Trust Formation in Healthcare AI: An Exploration of Older Adults' Perspectives

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Abstract

As artificial intelligence increasingly shapes healthcare systems, understanding how older adults—who interact with healthcare services more often and face particular difficulties—develop trust in these technologies becomes crucial. While the AIES community has previously examined AI's social implications across dimensions like gender and race, age remains an understudied axis of analysis. Through a participatory workshop with older adults in Germany, this paper investigates two central questions: (1) How do older adults perceive and experience trust in AI-driven healthcare technologies? (2) What are the key factors that shape trust in AI healthcare technologies among older adults? Our findings reveal that while older people trust certain abilities of AI systems, like medical image analysis, there is a strong emphasis on the necessity of human supervision to trust in these systems. Key trust factors elicited by our study are transparency about training data demographics and algorithmic decision-making processes. More importantly, a gradual exposure to AI systems in non-critical settings, prior positive experience with technology, and cultural context—particularly trust in locally developed systems with clear accountability measures and robust regulatory oversight are key elements in trust formation among older adults. This study offers contextualized insights to guide the equitable, community-driven design, deployment, and governance of AI healthcare technologies, aiming to better serve older populations. By centering inclusivity in technology development and advancing trustworthy AI systems, this work contributes to ethical, effective healthcare solutions tailored to the needs of aging communities.

Introduction

Artificial intelligence is increasingly shaping healthcare systems, promising innovative solutions and improved quality of care. However, as these technologies grow in influence, the question of trust becomes paramount—especially for populations that interact with healthcare systems in uniquely intensive ways, such as older adults. While the AIES community has insightfully examined the social implications of AI across dimensions such as gender and race, age has largely remained an invisible axis of analysis (Díaz et al. 2019; Stypińska 2023). This oversight is notable given the growing significance of AI in healthcare and the pressing need to understand how older adults perceive and trust these technologies.

To address this gap, our work brings together insights from socio-gerontechnology (Peine et al. 2021)—a field examining the social dimensions of technology use among older adults—and AI ethics and society research on trust in algorithmic systems and healthcare technologies (Grabb, Lamparth, and Vasan 2024; Hardalupas 2024, Fogliato et al. 2022; Harrington and Egede 2023; Kim et al. 2023b; Mehandru, Robertson, and Salehi 2022; Petti et al. 2023; Schor et al. 2024). Despite the growing literature in these areas, there remains limited empirically grounded research specifically exploring what trust in healthcare AI means for older adults and how this trust is formed and maintained.

According to the WHO, the global population over 60 is projected to nearly double from 12% in 2015 to 22% by 2050 (WHO 2025). Older adults are more likely to experience chronic conditions and negative health events, with even minor incidents often leading to serious decline (Mukaetova-Ladinska et al. 2020). Their experiences with increasingly digitized healthcare—especially AI—offer critical insights into how trust in such technologies is shaped. These insights are vital for designing equitable AI governance in healthcare, ensuring technologies support rather than burden marginalized groups unable to refuse them (Benjamin 2016). This paper explores two central questions:

RQ1: *How do older adults perceive and experience trust in AI-driven healthcare technologies?*

RQ2: *What are the key factors that shape trust in AI healthcare technologies among older adults?*

Through an empirically grounded approach, this study offers contextualized insights intended to advance understanding within the AIES community while informing the governance and design of AI technologies and healthcare systems that better serve older adults. The study provides one of the first in-depth empirical investigations of how older adults conceptualize and develop trust in AI healthcare technologies, revealing that trust formation is deeply rooted in the need for human oversight and connection, moving beyond theoretical frameworks to understand how trust manifests in empirical contexts for this understudied demographic. Trust, in this article, always refers to trusts reported by study participants in contrast to actual trust observed in real life situations. We explore trust in healthcare AI through a sociotechnical framework, emphasizing vulnerability, relationality, and the complex, context-dependent nature of trust (Gille, Jobin, and Ienca 2020; Kim et al. 2023b). Our research thereby advances a holistic, sociotechnical understanding of trust by examining how factors related to AI systems, human subjects, or contextual elements interact in shaping older adults' trust in AI healthcare technologies. It demonstrates that trust in AI is not just about its technical capabilities but is embedded in broader social contexts including geographic location, cultural values, and existing healthcare relationships. Our study contributes to empirically grounded, participatory research on trust in AI by centering older adults' perspectives, thereby enriching both inclusion practices in technology design and striving for more trustworthy AI in healthcare.

Related Work

This study sits at the intersection of socio-gerontechnology, healthcare AI adoption, and trust research. We argue that incorporating the often-overlooked social dimension of age and older adults' lived experiences deepens our understanding of trust in AI healthcare technologies and supports more community-centered AI development. We define older adults as those over 65, following international ageing policy and indicators like the old-age dependency ratio (OECD 2025). At the same time, we recognize old age as a socially constructed category with varied meanings, where chronological age represents only one aspect (Marshall and Katz 2016).

AI Technologies in Healthcare: The Perspectives of Older Adults

The increasing adoption of AI technologies in healthcare holds considerable promise for improving care quality and access—for instance, through enhanced diagnostics, early detection, and more personalized treatment. However, this progress is coupled with growing concern about potential risks, particularly those involving algorithmic bias, inequality, and discrimination (Baumgartner et al. 2023; Stypińska and Franke 2023). The development and deployment of AI in healthcare has attracted significant scholarly attention in the AI ethics and society fields. Recent work has critically examined algorithmic biases and mitigation approaches (Bach et al. 2023; Mehandru, Robertson, and Salehi 2022; Poulain, Bin Tarek, and Beheshti 2023; Salavati et al. 2024; Xiao et al. 2023), fairness (Poulain, Bin Tarek, and Beheshti 2023; Tal 2023; Xiao et al. 2023), and transparency and explainability (Schor et al. 2024; Szymanski, Vanden Abeele, and Verbert 2024) in data- and AI-based systems. Other strands of research have addressed ethical guidelines (Amugongo, Bidwell, and Corrigan 2023; Antoniak et al. 2024; Petti et al. 2023), institutional accountability (Sendak et al. 2020), and the organizational governance of AI in healthcare settings (Kim et al. 2023a).

There is widespread agreement that AI technologies can disproportionately impact different social groups, both directly and indirectly. Much of the critical scholarship has focused on race, gender, and intersecting identities (Benjamin 2019; Broussard 2023; Buolamwini and Gebru 2018; Myers-West, Whittaker, and Crawford 2019; Noble 2018; Wilson and Caliskan 2024). In contrast, the category of age—and specifically the experiences of older adults—has received comparatively limited attention (Chu et al. 2023; Stypińska 2023; Stypińska and Franke 2023). Yet research has highlighted important areas where age-related bias appears, such as in sentiment analysis (Díaz et al. 2019), emotion detection (Kim et al. 2021), and AI-assisted resume screening (Harris 2023). Although older adults are increasingly affected by digital and AI-driven healthcare, their lived experiences, agency, and needs remain significantly underexplored.

Integrating AI technologies into healthcare offers potential benefits for older adults, including early detection of health risks, improved safety, and enhanced personalization of care (Mukaetova-Ladinska, Harwood, and Maltby 2020; Shiwani et al. 2023). At the same time, several studies have pointed to risks specifically relevant to older adults—such as harms from unrepresentative training data (Ungar et al. 2024), design shaped by ageist assumptions (Neves et al. 2023; Voinea, Wangmo, and Vică 2024), and the disempowering effects of monitoring technologies (Czech et al. 2023). In response, there is growing support for participatory and inclusive design practices that engage older adults in envisioning and co-developing AI tools (Bergman et al. 2024; Brewer, Harrington, and Heldreth 2023). Yet, social gerontology research, similarly as critical reflections on the "participatory turn" in AI (Birhane et al. 2022; Sloane et al. 2022), has identified a lack of meaningful inclusion of older adults in technology co-design formats. Both critical AI ethics and social gerontology have highlighted the persistent lack of meaningful inclusion in co-design processes. It requires further power-sensitive settings that go beyond stereotypical assumptions about the needs and preferences of older adults and such that de-center technosolutionist approaches (Bischof and Jarke 2021; Maibaum, Bischof, and Hergesell 2023; Manchester and Jarke 2022).

Recent participatory research has begun to explore how older adults engage with specific AI tools such as chatbots (Harrington and Egede 2023) and voice assistants for health information seeking (Brewer, Harrington, and Heldreth 2023; Brewer et al. 2022; Harrington et al. 2022), as well as their views on ageing safely at home (Zhao et al. 2024). Other work has examined older adults' motivations for participating in human-computer interaction research, including curiosity, social engagement, and learning (Marzi, Klapperich, and Huldtgren 2023).

This study contributes to these emerging lines of inquiry by centering older adults' expectations, concerns, and perspectives on trust in current and future AI healthcare technologies. We build on prior research by focusing on the sociotechnical and experiential dimensions of trust in AI, specifically within the context of Germany's increasingly digitized healthcare system (Manzei-Gorsky, Schubert, and von Hayek 2022).

AI Technologies in Healthcare: The Role of Trust

Trust is a central concern in the design, implementation, and evaluation of AI in healthcare. Recent scholarship has explored conceptual definitions of trust (Jacovi et al. 2021; Liao and Sundar 2022; Manzini et al. 2024), frameworks for trustworthy AI (Scharowski et al. 2023; Thornton, Knowles, and Blair 2022; Toreini et al. 2020), and empirical studies on trust formation (Kasinidou et al. 2021; Kim et al. 2023b; Wang et al. 2024). However, there is limited empirical research on how different social groups—particularly older adults—perceive and develop trust in AI systems. Given the critical, high-stakes nature of healthcare and its inherent vulnerabilities (Campos-Castillo et al. 2016; Sutton et al. 2023), trust plays an especially vital role. As AI becomes more embedded in healthcare contexts, understanding trust across diverse populations is increasingly important.

As Thornton, Knowles, and Blair (2022, 1378) note, trust is a complex and nuanced phenomenon. Scholars often distinguish between particularized and generalized trust—trust in familiar individuals versus broader, less-known groups (Schilke, Reimann, and Cook 2021)—as well as interpersonal and institutional trust (Nelms 2022). Across these definitions, vulnerability emerges as a core dimension (Gallistl, von Laufenberg, and Lehner 2024). Trust involves a willingness to become vulnerable to another party, with or without direct oversight (Schilke, Reimann, and Cook 2021; Mayer, Davis, and Schoorman 1995, 712). In healthcare AI, trust encompasses both human and technological actors (Gille, Jobin, and Ienca 2020; Kim et al. 2023b), often entangled in complex relationships (Thornton, Knowles, and Blair 2022). Our approach builds on this sociotechnical understanding, emphasizing how trust is shaped by vulnerability, relationality, and context (Gille, Jobin, and Ienca 2020; Kim et al. 2023b).

AI ethics and society research on trust in healthcare AI has examined, on the one hand, the perspectives of healthcare staff, and on the other, the perspectives of patients. Scholars have investigated different factors that contribute to trust formation in AI systems. In the following, we engage with central studies on these interrelated factors, placing a focus on research on trust on AI healthcare technologies specifically.

Technical aspects such as system design and interface configuration significantly influence users' trust in healthcare AI systems (Burgess et al. 2023; Ferrario and Loi 2022; Harrington and Egede 2023; Schor et al. 2024; Sivaraman et al. 2023; Sun et al. 2024). Burgess et al. (2023) examine clinicians' views on an AI-based decision support prototype for type 2 diabetes care. Their findings underscore the importance of design features that allow clinicians to account for patient-specific variables and maintain control over AI outputs—both essential for building trust in clinical settings.

Patient perspectives have received comparatively less attention. Sun et al. (2024) show that interface design strongly shapes patient trust in large language model (LLM)-based systems. Participants preferred text-based over speech-based or embodied interfaces for serious topics like health, emphasizing clarity and ease of reference in information presentation. Harrington and Egede (2023) explore trust among Black older adults in chatbot design for health information seeking. Their study finds that avatar features reflecting users' racial and age identity can enhance interest and trust. They further argue that perceived humanness—through features like cultural familiarity, empathy, professionalism, and attire—can increase a chatbot's credibility.

Particularly explainability and transparency of AI healthcare technologies have been studied as factors of trust formation, while recent research has suggested understanding explainability and transparency not in "purely" technical terms but as situated in the broader socio-technical and organizational context of AI systems and in human-AI relations (Eyert and Lopez 2023; Kaur et al. 2022, Kim et al. 2023b; Norval et al. 2022), similarly with regards to healthcare AI (Burgess et al. 2023; Ferrario and Loi 2022; Jacobs et al. 2021; Schor et al. 2024). To this end, Schor et al. (2024), for example, argue for meaningful, contextually appropriate (Norval et al. 2022) transparency of AI systems, where clinicians as different users in multidisciplinary teams, as well as the timeliness and relevance of provided information, are to be taken into nuanced account in transparency efforts.

Contextual factors, such as background information and prior experiences with technologies, significantly shape trust in healthcare AI systems. Information about the organizations developing AI technologies can influence trust formation. In Burgess et al.'s (2023) study, clinicians evaluated a decision support prototype not only based on its functionality but also on institutional credibility, expressing greater trust in tools backed by medical institutions and discomfort when tools were affiliated with pharmaceutical companies. Similarly, Harrington and Egede (2023) found that both the perceived professionalism of a chatbot and the trustworthiness of its information source were crucial in shaping user trust across different avatar designs. Prior familiarity with technologies also plays a role; unfamiliarity with conversational chatbots can lead to hesitation in adoption (Harrington and Egede 2023). Sun et al. (2024) further highlight that interface familiarity and previous user experience strongly influence trust, especially when individuals engage with interfaces they already know and find easy to navigate.

Technical and contextual factors influencing trust in AI are often intertwined. Kim et al. (2023b) and Toreini et al. (2020) call for a holistic view that integrates human, AI, and contextual elements to fully capture the complexities of trust in AI systems. Building on this, and drawing from socio-gerontechnology and AI ethics literature, our study explores older adults' trust in three healthcare AI scenarios: (1) symptom checker apps, (2) clinical monitoring and diagnosis systems, and (3) robotics for ageing-in-place. We adopt a sociotechnical lens that highlights trust as rooted in vulnerability, shaped by the relational and context-specific dynamics of human-human and human-AI interactions (Burgess et al. 2023; Kim et al. 2023b). Our findings center the perspectives of older adults—a group often overlooked in AI research—and contribute to ongoing efforts to conceptualize trust in ways that are participatory, community-centered, and sensitive to the broader social contexts in which healthcare AI is deployed (Bergman et al. 2024; Birhane et al. 2022; Brewer et al. 2023; Harrington, and Heldreth 2023).

Methods

Workshop Design

As mentioned above, scholars have emphasized the need for more participatory, community-based approaches to researching the development, use, and implications of AI technologies, particularly with marginalized social groups (Bergman et al. 2024; Birhane et al. 2022; Brewer, Harrington, and Heldreth 2023; Zhao et al. 2024). To explore the expectations, hopes, and worries of older adults regarding current and future AI uses in healthcare and to work towards co-creating more age-inclusive perspectives on AI, we conducted a participatory research workshop with a group of twelve older adults in Berlin, Germany. This one-day on-site workshop took place in July 2024 and focused on the topic of "Ageing Across Time and Space in Healthcare", emphasizing the various phases of life and living environments of older adults in the context of healthcare. This research project has been approved by the ethics committee of the research institute.

The workshop design was informed by scenario-based focus groups which allowed to explore and discuss perceptions of AI technologies, drawing on concrete use cases of AI technologies in healthcare. The workshop centered on three thematic sessions exploring different AI technologies across time and space, namely: "AI in Diagnosis in 2024", "AI in the Hospital in 2030", and "AI for Ageing in Place in 2040". The sessions explored, respectively, AI-based symptom checker apps, clinical monitoring and diagnosis systems, and robotics for ageing-in-place. For each of the sessions, an interactive (i.e., using an AI-based app) or video-based scenario served as inspiration for subsequent focus group discussions. These discussions were guided by semi-structured interview guidelines. Each session was moderated by one of the authors, carefully following the group dynamics and facilitating that less active participants find a place to express their perspectives and opinions.

In the first session (S1), "AI in Diagnosis in 2024", the scenario focused on a fictional person who has developed a chronic cough and uses an AI-based symptom checker app to learn more about their symptoms, potential causes, and possible diagnoses. To simulate this use case, each participant group was provided with a tablet and instructed to try out a pre-installed symptom checker app for health information seeking, facilitating direct AI interactions. The participants were asked to interact with the app, based on the discussed fictional medical case, to follow its instructions, and to reflect aloud on their interactions with the app, such as outcome evaluation. To facilitate thematically relevant and structured discussions, we asked exploratory, reflective questions and moderated the group discussions. For this session, the questions included, for instance, "How comfortable did you feel using the app?", "How would you feel if you shared your personal symptoms?", and "In what ways do you think this app could be particularly useful or problematic for older adults?" exploring the participants' different perspectives and experiences.

The second session (S2), entitled "AI in the Hospital in 2030", builds on the fictional case introduced in the first session – a person with a chronic cough – who is now receiving treatment in a hospital where AI-based technologies are extensively used. To illustrate this scenario, we showed two short videos depicting such a clinical setting. The first one presented a media report documenting a case of monitoring of ICU patients through cameras that analyzed their movements and condition in real-time. The second video featured a media report on a digital documentation system to automatically transcribe conversations during doctor's appointments in hospitals for medical documentation. For this scenario, the interview guidelines included the following questions: "What are your thoughts on AI systems automating the diagnosis in hospitals?", "Would you like to have human oversight on this process?", and "What challenges or issues might arise for you from the widespread adoption of AI in hospitals by 2030, and what might be specific for older persons?"

In the third session (S3), "AI for Ageing in Place in 2040", we followed along the chronically ill older person's life course, now living independently at home using a robot meant to assist with daily tasks and to ensure safety by monitoring movements or medicine intake. To illustrate this scenario, we showed a promotional video of a technology company that develops robots assisting people at home. The focus group discussions prompted by this scenario were informed by questions such as: "How do you feel about the robots' ability to track your health and notify emergency services?", "Do you trust the robots to accurately monitor your health and respond in case of emergencies?", and "What do you see as the main concerns of using such robots at home?"

For each session, the focus group discussions took place in smaller subgroups: three subgroups for the first session (S1A, S1B, S1C) and two subgroups for the second and third session (S2A, S2B and S3A, S3B). Smaller group settings allowed for more in-depth interactions with the app (first session) and in-depth discussions of the videos (second and third session). Changing the composition and size of the (sub-)groups throughout the workshop furthermore facilitated more flexible and inclusive group dynamics, i.e., changing power dynamics between more and less vocal participants (Rutledge, Gilliam, and Closson-Pitts 2023). Finally, as the discussions of all subgroups were based on shared scenarios and interview guidelines, this approach allowed us to explore differences and similarities across the discussions, adding empirical depth. Accompanying the thematic sessions, an introduction and concluding session facilitated a space for participants to get to know each other and the researchers, and to share their motivations and expectations for participating as well as immediate reflections and feedback on the workshop.

Workshop Participants

To recruit older adults for the workshop, we employed a combination of offline and online outreach strategies. A call for participation was distributed in community centers located in socioeconomically diverse areas of the city, shared in local Facebook groups, and disseminated through an umbrella organization representing senior associations. Out of seventeen individuals who expressed interest, thirteen were selected aiming for a diverse composition of the participant group in regard to age, gender, educational background, occupation, and potential knowledge of and exposure to (AI-based) technologies, for example due to their profession. Ultimately twelve persons participated in the workshop, six male and six female participants between the ages of 68 and 77.

While the group represented a range of ages, genders, and educational levels, we encountered challenges in recruiting individuals aged 65 or older with a migration background who were fluent in German—the language of the workshop. This limitation reflects broader historical and structural barriers related to immigration and linguistic integration in Germany. The final participant group consisted of twelve older adults residing in Berlin, with professional experiences spanning healthcare (e.g., nursing, psychotherapy), education, software development, advocacy, and social work. Their educational qualifications ranged from vocational training to advanced academic degrees. While socioeconomic status was not explicitly measured, it was indirectly indicated by participants' retirement income sources (e.g., basic welfare pensions vs. pensions from skilled professions). Racial and ethnic data were not collected. Direct AI experience was limited to two participants (software developers), though healthcare-related exposure existed among clinicians and advocates.

Data Collection and Analysis

All workshop sessions were audio-recorded, transcribed, and translated from German into English using GDPR-compliant tools (f4x Audiotranskription, DeepL Pro Advanced). Data were analyzed using grounded theory (Charmaz 2006). Transcripts were qualitatively coded in two phases using MaxQDA. During open coding, each author coded three to four of the seven transcripts. A joint session yielded a collaboratively developed codebook of 18 codes (e.g., "human connection," "age discrimination," "intergenerational values"). In the second phase, all transcripts were re-coded using the finalized codebook, each coded at least four times. Authors then cross-validated 20% of each transcript (approx. 80 paragraphs/session), identifying strong code overlap. Discrepancies were resolved through discussion and consensus (O'Connor and Joffe 2020).

Findings

Our analysis of workshop discussions and participant narratives revealed complex patterns in how older adults conceptualize and develop trust in AI healthcare technologies. The workshop revealed that older adults' professional backgrounds play a role in their trust in AI healthcare technologies. Healthcare participants—

including nurses and older adult local organization members—emphasized the irreplaceable role of human connection, insisting AI must supplement, not replace, clinicians. They raised concerns about biased training data and the need for emotional support in care. In contrast, participants who had a tech background or more tech savvy in general focused on AI's technical efficacy, citing its superiority in tasks like medical imaging but agreed human oversight remained critical. All participants valued transparency, though healthcare and civil society participants prioritized demographic inclusivity, while tech professionals stressed explainability. Trust also depended on context, with locally-developed systems inspiring confidence. Below, we organize our findings according to our two research questions.

Human Oversight and Connection—RQ1: How Do Older Adults Perceive and Experience Trust in AI-Driven Healthcare Technologies?

Centrality of human oversight over AI. Our overall workshop findings indicate that older adults do not have a categorical opposition or distrust towards the implementation of AI systems in the healthcare services. In the workshop, however, participants almost always expressed a conditional trust in the systems, and the primal point of this condition was the human oversight of AI healthcare technologies. The participants indicated that they trust AI systems when the systems at stake are supervised by a human.

For our workshop participants, trust in AI healthcare technologies is a concept rooted in a belief that AI can be a valuable tool for enhancing their healthcare experience, while recognizing the importance of human oversight and the centrality of the patient-healthcare staff relationship. On multiple occasions, participants expressed their opinions on this human aspect in the implementation of AI systems in healthcare. In a workshop session (S2A), a conversation between P7 and P12 explored this question, and P12 stated that her trust in AI is conditioned upon it being a supplement rather than a replacement of humans in healthcare. When the participants were prompted with a video showing the use cases of AI in hospital settings to monitor patients through voice, image, and body metrics, in order to come up with a diagnosis, P7 expressed his overall trust in these systems, but also noted that he wanted the output to be checked by a human. For him, despite the efficient algorithmic processes, in the end, the result was to be confirmed by a human. In his own words, someone has to assert: "Yes, the diagnosis is correct." (P7, S2A). P12 responded to that and expressed the centrality of having her doctors by her side: "That would also be a criterion for me. So the machine. Yes, I had that five years ago. Yes, unfortunately, uh, machine, everything was great, but I still needed my doctors with me. So both still have to be there for me. Only AI I wouldn't, I wouldn't trust it" (S2A).

The participants emphasized that the videos of AI deployment in hospitals shown in the workshop session did not adequately address the crucial human element of healthcare – particularly the interpersonal interactions between medical staff and patients. They pointed out that hospitalization in Germany usually occurs due to serious health issues, and an essential part of healthcare delivery involves personal communication and human attention. The participants observed that while they saw an example of healthcare staff communicating through a screen, the demonstrations did not show whether this type of remote interaction could effectively replace the in-person human connection that patients may need when they are unwell. In the end, they expressed uncertainty about whether patients can receive adequate emotional support and personal care through an exclusively technology-mediated interaction. In the same vein, P11 expressed his distrust in contexts where AI is the sole point of interaction in hospital settings:

"Yes. So what happens if your computer crashes? We just had that at Microsoft with the update. Yes, I lack the basic trust. Younger people have that, they've grown up with technology. I lack it. I would never get into a car without a driver, and I don't know what will happen. If the computer, the whole system crashes, I feel uncomfortable" (S2A).

When they were asked to interact with an AI-based symptom checker app available in Germany, participants again expressed concern over the lack of human interaction, including the interpretative and sensory capabilities of humans (such as being able to touch, hear and see the patient by a traditional doctor) while a symptom checker app is dependent on self-reporting, and answers provided to a list of predetermined questions. As a participant (P2) put it, "I have less trust in such an app because the app can only ask me questions. The doctor can pat me on the back, he can measure my blood pressure, he can make all kinds of diagnoses. The app can't do that" (S1B).

While participants clearly demanded a human element in their interactions with AI systems in various settings, they however expressed their support and trust in AI's capabilities in analyzing data, detecting diseases, or recommending personalized treatments.

Trust in AI's efficiency for technical tasks. Participants articulated a nuanced view of trust in AI's technical capabilities, highlighting that trust levels vary depending on the specific application. They made distinctions between AI's capabilities in concrete and measurable tasks (like image recognition for cancer detection) where AI has proven its effectiveness through machine learning (Wang, Zhao, and Marostica, et al. 2024) and human validation and "softer" or more subjective areas (like general wellbeing assessment) where trust in AI systems may be less warranted. To express his positive view of AI's performance in concrete tasks, P7, for instance, found it "irresistible" that "machines learned to recognize [those] cancers better" (S2A).

The workshop discussions revealed that participants had concrete trust in AI's analytical and diagnostic capabilities, particularly in medical imaging and symptom detection. This trust was often based on direct comparisons between AI and human capabilities in specific medical tasks. Multiple participants expressed that AI systems could perform better than traditional human-based systems in certain diagnostic scenarios. For example, participants with professional experience in medical settings highlighted AI's superior efficiency in image analysis. One participant (P10) who had worked in an X-ray practice noted that while doctors struggle with analyzing complex medical images and face time constraints due to insurance requirements, AI systems can process these images more quickly and efficiently—"The doctor has really big problems defining all these images. It also takes a long time and it's also a question of what the health insurance company will pay for. Again. And it's simply quicker with software. Point," he said (S2B).

Another participant (P9) emphasized how this efficiency could actually improve the human aspects of healthcare, noting that when AI handles time-consuming image analysis, doctors gain more time for patient interaction and explanation:

"It will actually benefit the patient. I know the example from X-ray practice. An X-ray doctor sits there for a long, long time afterwards evaluating and diagnosing these images. And if the AI takes this time away from him and arrives at a result relatively quickly, then the doctor has more time to talk to the patient afterwards and explain things to him" (S2B).

Participants also recognized AI's potential for comprehensive symptom detection. They noted that AI monitoring systems could identify symptoms that patients might not self-report or that doctors might miss in traditional examinations. As one participant (P1) explained, AI's ability to recognize multiple symptoms through continuous monitoring could enable "a different diagnosis possible" and when combined with physician oversight, creates a "combination that makes it qualitatively superior" (S2B).

However, this trust in AI's technical capabilities was consistently framed within a collaborative human-AI framework. As summarized at the end of the session 2B and acknowledged by the group, "it has to be both" – requiring both human interaction and AI-supported diagnostics. A perspective that aligns with the broader finding that participants viewed AI as a powerful analytical tool that enhances, rather than replaces, human medical expertise. Below, we explore the factors affecting the formation of this trust.

AI System, User, and Context—RQ2: What Are the Key Factors That Shape Trust in AI Healthcare Technologies Among Older Adults?

The factors of trust in AI healthcare technologies that we found in our workshop discussions are shaped by a combination of factors relating to the AI system itself, the individual user, and the broader context of healthcare delivery, a framework that aligns with the one drawn by Kim et al., where they advocate for a holistic perspective in the study of trust in AI systems and consider "human, AI, and context-related factors of trust together" (Kim et al. 2023b; Toreini et al. 2020)

AI system-related factors. Older adults need assurance that AI systems produce correct and dependable outputs, particularly in matters concerning their health and well-being. In that, a significant concern that emerged in our workshop sessions was the lack of transparency regarding the data used to train AI systems, which raised questions about the accuracy and reliability of their outputs.

In the workshop (S1A), a conversation between three participants (P7, P11, P12) pointed out that users are often unaware of the specific population and types of illnesses represented in the training data of symptom checker apps, making it difficult to assess the system's applicability to their individual circumstances. P7 raised a fundamental question about population representation, noting "you don't know what kind of population it's being fed with... if it's fed with young people and the illnesses of young people, then as an older person I'm affected anyway by the fact that it doesn't respond adequately" (S1A). This observation highlighted how age-biased training data could lead to less reliable diagnoses for older adults and therefore less trust. The discussion expanded to encompass broader demographic concerns. Another participant (P11) pointed out gender-based diagnostic differences, particularly in cardiac care: "When it comes to heart attacks, women have completely different symptoms to men" (S1A). Others raised concerns about cultural and racial representation in medical AI systems (P12), with one participant (P7) noting that "certain diseases that are indeed linked to the color of," and her sentence to be completed by P12 "the skin color," and P7 continuing to warn that if "the app has been incorrectly designed only for white people, then it has its weaknesses" (S1A). The conversation further evolved to address gender identity representation in healthcare AI interfaces. P7 highlighted potential discrimination against transgender individuals, noting that most systems only offer binary gender options, which could affect the accuracy of diagnoses for trans individuals who might have unique medical needs.

This lack of transparency extends to the algorithms themselves, with users often left in the dark about how the AI system arrives at its diagnoses. One participant (P2) suggested that AI systems should provide a percentage indicating the certainty of the result, allowing users to better gauge the reliability of the diagnosis. She said: "So I would have liked it better if the app, in addition to this fortunately correct result, where it came from, gave a percentage of how high it itself estimates whether the result could be correct" (S1B). Another participant (P11) argued that AI systems should offer a more detailed explanation of the reasoning behind their conclusions, rather than simply presenting a "fait accompli"—for him an explainable AI algorithm is central to his trust: "Enter the data and what the application then does with it remains hidden and then you are presented with some kind of results. I would like people to say, well, this and that symptom has led us to such and such a percentage here and there" (S1B).

Human-related factors. Prior experiences and interactions with AI, as well as general familiarity with technology, shape trust perceptions. Two of our workshop participants (P6, P10; S2B) implied that a gradual interaction spread over a longer period of time with AI systems would make them to assess the systems better and evaluate better how to trust or not to these systems, that was agreed by the rest of the group, with one participant offered to "go even one step further," and introduce these systems from early school years (P3; S2B), which was supported by others (P9, P8; S2B).

This perspective was illustrated through participants' analogies to traditional healthcare relationships. One participant (P10) drew a parallel between building trust with healthcare staff and AI systems, sharing his decade-long experience with orthopedists. He described how trust grew through consistent positive interactions: "So then you're happy to go back and the trust grows" (S2B). The participant expressed hope that trust in AI diagnostic systems could develop similarly, while acknowledging the likely inevitability of AI in healthcare: "In a similar way, I hope that you can also build up trust in such diagnostic systems and in the end we probably won't even have any other choice" (S2B).

A particularly insightful observation emerged regarding the context in which people typically first encounter healthcare AI systems. One participant (P6) identified a "big problem" in that people often first interact with AI systems and medical robots when they are already unwell and hospitalized. She suggested that trust-building would be more effective if people could familiarize themselves with these technologies in less stressful environments: "But it would be much easier to build trust if they got to know them at home first" (S2B). The participant (P6) shared an example from long term care facilities where robots were introduced through demonstrations and videos, resulting in positive relationships between residents and the technology: "And of course they know they're not human, but they have a really good relationship" (S2B). This experience led to the conclusion that prior positive exposure in comfortable settings could facilitate easier acceptance of AI technologies in more critical healthcare situations.

Contextual factors. Geographic and cultural context emerged as a factor, albeit relatively minor compared to the system and human related ones, influencing trust in AI healthcare technologies. Participants sometimes expressed an implicit preference for technologies developed in Germany, particularly when discussing issues of data privacy and security. For example, when discussing the symptom checker apps, one participant (P2), upon learning that this particular app was developed in Germany, commented with satisfaction, "So now my trust in the app has grown" (S1B).

Participants viewed the geographical location of the developers as a factor in accountability, again implicitly opposing the US and China dominance in the design and development of these systems (P2, P11, P4, P5). The same participant (P2), after learning the address of the symptom checker app's developer in Berlin, jokingly remarked that he could "go there in person and punch them in the mouth if [they] crash" after stating that "Quite honest. That makes a good impression, I think, doesn't it? And it's a German company from Berlin" (S1B). This statement, though humorous, suggests that knowing the physical location of the developers enhanced the participant's perceived sense of control and the possibility of holding them accountable, thus increasing the trust levels of older people towards AI systems. Therefore, the proximity of and knowing the exact physical locations plays a role. Additionally, P5 stated that "on the other hand, Germany has an incredible bureaucracy and what is approved. It has to go through a whole series of inspection bodies. And I think that once it's approved, you can trust them" (S1B). Making it clear, despite the burdensomeness of the German bureaucratic processes, it provides for the workshop participants a context to develop a more grounded trust towards AI systems.

Discussion

Scholarly work often distinguishes between interpersonal trust, which arises in close relationships, and institutional trust, associated with larger collectives and interactions with less familiar individuals (Nelms 2022). Applying this to AI, interpersonal trust might manifest in a patient's trust in their doctor's recommendation to use an AI-powered diagnostic tool, while institutional trust could involve a patient's trust in the hospital, the AI system, or regulatory bodies overseeing the AI's development and deployment. However, it is essential to avoid reducing trust to merely an "information infrastructure", as this would prioritize receiving information about the trustee at the expense of acknowledging the complex social contexts in which trust truly emerges (Corsín Jiménez 2011). For example, simply providing patients with detailed technical information about an AI system's accuracy may not be sufficient to build trust if they lack confidence in the institutions or individuals responsible for its implementation. A similar point is made in the context of home health monitoring systems, where one of the sources emphasizes that clearly explaining data usage and privacy policies during onboarding can increase user trust (Czech et al. 2023). However, negative experiences, such as technical difficulties and dismissive responses from technicians, can erode trust (Czech et al. 2023). This highlights how reducing trust to an information infrastructure risks neglecting the contextual and often "messy" realities of human interaction. Understanding the dynamics of trust in AI requires acknowledging that users' prior experiences, cultural backgrounds, and personal vulnerabilities can all influence their trust judgments (Degachi et al. 2024; Kim et al. 2023b; Manzini et al. 2024; Schilke, Reimann, and Cook 2021).

The Patient-Healthcare Staff Relationship Is Central to Trust

There are few comparable states where humans are as vulnerable as when they are in need of receiving care from health professionals, sometimes as a result of a disease or accident (Sutton et al. 2023). Therefore, trust also becomes a high stakes issue in these settings and the conceptualization, use, and implementation of AI systems should be approached with particular care and caution. Our workshop findings highlighted the crucial role of the patient-healthcare staff relationship in shaping older adults' trust in AI healthcare technologies. The workshop participants prioritized human oversight over AI systems and human connection, valuing their relationship with healthcare professionals as a key factor in their trust assessments. This aligns with existing research emphasizing the importance of the human element in fostering trust, particularly in sensitive domains like healthcare (Czech et al. 2023). It suggests that the successful integration of AI into healthcare for older adults depends on preserving and strengthening the human element of care.

For that matter, AI should be positioned and used as a tool to enhance, rather than replace, human interaction in healthcare. Also, emphasizing the role of healthcare professionals in supervising, interpreting, and contextualizing AI outputs can help mitigate concerns and foster trust. It is also essential to be transparent about the role of AI in healthcare. Clearly communicating how AI is being used, its limitations, and the ongoing role of human oversight can help older adults feel more informed and empowered in their healthcare decisions.

Familiarizing with AI Before Critical Situations Is an Important Trust Factor

Early exposure and positive interactions with AI systems play a critical role in fostering trust, particularly in healthcare settings where trust is paramount for patient well-being and treatment adherence. When individuals have the opportunity to interact with AI in non-critical situations, it can reduce anxiety and uncertainty, leading to greater acceptance when AI is needed for their care. For example, introducing AI during routine checkups or through educational materials allows individuals to familiarize themselves with the technology's functionality in a low-stakes environment (Baughan et al. 2023; Degachi et al. 2024). This approach lessens the pressure associated with critical healthcare decisions, enabling patients to gradually acclimate to the presence of AI in their healthcare journey (Pareek, Velloso, and Goncalves 2024). Familiarization further allows patients to actively learn about AI's capabilities, understand its workings, and explore its potential benefits (Pareek, Velloso, and Goncalves 2024). By engaging in successful demonstrations or interactive exercises, patients can form positive associations with the technology, counteracting potential fears or skepticism (Baughan et al. 2023). Moreover, early familiarization provides a platform for addressing concerns and misconceptions. Openly discussing these issues demonstrates transparency and commitment to patient understanding, ultimately bolstering trust (Degachi et al. 2024). In essence, familiarization serves as a bridge and can lead to more trusting and productive human-AI collaborations in healthcare.

Cultural Context Is a Potential Factor in Trust

The group discussions reveal that cultural context can be a relevant, though complex, factor in shaping trust toward AI, especially in the context of healthcare. The older adult participants, situated within a German cultural context, expressed preferences for locally developed software, viewing the location of the developers as a factor in accountability. They also voiced concerns about data privacy practices in other countries, particularly the United States. Our findings suggest that cultural values and perceived national differences in technological development, data privacy regulations, and work ethics can influence trust assessments. This is especially relevant when considering older adults, who may be less familiar with AI and have heightened sensitivity to data privacy (Czech et al. 2023). Studies have shown that these factors can significantly influence trust in AI systems (Jacovi et al. 2021; Toney, Curlee, and Probasco 2024).

Trust in AI is not solely determined by the technical capabilities of a system but is intricately linked to sociocultural factors. The easy identification and perceived reputation of AI developers also plays a role. Harrington and

Egede emphasize the importance of understanding cultural preferences, particularly for Black older adults, and designing AI systems for health information seeking that resonate with diverse populations (Harrington and Egede 2023) . This approach involves acknowledging historical and systemic factors that may contribute to distrust of technology and healthcare systems. It is therefore clear that to foster trust across diverse cultures, it is crucial to design AI systems that are culturally sensitive and consider the varying weights placed on trust determinants. This would involve tailoring explanations and user interfaces to align with specific cultural preferences as well as promoting AI literacy through community centered educational initiatives to enhance understanding of AI's capabilities, limitations, and ethical implications.

Transparency and Explainability Are Crucial Trust Determinants

Participants repeatedly emphasized the importance of understanding how the AI system arrived at its diagnoses and recommendations. This desire for insight into the "black box" of AI decision-making aligns with calls for increased transparency and explainability in AI systems (Manzini et al. 2024; Mittelstadt 2019). This highlights the critical role of transparency and explainability in fostering trust as AI systems should be designed to provide clear, concise, and accessible explanations of their prediction and inference processes. User interfaces should allow users to explore the factors contributing to AI outputs, enabling them to understand the basis for recommendations and make informed decisions (Schor et al. 2024).

Thus, in the process of integrating AI into healthcare, it is crucial to prioritize trust, especially for older adults who may be less familiar with these technologies (Liao and Sundar 2022). Patients need clear and accessible information about how AI is being used in their healthcare, its limitations, and the measures in place to ensure responsible and ethical use (Kim 2024). It is equally important to emphasize the collaborative role of AI in healthcare, clearly delineating the responsibilities of both the technology and healthcare providers (Thornton, Knowles, and Blair 2022). This would help patients to understand that AI is a tool to enhance, and not to replace, human judgment and expertise.

Explainable AI techniques can play a key role in making AI recommendations more understandable and relatable to patients (Kim 2024; Schoeffer, De-Arteaga, and Kühl 2024). However, simply providing explanations would not be enough. These explanations must be tailored to the specific needs and preferences of older adults. An active involvement of older adults in the design and implementation of AI healthcare solutions could also be seen as a technique of making these systems more transparent and understandable to older people. This participatory approach can foster a sense of ownership and agency, making patients feel heard and respected (Brewer, Harrington, and Heldreth 2023). Furthermore, healthcare providers should create opportunities for open dialogue, encouraging older adults to voice their concerns, ask questions, and receive personalized explanations about AI (Toney, Curlee, and Probasco 2024). Addressing these concerns directly and transparently would be essential for building trust and mitigating potential anxieties.

Limitations

Our study was conducted over constructed, controlled, and speculative scenarios of interaction with healthcare AI, rather than uncontrolled and spontaneous situations, where trust dynamics in real-world healthcare settings could be observed. Therefore, we acknowledge that the participants' reactions and narratives may be limited by the study design, which may or may not play out the same manner in the real-world settings. Secondly, AI technologies are rapidly evolving, with constant emergence of new capabilities and functions. The findings of this study risk becoming outdated in the medium-term future if AI systems grow more sophisticated and integrated into healthcare practices. Thirdly, this study was conducted in a culturally and politically specific context of contemporary Germany, where trust norms and perceptions are historically contingent and rooted in the country's particular history (Luhmann 1982). Findings from this study may not be directly transferable to other countries with different cultural backgrounds or political memory.

Conclusion

Through a scenario-based participatory workshop with twelve participants, we explored trust as embedded in the sociotechnical realities of the German healthcare system. By grounding trust in the lived experiences of older adults, we offer a sociotechnical understanding that emphasizes human oversight of AI, the socio-geographic situatedness of trust, and familiarity with AI technologies as critical conditions for developing meaningful and reliable AI healthcare technologies. Our findings highlight key insights and recommendations for the design and deployment of trustworthy AI technologies in healthcare. These include the need for localized, culturally sensitive approaches to developing AI products for healthcare, transparency of AI and accountability of AI developers, and systems that align with older adults' lived realities, expectations, and wishes. These contributions can inform both the research within the AIES community on AI healthcare technologies, as well as broader efforts to create more equitable, trustworthy AI systems in healthcare.

Ethical Statement

While our findings highlight transparency, familiarity, cultural context, and human-AI collaboration as key trust fac-tors for older adults, we acknowledge critical ethical risks if these insights are misapplied. Crucially, our research seeks not to empower tech companies but to ensure older adults are neither discriminated against nor excluded from access to healthcare via lack of trust in the rapidly AI-driven healthcare landscape.

Marketers could exploit preferences for locally developed systems to emphasize geographic familiarity while neglecting algorithmic fairness, or weaponize transparency claims as superficial trust-building tactics without addressing systemic biases. As LaRosa and Danks (2018) caution, healthcare AI's impact on trust extends beyond technical performance to fundamentally reshape human relationships in care, necessitating regulatory frameworks that prioritize patient well-being over corporate interests. Participants' trust priorities—though rooted in lived experience—may not align with evidence-based safeguards such as bias audits, particularly given their limited technical exposure and age-related vulnerabilities to data exclusion. This tension mirrors findings by Chang et al. (2024), who demonstrate that older adults' trust in AI agents is dynamic, shifting across stages of cognitive decline and requiring adaptive accountability to balance autonomy with caregiver over-sight. To mitigate harm, we stress that user perspectives must inform—not replace—interdisciplinary frameworks pairing participatory insights with clinical, technical, and ethical validation. Regulatory guardrails, such as mandatory transparency reports, are essential to ensure trust-building aligns with equity and safety, preventing the very systems designed to empower older adults from perpetuating structural ageism or exploitation.

Positionality Statement

As a team of three researchers under 65—from Germany, Poland, Turkey, and all residents of Germany—working on algorithmic bias and ageism, our perspectives inevitably shaped the research. Our focus on algorithmic inequities may have influenced the workshop design, particularly the emphasis on demographic biases and skepticism toward purely technical solutions. While this lens aligned with participants' concerns about representation, it may have downplayed other trust factors, such as usability. Our European contexts—with shared concerns about data privacy and skepticism of U.S. or Chinese big tech dominance—may have amplified participants' preferences for locally developed systems. Conversely, being younger than the participant pool may have made us miss certain generational nuance.

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