature. In one of Asimov's novels, machines ask themselves the question of totally destroying men in order to preserve humanity*." (P2)

"*From what I know of it, I think it [AI] can only be beneficial. AI has a bad reputation because people immediately think that it will replace humans for all tasks. I just think AI isn't well enough sold well, there are a lot of bad ads and movies like "I. Robot" don't help. People think we're going to be ruled by robots and AI. We are far from it anyway*." (P6)

Social influence can condition the attitudes, beliefs, and actions of an individual. It is assumed for AI that media culture has created a social representation of AI, which affects people's beliefs and their emotional trust. interviewees who maintained a negative portrayal of AI through the media, such as the destruction of humanity, all had reservations about using the technology and did not show trust in AI.

Conclusion and Limitations

It is well-established that cognitive trust impacts emotional trust. In contrast with the common literature it is therein demonstrated however that emotional trust influences cognitive trust to build trust in AI among hospital practitioners. This outcome can pave exciting new ways in the highly rational environment of hospital practitioners. Importantly, it is observed that AI-related social imaginary plays a pivotal role in building trust. In addition to a person's character trait, the portrayal of AI in science fiction books and movies affects emotional trust. Three elements influencing cognitive trust were also identified: Peer review, AI assimilation, and AI as a medical process.

Some limitations to be carefully reviewed including the subjectivity nature of data collection and practitioner typology of interviewed, were detected in this research work. The first limitation is inherent to the author who conducted the interviews, being a hospital practitioner and a member of the health research center. On one hand, this had both enabled easy contact with hospital practitioners and fluent interviews. On the other hand, the subjective dimension was present when collecting data. Efforts were then made to greatly mitigate this subjective pattern during the data coding phase. Likewise, it was noticed that the field observer spontaneously approached practitioners with the same pharmacist profile since. Belonging to the community facilitates discussion. In contrast, the health research center also includes other profiles such as surgeons or researchers in biology. For these populations, ethnographic study can be mainly summarized in non-participating observations and quick questioning. In addition, questions related to the expectations of the use of AI were asked during the interviews. Nevertheless, this vast research subject was not addressed in this article. Future research will examine in detail how AI confidence and expectations manifest among hospital practitioners by including a larger population in interviews. For instance, the trust of AI in surgery, remains an unexplored field of investigation.

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