

Lay individuals' perceptions of artificial intelligence (AI)-empowered healthcare systems

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Abstract

With the recent advances in Artificial Intelligence (AI) technology, patient-facing applications have started embodying this novel technology to deliver timely healthcare information and services to the patient. However, little is known about lay individuals' perceptions and acceptance of AI-driven, patient-facing health systems. In this study, we conducted a survey with 203 participants to investigate their perceptions about using AI to consult information related to their diagnostic results and what factors influence their perceptions. Our results showed that despite the awareness and experience of patient-facing AI systems being low amongst our participants, people had a generally positive attitude towards such systems. A majority of participants indicated a high level of comfortability and willingness to use health AI systems, and agreed AI could help them comprehend diagnostic results. Several intrinsic factors, such as education background and technology literacy, play an important role in people's perceptions of using AI to comprehend diagnostic results. In particular, people with high technology and health literacy, and education levels had more experiences with using AI and tended to trust AI outputs. We conclude this paper by discussing the implications of this work, with an emphasis on enhancing the trustworthiness of AI and bridging the digital divide.

KEYWORDS

acceptability, artificial intelligence, diagnostic results, healthcare, trust

1 | INTRODUCTION

Artificial intelligence (AI) has been applied in medicine and clinical domains such as diagnostic imaging and genetic diagnosis to enhance decision-making, reduce diagnostic errors, and alert about any high-risk health outcomes (Jiang et al., 2017). With the recent rise in the capabilities of AI technology, the application areas of AI

have expanded to patient-facing domains, such as health education (Crutzen, Peters, Portugal, Fisser, & Grolleman, 2011), self-diagnosis (Ghosh, Bhatia, & Bhatia, 2018), health promotion (Grolleman, Dijk, Nijholt, & Emst, 2006), and mental health (Oh, Lee, Ko, & Choi, 2017). However, such patient-facing applications of AI are still sparse. The literature has demonstrated various benefits of patient-facing, AI-empowered

systems. For example, such systems can be beneficial for patients who may have health concerns outside of their regular physician's operating hours (Palanica, Flaschner, Thommandram, Li, & Fossat, 2019). People may also perceive AI systems as safer and more private interaction partners than primary physicians and thus, are more willing to disclose sensitive medical information and report stigmatic conditions to AI (Gratch, Lucas, King, & Morency, 2014).

Despite the demonstrated usefulness and benefit of health AI systems, little is known about lay individuals' perceptions and acceptance of this novel technology. In fact, the literature suggests that this technology currently has minimal adoption by and awareness among the general public (Nadarzynski, Miles, Cowie, & Ridge, 2019). Given the ongoing trends toward the use of health AI systems by lay individuals to make sense of their personal health information (e.g., laboratory test results, diagnostic results, etc.), it is critical to understand their perceptions about using this novel technology and what factors influence their willingness to use it. To this end, we conducted an online survey with 203 participants to investigate these questions in the context of comprehending radiology reports. This preliminary work is part of a large research effort to design and develop AI-driven, patient-facing applications to aid patients, especially those with low health numeracy and literacy, to better interpret their diagnostic results (e.g., laboratory test results, radiology report, etc.). Through this preliminary work, we hope to obtain an empirical understanding of lay people's perceptions of using AI systems to interpret diagnostic results. This work could inform the future research in designing patient-centered and trustworthy AI-driven information systems.

1.1 | Related work

The recent digitization of healthcare services in the United States, such as the adoption of electronic patient portals, offers patient direct and easy access to large pools of clinical data such as radiology reports and laboratory test results (Peacock et al., 2016). Increasing patient's access to their clinical data has been proven beneficial for enhancing patient-centered care (Basu et al., 2011; Ross et al., 2005). However, such data are not typically comprehensible to patients and patient portals provide very limited actionable and meaningful information (Hong et al., 2017). Even more concerning is that patients usually do not get timely explanation from their primary physician, leaving them wondering the meaning of the results and what to do next (Chen, Cheng, Tang, Siek, & Bardram, 2013). As such, patients and caregivers need to

seek health information and knowledge outside of clinical settings to better understand their diagnostic test results (Ma et al., 2018).

In recent years, due to the advancement of AI technology, AI-empowered health systems have emerged and are expected to provide pertinent medical advice to patients in real time to alleviate the financial burden and time cost of patients (Curioni-Fontecedro, 2017). For example, these systems can help patients understand their diagnostic results, get an overview of their health status, become aware of their illness, and manage their conditions (Patel et al., 2009). Despite its high potential, there is a limited understanding of lay individuals' perceptions about using this novel technology and what sociodemographic factors influence their perceptions. Our study set out to bridge this knowledge gap.

2 | METHODS

2.1 | Data collection

Data collection occurred in July 2019. This study has been approved by Pace University Institutional Review Board. We recruited 203 participants from Amazon Mechanical Turk to take our survey. To determine eligibility, we first asked potential respondents whether they had taken any clinical procedure (e.g., lab test, CT-scan) over the past 6 months and whether they had reviewed the diagnostic results. If they responded with "yes" to both questions, we asked them to read and sign the consent form and complete the survey. The survey took about 5 minutes to complete.

The survey was developed in an iterative manner by the researchers and pilot tested with a small group of people ($n = 5$) to ensure the clarity and appropriateness of the questions. The survey assessed two domain areas: (Basu et al., 2011) participant characteristics and (Chen et al., 2013) perceptions of AI in the context of interpreting diagnostic results. Participant characteristics we assessed included age, gender, race/ethnicity, education, and occupation. These demographic questions were created based on the format and recommendations provided in previous literature (Lor, Bowers, Krupp, & Jacobson, 2017). Participants were also asked to rate their technology literacy and health literacy on a scale of 1 to 5 (1 denotes low literacy, whereas five denotes high literacy). Explanations of technology literacy and health literacy were provided in the survey to facilitate the rating. Perceptions of AI-led health system included: prior experience with AI, comfortability of using AI to interpret diagnostic results, trustworthy of AI healthcare system (diagnostic capabilities and generated recommendations),

perceived capability and potential of health AI systems, as well as willingness to use AI in the future. The perception questions were adapted from a previous study examining the acceptability of AI chatbots (Nadarzynski et al., 2019).

It was assumed that many participants did not have experience with AI-driven healthcare systems to interpret their diagnostic results in the past; thus, we not only provided an explanation of health AI systems but also included a demo in the survey to illustrate the application of AI in predicting the normality indication of a lab report (e.g., whether the lab report describes a normal or abnormal result) (Figure 1). By doing so, we aimed to give participants a better sense of the capability of AI in diagnostic results interpretation so as to better situate them in the study context.

2.2 | Data analysis

We conducted descriptive statistical analysis on the data using IBM SPSS 25.0. Chi-square test or Fisher's exact test was used to examine whether there were differences in participant perception of using AI to interpret diagnostic test results based on the characteristics of participants, such as education background and technology literacy. All the tests were two-sided, and the level of significance was set as 0.05.

3 | RESULTS

3.1 | Characteristics of participants

Table 1 shows participant characteristics, which included an almost equivalent number of male and female participants (51.2% and 48.3%, respectively). Most of the participants are white (141/203, 69.5%), between 26 and 49 years old (129/203, 63.5%), have a bachelor or higher degree (134/203, 66.1%), have a full-time job (157/203, 77.3%), and self-reported having above medium health

literacy (111/203, 54.7%) and technology literacy (148/203, 72.9%).

3.2 | Lay Individuals' perceptions of AI

As Table 2 shows, most of our participants (77.3%) have no prior experience with AI to consult health information (e.g., diagnostic results). However, a majority of them reported "somewhat" and "very" comfortable with using AI (43.3% and 19.2%, respectively). More than half of the participants (58.6%) reported that they would trust AI-generated outputs, such as the prediction of the normality of test results. Furthermore, even though they agreed that AI has the potential to support their understanding of diagnostic results (64.5%), only 37.4% of participants considered AI having the same levels of diagnostic capability than a doctor has. Lastly, 46.8% of participants indicated that they are certainly willing to use AI to consult health information in the future, while 40.4% reported they may do that.

3.3 | Influencing factors on People's perceptions of AI

We also explored the influencing factors on people's perception of AI. In particular, we examined if there were associations between participants' demographics and their perceptions about using health AI systems. As Table 1 shows, ages of participants were statistically associated with the perception of AI's diagnostic capability (p -value = .015); younger people were more likely to agree that AI could provide the same level of diagnosis in comparison to a doctor (15/38, 39.5% for people between 18 and 25 years old, and 54/129, 41.9% for those between 26 and 49 years old). There also existed significant associations between the education levels and people's experience with AI in the past (p -value = .026), the trustworthiness of AI outputs (p -value = .005), and perceived AI's capability (p -value = .044). That is, people

The inner ear structures, including the semicircular canals, vestibule, and cochlea are unremarkable. The vestibular aqueduct is not enlarged. **LEFT: The internal auditory canal and cochlear aperture are both mildly asymmetrically smaller in comparison to the right side.** The left cochlear nerve is not discretely visualized at the expected position within the internal auditory canal. The facial nerve and superior/inferior vestibular nerves appear normal in position.

[Click to show/hide an artificial intelligence \(AI\) prediction](#)



AI suggests the highlighted sentence describes an **ABNORMAL** finding.

FIGURE 1 A demonstration of using AI to suggest the normality indication of diagnostic results

TABLE 1 Associations between characteristics of participants and their perceptions of using AI to interpret diagnostic test results

Participant characteristics	Total (N = 203), N(%)	Experience with AI	Comfortability	Trustworthiness	Perceived AI's capability	Perceived AI's potential	Willingness to use AI
Age		0.467	0.39	0.495	0.015*	0.075	0.527
18–25 years	38 (18.7)						
26–49 years	129 (63.5)						
50–64 years	32 (15.8)						
65 and older	4 (2.0)						
Gender		0.81	0.12	0.35	0.106	0.013*	0.274
Male	104 (51.2)						
Female	98 (48.3)						
Other	1 (0.5)						
Race/ethnicity		<0.001***	0.429	0.48	0.002**	0.884	0.076
Asian or Pacific islander	9 (4.4)						
African American	34 (16.7)						
Hispanic/Latino	12 (5.9)						
American Indian	4 (2.0)						
Caucasian	141 (69.5)						
Other	3 (1.5)						
Education		0.026*	0.074	0.005**	0.044*	0.748	0.934
Doctorate degree	6 (3.0)						
Master's degree	32 (15.8)						
Bachelor's degree	96 (47.3)						
Associate degree	28 (13.8)						
High school degree	40 (19.7)						
Other	1 (0.4)						
Health literacy		0.3	0.544	0.041*	0.11	0.409	0.883
High	44 (21.7)						
Medium to high	67 (33.0)						
Medium	81 (39.9)						
Low-medium	10 (5.0)						
Low	1 (0.4)						
Technology literacy		<0.001***	0.662	0.046*	0.144	0.022*	0.545
High	67 (33.0)						
Medium to high	81 (39.9)						

TABLE 1 (Continued)

Participant characteristics	Total (N = 203), N(%)	Experience with AI	Comfortability	Trustworthiness	Perceived AI's capability	Perceived AI's potential	Willingness to use AI
Medium	52 (25.6)						
Low-medium	2 (1.0)						
Low	1 (0.5)						

Note: * $p < .05$, ** $p < .01$, *** $p < .001$.

TABLE 2 Patient perceptions of using AI to interpret diagnostic test results

Perceptions of AI	Total (n = 203), category (n, %)
Q1: Have you ever used an intelligent chatbot to consult health information? (experience with AI)	Yes (46, 22.7%) No (151, 74.4%) Not sure (6, 2.9%)
Q2: How comfortable are you with using AI to understand your diagnostic results? (comfortability with AI)	Very comfortable (39, 19.2%) Somewhat comfortable (88, 43.3%) Neutral (46, 22.7%) Somewhat uncomfortable (22, 10.8%) Very uncomfortable (8, 4%)
Q3: Do you trust AI-generated information and recommendation? (AI trustworthiness)	Absolutely trust (15, 7.4%) Somewhat trust (104, 51.2%) Neutral (40, 19.7%) Somewhat not trust (36, 17.7%) No trust at all (8, 4.0%)
Q4: How much do you agree that AI have the same, if not better, levels of diagnostic capability than a doctor has? (perceived AI's capability)	Agree (76, 37.4%) Neither agree nor disagree (51, 25.1%) Disagree (76, 37.5%)
Q5: How much do you agree that AI has the potential to support your understanding of diagnostic results? (perceived AI's potential)	Agree (131, 64.5%) Neither agree nor disagree (52, 25.6%) Disagree (20, 9.9%)
Q6: Are you willing to use AI systems to interpret your health information in the future? (willingness to use AI)	Yes (95, 46.8%) Maybe (82, 40.4%) No (26, 12.8%)

with higher degrees were more likely to trust AI's predictions and recommendations (6/6, 100% for those with doctorate degree, and 23/32, 71.9% for those with master degree), and had more confidence in AI's diagnostic capability (4/6, 66.7% for those with doctorate degree, and 19/32, 59.4% for those with master degree) (Table 3). We also found that health and technology literacy played an important role in people's perceptions of AI. More specifically, health literacy was significantly associated with whether people trusted the capability of AI in providing credible information (p -value = .041). Similarly, technology literacy was strongly associated with whether having experiences with AI (p -value < .001). Interestingly, people with higher technology literacy were more likely to trust AI outputs (p -value = .046) and believe AI has a great potential to support the comprehension of diagnostic results (p -value = .022) (Table 4).

4 | DISCUSSION, LIMITATION, AND FUTURE DIRECTION

This preliminary work allowed us to gain an understanding of lay individuals' perceptions of using AI-driven systems to make sense of their diagnostic results, such as radiology reports. Despite the awareness and experience of patient-facing AI systems being low amongst our participants, people had a generally positive attitude towards such systems. For example, a majority of participants agreed that AI has the potential to support their understanding of diagnostic results. Furthermore, many participants stated that they felt comfortable with using AI and expressed the willingness to use AI-driven health systems to interpret their medical data in the future. However, we noticed only half participants indicated they would trust AI-generated medical advice, highlighting an emerging need to examine how to increase people's trust of AI in the context of seeking health information and support. Prior work has suggested that intelligent systems often failed to provide meaningful explanations to the user, which inhibits the establishment of trust (Vorm, 2018).

TABLE 3 Participant perceptions of using AI to interpret diagnostic test results and the association to education background

	Education						p value
	Total (n = 203), n(%)	High school (n = 40)	Associate (n = 28)	Bachelor (n = 96)	Master (n = 32)	Doctorate (n = 6)	
Q1: Experience with AI							
Yes	46 (22.7)	2 (5)	5 (17.9)	22 (22.9)	13 (40.6)	3 (50)	1 (100)
No	151 (74.4)	36 (90)	22 (78.6)	71 (74)	19 (59.4)	3 (50)	0 (0)
Not sure	6 (2.9)	2 (5)	1 (3.6)	3 (3.1)	0 (0)	0 (0)	0 (0)
Q2: Comfortability with AI							
Very comfortable	39 (19.2)	2 (5)	2 (7.1)	20 (20.8)	12 (37.5)	3 (50)	0 (0)
Somewhat comfortable	88 (43.3)	21 (52.5)	13 (46.4)	43 (44.8)	7 (21.9)	3 (50)	1 (100)
Neutral	46 (22.7)	10 (25)	10 (35.7)	20 (20.8)	6 (18.8)	0 (0)	0 (0)
Somewhat uncomfortable	22 (10.8)	5 (12.5)	1 (3.6)	11 (11.5)	5 (15.6)	0 (0)	0 (0)
Very uncomfortable	8 (4)	2 (5)	2 (7.1)	2 (2.1)	2 (6.3)	0 (0)	0 (0)
Q3: AI trustworthiness							
Absolutely trust	15 (7.4)	0 (0)	0 (0)	5 (5.2)	9 (28.1)	1 (16.7)	0 (0)
Somewhat trust	104 (51.2)	18 (45)	15 (53.6)	52 (54.2)	14 (43.8)	5 (83.3)	0 (0)
Neutral	40 (19.7)	12 (30)	8 (28.6)	15 (15.6)	4 (12.5)	0 (0)	1 (100)
Somewhat not trust	36 (17.7)	8 (20)	4 (14.3)	20 (20.8)	4 (12.5)	0 (0)	0 (0)
No trust at all	8 (4.0)	2 (5)	1 (3.6)	4 (4.2)	1 (3.1)	0 (0)	0 (0)
Q4: Perceived AI's capability							
Agree	76 (37.4)	9 (22.5)	8 (28.6)	36 (37.5)	19 (59.4)	4 (66.7)	0 (0)
Neither agree nor disagree	51 (25.1)	11 (27.5)	7 (25)	25 (26)	5 (15.6)	2 (33.3)	1 (100)
Disagree	76 (37.5)	20 (50)	13 (46.4)	35 (36.5)	8 (25)	0 (0)	0 (0)
Q5: Perceived AI's potential							
Agree	131 (64.5)	30 (75)	16 (57.1)	59 (61.5)	20 (62.5)	5 (83.3)	1 (100)
Neither agree nor disagree	52 (25.6)	7 (17.5)	10 (35.7)	24 (25)	10 (31.3)	1 (16.7)	0 (0)
Disagree	20 (9.9)	3 (7.5)	2 (7.1)	13 (13.5)	2 (6.3)	0 (0)	0 (0)
Q6: Willingness to use AI							
Yes	95 (46.8)	16 (40)	12 (42.9)	46 (47.9)	17 (53.1)	3 (50)	1 (100)
Maybe	82 (40.4)	16 (40)	13 (46.4)	38 (39.6)	12 (37.5)	3 (50)	0 (0)
No	26 (12.8)	8 (20)	3 (10.7)	12 (12.5)	3 (9.4)	0 (0)	0 (0)

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

TABLE 4 Participant perceptions of using AI to interpret diagnostic test results and the association to technology literacy

	Technology literacy					<i>p</i> value
	Total (n = 203), n(%)	1: Low (n = 1)	2: Low- medium (n = 2)	3: Medium (n = 52)	4: Medium- high (n = 81)	5: High (n = 67)
Q1: Experience with AI						<.001 ***
Yes	46 (22.7)	0 (0)	0 (0)	15 (28.8)	20 (24.7)	11 (16.4)
No	151 (74.4)	0 (0)	2 (100)	34 (65.4)	60 (74.1)	55 (82.1)
Not sure	6 (2.9)	1 (100)	0 (0)	3 (5.8)	1 (1.2)	1 (1.5)
Q2: Comfortability with AI						.662
Very comfortable	39 (19.2)	0 (0)	1 (50)	12 (23.1)	11 (13.6)	15 (22.4)
Somewhat comfortable	88 (43.3)	1 (100)	0 (0)	23 (44.2)	35 (43.2)	29 (43.3)
Neutral	46 (22.7)	0 (0)	0 (0)	10 (19.2)	21 (25.9)	15 (22.4)
Somewhat uncomfortable	22 (10.8)	0 (0)	1 (50)	5 (9.6)	12 (14.8)	4 (6)
Very uncomfortable	8 (4)	0 (0)	0 (0)	2 (3.8)	2 (2.5)	4 (6)
Q3: AI trustworthiness						.046*
Absolutely trust	15 (7.4)	0 (0)	1 (50)	7 (13.5)	4 (4.9)	3 (4.5)
Somewhat trust	104 (51.2)	0 (0)	0 (0)	22 (42.3)	41 (50.6)	41 (61.2)
Neutral	40 (19.7)	0 (0)	0 (0)	16 (30.8)	15 (18.5)	9 (13.4)
Somewhat not trust	36 (17.7)	1 (100)	1 (50)	6 (11.5)	18 (22.2)	10 (14.9)
No trust at all	8 (4.0)	0 (0)	0 (0)	1 (1.9)	3 (3.7)	4 (6)
Q4: Perceived AI's capability						.144
Agree	76 (37.4)	1 (100)	0 (0)	23 (44.2)	30 (37)	22 (32.8)
Neither agree nor disagree	51 (25.1)	0 (0)	1 (50)	17 (32.7)	19 (23.5)	14 (20.9)
Disagree	76 (37.5)	0 (0)	1 (50)	12 (23.1)	32 (39.5)	31 (46.3)
Q5: Perceived AI's potential						.022*
Agree	131 (64.5)	0 (0)	0 (0)	29 (55.8)	52 (64.2)	50 (74.6)
Neither agree nor disagree	52 (25.6)	0 (0)	1 (50)	19 (36.5)	20 (24.7)	12 (17.9)
Disagree	20 (9.9)	1 (100)	1 (50)	4 (7.7)	9 (11.1)	5 (7.5)
Q6: Willingness to use AI						.545
Yes	95 (46.8)	0 (0)	1 (50)	28 (53.8)	36 (44.4)	30 (44.8)
Maybe	82 (40.4)	1 (100)	0 (0)	17 (32.7)	34 (42)	30 (44.8)
No	26 (12.8)	0 (0)	1 (50)	7 (13.5)	11 (13.6)	7 (10.4)

Note: * $p < .05$, ** $p < .01$, *** $p < .001$.

Therefore, it is important to examine what types of AI explanations are needed by lay individuals to promote trust and increase satisfaction in health AI systems. Furthermore, the effects of AI explanations on people's perceptions remain understudied (Kizilcec, 2016). Without rigorous and empirical user evaluation, designers and developers of health AI systems are left with little guidance in terms of what system outputs to present and how. To fill this knowledge gap, future research should conduct experiments to evaluate the effect of different types of explanations on people's perceptions, decision making, and trust. Those results can then be used to inform the design of AI-driven, patient-facing applications to present information in a format that is meaningful, understandable, and trustworthy to the end-users. Second, we also found that several intrinsic factors (e.g., education, technology literacy, and health literacy) could impact people's perceptions. For example, people with high technology literacy, health literacy, and education levels had more experiences with using AI and tended to trust AI outputs more. This highlights a concerning issue that there exist significant disparities in the use of novel health technologies among certain groups, including those with low health literacy (Mackert, Mabry-Flynn, Champlin, Donovan, & Pounders, 2016). The future work will need to look into how to design AI-driven health systems to bridge the digital divide.

This study has several limitations. First, our participants self-reported their technology and health literacy. It is possible that the self-reported data is not fully reliable, despite explanations of these two notions were provided. In our future work, we will adopt well-established criteria to evaluate participants' technology proficiency and health literacy. Second, we only conducted a survey to investigate the perceptions of health AI systems. Given the complexity and multi-layered nature of this research subject, we plan to conduct more studies, including a follow-up interview study, to further investigate related issues. Lastly, our online survey might excluded those less literate people and older adults from participating in the study. Therefore, in our future work, we will include more marginalized populations to determine how to design patient-facing, AI-driven systems that can benefit them.

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