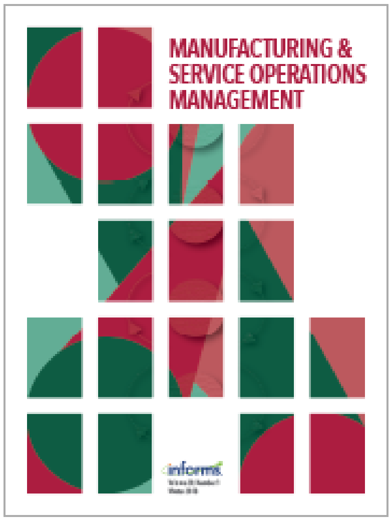

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Physician Adoption of AI Assistant

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Abstract. ***Problem definition*:** Artificial intelligence (AI) assistants—software agents that can perform tasks or services for individuals—are among the most promising AI applications. However, little is known about the adoption of AI assistants by service providers (i.e., physicians) in a real-world healthcare setting. In this paper, we investigate the impact of the AI smartness (i.e., whether the AI assistant is powered by machine learning intelligence) and the impact of AI transparency (i.e., whether physicians are informed of the AI assistant). ***Methodology/results*:** We collaborate with a leading healthcare platform to run a field experiment in which we compare physicians' adoption behavior, that is, adoption rate and adoption timing, of smart and automated AI assistants under transparent and non-transparent conditions. We find that the smartness can increase the adoption rate and shorten the adoption timing, whereas the transparency can only shorten the adoption timing. Moreover, the impact of AI transparency on the adoption rate is contingent on the smartness level of the AI assistant: the transparency increases the adoption rate only when the AI assistant is not equipped with smart algorithms and fails to do so when the AI assistant is smart. ***Managerial implications*:** Our study can guide platforms in designing their AI strategies. Platforms should improve the smartness of AI assistants. If such an improvement is too costly, the platform should transparentize the AI assistant, especially when it is not smart.

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Keywords: health intelligence • operational transparency • medical platform • field experiment • generative AI • chatbot

> AI is not going to replace physicians, but physicians who use AI are going to replace physicians who don't, and that may be the cautionary tale. —Dr. Keith Horvath, former director of U.S. National Institutes of Health

1. Introduction

Artificial intelligence (AI) is one of the most prominent technologies of industry 4.0, enabling the machine simulation of human behavior and intelligence (Olsen and Tomlin 2020). AI is transforming a wide range of industries, such as engineering, manufacturing, finance, and healthcare, and is predicted to add as much as $15.7 trillion to the global economy by 2030 (Wilson and Daugherty 2018). In healthcare, the use of AI is expected to grow substantially to support physicians and generate more than $150 billion in industry savings by 2025 (Sullivan 2018). An *AI assistant* (virtual assistant)—a software agent that can perform tasks or services for an individual—is perhaps the most promising type of AI application in healthcare, accounting for an expected $20 billion in annual savings (Kalis et al. 2018). For example, the UK National Health Service uses Molly, an AI-based nurse assistant, to interact with patients, ask questions about their health conditions, assess their symptoms, and direct them to the most effective care setting.

AI assistants are particularly valuable on medical platforms that, unlike on-site healthcare facilities, such as clinics or hospitals, do not provide medical assistants or nurses to aid physicians. Patients can now find physicians more easily and quickly through online platforms (Cohen 2018, Xu et al. 2021). For example, many healthcare platforms, such as *iCliniq* operating in the global market, *HealthTap* operating in the U.S. market, and *Chunyu* and *Haodf* operating in the Asian market, offer the functionality of allowing patients to immediately connect with and text physicians for consultation. However, patients often provide insufficient details or leave out critical information when describing their symptoms during online consultations (Yan et al. 2020). Thus, healthcare platforms are striving to apply AI techniques to aid physicians in providing quick responses and diagnoses given the exponential growth in demand for online consultation services (Bestsennyy et al. 2021). In this regard, medical platforms develop a particular type of AI assistant, namely, an auto reply system, that generates responses physicians can adopt (Jahanshahi et al. 2022); in fact, similar AI assistants, such as Google, which has developed a reply system that generates instant email responses for users, and Uber, which has devised a one-click chat feature to help drivers quickly and safely respond to customer text messages when driving, have already gained popularity in other settings. The responses generated by these AI assistants can be standard or smart or even human-like (such as ChatGPT).

However, little is known about the adoption behaviors of AI assistants because of limited samples and the challenge of obtaining data in real-world healthcare settings. This understanding is important because it is eventually the decision of healthcare service providers (i.e., physicians) as to whether and how to work with AI assistants (Russell 2010). We explore the impact of *AI smartness* on physician adoption behavior by investigating whether physicians respond differently to the smart (i.e., personalized) recommendations provided by the AI assistant empowered by machine learning intelligence that can mimic the diagnostic logic of physicians versus the non-smart (i.e., automated) recommendation provided by the AI assistant without a smart control. This question is particularly relevant for practice because the development of AI algorithms in healthcare is both complex and costly (He et al. 2019). Even if they are costless, smart or human-like AI assistants are not necessarily favored by service providers (Kim et al. 2019). In particular, professionals, such as physicians, may exhibit algorithm aversion and be averse to following algorithm outcomes even when they explicitly know that algorithms outperform humans (Dietvorst et al. 2015, Jussupow et al. 2021).

We also explore the impact of AI information disclosure—that is, informing physicians that they would be assisted by AI techniques in responding to patient consultations—which we term *AI transparency*. We particularly study the impact of AI transparency on physician's adoption, that is, whether physicians would respond differently to the AI assistant with different levels of transparency. In practice, governmental agencies often encourage a higher level of transparency among AI applications (MacCarthy 2020). For example, the European Commission (2019) set up a high-level group of AI experts stating that transparency is one of seven key requirements of AI, while the White House has released guidance for the regulation of AI applications to urge companies to improve AI transparency (White House 2020). Despite the growing calls for transparency, most firms keep the application of AI and the algorithms involved opaque to their users. In our context, providing information about AI assistants might backfire when physicians exhibit algorithm aversion.

To investigate the impact of AI smartness and transparency on physicians' adoption of AI assistants, we conduct a randomized field experiment by collaborating with a leading healthcare platform, whose name is concealed because of a non-disclosure agreement. As one of the largest medical platforms connecting millions of patients and physicians, the platform officially launched a new feature—an AI assistant—to aid physicians in their conversations with patients. In particular, when a physician receives a patient's diagnosis request, the assistant automatically sends the physician a recommendation for how to reply to the patient. We design and conduct a 2×2 field experiment, including two types of AI assistants (smart versus automated) and two information conditions (transparent versus non-transparent). The smart assistant is powered by AI algorithms utilizing big data analysis of all previous physician–patient conversations to generate specific questions regarding symptoms, whereas the automated assistant uses a more general preset format to ask patients to describe their symptoms further. Under the transparent condition, the platform publishes an announcement informing the physicians of the new AI assistant feature (i.e., smart or automated AI), whereas under the non-transparent condition, physicians do not receive any announcement about the new assistant feature. We then test the effect of smartness and transparency on physicians' adoption behavior in *adoption rate* (i.e., whether to adopt the recommendation provided by the assistant) and, if they adopt, *adoption timing* (i.e., when to start adopting the recommendation provided by the AI assistant).

We find that AI smartness significantly increases the adoption rate by 32.6%, shortening the adoption timing by 49.9% under the transparent condition. This positive effect is even larger under the non-transparent condition: smartness increases physicians' adoption rate by 218.4% and reduces adoption timing by 57.6%. This is because the smart assistant can accurately tailor its recommendations to each patient's symptom description, allowing these recommendations to be more professionally applied to the patients' medical conditions than automated recommendations. The personalization and professionalism of the smart assistant allow physicians to perceive higher performance and usefulness in AI, thereby increasing their willingness to adopt it.

We also find that AI transparency significantly shortens the adoption timing of the automated assistant by

58.0% and the smart assistant by 50.4%. However, interestingly, the impact of transparency on the adoption rate is contingent on the smartness level of the AI assistant. Transparency significantly increases the adoption rate when the assistant is not equipped with machine learning algorithms because the information (that assistants are from the platform) can boost physicians' perceived credibility and usefulness of AI. This aspect is particularly crucial for non-smart (automated) recommendations, which are likely to be viewed as less credible and useful by physicians than smart recommendations. However, if AI demonstrates a high level of performance in providing personalized recommendations, physicians perceive the usefulness of personalized recommendations over time even without AI transparency.

Overall, there is a lack of understanding of how service providers respond to AI applications; this paper is among the first to empirically explore the adoption behavior of the medical service provider (namely, physician) on one emerging AI application (i.e., AI assistant). In contrast to the traditional wisdom that increasing AI technology transparency to users would backfire, we find that transparency can actually enhance the physician's adoption in a medical platform, particularly when the AI assistant is not smart.

2. Literature Review and Our Contribution

Our study is related to three streams of literature: (i) technology adoption, (ii) operational transparency, and (iii) healthcare operations.

2.1. Technology Adoption

The rich literature on technology adoption has measured adoption behavior in terms of the adoption rate and adoption timing (Damanpour and Gopalakrishnan 2001; Hoppe 2002; Gao et al. 2020, 2022). For example, this stream of literature examines the adoption and adoption timing of new technologies by a firm in competitive environments (Farzin et al. 1998, Milliou and Petrakis 2011) or outsourcing markets (Aliprанti et al. 2015). Venkatesh et al. (2003) identify the factors—such as expected technology performance and facilitation from organizational support—that influence individual technology adoption behavior over time.

The emerging AI technology creates value in various fields, such as procurement (Cui et al. 2022), job evaluation (Tong et al. 2021), and legal decision making (Cohen et al. 2024). One focus of the literature is on adoption decisions regarding AI tools. For example, Gursoy et al. (2019) find that consumers' perceptions of AI performance consistently influence their adoption decisions over time. Fan et al. (2020) suggest that the organizational environment is critical to health professionals' initial trust in AI. Although AI algorithms consistently outperform human decision-makers, some studies reveal that people are often reluctant to adopt algorithms' recommendations and exhibit algorithm aversion (Dietvorst et al. 2015, Longoni et al. 2019, Jussupow et al. 2021). For example, people are less inclined to accept preventive health interventions based on AI compared with interventions provided by experts (Kyung and Kwon 2024); humans prefer to use their own predictions rather than follow machine forecasts (Dietvorst et al. 2018), while workers are reluctant to adopt algorithmic suggestions when packing products (Sun et al. 2022). This stream of literature also identifies significant differences in whether people follow algorithmic recommendations across situations and task types (Castelo et al. 2019). The extant literature focuses on firms' or consumers' adoption behaviors of AI (Nadarzynski et al. 2019, Wang et al. 2023, Kyung and Kwon 2024). We add to this stream of literature by investigating the adoption behavior of medical service providers regarding one particular type of AI, namely, AI assistant, in a healthcare setting.

2.2. Operational Transparency

Previous literature indicates the benefits of transparency in various service operation settings (Buell 2019, Cohen et al. 2023). Process transparency, for example, can increase quality ratings and customer satisfaction, and customer transparency can increase service quality and efficiency (Buell et al. 2017). However, the prior literature identifies that transparency in AI applications can bring negative results. For example, Luo et al. (2019) find that consumers purchase less when they are aware that the conversational agents are chatbots; Tong et al. (2021) show that employees have a negative perception of performance feedback once they are aware that AI provides their performance evaluations; and Lehmann et al. (2022) find that, when algorithms help people make decisions, providing transparency on simple algorithms reduces the use of AI advice. This study follows this literature to investigate the effect of transparency in a different yet important application context, namely, AI assistants on a medical platform. We find that transparency can boost AI adoption, especially when AI tools provide automated services and are not equipped with algorithms.

2.3. Healthcare Operations

Recent studies in healthcare operations focus on the use of technology in enabling innovative models of delivery service (Bavafa et al. 2018, Kc et al. 2020). Our study is closely related to one such new model, that is, online consultations on healthcare platforms. The literature highlights the benefits of online consultations, such as mitigating geographic healthcare disparity

(Hwang et al. 2022), increasing the number of off-line appointments for providers (Fan et al. 2023), and improving the professional reputation of physicians (Huang et al. 2021). The literature also explores the key factors determining patients' use of online healthcare services and finds that physicians' performance and response speed are important factors (Sun et al. 2013). We complement this literature by exploring physicians' adoption behaviors of AI assistants that can help them reduce response times in online consultations.

2.4. Our Contribution

To the best of our knowledge, this is the first study to empirically explore how AI assists service providers (physicians) using a randomized field experiment. In contrast to the existing literature showing that operational transparency may hinder consumers' adoption of AI technologies, our field experiment reveals that operational transparency can actually foster the service providers' adoption.

3. Research Hypotheses

We study physician adoption behaviors regarding AI assistants on a leading healthcare platform. At the beginning of each consultation, the assistant automatically recommends what questions the physician should ask the patient to gather necessary information, and the physician then decides whether to adopt the recommendation. We measure physicians' adoption rate (i.e., whether they adopt) and adoption timing (i.e., when they adopt for the first time) and explore the effects of two AI strategies: (i) AI smartness (whether the AI assistant is equipped with an advanced algorithm) and (ii) AI transparency (whether physicians are explicitly informed of AI adoption).

3.1. Effect of AI Smartness

AI smartness refers to the strategy by which an assistant provides highly personalized recommendations to physicians. Specifically, our collaborating platform equips the smart assistant with an industry-leading machine learning algorithm that learns from big data from previous physician–patient consultations. Using natural language processing, the algorithm can understand a patient's question and reply to the patient by imitating the diagnostic logic of physicians (see Online Appendix Figure A1(b)). In contrast, the automated assistant automatically recommends to providers a standardized paragraph without personalization (see Online Appendix Figure A1(a)).

In accordance with the Unified Theory of Acceptance and Use of Technology, individual perceptions of technology performance and usefulness stand as pivotal factors shaping their adoption of technology (Venkatesh et al. 2003). Specifically, for the adoption of advanced technology such as AI, people factor in its perceived usefulness (Gursoy et al. 2019, Fan et al. 2020, Glikson and Woolley 2020). Such perceptions are based on the personalization and accuracy of AI technology (Shin 2021), particularly in healthcare (Davenport and Kalakota 2019, Longoni et al. 2019). In this context, the highly personalized and accurate advice generated by AI demonstrates immense value within the domain of healthcare (Johnson et al. 2021). We interviewed several highly experienced physicians with years of expertise in both online and off-line consultations. These physicians confirm the need for a highly intelligent level of AI in healthcare and express their anticipation of AI's role in providing specialized and personalized recommendations.[1] In our context, with smartness, the assistant can accurately tailor its recommendations to each patient's symptom description, which can be more professionally applied to patients' medical conditions than automated recommendations. Therefore, we hypothesize that physicians perceive higher performance from the smart assistant than the automated assistant, leading to both a higher adoption rate and earlier adoption timing.

Hypothesis 1 (AI Smartness). (a) *The AI adoption rate of physicians is higher under the smart AI strategy than under the automated AI strategy.* (b) *The AI adoption timing of physicians is earlier under the smart AI strategy than under the automated AI strategy*.

3.2. Effect of AI Transparency

AI transparency refers to the strategy in which the platform explicitly introduces an AI assistant to physicians. Specifically, the platform provides information regarding its AI assistant—such as introduction time, type (smart versus automated AI), and functionality—to physicians.

AI transparency is a key determinant for physicians' adoption of the AI assistant. The platform that furnishes physicians with precise information about AI assistants can foster physician adoption in two ways. First, a transparent introduction explicitly reminds physicians of the functionality of new features and serves to immediately draw their attention to the benefits of adopting the technology (Castaño et al. 2008). Second, the transparent introduction by the platform can be viewed as organizational support that plays a crucial role in driving the initial adoption of a technology when people do not perceive its credibility and usefulness (Venkatesh et al. 2003, Yu 2012, Fan et al. 2020). Taken together, AI transparency can be effective in encouraging physicians to adopt AI assistants regardless of smart level, especially in the early stages when physicians are unfamiliar with AI features. We, thus, hypothesize that AI transparency leads to an earlier adoption timing for AI assistants in Hypothesis 2(b).

However, the impact of the transparency strategy on the adoption rate (i.e., the number of physicians who adopt AI assistants) depends on the smartness level (or usefulness) of the assistant. Prior research shows that the perceived credibility of the information source has a positive impact on the usefulness of the information (Angst and Agarwal 2009): individuals are more likely to trust and utilize recommendations from sources they perceive as credible. Consequently, providing extensive and precise information contributes to increased credibility, ultimately resulting in higher adoption rates (Nicolaou and McKnight 2006, Bansal and Muthulingam 2022), especially in healthcare settings (Panigutti et al. 2022, Sivaraman et al. 2023). Accordingly, for an automated assistant, after receiving precise information regarding how AI outcomes are generated, physicians comprehend that recommendations are formulated through a rigorous scientific process, instilling trust in them (He et al. 2019). Nevertheless, for a smart AI assistant, which physicians are likely to perceive as more credible than an automated assistant, the impact of AI transparency on adoption rates might be less pronounced. This is because, even without transparency, physicians would gradually find the usefulness of personalized recommendations and surmise that such guidance emanates from the algorithm (Davenport and Kalakota 2019) and eventually adopt it. We then hypothesize that AI transparency can promote the adoption of automated AI but not of smart AI in Hypothesis 2(a).

Hypothesis 2 (AI Transparency). (a) *AI transparency increases the adoption rate of automated AI but has no effect on smart AI.* (b) *The AI adoption timing of physicians is earlier under the transparent AI strategy than under the non-transparent AI strategy.*

4. Experimental Design

The collaborating platform is a leading healthcare platform in China. By the end of 2020, it had accumulated more than 140 million registered patient users and more than 630,000 registered physicians, covering pediatrics, surgery, internal medicine, gynecology, and other departments. All registered physicians also practice in brick-and-mortar hospitals, allocating their free time to provide consultations on the online platform. The platform has delivered more than 400 million medical consultations. Specifically, patients can connect with physicians and obtain professional medical advice through text consultations on this platform. Patients need to make payments to the platform for consultations, while physicians receive compensation for their services from the platform. Compensation for physicians with the same professional title predominantly hinge on their consultation volume. Factors such as response speed rating and patient satisfaction can influence physicians' consultation volume, subsequently affecting their income. As shown in Online Appendix Figure A2,[2] a patient first needs to fill out the symptom description form, and the platform then automatically directs the patient to an available physician with relevant expertise and opens the dialogue interface in which the physician further asks the patient for detailed information to render a diagnosis. In particular, patients often do not provide all the details about their symptoms or leave out critical information in the description form, so physicians have to ask patients to provide additional information to support the diagnosis.

To improve the efficiency of physicians' responses through more effective collection of relevant information, the platform develops a new feature—AI assistant—which automatically suggests which questions a physician should ask first whenever the physician is connected with a patient. The AI suggestions are observable only to physicians who can choose whether to adopt the recommended content. If the physician decides to adopt the recommendation, the physician can simply click on the AI recommendation, and it will appear in the dialog. The physician can either edit it or send it directly to the patient as is. Otherwise, physicians have to type the response content entirely themselves.

4.1. Study Design

We collaborate with the platform to test physicians' adoption of AI under different strategies in a 2×2 field experiment. Specifically, to study the effect of smartness, the platform develops two types of AI assistants, that is, the smart assistant providing personalized recommendations based on a machine learning algorithm versus the automated assistant providing fixed recommendations. To study the effect of AI transparency, the platform designs two information conditions, that is, explicitly introducing the AI assistant information to physicians or not disclosing the information at all. In sum, we consider two types of assistants (smart and automated) and two information conditions (transparent and non-transparent). We tailor the application of AI to incorporate different assistant types and information conditions. We then record and compare the physicians' adoption of the recommendation in each consultation. Table 1 summarizes the study design.

We randomly select a sample of 680 registered physicians from the following departments: (1) pediatric, (2) gynecology and obstetrics, (3) dermatology, (4) internal medicine, and (5) surgery. These five departments constitute the majority of consultation volume on the platform. Physicians are randomly assigned to one of the four (2×2) treatment arms. Therefore, we have 340 physicians per assistant type, 340 physicians per

Table 1. Field Experiment Design

Date	November 12, 2021, to November 26, 2021			
	Transparent conditions × Assistant types			
	Non-transparent		Transparent	
Design	Smart	Automated	Smart	Automated
Planned number of physicians	170	170	170	170
Valid number of physicians	152	143	147	141
Number of consultation	9,300	8,596	8,458	7,701

Note. The difference between the planned and valid sample sizes is because 90 physicians did not answer patient questions on the platform during the experiment and seven physicians answered patient questions but did not click to read the announcement.

information condition, and 170 physicians per treatment arm, meaning that each physician is always helped by one type of assistant and under one informational condition over the two-week experimental period.

To ensure that physicians are randomly assigned to each treatment group, we conduct a randomization check across the following eight physician characteristics: (i) age, (ii) gender (i.e., 1 = male and 0 = female), (iii) department (i.e., the department in which the physician practices), (iv) hospital type (i.e., the type of offline hospital where the physician practices out of seven levels), (v) professional title (i.e., the professional level of the physician as qualified by the government out of four levels), (vi) professional rating (i.e., the accumulated score awarded for a physician's professional performance on the platform out of 100; the better the professional performance is, the higher the score), (vii) service rating (i.e., the accumulated score awarded for a physician's service quality on the platform out of 100; the better the service quality is, the higher the score), and (viii) reply speed rating (i.e., the accumulated score awarded for a physician's reply speed on the platform out of 100; the shorter the reply time is, the higher the score). We show the summary statistics for these variables in Table 2 and the results of the randomization check in Online Appendix Table A1. The *p*-values are all larger than 0.05, which ensures that there are no systematic differences in physicians' characteristics across experimental groups.

4.2. Study Procedure

The medical platform officially launched a new feature—AI assistant—to help physicians between November 13, 2021, and November 26, 2021, during which time selected physicians received a single recommendation from the AI assistant at each consultation. Without the help of an AI assistant, physicians need to type the response content themselves. The automated AI assistant provides the fixed recommendation that covers almost all the information about the patient's symptoms that the physician needs to render a diagnosis: "To support your doctor's diagnosis, please describe your time to onset of disease, specific symptoms, and possible triggers in detail, and upload the test sheet (if available)." This means that physicians helped by automated AI always receive the same recommendation for each consultation. Online Appendix Figure A1(a) gives an example of a consultation serving page for a physician helped by the automated assistant.

The smart AI assistant provides algorithm-generated recommendations; the platform develops a machine learning algorithm that utilizes the massive data set of past patient–physician consultations on this platform, mimicking physicians' behavior and intelligence to generate personalized recommendations. Consequently, smart AI is personalized and accurately tailored to the patient's specific description and illness. Online Appendix Figure A1(b) gives an example of a consultation serving page for a physician helped by the smart assistant.

The platform posts the following announcement to physicians on the day before the experiment begins. Online Appendix Figure A3 gives an example of the physician's online consultation home page. For those physicians under the transparent condition, if they have a smart AI assistant, then they receive the following notification: "Hello. We will introduce a new feature called AI assistant beginning at 12:00 on November 12. The AI assistant will help you gather information about your patients' symptoms by automatically sending you a recommendation generated by the machine learning algorithm. Please feel free to use it." Otherwise, physicians receive the following: "Hello. We will introduce a new feature called AI assistant beginning at 12:00 on November 12. The AI will help you gather information about your patients' symptoms by automatically sending you an automated and fixed recommendation. Please feel free to use it." Online Appendix Figure A4, (a) and (b), illustrate the platform announcement page when recommendations are automated and smart, respectively. The physicians under the non-transparent condition do not receive any information at all.

We then test the effect of smartness and transparency on physicians' adoption behavior in terms of adoption rate (i.e., whether to adopt the recommendation provided by the assistant) and, if they adopt, adoption

Table 2. Summary Statistics

			Transparent			Non-transparent		
	Smart	Automated	All	Smart	Automated	All	Smart	Automated
Age	37.89	37.05	37.59	37.89	37.29	37.35	37.89	36.82
	(9.17)	(8.72)	(9.20)	(9.72)	(8.66)	(8.70)	(8.61)	(8.80)
Gender	0.56	0.54	0.57	0.56	0.58	0.54	0.57	0.51
	(0.50)	(0.50)	(0.50)	(0.50)	(0.59)	(0.50)	(0.50)	(0.50)
Hospital type	4.59	4.70	4.67	4.59	4.75	4.62	4.59	4.65
	(1.75)	(1.67)	(1.68)	(1.76)	(1.60)	(1.74)	(1.74)	(1.74)
Professional title	1.85	1.88	1.89	1.83	1.94	1.85	1.88	1.82
	(0.80)	(0.83)	(0.83)	(0.84)	(0.81)	(0.81)	(0.76)	(0.86)
Professional rating	99.46	99.50	99.50	99.49	99.52	99.46	99.44	99.48
	(1.00)	(1.04)	(1.05)	(0.97)	(1.13)	(0.94)	(0.96)	(0.93)
Service rating	98.21	97.95	98.03	98.15	97.90	98.14	98.27	98.01
	(2.79)	(3.06)	(2.97)	(2.85)	(3.09)	(2.88)	(2.73)	(3.03)
Reply speed rating	95.42	95.69	95.42	95.42	95.43	95.68	95.42	95.94
	(11.49)	(11.23)	(12.01)	(11.77)	(12.28)	(10.67)	(11.24)	(10.11)
Observations	340	340	340	170	170	340	170	170

Notes. This table reports the mean and standard deviation (in parentheses) of physician characteristics. "Smart" and "Automated" indicate smart and automated AI, respectively. "Gender" indicates the percentage of male physicians.

timing (i.e., when to adopt the recommendation provided by the AI assistant).

Within this two-week experiment, we record physicians' participation in online consultations. Among the 680 preselected physicians, 590 physicians participate in at least one consultation session. We also record physicians' click history of reading the announcement and eliminate seven physicians who did not read the announcement. As a result, we have 583 valid physicians in our sample, containing 34,055 consultations. To ensure our analysis in Section 5 is not confounded by the characteristics of the valid physicians, we conduct a balance check of physician characteristic variables across four groups for the valid physicians. As shown in Online Appendix Table A2, the p-values are all larger than 0.05, ensuring that there are no significant differences in the characteristics of valid physicians across experimental groups.

At the end of the experiment, we asked the valid physicians to evaluate the assistants they encountered during the experiment. In particular, we require physicians to evaluate how much they agree with the following: (1) they are willing to adopt smart (automated) recommendations from AI assistants, (2) they perceive smart (automated) recommendations as useful, (3) they perceive smart (automated) recommendations as accurate. The level of agreement is measured on a five-point semantic differential scale from one (strongly disagree) to five (strongly agree) with the results presented in Online Appendix Table A6.

5. Results

In this section, we study the effect of AI smartness and transparency on the AI adoption behaviors of physicians, that is, adoption rate (that is, whether physicians adopt recommendations) and, if they do, the adoption timing (that is, when physicians begin to adopt recommendations). That is, the analyses of the adoption rate are based on 583 valid physicians, and the analyses of adoption timing are based on 395 physicians who adopt AI. We examine the effect of smartness in Section 5.1 and the effect of transparency in Section 5.2.

5.1. Effect of AI Smartness

5.1.1. Adoption Rate. We first investigate the effect of AI smartness on physicians' adoption. Adoption is the process by which physicians learn about and start using AI assistants. We record whether each physician adopts the recommendations at least once and use it to compute the adoption rate, that is, the percentage of physicians who adopted AI assistants' recommendations. Table 3 presents the summary statistics for the adoption rate of smart and automated assistants. Figure 1 presents a visual illustration.

The overall adoption rate of automated assistant is 46.83%, which is significantly lower than the 87.63% adoption rate of the smart assistant (p-value < 0.01). This result suggests that physicians are more likely to adopt smart than automated assistants. We formally test the effect of AI smartness on physicians' adoption, specified as follows:[3]

$$Adoption_j = \alpha + \beta Smart_j + \gamma Controls_j + \varepsilon_j, \qquad (1)$$

where j indicates all valid physicians in the experiment; $Adoption_j$ is a binary variable representing whether physician j adopts AI (i.e., equals one if the physician

Table 3. Summary Statistics of Adoption Rate by AI Smartness

	Non-transparent		Transparent		All data	
	Automated	Smart	Automated	Smart	Automated	Smart
Sample size	143	152	141	147	284	299
Adoption rate, %	27.27	86.84	66.67	88.43	46.83	87.63
Difference, %		59.57		21.76		40.80
p-value of *t*-test		0.00		0.00		0.00

Notes. This table reports the adoption rate of smart and automated AI assistants. "Smart" and "Automated" indicate smart and automated AI, respectively. "All data" refers to all information conditions.

adopts AI and zero otherwise); $Smart_j$ is a categorical variable that represents whether assistants are smart or automated (i.e., equals one when AI is smart and zero otherwise); and $Controls_j$ is a vector of control variables regarding physician characteristics, including age, gender, department, hospital type, professional title, professional rating, service rating, and reply speed rating. Although the control variables are not required in the regression of a randomization design, we include them to improve estimation efficiency and show the robustness of our results.

The estimation results are presented in Table 4, in which the omitted type is automated AI. The variable *Smart* captures differences in physicians' adoption of smart and automated assistants. The coefficients of *Smart* are significant and positive in all conditions (p-value < 0.01). Specifically, this coefficient is 0.586 under the non-transparent condition, indicating that the probability of physicians adopting AI recommendations increases by 58.6% when the assistant is smart rather than automated. Under the transparent condition, the coefficient is 0.219, showing that the probability of a physician adopting smart recommendations is 21.9% higher than the probability of adopting automated recommendations. These results imply that the adoption rate of the smart assistant is significantly higher than that of the automated assistant, thus supporting Hypothesis 1(a). Smartness can increase the adoption of the AI assistant, likely because those recommendations provided by smart AI are based on a machine learning algorithm that can be accurately tailored to a patient's specific problems, thereby increasing physicians' perceived usefulness of the AI assistant.

5.1.2. Adoption Timing. For physicians who adopt the AI assistant, we record the time when they first start using the recommendation as the measure of adoption timing, that is, the time interval between when the physician first engages in an online consultation during the experiment period and the first use of the recommendation.[4] Table 5 and Figure 2 summarize the timing of

Figure 1. (Color online) Effect of AI Smartness on Adoption Rate

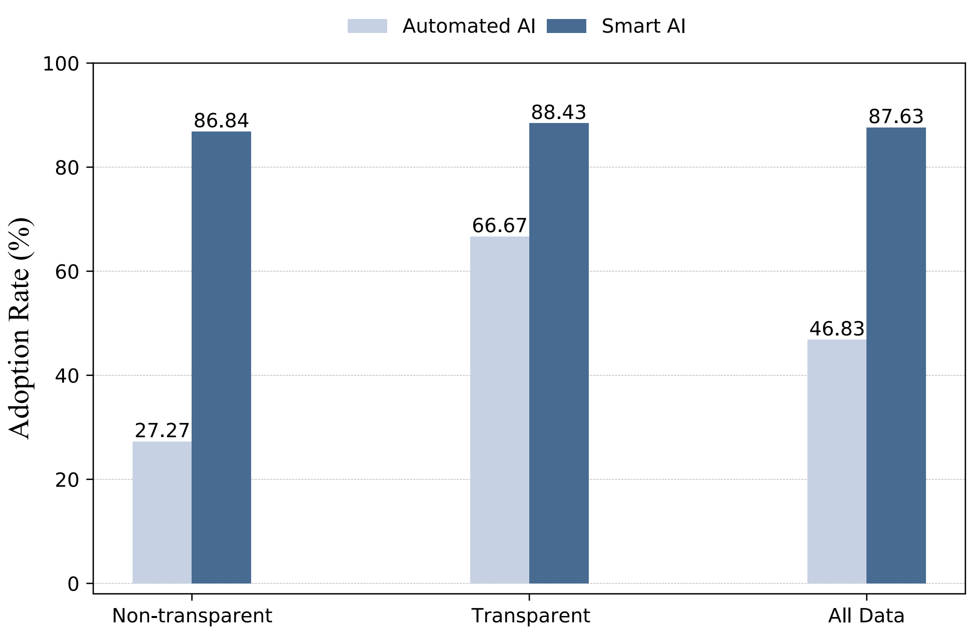


Table 4. Effect of AI Smartness on Adoption Rate

	Dependent variable: *Adoption*		
	Non-transparent (1)	Transparent (2)	All data (3)
Smart	0.586***	0.219***	0.404***
	(0.046)	(0.047)	(0.035)
Controls	Yes	Yes	Yes
Observations	295	288	583
R^2	0.408	0.112	0.220

Notes. This table tests the effect of AI smartness on the adoption of AI assistants under three different samples. Results from columns (1) and (2) are based on samples under non-transparent and transparent conditions, respectively. Results from column (3) are based on the full sample.

***$p < 0.01$.

the adoption of smart and automated assistants. We find that the overall adoption time for smart AI is 17.64 hours, which is significantly lower than the corresponding one (32.74 hours) for automated AI (p-value = 0.01). We also formally examine the effect of AI smartness on adoption timing:

$$Timing_i = \alpha + \beta Smart_i + \gamma Controls_i + \varepsilon_i, \qquad (2)$$

where i indicates physicians who adopt AI and $Smart_i$ is a categorical variable that represents smart or automated assistants. The estimation results are presented in Table 6, in which the omitted type is the automated AI. The coefficient of *Smart* represents the increase in the adoption timing of the smart assistant relative to the automated assistant, which is significantly negative (p-value < 0.1). This finding implies that physicians start to adopt the smart assistant earlier than the automated assistant, thereby supporting Hypothesis 1(b). Smartness can accelerate the adoption of AI because it can help physicians perceive the usefulness of recommendations more quickly.

5.2. Effect of AI Transparency

5.2.1. Adoption Rate. Online Appendix Table A3 summarizes the adoption rate under the non-transparent and transparent conditions. As per this table, for the smart assistant, the adoption rate is 86.84% under the non-transparent condition and 88.43% under the transparent condition; for the automated assistant, the adoption rate is 27.27% under the non-transparent condition and 66.67% under the transparent condition. This finding implies that transparency significantly increases the adoption rate of automated AI (p-value < 0.01), having no significant influence on the adoption rate of smart AI (p-value = 0.68).

We also formally test the difference in the adoption rate based on information conditions as follows:

$$Adoption_j = \alpha + \beta Transparent_j + \gamma Controls_j + \varepsilon_j, \qquad (3)$$

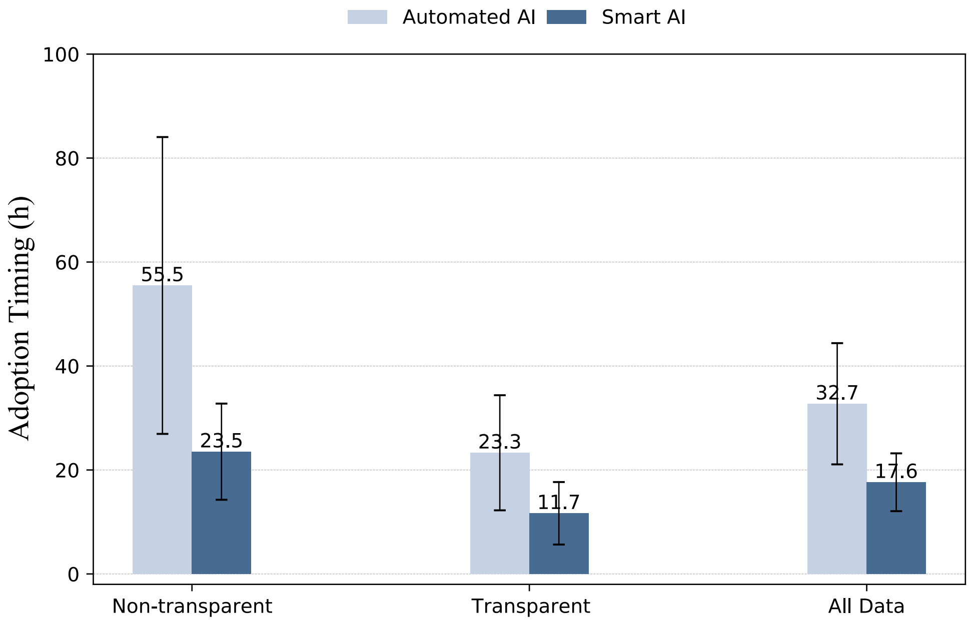
where j indicates all valid physicians in the experiment and; $Transparent_j$ is a categorical variable that represents whether the strategy is transparent or non-transparent (i.e., equals one if AI is transparent and zero otherwise). Table 7 presents the estimation results, in which the omitted condition is the non-transparent condition. The coefficient of *Transparent* represents physicians' additional adoption increase under the transparent condition relative to that under the non-transparent condition. We find that the coefficients of *Transparent* are significantly (or insignificantly) positive under the automated AI (smart AI) conditions. Moreover, the coefficients are significantly positive under all data conditions (p-value < 0.01). Furthermore, with AI transparency, the probability of the physician adopting AI increases by 39.4% (coefficient = 0.394) under the automated AI condition and 19.5% (coefficient = 0.195) under the all data condition. These results indicate that transparency can increase physicians' adoption of the automated assistant but has no significant influence on the adoption of the smart assistant, thereby supporting Hypothesis 2(a). That is, AI transparency can effectively increase the adoption of the AI assistant only if the assistant is automated. This is because the information provided by the platform can bolster physicians' perceived credibility, thereby elevating the perceived usefulness and adoption of AI. Consequently, transparency plays a crucial role in increasing the adoption rate of the automated assistant. However, the smart assistant provides personalized recommendations that, over time, allow physicians to perceive its usefulness and adopt it even without the help of transparency. Therefore, transparency ultimately has no effect on the adoption rate of the smart assistant.

Table 5. Summary Statistics of Adoption Timing by AI Smartness

	Non-transparent		Transparent		All data	
	Automated	Smart	Automated	Smart	Automated	Smart
Sample size	39	132	94	130	133	262
Mean, hours	55.49	23.52	23.31	11.67	32.74	17.64
Standard deviation, hours	90.99	54.20	54.77	34.94	68.65	45.96
Mean difference		−31.97		−11.64		−15.10
p-value of t-test		0.01		0.05		0.01

Notes. This table reports the adoption timing of AI assistants. "Smart" and "Automated" indicate smart and automated AI, respectively.

Figure 2. (Color online) Effect of AI Smartness on Adoption Timing



5.2.2. Adoption Timing. Online Appendix Table A4 summarizes the AI adoption timing under the non-transparent and transparent conditions. We find that AI transparency significantly advances the process of smart and automated assistant adoption (p-value < 0.05): the adoption timing of the smart assistant is 23.52 hours when AI is nontransparent and 11.67 hours when AI is transparent, and the adoption timing of the automated assistant is 55.49 hours when AI is non-transparent and 23.31 hours when AI is transparent.

We also formally examine the effect of AI transparency on the timing of AI adoption:

$$Timing_i = \alpha + \beta Transparent_i + \gamma Controls_i + \varepsilon_i, \quad (4)$$

where i indicates physicians who adopt AI. The estimation results are presented in Table 8, in which the omitted condition is the non-transparent condition; the coefficient of *Transparent* represents the increase in the adoption timing of AI under the transparent condition relative to the non-transparent condition. We find that the coefficients of *Transparent* are negatively significant (p-value < 0.05) in all cases. This finding indicates that AI transparency significantly reduces the adoption timing of both smart and automated assistants, thereby supporting Hypothesis 2(b). Through the transparent introduction of the AI assistant, physicians receive relevant information about the assistant and perceive the platform's support for this function. Therefore, AI transparency effectively encourages physicians to adopt assistants, especially in the early stages when physicians are unfamiliar with such technology; adoption timing for smart and automated AI is earlier under the transparent strategy than under the non-transparent strategy. Please see the physicians' adoption

Table 6. Effect of AI Smartness on Adoption Timing

	Dependent variable: *Adoption timing*		
	Non-transparent (1)	Transparent (2)	All data (3)
Smart	−26.056*	−12.220*	−15.778**
	(14.609)	(7.018)	(6.644)
Controls	Yes	Yes	Yes
Observations	171	224	395
R^2	0.141	0.078	0.050

Notes. This table tests the effect of AI smartness on the adoption timing of AI under three different samples. Results from columns (1) and (2) are based on samples under the non-transparent and the transparent conditions, respectively. Results from column (3) are based on the full sample.
$^{**}p < 0.05$; $^{*}p < 0.1$.

Table 7. Effect of AI Transparency on Adoption

	Dependent variable: *Adoption*		
	Smart (1)	Automated (2)	All data (3)
Transparent	0.018	0.394***	0.195***
	(0.038)	(0.055)	(0.038)
Controls	Yes	Yes	Yes
Observations	299	284	583
R^2	0.065	0.197	0.080

Notes. This table tests the effect of AI transparency on the adoption of AI assistants under three different samples. Results from columns (1) and (2) are based on samples under "Smart" and "Automated" types, respectively. Results from column (3) are based on the full sample.
$^{***}p < 0.01$.

Table 8. Effect of AI Transparency on Adoption Timing

	Dependent variable: *Adoption timing*		
	Smart (1)	Automated (2)	All data (3)
Transparent	−13.184**	−32.872**	−15.593***
	(6.108)	(15.553)	(5.933)
Controls	Yes	Yes	Yes
Observations	262	133	395
R^2	0.076	0.107	0.052

Notes. This table tests the effect of AI transparency on the adoption timing of AI under three different samples. Results from columns (1) and (2) are based on samples under "Smart" and "Automated" types, respectively. Results from column (3) are based on the full sample.
$^{***}p < 0.01$; $^{**}p < 0.05$.

of the AI assistant over time in Online Appendix Figure A6. To further illustrate this point, we next study the interaction effect of AI transparency and AI smartness on physicians' adoption behaviors in Section 6.1.

6. Mechanism

In this section, we validate the underlying mechanisms behind the effect of AI smartness and transparency on physician adoption behaviors.

6.1. Interaction Effect

6.1.1. Adoption Rate. As demonstrated in Section 3, we conjecture that enhancing the personalization of recommendations or providing precise information about AI assistants can increase the perceived usefulness of recommendations among physicians, thus fostering their adoption. That is, the positive effect of smartness and transparency in increasing the adoption rate of AI may be substituted. We then formally study the interaction effect of AI smartness and AI transparency:

$$Adoption_j = \alpha + \beta_0 Smart_j + \beta_1 Transparent_j + \beta_2 Smart_j \times Transparent_j + \gamma Control_j + \varepsilon_j, \tag{5}$$

where j indicates all valid physicians in the experiment and β_2 is the moderating effect of AI smartness on the adoption increase associated with AI transparency. The estimation results are presented in column (1) of Table 9, in which the coefficient of *Smart* × *Transparent* represents the moderating effect of the smart AI strategy on the adoption rate increase associated with using the transparent AI strategy. We find that the coefficient of *Smart* × *Transparent* is negatively significant (p-value < 0.01); AI smartness mitigates the adoption increase associated with using AI transparency. That is, the role of the transparent AI strategy in increasing adoption is no longer effective when using the smart strategy. This result is consistent with Online Appendix Figure A6, in which the cumulative number of physicians adopting smart AI under the transparent strategy is larger than under the non-transparent strategy in the earlier stage, but the difference disappears over time.

Table 9. Interaction Effects of AI Smartness and AI Transparency

	Dependent variable: *Adoption* (1)	Dependent variable: *Adoption timing* (2)
Smart	0.592***	−31.572**
	(0.046)	(15.007)
Transparent	0.392***	−32.175**
	(0.054)	(15.344)
Smart × *Transparent*	−0.379***	18.096
	(0.066)	(16.460)
Controls	Yes	Yes
Observations	583	395
R^2	0.305	0.084

Note. This table tests the interaction effect of AI smartness and AI transparency.
$^{***}p < 0.01$; $^{**}p < 0.05$.

6.1.2. Adoption Timing. We also formally study the interaction effect of AI smartness and transparency on adoption timing:

$$Timing_i = \alpha + \beta_0 Smart_i + \beta_1 Transparent_i + \beta_2 Smart_i \times Transparent_i + \gamma Control_i + \varepsilon_i, \tag{6}$$

where i indicates physicians who adopt AI and β_2 is the moderating effect of AI smartness on the adoption timing increase associated with AI transparency. The estimation results are presented in column (2) of Table 9, in which the coefficient of *Smart* × *Transparent* represents the moderating effect of the smart AI strategy on the adoption timing reduction associated with using the transparent AI strategy. The coefficient of *Smart* × *Transparent* is insignificant; AI smartness does not affect the adoption timing reduction associated with the use of AI transparency. That is, AI transparency reduces the adoption timing regardless of the smartness level of the assistant, which is consistent with Online Appendix Figure A6, showing that the growth rate of the cumulative number of physicians adopting the smart assistant increases in the early stages of implementation and is higher under the transparent AI strategy than under the non-transparent AI strategy. This finding means that, for smart AI, a transparent strategy can still expedite physicians' adoption behaviors (earlier adoption timing).

6.2. Physician Feedback

At the end of the experiment, we invited physicians to assess the AI assistant they encountered during the experiment. Specifically, physicians provided feedback on their willingness to adopt AI assistants, their perceived usefulness of the recommendations, and their perceived accuracy of the recommendations. Online Appendix Table A6 summarizes the results.

To validate the feedback data, we compare physicians' self-reported level of willingness to adopt AI with their actual adoption behavior in the experiment:

$$Q1_m = \alpha + \beta Adoption_m + \gamma Controls_m + \varepsilon_m, \qquad (7)$$

where m indicates all physicians providing feedback, $Q1_m$ represents a physician's willingness to use recommendations (out of five, higher scores indicate greater willingness to use) and $Adoption_m$ is a binary variable representing whether physician m adopts AI (one if the physician adopts AI and zero otherwise). The estimation results are shown in Online Appendix Table A5. The coefficients of *Adoption* are significant and positive across all groups (p-value < 0.01). These results indicate that physicians who adopt AI assistants report a higher willingness to use recommendations, thereby helping validate our feedback data.

6.2.1. AI Smartness. In Section 3.1, we hypothesize that physicians perceive smart AI as more useful and reliable than automated AI because the smart assistant provides personalized recommendations, which is crucial for increasing AI performance and fostering AI adoption (Davenport and Kalakota 2019, Shin 2021). As per Online Appendix Table A6, under the non-transparent condition, physicians' agreement level of usefulness is 4.28 for the smart assistant and 3.26 for the automated assistant; physicians perceive the smart assistant as significantly more useful than the automated assistant (p-value < 0.01). This trend persists under the transparent condition, in which the physicians' agreement level of usefulness of the smart assistant is 4.39, which is significantly higher than that for the automated assistant 3.88 (p-value $= 0.01$). Similarly, physicians' agreement level of accuracy for smart recommendations is significantly higher than automated recommendations in all information conditions (p-value < 0.1); under the non-transparent (transparent) condition, the agreement level of accuracy for smart AI is 4.07 (3.98), which is higher than 3.13 (3.60), the agreement level of accuracy for automated AI.

To further substantiate the impact of AI smartness on physician adoption behavior, we interviewed nine physicians with an average of 16 years of medical practice experience. Specifically, we presented examples of smart AI with personalized recommendations and automated AI with fixed recommendations to physicians. We then asked them to share their preferences regarding adopting smart versus automated AI. Physicians' quotes are summarized in Online Appendix Table A7. The results show a unanimous preference for the smart assistant with respondents believing that personalized recommendations would help them gather patient information more accurately and efficiently than fixed recommendations. In other words, smart AI is deemed more useful.

6.2.2. AI Transparency. In Section 3.2, we hypothesize the transparency can facilitate the adoption process of both types of assistance. This is because the information provided by the platform about AI assistants enhances the physicians' perceived credibility and usefulness of AI in two ways. First, the platform's provision of information can effectively endorse AI assistants and, thus, encourage physicians to adopt AI assistants, particularly when physicians are unfamiliar with them (Venkatesh et al. 2003, Fan et al. 2020). Accordingly, more physicians are likely to adopt AI in the earlier stage under the transparent condition than the non-transparent condition, which aligns with the trend illustrated in Online Appendix Figure A6. Second, precise information about AI assistants can enhance the credibility and usefulness of AI recommendations (Nicolaou and McKnight 2006, Angst and Agarwal 2009, Bansal and Muthulingam 2022). Nevertheless, transparency only increases the adoption rate of the automated assistant and might hold less value for the smart assistant. This is because, even without transparency, physicians would gradually perceive the usefulness of smart recommendations.

Because transparency enhances physicians' perception of the usefulness and credibility of AI, often exerting a lasting influence on their beliefs, we validate the mechanism based on physicians' feedback on AI. Online Appendix Table A6 indicates that, for the automated assistant, physicians' agreement level regarding its usefulness is 3.26 under the non-transparent condition and 3.88 under the transparent condition; transparency significantly increases the physicians' perceived usefulness of the automated assistant (p-value $= 0.01$). Conclusions regarding accuracy are consistent with the findings related to usefulness. Physicians' agreement level regarding the accuracy of automated assistant is 3.13 and 3.60 under non-transparent and transparent conditions, respectively; transparency also significantly increases the physicians' perceived accuracy of the automated assistant (p-value $= 0.07$). However, under the non-transparent condition, physicians' agreement level of usefulness and accuracy for the smart assistant is 4.28 and 4.07, respectively. Under the transparent condition, the agreement level is 4.39 for usefulness and 3.98 for accuracy; there are no significant differences in physicians' perceived usefulness and accuracy of smart AI across information conditions. Overall, physicians' feedback confirms that AI transparency enhances their perceived credibility and usefulness of automated AI but has no effect on smart AI.

To delve deeper into the mechanisms behind the transparency strategy, we conducted interviews with nine physicians who had substantial experience in online consultations. We showed the announcement content and examples of smart and automated recommendations to physicians and then asked them to share their perspectives on how and why AI transparency would impact their adoption behavior regarding AI; their quotes are shown in Online Appendix Table A8. All interviewed physicians expressed the unanimous opinion that information about AI assistants released by the platform could facilitate their adoption behaviors. In particular, the transparent strategy can (i) facilitate physicians' comprehension of the usefulness of AI tools through the acquired information and (ii) foster physicians' trust in AI through endorsement by the platform.

7. Robustness Check

In this section, we conduct additional analysis to check the robustness of our key findings regarding the effect of AI smartness and transparency.

7.1. Potential Alternate Mechanisms

7.1.1. Postadoption Usage. The physician's adoption behavior on AI assistants might be short term (i.e., one-time accidental use or a few trial uses). For example, physicians may adopt the AI assistant once only out of curiosity; platform announcements may draw special attention to the AI assistant and remind physicians to give it a try. To test this, we measure the postadoption usage frequency, that is, the ratio of the number of times a physician uses the AI to the number of consultations in which the physician participates after first adopting AI. If the physician has never used an AI assistant, then the usage frequency is zero.

Online Appendix Table A9 and Figure A7 summarize the usage frequency of smart and automated AI. We find that the overall usage frequency of smart AI is 48.93% and the automated is 16.37%. The usage frequency of the smart assistant is significantly higher than that of the automated assistant (p-value < 0.01). We formally test the effect of AI smartness on the usage frequency:

$$Usage\ Frequency_j = \alpha + \beta Smart_j + \gamma Controls_j + \varepsilon_j, \quad (8)$$

where j indicates all valid physicians in the experiment and $Smart_j$ is a categorical variable that represents whether assistants are smart or automated (i.e., equals one when AI is smart and zero otherwise). The estimation results are shown in panel A of Online Appendix Table A10, in which the omitted variable is automated AI; the coefficient of *Smart* represents the increase in the adoption of the smart assistant relative to that of the automated assistant. We find that the coefficients of *Smart* are significantly positive under all conditions (p-value < 0.01), which confirms that smartness can facilitate physicians' adoption of AI, thereby supporting Hypothesis 1(a).

Online Appendix Table A11 summarizes the usage frequency of AI under different information conditions. As can be seen, for automated AI, the overall usage frequency under the non-transparent condition is 10.08%, which is significantly lower than the 22.75% under the transparent condition (p-value < 0.01). However, for smart AI, the overall usage frequency under the non-transparent condition is 49.54%, which is not significantly higher than the 48.30%, under the transparent condition. We formally test the effect of AI transparency on the usage frequency:

$$Usage\ Frequency_j = \alpha + \beta Transparent_j + \gamma Controls_j + \varepsilon_j. \quad (9)$$

The estimation results are shown in panel B of Online Appendix Table A10. Column (I) of Online Appendix Table A10 shows that the coefficient of *Transparent* is insignificant, indicating that AI transparency has no effect on the usage frequency of smart AI. Column (II) of Online Appendix Table A10 shows that the coefficient of *Transparent* is significantly positive under the automated AI condition (p-value < 0.01); AI transparency increases the usage frequency of the automated assistant. These results are consistent with our main result regarding the adoption rate.

In sum, AI smartness and transparency exert a long-term effect on physicians' adoption and perception of AI. Therefore, accidental adoption behaviors or the reminder effect caused by platform announcements may not be the primary factor driving physicians' adoption behaviors.

7.1.2. Entry Time Effect. In the experiment, each physician started the first consultation at a different time, which may impact the physician's adoption timing. To test this, for physicians who adopt the assistant, we calculate the time interval between the start of the experiment and the first time a physician uses the recommendation and define it as the acceptance timing.[5] Online Appendix Table A12 and Figure A8 summarize the acceptance timing for smart and automated assistants. We find that the overall acceptance timing of smart AI is 40.63 hours and that of automated is 61.56 hours. The acceptance timing of smart recommendations is significantly shorter than that of automated recommendations (p-value = 0.01). We formally test the effect of AI smartness on the acceptance timing:

$$Acceptance\ Timing_i = \alpha + \beta Smart_i + \gamma Controls_i + \varepsilon_i, \quad (10)$$

where i indicates physicians who adopt AI, and $Smart_i$ is a categorical variable that represents smart or automated AI. The estimation results are presented in panel

A of Online Appendix Table A13, in which the omitted type is automated AI. The coefficients of *Smart* are negatively significant under all information conditions (p-value < 0.1), which confirms that the acceptance timing of the smart assistant is earlier than that of the automated assistant. These results imply that AI smartness can accelerate the adoption of assistants, thereby supporting Hypothesis 1(b).

Online Appendix Table A14 summarizes the acceptance timing under different information conditions. As per this table, the overall acceptance timing of AI assistants under the transparent strategy is 39.38 hours, and under the non-transparent strategy, it is 58.56 hours; AI transparency significantly reduces the adoption timing of AI assistants (p-value = 0.01). We also formally examine the effect of AI transparency on the acceptance timing:

$$Acceptance\ Timing_i = \alpha + \beta Transparent_i + \gamma Controls_i + \varepsilon_i. \tag{11}$$

Panel B of Online Appendix Table A13 shows the estimation results. The coefficient of *Transparent* represents the increase in acceptance timing under the transparent condition relative to the non-transparent condition. We find that the coefficients of *Transparent* are negatively significant for all types of AI assistant (p-value < 0.05), which confirms that the acceptance timing of assistants is earlier under the transparent AI strategy than under the non-transparent AI strategy. These results imply that transparency can accelerate the adoption of AI assistants, thereby supporting Hypothesis 2(b).

7.2. Consultation Volume Effect

In our main analysis, we measure adoption timing by the time interval between physicians' first engagement in the consultation and their first usage of the recommendation. Because of the varying number of consultations physicians undertake within the same time interval, the frequency of physicians encountering recommendations differs, which may affect their adoption timing. We now quantify the number of consultations physicians engaged in before their first usage of assistants and define this metric as the acceptance number. Online Appendix Table A15 and Figure A9 summarize the acceptance number for smart and automated assistants. In particular, the overall acceptance number of the automated assistant is 9.92, and the smart assistant is 4.03; the acceptance number of automated AI is significantly larger than the smart AI (p-value < 0.05). We formally test the effect of AI smartness on acceptance number,

$$Acceptance\ Number_i = \alpha + \beta Smart_i + \gamma Controls_i + \varepsilon_i. \tag{12}$$

The estimated results are presented in panel A of Online Appendix Table A16. The coefficients of Smart capture differences in the acceptance number of smart and automated AI, which are significant and negative in all conditions (p-value < 0.1). This result implies that AI smartness can significantly accelerate the adoption of AI and is consistent with our main results.

Online Appendix Table A17 summarizes the acceptance number under different information conditions. We find that transparency significantly advances the adoption of AI (p-value < 0.1); the overall acceptance number of AI is 8.63 under the non-transparent strategy and 4.01 under the transparent strategy. We also formally test the effect of transparency on acceptance number:

$$Acceptance\ Number_i = \alpha + \beta Transparent_i + \gamma Controls_i + \varepsilon_i. \tag{13}$$

The estimated results are presented in panel B of Online Appendix Table A16, in which the coefficient of Transparent represents the increase in the acceptance number of AI under the transparent condition. We find that the coefficients of *Transparent* are significant and negative for all types of AI assistants (p-value < 0.1). This indicates that AI transparency significantly shortens the acceptance number for both smart and automated AI, thus affirming the robustness of our findings.

7.3. Heterogeneous Treatment Effect

We test whether any physician characteristics (i.e., age, gender, department, hospital type, professional title, service rating, and reply speed rating) could change the effect of smartness and transparency on AI adoption. These physician characteristics are considered in our main analysis as control variables to enhance the robustness of our results.

For the effect of smartness on adoption, we use the following estimation:

$$\begin{aligned} Adoption_j = \alpha + \beta Smart_j + \beta_1 Moderator_j + \beta_2 Smart_j \\ \times Moderator_j + \gamma Control_j + \varepsilon_j, \end{aligned} \tag{14}$$

where β_2 represents how a physician's characteristic moderates the effect of smartness on the adoption; $Moderator_j$ represents age, gender, department, hospital type, professional title, service rating, and reply speed rating; and $Control_j$ includes all other control variables except for the tested moderator. The estimated results are shown in panels A and B of Online Appendix Table A18. We have three key findings. First, the coefficient of *Smart* × *Reply* is significantly positive (p-value < 0.01) under the non-transparent condition but significantly negative (p-value < 0.05) under the transparent condition. For insight, when AI is not transparent, physicians with faster previous reply speed are more susceptible to the influence of AI smartness because of their proficiency in technology and service processes. Nevertheless, under the transparent condition, physicians with slower previous reply speed exhibit greater motivation and inclination to utilize the significant enhancements provided by AI smartness within their response workflows. Second, under the transparent condition, the coefficient of *Smart* × *Gender* is significantly negative (p-value < 0.1), indicating a more pronounced positive effect of AI smartness on adoption rates among female physicians. This is perhaps because females are more likely to embrace AI technologies effectively. Third, the coefficient of *Smart* × *Hospital* is significantly positive (p-value < 0.05). That is, physicians practicing in higher ranked hospitals demonstrate a stronger inclination toward adopting new technologies. Therefore, it may be more effective to strategically focus on larger scale and top-ranked hospitals when implementing emerging technologies and applications, such as AI.

For the effect of AI smartness on adoption timing, we use the following estimation:

$$Timing_i = \alpha + \beta Smart_i + \beta_1 Moderator_i + \beta_2 Smart_i \times Moderator_i + \gamma Control_i + \varepsilon_i. \tag{15}$$

The estimated results are shown in panels C and D of Online Appendix Table A18. We find that none of the studied characteristics has an impact on the effect of AI smartness on adoption timing.

For the effect of AI transparency on adoption, we use

$$\begin{aligned} Adoption_j = \alpha &+ \beta Transparent_j + \beta_1 Moderator_j \\ &+ \beta_2 Transparent_j \times Moderator_j \\ &+ \gamma Control_j + \varepsilon_j. \end{aligned} \tag{16}$$

Panels A and B of Online Appendix Table A19 present the estimation results, which show that none of the physician characteristics impacts the effect of AI transparency on the adoption of smart AI. For automated AI, the coefficient of *Transparent* × *Reply* is significantly positive (p-value < 0.01). That is, physicians with faster previous reply speed may value efficiency and, consequently, are more likely to be impacted by AI transparency.

For the effect of transparency on adoption timing, we use

$$\begin{aligned} Timing_i = \alpha &+ \beta Transparent_i + \beta_1 Moderator_i \\ &+ \beta_2 Transparent_i \times Moderator_i \\ &+ \gamma Control_j + \varepsilon_i. \end{aligned} \tag{17}$$

The estimated results are shown in panels C and D of Online Appendix Table A19. We find that the coefficient of *Transparent* × *Hospital* is significantly negative (p-value < 0.1), meaning that a higher hospital ranking enhances the effectiveness of AI transparency in reducing the adoption timing of smart AI. This is because physicians practicing in high-ranked hospitals often adhere strictly to rules when providing services. Consequently, they are more likely to follow the endorsement of the platform (through transparency) as the platform creates the consultation rules.

8. Conclusions

AI has recently experienced explosive growth in the healthcare industry. The extant literature mostly focuses on the perspective of patients (Longoni et al. 2019, Nadarzynski et al. 2019, Cadario et al. 2021), whereas little work has been carried out from the perspective of physicians, which is the key to a large-scale implementation of AI in healthcare operations. In this study, we fill this gap by exploring how physician AI adoption behaviors are affected by two strategies: the smartness strategy, that is, equipping AI tools with machine learning algorithms, and the transparency strategy, that is, explicitly introducing AI applications to physicians.

By conducting a randomized field experiment, we compare physicians' adoption rate and adoption timing of smart and automated AI assistants under transparent and non-transparent conditions. We find that AI smartness increases physicians' willingness to adopt AI assistants; equipping the AI assistant with a machine learning algorithm increases the adoption rate and shortens the adoption timing. We also find that AI transparency shortens the adoption timing of AI. Moreover, and perhaps interestingly, we find that AI transparency increases the adoption rate when AI is not smart but fails to do so when AI is smart.

8.1. Managerial Implications

Our study can guide platforms in designing their AI strategies. First, if a platform intends to develop AI tools, it should equip those tools with smartness control, that is, develop an AI algorithm to generate more intelligent and personalized outcomes. Second, if a platform has difficulties developing machine learning algorithms, our analysis suggests that the platform should adopt a transparency strategy, that is, publish an announcement that introduces information about the functions of AI when its AI assistant is not equipped with intelligent AI algorithms and provides automated recommendations. Third, if a platform plans to introduce a new AI function, then our result suggests that the platform can benefit from a simple and low-cost strategy, that is, AI transparency, as such a strategy might effectively advance and increase AI adoption in the early stages of implementation.

Our work can also provide implications for service providers and governmental agencies in the era of AI. For service providers, especially those in fields such as healthcare, they may not be replaced by AI, but those who embrace AI could do so (Wilson and Daugherty 2018). Our results suggest that enhanced information about AI can facilitate the AI adoption process. People should be willing to embrace emerging technologies and cultivate a mindset of continuous learning to equip themselves to better face the opportunities and challenges presented by new technologies.

For healthcare policymakers, advocating for transparency in new technology applications is a typical response driven by ethical considerations in the regulatory realm. While policymakers may encounter several challenges in regulating transparency in AI applications, our findings offer evidence for the advantages of such corporate transparency regarding AI implementation and thus provide support for its advocates.

8.2. Future Research

Several research directions warrant exploration in the future. First, our study focuses on the adoption behavior of physicians, that is, service providers, toward AI. Patient attitudes and feedback about AI assistants are also fascinating topics worth studying. Second, this research was conducted in China, where the use of AI may be more acceptable because of population density. The distinct contextual backgrounds, including political regulations and privacy concerns, could mute or expedite AI adoption. Therefore, it would be interesting to expand our study in other countries. Third, as our study has the potential to enhance future comprehension of the human–AI interaction process, further research could expand beyond the current scope of service delivery systems we have considered. For example, it would be interesting to explore AI-assisted off-line healthcare systems or telemedicine video consultation as well as AI-enabled chat systems such as ChatGPT.

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Endnotes

[1] The details of the interviews are presented in Section 6.2, and the interview quotes are summarized in Online Appendix Table A7.

[2] The sensitive information in figures of this paper has been concealed because of the non-disclosure agreement.

[3] We also conducted logistic regression to estimate the treatment effect on the adoption rate, and our qualitative insights were found to remain robust.

[4] Online Appendix Figure A5 shows how to calculate adoption timing.

[5] Online Appendix Figure A5 shows how to calculate acceptance timing.

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