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Proactive vs. passive algorithmic ethics practices in healthcare: the moderating role of healthcare engagement type in patients' responses

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Abstract

Background Artificial intelligence (AI) is transforming healthcare, but concerns about algorithmic biases and ethical challenges hinder patient acceptance. This study examined the effects of proactive versus passive algorithmic ethics practices on patient responses across different healthcare engagement types (privacy-focused vs. utility-focused).

Methods We conducted a 2 × 2 online experiment with 513 participants in China. The experiment manipulated the healthcare provider's algorithmic ethics approach (proactive vs. passive) and the healthcare engagement type (privacy-focused vs. utility-focused). Participants were randomly assigned to view a scenario describing a hospital's AI diagnostic system, then completed measures of attitudes, trust, and intentions to use the AI-enabled service.

Results Proactive algorithmic ethics practices significantly increased positive attitudes, trust, and usage intentions compared to passive practices. The positive impact of proactive practices was stronger for privacy-focused healthcare (e.g., mental health services) compared to utility-focused services emphasizing care optimization.

Conclusions This study underscores the critical role of proactive, context-specific algorithmic ethics practices in cultivating patient trust and engagement with AI-enabled healthcare. To optimize outcomes, healthcare providers must strategically adapt their ethical governance approaches to align with the unique privacy-utility considerations that are most salient to patients across different healthcare contexts and AI use cases.

Clinical trial number Not applicable.

Keywords Algorithmic ethics, Privacy-utility tradeoff, Patient response, Healthcare engagement type, AI in healthcare

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Introduction

Artificial intelligence (AI) is revolutionizing healthcare, providing unparalleled opportunities to enhance patient care and optimize clinical decision-making, and improve operational efficiency [17, 21, 28, 37, 63]. AI-powered systems, such as machine learning algorithms and natural language processing tools, are being increasingly deployed across various healthcare domains, including early detection and diagnosis [13, 28, 49, 58], treatment planning [46], patient monitoring [14, 65], and drug discovery [26]. However, despite the significant progress of AI technology in the medical field, this tremendous potential has not been widely accepted and trusted by patients [39]. For example, a survey conducted by Carnegie Mellon University also revealed that over 60% of Americans were unwilling to rely on AI algorithms for making important medical decisions, such as diagnosing and treating cancer. Respondents expressed concerns that AI systems might lack human empathy and judgment, and fail to fully consider patients' individual differences [12].

Underlying many of these potential concerns, especially those related to fairness, judgment, and the adequate consideration of individual differences, are significant technical and ethical challenges, primarily biases stemming from data and model design [23, 47]. AI systems are only as unbiased as the data they are trained on and the models they employ [23]. In other words, biases in medical datasets, such as underrepresentation of certain demographic groups or historical inequities in healthcare access, can become embedded in AI models, leading to inaccurate predictions and recommendations. These technical limitations can exacerbate the perception that AI systems cannot fully grasp the nuanced, individual circumstances of each patient in the way that human providers can. Moreover, the choice of variables, model architecture, and performance metrics can introduce additional biases, further exacerbating disparities in healthcare [47]. As AI is widely applied in the medical field, these data- and algorithm-driven biases underscore the ethical challenges that have become increasingly prominent [42, 44, 61, 66], including fairness in healthcare access, transparency of algorithmic decision-making, patient autonomy in AI-assisted diagnosis, and the protection of sensitive health data privacy.

To better harness the potential of AI medical diagnosis and alleviate patients' concerns, many AI medical service providers have taken proactive measures to anticipate and mitigate data- and algorithm-driven biases and ethical risks before they cause harm. For instance, IBM launched a new Watson health capability to enhance transparency in their AI systems. These initiatives aim to improve transparency and accountability by providing greater insight into the chatbot's operations and decision-making processes [29]. This proactive effort, known as proactive algorithmic ethics practices, involve taking deliberate steps such as establishing AI ethics committees, conducting algorithmic audits, ensuring transparency and explainability of AI decisions, actively seeking patient feedback, etc. However, not all service providers follow this proactive approach, instead, some adopt the opposite - passive algorithmic ethic practice that only make minimal efforts to implement ethical practices [43].

Although healthcare service providers are encouraged to go beyond legal compliance and take proactive roles in addressing AI ethics [45], they still face challenges in determining appropriate resource allocation for algorithmic ethics practices [9, 19, 57]. Several potential factors might explain this hesitation, including resource constraints [19, 38], concerns about impacts on care delivery [50, 59], and uncertainty about patient responses [36, 39]. In specific, investing in algorithmic ethics programs - such as establishing AI ethics committees, conducting regular algorithmic audits, and ensuring transparency and explainability of AI decisions - can be costly for healthcare providers already operating on tight budgets [19]. Besides, devoting substantial resources to algorithmic ethics may undermine a provider's capacity to offer accessible, superior care, potentially leading to more harm than benefit for the patients and communities they serve [59]. With the cost-benefit balance unclear, many healthcare leaders tend to adopt a "wait and see" approach [38]. In other words, the most fundamental reason for this hesitation might be that healthcare providers don't fully understand how patients perceive and react to service providers' passive versus proactive ethical algorithmic practices. This lack of understanding makes them reluctant to make more extensive, voluntary commitments to establish ethical principles for AI use in healthcare. In other words, without a clear grasp of patients' attitudes and responses, healthcare providers are unsure about the potential benefits and risks associated with adopting proactive algorithmic ethics practices.

This uncertainty is compounded by the fact that the effectiveness and justifiability of algorithmic conclusions heavily depend on the quality and accuracy of the input data [66]. Obtaining high-quality data is often difficult due to privacy concerns, which directly impacts the perceived reliability and ethical soundness of AI systems, further contributing to providers' hesitation in investing in proactive ethical measures. Some researchers suggest that access to privacy-sensitive data may be important for addressing certain ethical risks in healthcare AI, particularly those related to bias and fairness [23, 47, 66]. However, the willingness of patients to share such data varies significantly depending on the type of the healthcare service they are engaging with [24, 33, 70], as well as their assessment of the trade-off between privacy concerns and potential benefits of healthcare engagement [7, 10, 22, 34, 55]– [56]. This trade-off can be explained by privacy calculus theory [16], which posits that individuals engage in a cost-benefit analysis when deciding whether to disclose personal information, weighing the potential risks of privacy loss against the anticipated benefits. In the healthcare domain, this calculus is particularly salient, as different types of medical services involve varying degrees of privacy-sensitive information and potential health utility. In other words, different healthcare scenarios present varying degrees of privacy focus and utility focus, which might influence patients' attitudes towards data sharing and, consequently, their reactions to AI-enabled healthcare services.

Therefore, this study aims to answer the following questions: (1) Do proactive algorithmic ethics practices lead to more positive patient responses including attitudes, trust, and usage intentions compared to passive practices? (2) How do healthcare engagement type and algorithmic ethics practices (proactive vs. passive) jointly influence patient responses? (3) What insights can be gained from this interaction to guide healthcare providers in designing effective AI strategies and allocating resources for ethics initiatives? To answer these questions, this study designed a 2 (algorithmic ethics practices: proactive vs. passive) × 2 (healthcare engagement type: privacy-focused vs. utility-focused) scenario-based experiment.

Conceptual framework and hypotheses

Proactive versus passive algorithmic ethics practices in healthcare

As AI algorithms in assisting medical diagnosis and treatment become increasingly prevalent in healthcare, practitioners face a critical choice in how to manage the ethical challenges that arise because algorithms are not ethically neutral [66]. They can adopt either proactive or passive algorithmic ethics practices, which differ in the level of effort and commitment to addressing issues such as fairness, accountability, and transparency. Proactive algorithmic ethics practices involve taking deliberate steps to anticipate and mitigate potential ethical risks before they cause harm. This may include establishing AI ethics committees, conducting regular algorithmic audits, providing clear explanations for AI-generated recommendations, and actively seeking patient feedback [9, 43]. For example, proactive healthcare providers might implement transparency measures such as algorithmic impact assessments, which seek to raise awareness and improve dialogue over potential harms of machine learning algorithms [57]. In contrast, passive algorithmic ethics practices are characterized by a lack of such dedicated efforts, and are more reactive and focused on meeting minimum compliance requirements [43]. They may deploy AI systems without fully assessing their impact on different patient populations or engaging in meaningful transparency [53]. The distinction between proactive and passive algorithmic ethics practices is particularly salient in healthcare, where algorithmic decisions can have significant impacts on patient outcomes [30].

Previous studies have empirically demonstrated the importance of ethical considerations in shaping user attitudes and behaviors toward algorithmic systems. For instance, Lepri et al. (2018) found that transparency and fairness in algorithmic decision-making significantly increased user trust and acceptance [36]. Similarly, Shin (2021) demonstrated that algorithmic transparency practices positively influenced users' perceptions of AI systems' ethicality and their subsequent willingness to adopt these technologies [59]. In the healthcare context specifically, Asan et al. (2020) showed that ethical aspects such as explainability and consistency in AI systems were key determinants of clinicians' trust in and adoption of medical AI tools [3]. This underscores the importance of healthcare providers taking a proactive stance in creating an environment conducive to responsible AI use. However, there is limited evidence directly comparing the effects of proactive and passive AI ethics practices on patient responses in the healthcare context. While previous research suggests that proactive ethic practices may lead to more favorable outcomes (e.g., Morley et al., 2020) [43], empirical investigation is needed to validate this assertion and explore the underlying mechanisms. Therefore, our study aims to address this gap by examining how proactive and passive algorithmic ethics practices influence patients' attitudes towards healthcare providers, their trust in these providers, and their intentions to use AI-enabled healthcare services. By shedding light on these relationships, we seek to provide actionable insights for healthcare organizations navigating the ethical challenges of AI adoption.

Effects of passive versus proactive algorithmic ethic practice

Previous literature on organizational ethics suggests that an organization's ethical practices significantly influence stakeholder attitudes and behaviors [74]. When organizations proactively adopt positive ethical practices, they send positive signals to stakeholders, indicating that the organization values ethics and responsibility [68]. These practices shape the organization's positive ethical image and enhancing stakeholder favorability and engagement [35, 40, 60]. Besides, this positive ethical image, in turn, influences stakeholders' perceptions of the organization's characteristics, which forms the basis for the identification process. C-C identification theory further enriches this perspective by positing that consumers' identification with a company depends on the perceived congruence between their self-concept and the company's characteristics [5, 27]. When consumers perceive a strong alignment between their own values and the organization's ethical practices, they are more likely to feel a sense of connection and oneness with the organization [18]. This means that consumers start to define themselves in terms of the organization's characteristics, believing that their identity is closely tied to or overlaps with the identity of the organization. Integrating these two perspectives, we can propose that organizations' proactive adoption of ethical practices not only sends positive signals and shapes a positive ethical image but also enhances stakeholders' identification with the organization by increasing the perceived congruence between their self-concept and the organization's characteristics.

Consistent with this reasoning, providers that actively engage in establishing and implementing algorithmic ethics guidelines, such as ensuring fairness, accountability, and transparency in AI decision-making processes, send a strong signal to patients that they prioritize ethical considerations in their use of AI technologies on one hand. On the other hand, these proactive practices contribute to building a positive ethical image of the healthcare provider, which resonates with patients who value responsible and trustworthy healthcare services. Patient attitudes, which encompass their overall evaluations, feelings, and behavioral tendencies towards healthcare providers [1, 8], are likely to be more favorable when patients perceive a strong alignment between their own values and the provider's ethical practices. In other words, patients are more likely to feel a strong sense of identification with these providers. This identification, in turn, manifests in more favorable patient attitudes, such as increased satisfaction, and loyalty towards the healthcare provider.

Furthermore, organizational ethical practices are also crucial for building stakeholder trust [52, 73], and this trust-building process can be enhanced by fostering strong consumer-company identification. Trust serves as a fundamental belief that patients hold in their healthcare providers, rooted in the confidence that these professionals will consistently act in the patients' best interests, maintain the utmost confidentiality with sensitive information, and provide accurate, reliable, and timely guidance [1, 3]. When healthcare providers proactively adopt and implement AI ethics practices, they demonstrate their commitment to ethical principles and values, which serves as tangible evidence of their qualities such as honesty, respect, accountability, and integrity [61]. These proactive ethical practices align with patients' values and expectations, enhancing their identification with the healthcare provider. This identification process strengthens the trust-building mechanisms, as patients who strongly identify with a healthcare provider are more likely to perceive the provider as trustworthy and reliable [32, 51]. This proactive approach goes beyond mere compliance with regulations and showcases a genuine commitment to ethical behavior, thus fostering patient trust.

In addition to trust, organizational ethical practices shape stakeholders' behavioral intentions [67]. Previous research has indicated that ethically-oriented corporate social responsibility activities can increase consumer purchase intentions [4, 41, 62]. In the context of healthcare, patients' behavioral intentions may include their willingness to engage with and adhere to the provider's AI-based services and recommendations. When healthcare providers proactively address ethical concerns related to AI, such as ensuring transparency in AI decision-making, and mitigating potential biases, they are more likely to perceive the provider's values and actions as aligned with their own, thus increasing their sense of identification [18]. This identification can enhance patients' perceptions of the provider's reliability and competence, as they feel a stronger connection and shared values with the provider. Consequently, patients are more likely to embrace AI-driven healthcare solutions readily, leading to increased acceptance and willingness to use AI services.

In contrast, passive practices, where healthcare providers merely react to ethical issues or comply with minimum standards, may not evoke the same level of positive identification and attitudinal responses from patients. This lack of proactive engagement may hinder the development of consumer-company identification, as patients may not perceive a strong congruence between their own values and the provider's practices [5, 18]. Moreover, passive practices may raise doubts about the provider's genuine commitment to ethics and trustworthiness [68], as patients may question the provider's integrity and benevolence, which are essential components of trust [48]. Consequently, when patients do not perceive a strong alignment between their own values and the provider's ethical practices, they may be less likely to embrace and trust AI-based services and recommendations. This lack of identification and trust can lead to increased skepticism and reluctance to adopt AI-driven healthcare solutions, as patients may doubt the provider's ability to address ethical concerns effectively. Based on the literature reviewed above, we develop and test the following hypotheses (H1-H3), which will be systematically examined in our analyses and discussed in our results section. Therefore, we thus argue that:

H1: Proactive algorithmic ethics practices will lead to more positive patient attitudes towards the healthcare provider compared to passive practices.

H2: Proactive algorithmic ethics practices will lead to higher levels of patient trust in the healthcare provider compared to passive practices.

H3: Proactive algorithmic ethics practices will lead to stronger patient intentions to use AI-enabled healthcare services compared to passive practices.

The moderating role of healthcare engagement type

Healthcare engagement type refers to the nature of healthcare service that patients choose to engage in, based on their prioritization of privacy protection versus health utility. This construct recognizes the active role patients play in their healthcare decisions and reflects the varying degrees of privacy concerns and outcome expectations across different medical scenarios. In specific, privacy-focused healthcare engagements are characterized by a higher priority placed on privacy protection by patients. These typically include services such as mental health consultations, sexual health services, or genetic testing [70], where patients are more concerned about the confidentiality and security of their sensitive personal information. In contrast, utility-focused healthcare engagements are those where patients prioritize treatment effectiveness and health outcomes over privacy concerns. Examples include chronic disease management, physical rehabilitation, or emergency care [25, 39]. In these scenarios, patients are generally more willing to share personal information if it leads to better-personalized care and improved health outcomes.

We argue that healthcare engagement type can serve as a boundary condition for the effectiveness of healthcare providers' algorithmic ethics practices in shaping patient responses. When patients engage in privacy-focused healthcare services, they tend to be highly sensitive to potential privacy risks and place a greater value on robust data protection measures that safeguard the confidentiality and security of their personal information. In these situations, patients are more likely to scrutinize how their data is being collected, used, and shared by healthcare providers, and they may be more hesitant to disclose sensitive information if they perceive any potential threats to their privacy. In this context, proactive algorithmic ethics practices can be particularly effective in sending strong positive signals about the healthcare provider's commitment to data transparency, fairness, and privacy protection. Moreover, by implementing proactive ethics practices healthcare providers can demonstrate that their data practices are aligned with patients' values and expectations regarding privacy. This alignment is especially important for patients participating in privacy-sensitive healthcare services, as they may be more attentive to these signals compared to those engaging in utility-focused services. This notion is supported by Ploug and Holm (2020), who emphasize the importance of respecting patient privacy preferences in enhancing trust in AI-based diagnostics, particularly for privacy-sensitive individuals [53]. Similarly, Esmaeilzadeh (2020) finds that privacy concerns significantly moderate the effect of perceived benefits on attitudes toward AI-based tools in healthcare [20], suggesting that patients with higher privacy concerns are more likely to appreciate and respond positively to proactive data protection measures.

In contrast, as patients' healthcare engagement shifts towards being more utility-focused, such as in cases of chronic disease management or emergency care, the impact of proactive algorithmic ethics practices may be less pronounced. In these scenarios, patients are primarily driven by the potential health benefits and outcomes that AI technologies can offer, such as improved diagnostic accuracy, personalized treatment plans, and enhanced care efficiency. As a result, they may be more willing to share their personal health information and less sensitive to the specific data handling practices by the healthcare provider, as long as they perceive that the AI system can deliver tangible improvements to their health and well-being. For these utility-focused healthcare engagements, the positive signals and perceived value alignment generated by proactive AI ethics practices may be less salient or impactful compared to privacy-focused engagements. While patients are still likely to appreciate and value the healthcare provider's commitment to ethical AI practices, their primary focus remains on the anticipated health benefits and outcomes. In other words, the perceived utility of the AI system in improving their health may outweigh or partially offset any concerns about data privacy or ethical risks, making the marginal impact of proactive algorithmic ethics practices less pronounced. This notion is supported by Xu et al. (2022), who find that the impact of personalization on individuals' willingness to disclose personal information is moderated by their privacy calculus [72]. Specifically, the effect of personalization on disclosure intentions is weaker for individuals who perceive greater benefits relative to risks. This suggests that when patients perceive significant health benefits from engaging with an AI system, they may be more willing to trade off some level of privacy for the expected utility gains, thereby reducing the relative importance of proactive algorithmic ethics practices in shaping their attitudes and behaviors. Based on the literature reviewed above, we develop and test the following hypotheses (H4-H6), which will be systematically examined in our analyses and discussed in our results section. Therefore, we thus argue that:

H4: There will be an interaction effect between algorithmic ethics practices and healthcare engagement type on patient attitudes towards the healthcare provider, such that: (a) For privacy-focused healthcare engagements, proactive ethics practices will lead to significantly more positive attitudes compared to passive practices. (b) As the healthcare engagement type shifts towards being more utility-prioritized, the positive effect of proactive algorithmic ethics practices on attitudes will diminish, demonstrating a decreasing marginal effectiveness of ethical practices.

H5: There will be an interaction effect between algorithmic ethics practices and healthcare engagement type on patient trust in the healthcare provider, such that: (a) For privacy-focused healthcare engagements, proactive algorithmic ethics practices will lead to significantly high levels of trust in healthcare providers compared to passive practices. (b) As the healthcare engagement type shifts towards being more utility-focused, the positive effect of proactive algorithmic ethics practices on patient trust will diminish, demonstrating a decreasing marginal effectiveness of ethical practices.

H6: There will be an interaction effect between algorithmic ethics practices and healthcare engagement type on patient intentions to use AI-enabled healthcare services, such that: (a) For privacy-focused healthcare engagements, proactive algorithmic ethics practices will lead to significantly stronger intentions to use AI-enabled services from healthcare providers compared to passive practices. (b) As the healthcare engagement type shifts towards being more utility-focused, the positive effect of proactive algorithmic ethics practices on patient intentions to use AI-enabled services will diminish, indicating decreasing marginal effectiveness of ethical practices.

Methodology

Study design

To test our hypotheses, we conducted a 2 (algorithmic ethics practices: proactive vs. passive) × 2 (healthcare engagement type: privacy-focused vs. utility-focused) scenario-based experimental design. This approach allowed us to examine both the main effects of algorithmic ethics practices and healthcare engagement type independently, as well as their interaction effects on our three dependent variables: attitudes toward the healthcare provider, trust in the healthcare provider, and intentions to use AI-enabled healthcare services. For each dependent variable, we first tested for main effects to determine the overall impact of algorithmic ethics practices (H1-H3), followed by tests of interaction effects to assess whether the impact of algorithmic ethics practices varied across different healthcare engagement types (H4-H6). Figure 1 provides a visual representation of the experimental design and procedure.

Participants

We recruited 550 Chinese participants via Credamo [https://www.credamo.com] for our study, of which 513 provided valid responses. Credamo is an online survey platform widely used in behavioral research, known for providing reliable and diverse samples [15, 64]. Of the 513 participants, 66.3% were female, and the majority (48%) fell within the 18–24 age range. Most participants (86.6%) had some college education, and over half (59.1%) said they had an AI-assisted medical procedure or diagnosis in the last year.

Stimulus materials

News article

One news article and four scenarios were created to manipulate algorithmic ethics practices level and patient's healthcare engagement type. The news article contained information about the healthcare provider's implementation of an AI algorithm-enabled diagnosis and treatment recommendation system, and was designed to inform participants about the required AI algorithm-enabled responsibilities healthcare provider must comply with regarding AI algorithm use for diagnosis. The news article was created specifically for this study to establish a consistent baseline of knowledge across all participants regarding the standard responsibilities healthcare providers must fulfill when implementing AI diagnosis systems. In the debriefing session, participants were informed that this news article was created for research purposes. This approach allowed us to control for potential differences in participants' prior knowledge about AI in healthcare while maintaining experimental control.

Experimental scenarios

Following the news article, participants were randomly assigned to one of four experimental scenarios representing the 2 × 2 design: Scenario A: Proactive ethics + Privacy-focused healthcare; Scenario B: Proactive ethics + Utility-focused healthcare; Scenario C: Passive ethics + Privacy-focused healthcare; Scenario D: Passive ethics + Utility-focused healthcare. In other words, participants read the same news article across conditions, but read different scenarios based on the specific condition they were assigned to. The scenarios varied in their descriptions of the healthcare provider's algorithmic ethics approach (proactive vs. passive) and healthcare engagement type (privacy-focused vs. utility-focused) for the AI system to generate personalized recommendations. To operationalize our experimental conditions, we developed a detailed scenario describing the implementation of an AI algorithm-assisted diagnosis system at a local hospital. The scenario, titled 'HealthAI+', was designed to be relatable and easy to understand for participants. All participants were presented with the following base scenario: "Imagine that the main hospital in your city has recently introduced an AI algorithm-assisted diagnosis system called 'HealthAI+'. This system is designed to help doctors diagnose diseases more quickly and accurately, and to develop personalized treatment plans. You've received an email from the hospital inviting you to use this new service. The email contains

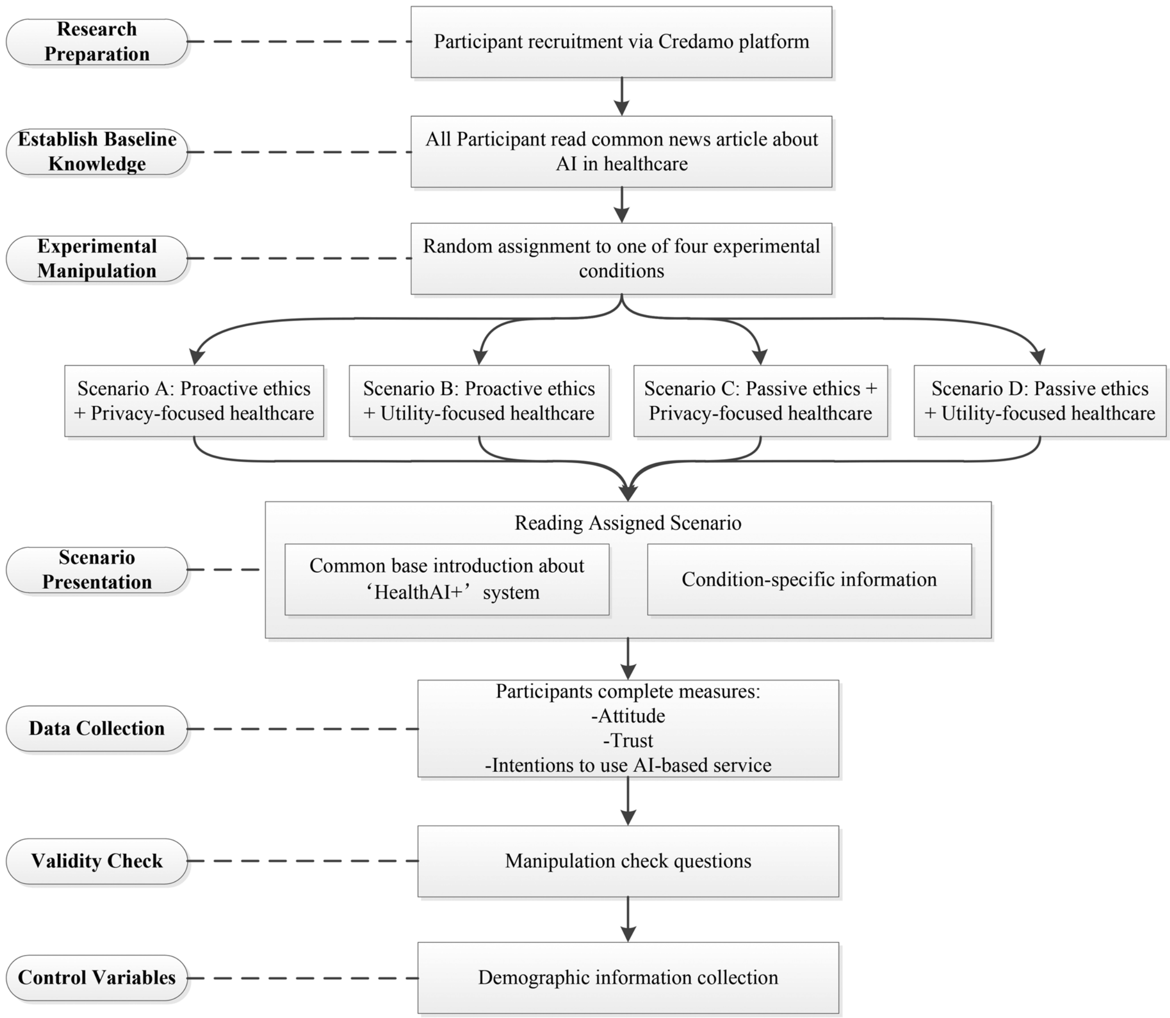

Fig. 1 Visual representation of the experimental design and procedure

the following information". Following this base scenario, participants were then presented with condition-specific variations that reflected either proactive or passive algorithmic ethics practices, and either privacy-focused or utility-focused healthcare engagement types.

Using a random assignment procedure, participants were divided into four experimental groups. In the proactive algorithmic ethics condition, the healthcare provider was described as having taken several proactive measures to ensure the ethical development and deployment of the AI algorithm system. These measures included establishing an AI ethics committee, conducting regular algorithmic audits, providing clear explanations for AI-generated recommendations, and actively seeking patient feedback. In contrast, in the passive algorithmic ethics condition, the healthcare provider was described as merely complying with the minimum legal requirements for AI algorithmic use, without any additional ethical initiatives. The patient's healthcare engagement type manipulation was embedded within the scenario as part of the description of the AI system's data collection process. In the utility-focused healthcare engagement type condition, "Imagine you are considering using the hospital's AI-assisted chronic disease management service for a condition like diabetes or heart disease. This service involves regular monitoring of various health metrics (e.g., blood sugar levels, heart rate, blood pressure) and lifestyle factors to optimize your treatment plan. The AI analysis of this data will provide them with above-standard diagnosis (20% increase in accuracy), personalized treatment plans (30% reduction in side effects), and predictions of potential health risks (3–5 years early warning)." In the privacy-focused healthcare engagement type condition, "Imagine you are considering using the hospital's AI-assisted mental health consultation service. This service involves discussing sensitive personal information about your thoughts, feelings, and experiences, as well as providing access to your mental health records, genetic test results, and authorizing the AI system to access your social media accounts. The AI analysis of this data will be used to provide standardized diagnosis with accuracy comparable to traditional methods." After reading the scenario, participants completed a questionnaire measuring their attitudes towards the healthcare provider, trust in the provider, and intentions to use the AI-enabled healthcare service. They also responded to manipulation check questions and provided demographic information.

Measurement

Independent variables

The independent variables, algorithmic ethics practices and healthcare engagement type, were manipulated through the scenario descriptions as detailed in Sect. 3.2.2.

Dependent variables

Attitudes towards the healthcare provider were measured using a 4-item, 7-point semantic differential scale adapted from Alsaad (2021) [2]. The participants used bipolar words including "acceptable/unacceptable," "right/wrong", "good/bad," and "unethical/ethical" to score how they felt about the healthcare provider (α = 0.828). *Trust in the healthcare provider* was assessed using a 4-item, 7-point Likert scale adapted from [11]. Sample items included " I believe that this healthcare provider 'is not honest at all/is very honest', 'cares about its interests only/cares about its customers all the time' and 'is opportunistic/is dependable'" (α = 0.831). *Intentions to use the AI-enabled healthcare service* were taken from prior studies and adjusted to fit our research context using a 3-item, 7-point Likert scale adopted from Shi et al. (2024) and Hsieh (2023) [28, 58]. Statements like "I would be willing to use this AI-enabled healthcare service" and "I would recommend this AI-enabled healthcare service to others" were used by participants to express their agreement (α = 0.834).

Control variables

We also controlled several demographic variables, including age, gender, education level, and prior experience with AI-enabled healthcare given their potential influence on the dependent variables, because previous studies have found that these demographic variables might be related to patients' attitude, and behavioral intention [28].

Data analysis

Data analysis was conducted using SPSS version 27.0. After data cleaning and checking for assumptions, we performed a series of two-way analyses of covariance (ANCOVAs) to test our hypotheses. For hypotheses 1–3, examining the main effects of algorithmic ethics practices, we conducted one-way ANOVAs to compare mean differences between the proactive and passive conditions for each dependent variable (attitudes, trust, and usage intentions). For hypotheses 4–6, testing the interaction effects between algorithmic ethics practices and healthcare engagement type, we conducted 2 × 2 factorial ANCOVAs with algorithmic ethics practices (proactive vs. passive) and healthcare engagement type (privacy-focused vs. utility-focused) as independent variables, while controlling for age, gender, education level, and prior experience with AI-enabled healthcare as covariates. For significant interaction effects, we conducted simple effects analyses to examine the impact of algorithmic ethics practices within each healthcare engagement type condition.

Results

Manipulation check

To assess the effectiveness of our experimental manipulations, we conducted a series of independent samples t-tests. Participants in the proactive algorithmic ethics condition perceived the healthcare provider as having more proactive algorithmic ethics practices compared to those in the passive algorithmic ethics condition (M = 5.60 vs. 4.02, p <.001. For the healthcare engagement type manipulation, we asked participants to rate the perceived privacy sensitivity and utility focus of the healthcare service described in their scenario. Participants in the privacy-focused healthcare engagement condition (mental health consultation) rated the service as significantly more privacy-sensitive compared to those in the utility-focused condition (chronic disease management) (M = 5.87 vs. 3.45, p <.001). Conversely, participants in the utility-focused condition rated the service as having a significantly higher focus on health outcomes and treatment effectiveness compared to those in the privacy-focused condition (M = 5.93 vs. 3.72, p <.001).

Hypotheses testing

Main effects of algorithmic ethics practices

To test our hypotheses, we conducted a series of 2 (algorithmic ethics practices: proactive vs. passive) × 2 (healthcare engagement type: privacy-focused vs. utility-focused) between-subjects two-way analysis of covariance (ANOVAs) test for each dependent variable: Attitude, Trust, and Intention. We first examined the influence of the control variables (age, gender, education level, and prior experience with AI-enabled healthcare) on the dependent variables. The ANCOVA results indicated that prior experience with AI-enabled healthcare reported more favorable attitudes, higher trust levels, and stronger usage intentions (all p <.001) compared to those without such experience, while men showed more favorable attitudes, higher trust levels, and stronger usage intentions (all p <.05) compared to women. However, age, and education level did not show any significant main effects (all $p > .05$). After controlling for these variables, we proceeded with the primary hypothesis tests.

Hypothesis 1 predicted that proactive algorithmic ethics practices would lead to more positive attitudes towards the healthcare provider compared to passive practices. As analysis results shown, participants exposed to proactive algorithmic ethics practices reported more favorable attitudes toward the healthcare provider ($M = 5.67$, $SD = 1.00$) than those exposed to passive practices ($M = 4.28$, $SD = 1.52$). This difference was statistically significant, as evidenced by the results of a one-way ANOVA ($F(1, 504) = 154.677$, $p < .001$, $\eta^2 = 0.235$), thus providing support for H1. Hypothesis 2 proposed that proactive algorithmic ethics practices would lead to higher levels of trust in the healthcare provider compared to passive practices. Participants exposed to proactive algorithmic ethics practices reported more favorable trust toward the healthcare provider ($M = 5.57$, $SD = 0.88$) than those exposed to passive practices ($M = 4.31$, $SD = 1.50$). This difference was statistically significant, as evidenced by the results of a one-way ANOVA ($F(1, 504) = 141.976$, $p < .001$, $\eta^2 = 0.220$), thus providing support for H2. Hypothesis 3 suggested that proactive algorithmic ethics practices would lead to stronger intentions to use AI-enabled healthcare services. As analysis results shown, participants exposed to proactive algorithmic ethics practices reported more favorable attitudes toward the healthcare provider ($M = 5.37$, $SD = 1.17$) than those exposed to passive practices ($M = 4.14$, $SD = 1.74$). This difference was statistically significant, as evidenced by the results of a one-way ANOVA ($F(1, 504) = 2.989$, $p < .084$, $\eta^2 = 0.041$), thus providing support for H3.

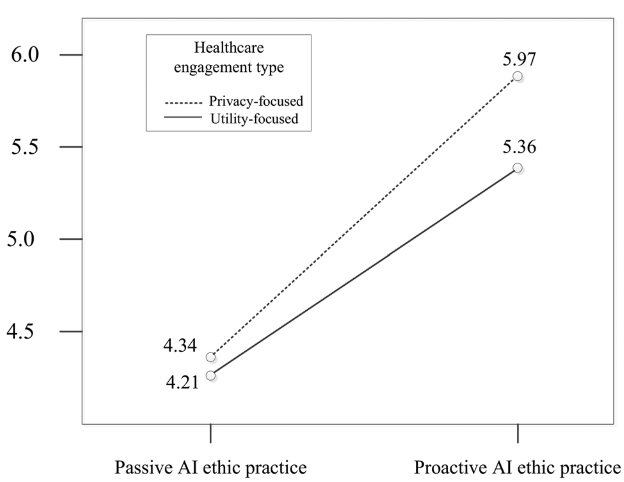

Fig. 2 Interaction effects between algorithmic ethic practice level and healthcare engagement type on attitude

Interaction effects of algorithmic ethics practices and healthcare engagement type

Hypotheses 4–6 predicted an ordinal interaction effect between algorithmic ethics practices and healthcare engagement type on patient attitudes, trust, and usage intentions, respectively. For patient attitudes (H4), our analysis revealed a significant interaction effect between algorithmic ethics practices and healthcare engagement type on patient attitudes ($F(1, 506) = 4.398$, $p = .036$, $\eta^2 = 0.001$). Simple effects analyses revealed that proactive ethics practices led to more favorable attitudes in both privacy-focused ($M_{proactive} = 5.97$ vs. $M_{passive} = 4.34$; $F(1,506) = 150.999$, $p < .001$, $\eta^2 = 0.018$) and utility-focused contexts ($M_{proactive} = 5.36$ vs. $M_{passive} = 4.21$; $F(1,506) = 10.915$, $p < .001$, $\eta^2 = 0.001$), with the effect being stronger in the privacy-focused context. This pattern supports both H4a and H4b, demonstrating that while proactive ethics practices improve attitudes across contexts, their impact is more pronounced in privacy-focused healthcare settings. However, as the healthcare engagement type shifted towards being more utility-focused, the positive effect of proactive ethics on attitudes diminished, demonstrating a decreasing marginal impact.

For trust (H5), the analysis revealed a marginally significant interaction effect ($F(1, 504) = 3.729$, $p = .054$, $\eta^2 = 0.004$). In the privacy-focused condition, proactive practices significantly enhanced trust ($M_{proactive} = 5.83$ vs. $M_{passive} = 4.31$; $F(1,504) = 141.976$, $p < .001$, $\eta^2 = 0.015$). The effect remained significant but was weaker in the utility-focused condition ($M_{proactive} = 5.31$ vs. $M_{passive} = 4.30$; $F(1,505) = 4.734$, $p < .001$, $\eta^2 = 0.001$). These results support H5a and H5b, indicating that the trust-building effect of proactive ethics practices is more potent in privacy-sensitive healthcare contexts. However, as the healthcare engagement type shifted towards being more utility-focused, the positive effect of proactive ethics on attitudes diminished, demonstrating a decreasing marginal impact. For usage intentions (H6), contrary to our expectations, the interaction effect was not significant ($F(1, 506) = 1.357$, $p = .245$, $\eta^2 = 0.002$). While proactive practices increased usage intentions across both healthcare engagement types ($M_{proactive} = 5.73$ vs. $M_{passive} = 4.26$; $F(1,506) = 98.81$, $p < .001$, $\eta^2 = 0.015$; $M_{proactive} = 5.02$ vs. $M_{passive} = 4.02$; $F(1,506) = 9.96$, $p < .002$, $\eta^2 = 0.002$), the effect magnitude did not significantly differ between privacy-focused and utility-focused conditions. This finding fails to support H6b, suggesting that the impact of algorithmic ethics practices on usage intentions remains relatively consistent regardless of healthcare engagement type.

To visualize these relationships, we have plotted the interaction effects for each dependent variable (see Figs. 2, 3 and 4). The plots clearly illustrate the more

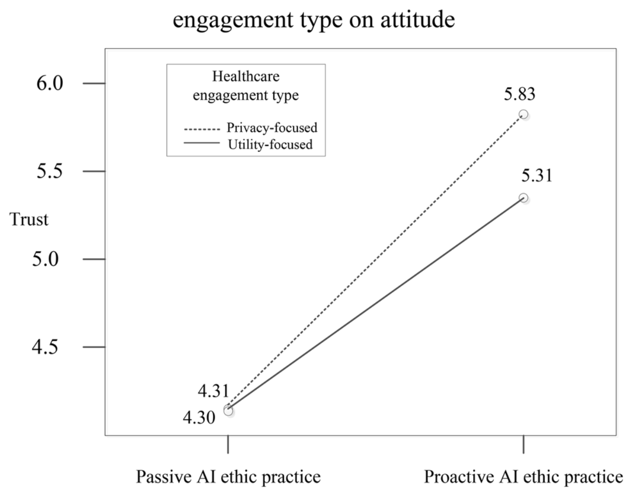

Fig. 3 Interaction effects between algorithmic ethic practice level and healthcare engagement type on trust

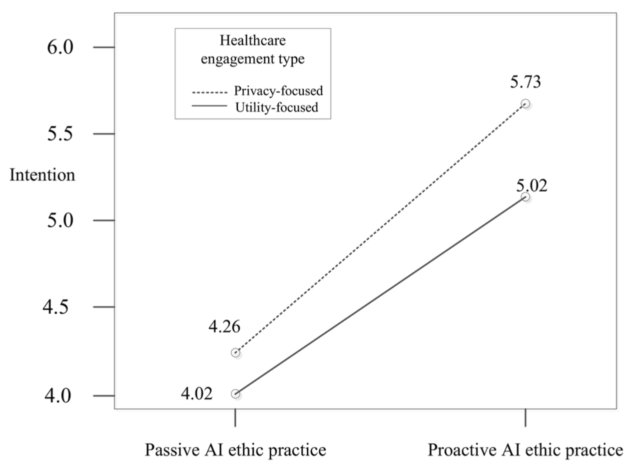

Fig. 4 Interaction effects between algorithmic ethic practice level and healthcare engagement type on intention

pronounced effect of proactive practices in privacy-focused contexts for attitudes, trust, and intention when compared to utility-focused context. Therefore, hypothesis 4 (a), 5(a), and 6 (a) was supported. However, for usage intention, while both proactive ethics practices and privacy-focused services showed significant main effects, their interaction was not significant, indicating that H6(b) was not supported. These findings collectively suggest that healthcare engagement type plays a moderating role in how algorithmic ethics practices influence patient attitudes and trust, though its moderating effect on usage intentions was not statistically supported. This pattern indicates that while proactive ethics practices consistently enhance patient outcomes, their effectiveness varies depending on the healthcare context, particularly for attitudinal and trust-related responses.

Discussion

Our study provides empirical support for the differential effects of proactive and passive algorithmic ethics practices on patient responses in healthcare. Our findings reveal that patients show more favorable attitudes, higher trust, and stronger usage intentions towards providers who actively address ethical issues. Drawing upon the organizational ethics perspective and consumer-company identification theory, we argue that proactive algorithmic ethics practices send positive signals and create perceived value alignment, enhancing patients' identification with the healthcare provider. This identification, in turn, leads to more positive attitudes, trust, and usage intentions. In contrast, passive practices may not evoke the same level of positive identification and attitudinal responses, as they may hinder the development of consumer-company identification and raise doubts about the provider's commitment to ethics. However, the impact of algorithmic ethics practices varies depending on the healthcare engagement type. In privacy-focused contexts, proactive practices have a more pronounced effect on shaping positive patient responses, as patients are more sensitive to privacy protection. In utility-focused engagements, the marginal impact of proactive practices is relatively smaller, as perceived health utility may partially offset privacy concerns.

Theoretical implications

First, our study enriches the empirical research on the impact of algorithmic ethics practices in the healthcare domain by revealing the differential effects of proactive and passive algorithmic ethics practices in shaping patients' responses. While prior studies have explored the ethical considerations in algorithm design and implementation [42, 44, 66], few have empirically quantified their impacts on patient attitudes, trust, and usage intentions. Our research addresses this gap, providing theoretical grounding for healthcare organizations to adopt proactive algorithmic ethics practices. This extends the growing body of literature on AI ethics in healthcare [9, 19, 43] by offering novel insights into how different approaches to ethical AI governance shape patient perceptions and behaviors.

Second, drawing upon the organizational ethics perspective and consumer-company identification theory, our study uncovers the underlying mechanism through which algorithmic ethics practices elicit more favorable patient responses. We find that by sending positive signals and creating perceived value alignment regarding transparency, accountability, and fairness, proactive ethics practices enhance patients' identification with the healthcare provider, leading to more positive attitudes, higher trust, and stronger usage intentions. This finding extends the application of organizational ethics [68, 74] and identification theories [5, 27] to the context of AI in healthcare, offering a new theoretical lens for future research to build upon. It also contributes to the growing literature on trust in AI-enabled healthcare services [3, 28, 37] by highlighting the critical role of ethical AI practices in fostering patient trust.

Third, our study deepens the understanding of the privacy-utility tradeoff by revealing how healthcare engagement type moderates the impact of algorithmic ethics practices on patient attitudes and behaviors, thereby offering insights into resolving the privacy paradox. The privacy paradox, which refers to the discrepancy between individuals' stated privacy concerns and their actual information disclosure behaviors [22, 34], has been a long-standing puzzle in privacy research. While prior studies have examined various factors that may influence this tradeoff, such as personalization [72], few have investigated how the interplay between organizational practices and contextual factors may shape individuals' privacy calculus and help reconcile the privacy paradox.

Practical implications

Our findings offer several actionable insights for healthcare providers and policymakers aiming to promote the ethical adoption of AI algorithms in healthcare. First, our results underscore the value of proactive algorithmic ethics practices in fostering patient trust and acceptance. Healthcare organizations should go beyond mere legal compliance and actively engage in efforts to ensure the transparency, fairness, and accountability of their AI systems. This may involve establishing dedicated AI ethics committees, conducting regular algorithmic audits, providing clear explanations of AI decisions, and actively seeking patient input and feedback. By adopting such practices, healthcare providers can demonstrate their commitment to ethical AI governance, enhance patients' identification with their values, and ultimately cultivate more positive attitudes, trust, and usage intentions.

Second, our study highlights the importance of tailoring algorithmic ethics strategies based on patients' healthcare engagement type, while maintaining strong ethical standards across all contexts. For privacy-focused healthcare services, such as mental health consultations or genetic testing, healthcare providers should emphasize robust data protection measures and transparent communication about their ethical AI practices. This can help alleviate patients' heightened privacy concerns and foster trust in these sensitive contexts. For utility-focused healthcare services, such as chronic disease management or emergency care, healthcare providers should integrate their strong ethical practices with clear demonstrations of the health benefits that AI technologies can deliver. While our findings suggest that the marginal impact of proactive ethics on patient responses may be relatively smaller in utility-focused contexts, this should not be interpreted as diminishing the fundamental importance of ethical practices. Rather, providers should maintain comprehensive ethical practices as a baseline requirement while also effectively communicating the personalized health benefits, creating a synergistic approach that addresses both ethical concerns and utility expectations.

Third, our findings suggest that healthcare providers should invest in patient education and empowerment initiatives to help individuals navigate the privacy-utility tradeoffs associated with AI-enabled healthcare services. This may involve providing accessible information about the data collection and analysis processes, the potential benefits and risks, and the available privacy control options. By equipping patients with the knowledge and tools to make informed decisions about their personal health information, healthcare organizations can foster a sense of agency and trust, thereby encouraging greater adoption of AI technologies.

Limitations and future research directions

Our study has several limitations that offer opportunities for future investigation. First, our study relied on a hypothetical scenario and self-reported measures of patient responses. While this approach allowed us to maintain experimental control and establish internal validity, it may limit the generalizability of our findings to real-world healthcare settings. Future research could employ field experiments or longitudinal designs to examine the effects of algorithmic ethics practices on actual patient behaviors and long-term outcomes. Second, our study focused on a single healthcare context and a limited set of algorithmic ethics practices. Future research could explore a broader range of AI ethics practices (e.g., data governance mechanisms, algorithmic impact assessments, human oversight, and redress procedures). Such investigations would help to provide a more comprehensive understanding of the contextual factors that shape the effectiveness of AI ethics practices in healthcare. Third, while we examined patients' healthcare engagement type as a key moderator, there may be other individual difference variables that influence patients' responses to algorithmic ethics practices and data disclosure requirements. For example, patients' self-efficacy in technology, health literacy, and cultural background may all play a role in shaping their privacy calculus and reactions to AI-enabled healthcare services. Future research could explore these and other individual-level factors to develop a more nuanced and patient-centric understanding of algorithmic ethics in healthcare. Finally, our study was conducted in the China, which has a unique healthcare system and cultural context. Future research could examine the generalizability of our findings to other countries and cultures, particularly those with different healthcare regulations, privacy norms, and levels of trust in medical institutions. Cross-cultural comparisons could provide valuable insights into the universal and context-specific factors that influence patient responses to algorithmic ethics practices in healthcare.

Supplementary Information

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Supplementary Material 1

Author contributions

S.S. substantial contributions to conception and design. QL.L. and ZQ.C: data collection. QL.L: analysis and interpretation of data. S.S. and QL.L: article writing or relevant critical review of intellectual content. Three authors read and approved the final manuscript.

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Data availability

The datasets used and analyzed in the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

The study design and ethical considerations were approved by the Ethics Committee of Chongqing University of Technology, and was conducted in accordance with the Declaration of Helsinki. All participants provided informed written consent, ensuring data privacy and adherence to ethical guidelines.

Human ethics and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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