Directionality in AI Advice: Experimental Evidence from Healthcare*

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Abstract

Generative AI is fast becoming the first place people turn for expert advice. The advice it provides can be directional rather than neutral, shaped in part by the choices of its designers and regulators. When clients consult AI before meeting an expert, they carry this directionality into a relationship that once rested on the expert's judgment alone. We study its consequences in healthcare through a large-scale preregistered field experiment at a Chinese hospital, where we randomize patients' access to an AI chatbot before their outpatient visit. Examination of the conversation logs between patients and AI shows that it routinely cautions against the use of medications, especially Traditional Chinese Medicine and antibiotics, while issuing clean recommendations for diagnostic testing, consistent with the liability-driven guardrails encoded in AI training. This directionality propagates into clinical practice. Prescription rates decline among treated patients while diagnostic testing increases, and these effects are more pronounced among physicians who are receptive to patient input and those with more intensive prescribing styles. Beyond shifting healthcare utilization, survey results show that AI access reduces patient compliance and satisfaction, shifting the balance of authority between patients and physicians.

Keywords: Generative AI, Information Asymmetry, Healthcare Field Experiment.

JEL Codes: I11, I18, O33, D82.

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1 Introduction

Generative artificial intelligence (AI) is fast becoming the first place people turn for advice. But that advice may not be neutral. AI's responses can reflect the priorities of those who build and govern these systems. For example, to meet safety standards and limit legal exposure, developers install guardrails that steer their models away from responses that invite liability and toward safer ones. This directionality matters because AI is increasingly involved in decisions people once delegated entirely to experts, in domains such as healthcare, law, and finance. As more people consult AI before turning to an expert, these design choices can propagate into real decisions at scale.

This paper examines how directional advice from AI shifts the decisions experts and clients reach, in the context of healthcare. Healthcare is a canonical credence-good market characterized by severe informational asymmetries and substantial expert discretion (Arrow, 1963; Darby and Karni, 1973; McGuire, 2000), and it has now become a common use case for consumer-facing generative AI tools.[1] Its high stakes have drawn both policy attention and liability-driven guardrails from developers around health-related topics. When patients consult AI for medical advice, the information they receive narrows the asymmetry that underlies physician discretion. The information is also non-neutral, reflecting the defensive cautions these guardrails encode.

To test how AI advice propagates into practice, we conduct a preregistered, month-long field experiment that provides the first randomized evidence on how patients' access to generative AI reshapes clinical decisions and the patient-physician relationship. Our randomized controlled trial takes place in a large public hospital in China and involves over 10,000 outpatient visits. Patients are randomly assigned to receive, or not receive, access to an LLM-based chatbot prior to their appointments. The chatbot invites patients to describe their symptoms and health concerns in detail before the visit and provides free access to AI-generated, personalized guidance and general medical information.

We implement a two-layer randomization design. We first randomize physicians into an *Exposed* group or an *Unexposed* group. Among patients scheduling appointments with *Exposed* physicians, half are randomly assigned to receive access to the chatbot (*Treatment*) and half to receive no access (*Control*). Patients scheduling appointments with *Unexposed* physicians never receive chatbot access.

[1] Health-related queries are among the three most common use cases of ChatGPT (https://openai.com/index/introducing-gpt-5/).

This design allows us to compare clinical outcomes between patients with and without access to the chatbot who see the same physician, while also testing for within-physician spillovers in clinical practice affecting patients without access.

We first examine take-up of the chatbot and the content of the advice it provides. Linking usage logs to hospital administrative records, we find that roughly 17 percent of patients offered access used it before their visit, with higher take-up among younger, male, and employed patients and first-time visitors. Turning to the content of these interactions, we find a sharp asymmetry in the advice the chatbot provides. When discussing medications, the chatbot almost always attaches cautions, warning about side effects, contraindications, and the risks of self-medication. Such cautions appear in 69.7% of general medication mentions, 90.8% of Traditional Chinese Medicine (TCM) mentions, and 87.6% of antibiotic mentions, while clean recommendations are rare, at 3.8% for TCM and 7.8% for antibiotics. Diagnostic testing is treated very differently, with the chatbot issuing clean recommendations 94.5% of the time. This asymmetry tracks the liability concerns of LLM developers. Recommending a specific medication carries substantial legal risk if it leads to adverse health outcomes, whereas encouraging diagnostic testing does not, and the cost of unnecessary tests falls on patients and the health system rather than the developer. The advice patients carry into the consultation is therefore directional, steering away from medication and toward diagnostic testing.

This directionality propagates into clinical decisions. Within-physician comparisons show that chatbot access reduces the likelihood of receiving any prescription by about 4.6 percentage points relative to a baseline of 87%, driven partly by declines in TCM and antibiotic prescribing. At the same time, chatbot access increases the probability that a visit includes diagnostic testing by roughly 2.7 percentage points from a baseline of 23%. The direction of each treatment effect mirrors the direction of the AI's advice. These shifts lower medication expenditures and modestly raise diagnostic spending, leaving total healthcare expenditures unchanged. We find no evidence of worse short-term outcomes; if anything, treated patients are 1.2 percentage points less likely to revisit the same hospital within two weeks, though this estimate is only marginally significant and may reflect care-seeking behavior rather than improvements in health.

Our main results report intent-to-treat effects based on randomized access to the chatbot, regardless of actual usage. We additionally estimate treatment-on-the-treated effects by instrumenting actual chatbot usage with randomized assignment. Chatbot usage reduces the likelihood of receiving

any prescription by 27 percentage points, increases diagnostic testing by 16 percentage points, and lowers two-week revisits by 7.0 percentage points. These effects are roughly five times larger than the corresponding intent-to-treat estimates, reflecting the partial take-up rate of 17%, and should be interpreted as local average treatment effects for patients who choose to use the chatbot when access is provided.

The effects are concentrated among the physicians for whom the intervention has the greatest scope to alter decisions. Because the chatbot operates by changing patients' information and the requests they make, its influence should depend on a physician's receptiveness to patient input and on the extent of baseline prescribing that AI-assisted patients might constrain. We find that the reduction in prescribing and the increase in testing are concentrated among physicians who self-report being open to patient input, and largely absent among physicians who emphasize strict authority. The reductions are also larger among physicians who prescribe most intensively at baseline, whether measured by their stated attitudes toward these medications or by their actual pre-experiment prescribing.

Next, we examine whether within-physician spillovers arise from physician learning or behavioral adjustment following repeated interactions with AI-prepared patients. Such spillovers would imply that patients who do not directly use the chatbot, such as older or less educated patients, could nevertheless benefit indirectly from generative AI. However, we find no evidence of such spillovers. Among patients without chatbot access, clinical outcomes do not differ between those who see *Exposed* physicians and those who see *Unexposed* physicians. We also find no persistence of effects: differences in clinical practice across physician groups are entirely driven by visits involving chatbot-access patients and disappear immediately after the experiment ends. This null result is economically informative. It suggests that generative AI does not automatically reshape expert norms or clinical decision-making, at least at the exposure rate in our experiment. Instead, the effects operate primarily through direct patient use. From a policy perspective, this implies that unequal access to AI tools may translate directly into unequal benefits, since improvements do not diffuse passively through provider learning.

Finally, to understand how patient access to the chatbot affects patient behavior and the physician–patient relationship, we combine administrative medical records with survey data from patients and physicians. We find that access to the chatbot does not materially change observable patient

behavior, including appointment attendance, medication purchases, or completion of diagnostic tests. However, survey evidence points to a divergence in perceptions of the consultation experience. Patients with chatbot access report lower overall satisfaction, perceive communication with physicians as less smooth, and express lower intended compliance with medical advice. Physicians who interact with AI-prepared patients also report lower patient compliance, but at the same time perceive these patients as easier to communicate with, with clearer symptom descriptions and a better understanding of their condition. The reduction in both intended and observed compliance is consistent with Finkelstein et al. (2022) and suggests that generative AI may shift informational authority within clinical encounters, reshaping how patients view physician expertise and potentially weakening adherence.

The welfare implications are difficult to assess. The intervention reduces prescribing in categories where overuse is well-documented and increases diagnostic testing, a pattern consistent with welfare improvement if overuse is the relevant margin. However, we cannot rule out that some reduced prescriptions represent clinically appropriate care, or that increased diagnostic testing generates costs without commensurate benefit. The reduction in compliance is similarly ambiguous, since lower adherence may avert unnecessary treatment or forgo beneficial treatment. We do not attempt to sign the net welfare effect. We emphasize instead that the direction of these changes reflects the defensive guardrails encoded in AI training, objectives that need not coincide with those that optimize clinical care.

This study makes multiple contributions to the economics literature. First, and most centrally, we provide the first large-scale evidence on a question that has received little attention: how do the norms and constraints encoded in AI training propagate into real-world decisions at scale? LLMs exhibit systematic behavioral patterns shaped by their design, including tendencies that vary with model architecture, training data, and scale (e.g., Filippas et al., 2024; Bowen et al., 2025; Garg and Fetzer, 2025; Bini et al., 2025; Waight et al., 2026). In high-stakes domains such as healthcare, these patterns are not incidental. Major AI developers have explicitly encoded defensive, liability-driven guardrails into their models, steering them away from specific treatment recommendations and toward caution and diagnostic clarification. When such models are deployed as consumer-facing information tools, these encoded constraints enter real-life decisions at scale.[2] Our findings suggest

[2] Luettgau et al. (2025) shows that a large majority of users follow personal advice from AI chatbots, even in

this propagation mechanism may be quantitatively important, with the potential to shift aggregate outcomes such as population-level healthcare utilization.

More broadly, we contribute to the rapidly growing economics of AI literature. Much of the existing work studies generative AI as a production technology that augments worker productivity or substitutes for labor in specific tasks (e.g., Dell'Acqua et al., 2023; Peng et al., 2023; Noy and Zhang, 2023; Cui et al., 2024; Brynjolfsson et al., 2025; Dillon et al., 2025; Reimers and Waldfogel, 2026). Viewed through the lens of expert–client relationships, a smaller stream examines AI tools that assist experts themselves, including physicians (Abaluck et al., 2026; He and Xia, 2026), financial analysts (Bertomeu et al., 2025), and legal workers (Choi et al., 2024). Much less is known about generative AI as a tool for consumers who face informational disadvantages relative to the experts they rely on. The limited existing work includes Spatharioti et al. (2023), who use online experiments to examine how LLM-based tools help consumers search for and compare products, Ash et al. (2025), who randomize voters' access to AI-powered chatbots that answer questions about ballot initiatives, and Shah and Levy (2026), who document that generative AI has substantially increased self-representation in U.S. federal civil courts. By providing patients with access to an LLM-based chatbot prior to outpatient visits, our study offers large-scale randomized evidence on how generative AI can empower informationally disadvantaged clients by reducing their reliance on expert authority and reshaping the dynamics of the expert–client relationship.[3]

Next, we contribute to a literature on the role of patient information in healthcare. Existing studies typically examine information asymmetries in healthcare by exploiting whether patients are physicians themselves (Grytten et al., 2011; Johnson and Rehavi, 2016; Frakes et al., 2021; Chen et al., 2025) or have family members in the medical profession (Artmann et al., 2022; Chen et al., 2022; Finkelstein et al., 2022) as sources of variation in patients' information, but the evidence from this literature is mixed. Some studies find that better-informed patients experience less overtreatment (Johnson and Rehavi, 2016), while others report only limited effects (Frakes et al., 2021; Artmann

high-stakes contexts.

[3]Recent randomized trials in clinical settings have tested integrating LLM tools into hospital workflows. Wan et al. (2024) find that an LLM chatbot assisting nurses at outpatient reception improves patient satisfaction and communication efficiency, and Tao et al. (2026) show that a pre-consultation chatbot performing clinical history-taking, preliminary diagnoses, and test ordering reduces specialist consultation time and improves coordination. Both studies deploy AI to augment provider functions and find improved patient satisfaction. In contrast, our study deploys AI as a patient-side information tool and examines its effects on both clinical decisions and the broader dynamics of the physician–patient relationship.

et al., 2022). These sources of variation supply patients with neutral health information, whereas the information generative AI provides is directional, shaped by the priorities of its developers. By leveraging LLM-based technology, our study contributes to this body of literature by randomly providing a subset of patients with access to personalized, easy-to-understand information on their health conditions.[4] More broadly, the project also relates to studies of health-related information and education programs in developing country settings, as surveyed in Dupas (2011b).

Going beyond clinical decisions, we examine how access to information reshapes patient–physician interactions. Similar to Currie et al. (2011), who show that knowledgeable simulated patients constrain physicians' propensity to overprescribe antibiotics but experience less courteous interactions, we find that patients' access to LLM tools reduces prescribing while worsening self-reported experiences. At the same time, patients with access to LLM tools report lower compliance with physician recommendations, consistent with observational evidence that patients with family members in the medical profession exhibit reduced adherence (Finkelstein et al., 2022). These findings highlight the importance of looking beyond treatment and testing decisions to understand how information technologies reshape relational dynamics in clinical care.

Finally, our study contributes to a broad literature on credence goods markets. These markets are economically significant and pervasive. From real estate (Levitt and Syverson, 2008) and financial advice (Mullainathan et al., 2012) to pharmacy (Bronnenberg et al., 2015), automobile and computer repair (Schneider, 2012; Busse et al., 2017; Rasch and Waibel, 2018; Kerschbamer et al., 2023), and taxi services (Balafoutas et al., 2013, 2017), consumers routinely delegate decisions to better-informed experts whose recommendations they cannot easily verify. A common thread across these settings is that informational asymmetries between experts and clients create scope for overtreatment, fraud, or misallocation. Consistent with this, Balafoutas et al. (2013), Busse et al. (2017), and Kerschbamer et al. (2023) show that reducing informational asymmetries can discipline expert behavior. Our study extends this literature by showing that generative AI can serve as a scalable consumer-side information technology, shifting expert–client relationships in one of the most consequential credence goods markets: outpatient healthcare.

[4]Related literatures study other types of health information, including second opinions (Mimra et al., 2016), patient decision aids that provide standardized materials about specific treatment options (surveyed by Stacey et al., 2017, 2024), provider report cards and online ratings that disclose information about healthcare provider quality (e.g., Dranove et al., 2003; Kolstad, 2013; Angerer et al., 2026), and educational campaigns on health risks and the importance of diagnostic testing (e.g., Dupas, 2011a; Lopez et al., 2024).

2 Institutional Background

2.1 Generative AI in Healthcare: Adoption and Guardrails

Generative AI has rapidly become a major channel through which people access health information. Health-related queries are among the most common use cases of large language models: OpenAI reports that approximately 230 million people discuss their health with ChatGPT each week,[5] and surveys indicate that roughly one in six American adults consults an AI chatbot for health information at least once a month (Kaiser Family Foundation, 2024). This growth has occurred largely ahead of formal regulatory frameworks, creating a setting in which AI systems interact with patients at massive scale without the oversight structures that govern licensed medical professionals.[6]

In response to safety concerns and legal exposure, major AI developers have explicitly encoded defensive guardrails into their models for health-related interactions.[7] OpenAI's published model specification instructs its systems to avoid providing tailored medical advice, to refrain from recommending specific treatments or medications, and to direct users to licensed professionals instead.[8] Anthropic has similarly stated that Claude is designed to include contextual disclaimers, acknowledge uncertainty, and direct users to healthcare professionals for personalized guidance.[9] These guardrails are not merely stylistic: they are the product of deliberate training choices that systematically shape model outputs toward caution, diagnostic clarification, and deference to professional judgment. As a result, when patients consult these tools for health decisions, the defensive logic embedded in AI training enters real-world healthcare decisions at scale.

2.2 Healthcare Market and Institutional Context in China

Healthcare expenditures have risen rapidly worldwide. Economic research points to both demand-side and supply-side mechanisms as drivers of high healthcare spending. On the demand side, beyond

[5] https://openai.com/index/introducing-chatgpt-health/.

[6] The regulatory debate over AI's role in healthcare is actively evolving. California's Assembly Bill 489, signed into law in October 2025, directly addresses the boundary between AI and licensed medical practice: it prohibits developers and deployers of AI systems from using any terms, phrases, or design elements that imply the system is providing care from a licensed healthcare professional, and authorizes state licensing boards to investigate and penalize violations. https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=202520260AB489.

[7] These liability-driven design choices echo a long-standing literature documenting physicians' own defensive responses to perceived legal and dispute risk (e.g., Kessler and McClellan, 1996; Studdert et al., 2005; Carroll et al., 2021; Liu et al., 2023; Fang et al., 2025)

[8] https://model-spec.openai.com/2025-04-11.html.

[9] https://www.anthropic.com/news/healthcare-life-sciences.

the classic moral hazard problem,[10] patients often lack the medical knowledge needed to evaluate the necessity of care and may request treatments that are not clinically indicated. Physicians may comply with such requests, contributing to overutilization (e.g., Kravitz et al., 2005; Kotwani et al., 2010; Linder et al., 2014; Finkelstein et al., 2016; Lopez et al., 2022). On the supply side, physician characteristics and financial incentives directly shape treatment decisions, generating systematic variation in medical expenditures, including overspending and inefficiencies (e.g., Iizuka, 2012; Das et al., 2016; Finkelstein et al., 2016; Cutler et al., 2019; Badinski et al., 2023; Currie et al., 2026).[11]

Overutilization, particularly in the form of overprescription, is well documented in China (e.g., Li et al., 2012; Lu, 2014; Fang et al., 2021). The healthcare system in China is predominantly state-run, with public hospitals delivering the vast majority of services. Despite ongoing payment reforms, hospitals continue to operate largely under a fee-for-service payment model and receive limited direct government subsidies. As a result, hospital revenue remains closely tied to service volume. Pharmaceutical sales occur primarily within hospitals rather than through independent retail pharmacies. Between 2014 and 2019, drug expenditures represented more than 60 percent of inpatient spending and roughly 70 percent of outpatient spending in public hospitals.[12] These shares are substantially higher than those observed in many high-income health systems, where prescription drugs account for a considerably smaller fraction of total health expenditures.[13]

Motivated by this institutional setting, we examine whether providing patients with easy-to-understand, personalized medical information reduces prescription intensity in China. On the demand side, improved information may reduce patients' request for clinically unnecessary treatments. On the supply side, better-informed patients may constrain physicians' discretion to prescribe treatments that exceed clinical necessity when financial and institutional incentives favor higher prescribing.

Beyond overall prescribing, we focus on three drug categories: Traditional Chinese Medicine (TCM), antibiotics, and opioids. TCM is widely prescribed in Chinese public hospitals but is

[10] China has near-universal health insurance coverage through two main public schemes: the Urban Employee Basic Medical Insurance (UEBMI), which covers formal-sector workers, and the Urban and Rural Resident Basic Medical Insurance (URRBMI), which covers rural residents and non-working urban populations.

[11] Moreover, Gottschalk et al. (2020) document that patients with higher socioeconomic status are significantly less likely to receive unnecessary treatment recommendations, indicating that physicians' propensity to overtreat depends on patient characteristics.

[12] China Health Statistical Yearbook, various years.

[13] Across OECD countries, pharmaceutical spending typically accounts for roughly 15–20% of total health expenditures. https://www.oecd.org/en/data/indicators/pharmaceutical-spending.html.

characterized by less standardized evidence on effectiveness and side effects,[14] and often higher or more variable pricing. Antibiotic overprescription has been well documented in China (Currie et al., 2013, 2014) and in the United States (Fleming-Dutra et al., 2016), raising concerns about antimicrobial resistance. Opioids, while less prevalent in China than in the United States (Maclean et al., 2020), have drawn substantial international attention due to concerns about misuse and addiction. We focus on these three categories because they are highly policy relevant and have been central to regulatory efforts and public health debates.

The absence of primary care gatekeeping in China further amplifies the informational asymmetries patients face. Unlike systems organized around general practitioners or family medicine, Chinese patients schedule appointments directly with specialists without prior referral or triage by a generalist physician. As a result, patients arrive at outpatient specialist consultations without access to a trusted intermediary who might explain their condition in plain terms or provide continuity of medical guidance over time. The informational disadvantage patients face is therefore considerably more severe than in settings where a family doctor serves as an ongoing informational resource. Compounding this, physician–patient interactions in the Chinese outpatient system are largely episodic rather than ongoing: the same patient rarely sees the same specialist repeatedly. In credence-good markets, repeated interaction is one of the few mechanisms that can discipline expert behavior even absent formal oversight (Dulleck and Kerschbamer, 2006; Fong et al., 2022). Its near-absence in Chinese outpatient care leaves patients especially vulnerable to physician discretion and makes the potential value of patient-side information particularly large.

Time pressure further limits patients' ability to overcome these informational disadvantages. Public hospitals operate under severe capacity constraints, and outpatient consultations are brief, averaging about nine minutes per visit in our partnering hospital. Limited consultation time restricts explanation, counseling, and patient engagement, making patients' advance preparation and clear communication particularly valuable. In this setting, additional health information and support from generative AI tools may be especially relevant.

[14] Under new regulations effective July 1, 2026, TCMs that do not clearly disclose contraindications, adverse reactions, or precautions will not be approved upon re-registration. Reports indicate that over 70 percent of currently approved products may be affected. https://www.news.cn/politics/20260129/853dc80d18fb43d2b1d61676c46b5675/c.html.

3 Experimental Design and Data

We conducted our experiment within this context by partnering with a large public hospital in Sichuan Province. The hospital employs 200 outpatient physicians who handle approximately 900 visits per day on average. As a city-level tertiary hospital, it is representative of the mid-tier public institutions that serve roughly 40% of China's population and account for 35% of nationwide outpatient visits, ensuring the external validity of our findings. The patient population is predominantly rural and has limited exposure to digital technologies, providing a low baseline of AI adoption that minimizes the risk of background usage diluting the treatment effect. The hospital's electronic medical record system captures detailed visit-level data on diagnoses, prescriptions, diagnostic test orders, and other clinical details. Its online appointment platform allows us to randomize chatbot access at the time patients book their appointments.

3.1 Intervention

Our intervention is a generative AI chatbot powered by a large language model built on a widely used general-purpose architecture, adapted for healthcare-related interactions, and integrated into the hospital's online appointment system. Immediately after a patient completes an online appointment booking, which occurs on average one day before the visit, those randomly assigned to the treatment group receive a personalized link to the chatbot. Simultaneously, the hospital sends a separate message encouraging patients to use the tool prior to their visit. Panels (a) and (b) of Figure 1 present the chatbot's initial landing screen and consultation interface.

The chatbot supports pre-visit patient preparation by eliciting symptom descriptions, interpreting and analyzing patient health concerns, and providing general medical information. Throughout all interactions, the interface prominently reminds users that the chatbot does not replace professional medical advice and that clinical decisions should follow physicians' recommendations. The system automatically logs all user interactions, including timestamps and message content. These records provide an objective measure of engagement with the intervention, which we link to administrative and clinical outcomes using unique patient identifiers. This structure enables estimation of both intent-to-treat and treatment-on-the-treated effects.

The intervention is designed to reduce informational asymmetries that characterize outpatient

care and, in doing so, may affect both communication and clinical decision-making. First, by prompting patients to organize and describe symptoms and to review relevant health information before the visit, the chatbot may improve pre-visit preparation and facilitate clearer communication during the consultation. This is particularly important in our setting, where the average outpatient visit lasts approximately nine minutes, making efficient and precise communication essential. Beyond communication, access to structured medical information may improve patients' understanding of their health conditions, typical diagnostic pathways, and the role of medications and tests. Better-informed patients may therefore be less likely to request unnecessary treatments or prescriptions, reducing demand-driven overuse. In addition, the information patients receive is not neutral: defensive guardrails encoded in AI training tend to caution against medication use and encourage diagnostic clarification, and patients may carry this directional bias into their consultations. Finally, by narrowing informational gaps, the chatbot may shift the balance of authority within the consultation. Patients who arrive with greater knowledge and more structured questions may be better positioned to question recommendations and constrain physician incentives to over-prescribe or over-treat. Together, our intervention can reshape the clinical interaction between patient and physicians through multiple channels.

3.2 Two-Layer Randomization

We implement a two-layer randomized experimental design to identify the direct effects of providing patients with access to the chatbot while creating variation to detect within-physician spillovers. We first randomize physicians into an *Exposed* group (two-thirds) or an *Unexposed* group (one-third), stratified by seniority, education, and specialty. Among patients scheduling appointments with *Exposed* physicians, half are randomly assigned to the *Treatment* group, with chatbot access, and half to the *Control* group, without access to the chatbot. Patients scheduling appointments with *Unexposed* physicians do not receive chatbot access, so *Unexposed* physicians never interact with AI-assisted patients.

Panel (c) of Figure 1 summarizes the two-layer randomization. This design generates three analytically distinct groups. Comparisons between the *Treatment* and *Control* groups identify the direct effect of patient access to the chatbot within the same physician panel. Comparisons involving the *Unexposed* group allow us to detect within-physician spillovers arising from physician learning or

behavioral adjustment following repeated interactions with AI-prepared patients.

The three analytical groups are formally labeled as:

1. **Treatment:** Patients with chatbot access, seeing *Exposed* physicians.
2. **Control:** Patients without chatbot access, seeing *Exposed* physicians.
3. **Unexposed:** Patients without chatbot access, seeing *Unexposed* physicians.

3.3 Data and Sample

The experiment was conducted between June 2 and July 3, 2025, at our partnering hospital. Because the intervention is delivered through the online appointment system, we restrict the sample to patients who scheduled outpatient visits online during this period. Patients who walked in without an online appointment, approximately one third of total outpatient visits, are excluded from both the experiment and the analysis sample.[15]

During the experimental period, 179 physicians provided outpatient care. Of these, 117 (two thirds) were randomized to the *Exposed* group and 62 (one third) to the *Unexposed* group. Panel A of Table 1 reports balance tests at the physician level and shows that the two groups are well balanced across observed characteristics, including age, gender, seniority, education, and specialty, with no statistically significant differences.

A total of 11,666 patients completed visits with *Exposed* physicians after being randomized with equal probability into the *Treatment* or *Control* group, and 6,010 completed visits with *Unexposed* physicians. Of the patients randomized, 6.6 percent did not ultimately attend their scheduled visit. Attrition rates are balanced across treatment groups, suggesting that chatbot access did not influence the decision to show up, which is itself an important margin of patient behavior. We exclude no-show patients from all analyses, so the figures above reflect only completed visits.

Panel B of Table 1 reports balance tests at the patient level, comparing the *Treatment* and *Control* groups as well as the *Treatment* and *Unexposed* groups. Across these comparisons, we find no statistically significant differences in age, gender, occupation, first-time visit status, or advance booking time. The average patient is approximately 45 years old, and a large share report working as farmers (44%) or being unemployed or retired (24%). This demographic profile suggests that baseline

[15]We additionally exclude pediatric patients from the experiment. Approximately 0.6% of patients who booked an appointment but did not complete payment are also excluded from the analysis sample.

familiarity with generative AI tools is likely to be limited in this population. Appointments are booked, on average, approximately 25 hours in advance, giving treated patients adequate opportunity to use the chatbot if they choose to do so.

Medical Records. We observe administrative outpatient medical records for all visits during the study period. These records include patient and physician identifiers, visit timestamps, diagnoses, detailed drug prescriptions, and orders for diagnostic examinations. For each prescribed drug and diagnostic test, we observe the listed price, which captures medical expenditures prior to insurance reimbursement. These data allow us to construct visit-level measures of clinical decision-making, treatment intensity, and spending outcomes.

Patient Survey. We invited patients to complete a brief post-consultation survey on the day of the visit or the following day, offering a monetary incentive of 2 to 10 RMB. The survey elicits patients' overall satisfaction with the visit, perceived quality of communication, and intended adherence to medical advice. For patients in the *Treatment* group, the survey includes additional questions on chatbot usage and perceived usefulness. In total, we collected 2,247 patient responses, corresponding to a 13 percent response rate. The sample includes 640 respondents from the *Treatment* group, 789 from the *Control* group, and 818 from the *Unexposed* group.

Physician Survey. Following the conclusion of the one-month experiment, we surveyed all physicians who conducted outpatient consultations during the study period. Of 179 physicians, 171 completed the questionnaire, yielding a response rate of 95.5 percent. The survey elicits physicians' assessments of their patients along four dimensions: clarity of symptom descriptions, understanding of their own health conditions, ease of communication during the visit, and potential adherence to medical advice. Both *Exposed* and *Unexposed* physicians were also asked to estimate how frequently their patients used AI tools prior to visits.

Taken together, the physician and patient surveys complement the administrative data by validating treatment exposure and providing insight into how AI-assisted health information affects consultation dynamics and patient welfare.

3.4 Chatbot Take-up

Although all patients in the *Treatment* group received free access to the chatbot prior to their consultation, actual usage was voluntary. Linking the usage logs to the hospital administrative system, we find that 998 patients (approximately 17 percent) of the *Treatment* group used the chatbot before their visit. By design, patients in the *Control* group were not given access and therefore could not use the tool. Appendix Table A1 reports first-stage estimates of the relationship between treatment assignment and chatbot usage. Assignment to the *Treatment* group increases the probability that a patient uses the chatbot by 17 percentage points.

Take-up among treated patients is self-selected and varies systematically with observable characteristics. Appendix Table A2 shows that, conditional on being assigned access, younger patients, men, employed patients, and first-time visitors are significantly more likely to use the chatbot. This selective adoption pattern has two implications for the analyses that follow. First, because only a subset of treated patients actively use the chatbot, intent-to-treat estimates reflect the effect of offering access at this take-up rate. Second, the demographic profile of adopters suggests that the benefits of generative AI tools may not be evenly distributed across patient populations, a distributional concern we revisit in Section 5.

4 Main Results

4.1 The Directional Content of Patient–AI Conversations

We begin by examining how adopters in the *Treatment* group used the chatbot and what their conversations reveal about the advice they received.

Our analytic sample consists of 1,192 conversation turns from 956 patients, where each turn comprises one patient message and the chatbot's reply, and a single conversation may span multiple turns. Two-thirds of patient messages (66.7%) describe symptoms and request a diagnosis or underlying cause. The remainder inquire about treatment options (11.7%), logistical matters (6.6%), lifestyle and self-care (5.5%), whether to undergo specific tests (4.9%), and the interpretation of test results or prior diagnoses (3.1%). Patients thus turn to the chatbot primarily to make sense of their symptoms, not to solicit specific treatments. Appendix B.1 reports the full distribution of intent

labels along with example messages and details the classification procedure.

We next examine how the AI engages with four clinically relevant topics that map directly onto our outcomes of interest: diagnostic testing, general medication (excluding TCM and antibiotics), Traditional Chinese Medicine (TCM), and antibiotics. A single response typically spans multiple topics. For each topic mentioned, we use GPT-4o to assign two independent binary flags: whether the AI *recommends* the test or treatment, and whether it raises any *caution* or advises against its use. Because the two flags are independent, each mention falls into one of four categories: recommend without caution, recommend with caution, caution without recommending, or neither. Appendices B.2 and B.3 provide further detail on the topic identification and stance classification procedures. Table 2 reports the results.

Two patterns stand out. First, it is the AI, not the patient, that typically introduces these topics into the conversation. Patients mention general medication in only 11.4% of turns and diagnostic testing in only 8.5% of turns, yet the AI raises medication in 58.9% of replies and testing in 58.2% of replies. Across all four topics, the AI initiates discussion in the majority of mentions. The chatbot is not merely responding to patient queries; it actively shapes the informational content that patients carry into the clinical encounter.

Second, the AI's stance differs sharply between medications and diagnostic testing. Whenever the AI discusses any form of medication, it almost invariably pairs the discussion with cautions: 69.7% of general medication mentions, 90.8% of TCM mentions, and 87.6% of antibiotic mentions include warnings about side effects, contraindications, dosing concerns, or self-medication risks. Clean recommendations—unaccompanied by any caution—are rare for medications, particularly for TCM (3.8%) and antibiotics (7.8%). Diagnostic testing is treated very differently: when the AI discusses testing, it issues clean recommendations in 94.5% of cases, with cautions appearing in only 3.3% of mentions.

These patterns are consistent with the liability concerns faced by LLM developers, especially in high-stakes settings like the medical domain. Recommending specific treatments or medications carries substantial legal risk if those recommendations lead to adverse outcomes, while recommending diagnostic testing carries little legal risk, and the costs of unnecessary tests are borne by patients and the health system rather than the developer. To minimize legal liability, developers such as OpenAI and Anthropic explicitly build safety guardrails into their models around health-related

topics. As a result, AI responses are highly cautious about medications and tend to encourage testing for diagnostic clarification, even when this stance is not always aligned with medical guidelines that optimize for the health care system as a whole. The information patients receive from the chatbot is therefore not necessarily a neutral distillation of medical knowledge, but a view shaped by the priorities of those who build and govern these systems.

As our treated patients receive this non-neutral AI advice before their visits, the encoded caution toward medications and the encouragement of diagnostic testing may propagate into their clinical decisions, which we examine next using medical records.

4.2 Clinical Outcomes Across Experimental Groups

We graphically present mean outcomes for the *Treatment*, *Control*, and *Unexposed* groups over the experimental period, beginning with prescribing behavior. Panel (a) of Figure 2 shows that access to the chatbot reduces the likelihood that a visit results in any prescription. The share of visits with at least one prescribed medication is 4.5 percentage points lower in the *Treatment* group than in the *Control* group (significant at the 5% level), where the baseline prescribing rate is 88.8%. The prescribing rate in the *Treatment* group is also significantly lower than in the *Unexposed* group, while rates in the *Control* and *Unexposed* groups are statistically indistinguishable.

We next examine prescribing patterns across major medication categories, including Traditional Chinese Medicine (TCM), antibiotics, and opioids. Panels (b) and (c) of Figure 2 show sizable reductions in TCM and antibiotic prescribing in the *Treatment* group, with statistically significant differences relative to both comparison groups. Opioid prescribing is also lower among treated patients, but the differences relative to the *Control* and *Unexposed* groups are not statistically significant. This is expected given the low baseline rate of opioid prescribing in China, below 3% in both the *Control* and *Unexposed* groups, as shown in Panel (d).

In contrast, physicians seeing treated patients are more likely to order diagnostic tests. Panel (e) shows that 21–22% of visits in the *Control* and *Unexposed* groups involve at least one diagnostic test, compared with 24.7% in the *Treatment* group. The increase in testing is statistically significant in both comparisons. This pattern of reduced prescribing and increased diagnostic testing is consistent with the directionality in the AI advice we observe from the conversation logs.

We next assess whether these changes in clinical management are associated with differences in

patient outcomes. One outcome observed in our administrative data is whether a patient revisits the same hospital within two weeks of the initial consultation. Panel (f) of Figure 2 shows that patients in the *Treatment* group are 1.1 percentage points less likely to revisit within two weeks than patients in the *Control* group, a 7% reduction that is statistically significant. The same conclusion holds when comparing treated patients to the *Unexposed* group, whose two-week revisit rate is similar to that of the *Control* group. The reduction in short-term revisits is consistent with improvements in the effectiveness of initial consultations, but it may also reflect other mechanisms. Better-prepared patients may feel less need to seek follow-up care even absent changes in clinical quality. We therefore do not interpret this reduction as direct evidence of improved clinical outcomes. In this rural setting, where patients often face substantial travel costs, reductions in revisits nonetheless have welfare implications, even if the underlying channels remain unclear.

4.3 Within-Physician Intent-to-Treat Effects

Because outcomes are similar in the *Control* and *Unexposed* groups, our main regression analyses restrict the sample to visits with *Exposed* physicians.[16] Within this sample, we estimate the causal effects of offering access to the LLM-based chatbot on clinical outcomes using the following specification:

$$Y_{ip} = \alpha + \beta \text{Treated}_{ip} + \gamma X_{ip} + \delta_p + \varepsilon_{ip} \tag{1}$$

where the unit of observation is an outpatient visit by patient i to physician p. The outcome variable Y_{ip} represents outcomes from the consultation: prescriptions, diagnostic tests, and healthcare expenditures. The key explanatory variable, Treated_{ip}, is a binary indicator equal to one if patient i was randomly assigned to receive chatbot access prior to the visit. We include a vector of patient characteristics X_{ip} (age, gender, occupation, and first-time visit status) and physician fixed effects δ_p. The error term ε_{ip} captures unobserved factors affecting individual visits. All regressions are estimated using robust standard errors.[17]

The coefficient of interest, β, identifies the *Intent-to-Treat* (ITT) effect of being assigned chatbot access, regardless of actual usage. This approach preserves the integrity of the randomization and

[16] We return to the *Unexposed* group in later analyses to formally test for spillovers.

[17] Standard errors are not clustered because randomization occurs at the individual patient level (Abadie et al., 2023). Appendix Tables A3–A6 report estimates with standard errors clustered at the physician level; results and significance levels are similar.

provides policy-relevant estimates of the effect of *offering* AI tools in a real-world clinical setting. It is important to note that if within-physician spillovers occur, for example, if physicians adjust their general practice patterns for all patients after interacting with AI-informed ones, the control group may also be indirectly affected. In that case, our estimate of β understates the true effect of chatbot exposure.

Table 3 reports within-physician intent-to-treat estimates of the effects of offering chatbot access on clinical practice patterns among visits with *Exposed* physicians. Consistent with the graphical evidence, the regression results show that access to the chatbot significantly reduces the likelihood that a visit results in any prescription by 4.6 percentage points relative to a sample mean of 87%. This decline is driven partly by reductions in prescribing of Traditional Chinese Medicine and antibiotics, which fall by 2.2 and 1.5 percentage points, respectively, while opioid prescribing declines but the effect is not statistically significant. At the same time, chatbot access increases the probability that a visit involves any diagnostic test by 2.7 percentage points relative to a sample mean of 23%. Finally, treated patients are about 1.2 percentage points less likely to revisit the same hospital within two weeks; the effect is marginally statistically significant. Estimates are nearly identical with and without controls for patient characteristics and physician fixed effects, confirming that the randomization successfully balanced patient and physician characteristics.[18]

Table 4 reports intent-to-treat effects on healthcare expenditures, measured as the sum of listed prices for prescribed drugs and diagnostic tests before insurance reimbursement. Consistent with the prescribing changes documented in Table 3, chatbot access reduces medication expenditures, with reductions in both TCM and Western Medicine expenditures significant at the 10% level. In the specification that controls for patient characteristics and physician fixed effects, TCM expenditures decline by approximately 1.76 RMB, a 13% reduction relative to the sample mean, while Western Medicine expenditures decline by about 5.0 RMB relative to a sample mean of 64.8 RMB. Diagnostic expenditures increase by roughly 6.3 RMB, though this estimate is not statistically significant. Because these changes offset, we find no statistically significant effect of chatbot access on total healthcare expenditures.

[18]Some patients visit the hospital more than once during the experiment period. To address the concern that the same patient could be assigned to different treatment conditions across visits, Appendix Table A7 restricts the sample to each patient's first visit. Results are qualitatively and quantitatively similar to the main estimates.

4.4 Treatment-on-the-Treated Effects

The results above report intent-to-treat effects based on randomized access to the chatbot, regardless of whether patients actively used the tool. We now estimate treatment-on-the-treated effects, which recover the average effect of chatbot usage among patients who complied with the assignment. We instrument actual chatbot usage with randomized assignment to the *Treatment* group, using the same within-physician specification as in the intent-to-treat analysis.

Table 5 reports the effects of chatbot usage on clinical practice patterns. Consistent with the intent-to-treat results, chatbot usage is associated with a 27 percentage point reduction in the probability that a visit results in any prescription, partly driven by declines of about 13 percentage points in Traditional Chinese Medicine prescribing and 9 percentage points in antibiotic prescribing. At the same time, chatbot usage increases the likelihood of diagnostic testing by roughly 16 percentage points and reduces the probability of a two-week revisit by 7 percentage points. These magnitudes are approximately five times larger than the corresponding intent-to-treat estimates, reflecting partial take-up of the chatbot (17 percent in the *Treatment* group). The instrumental variable estimates therefore represent local average treatment effects for patients who use the chatbot when offered access. Overall, the scale of these effects suggests that generative AI tools can meaningfully alter clinical decision-making in ways that, if adopted broadly, would translate into substantial changes in healthcare utilization at the system level.

Table 6 reports the local average treatment effects on healthcare expenditures. Chatbot usage is associated with sizable reductions in medication expenditures, with TCM expenditures declining by 10 RMB and Western Medicine expenditures declining by roughly 30 RMB, both statistically significant at the 10 percent level. These reductions are offset by an increase in diagnostic expenditures of approximately 37 RMB, although this estimate is imprecisely estimated. For both Tables 5 and 6, first-stage F-statistics exceed 1,100 across specifications, indicating a strong first stage.

4.5 Heterogeneous Treatment Effects

The effects documented above could vary across physicians. As the chatbot works by changing what patients know and ask for, its influence on clinical decisions should depend on how receptive each physician is to patient input and on whether their baseline practice involves overprescribing

that better-informed patients can help constrain. We examine heterogeneity along both dimensions, using measures from the physician survey and from pre-experiment prescribing records.

We first split physicians by their stance toward patient input, using two measures from the physician survey. We asked physicians whether they view medical knowledge acquired by patients from external sources as helpful and whether patients should strictly follow physicians' recommendations. These measures capture variation in physician openness and authority style. Panel A of Table 7 shows that the reduction in medication prescribing and increase in diagnostic testing are substantially larger among physicians who report being highly open to patient-acquired health knowledge. In contrast, Panel B shows that the treatment effects are significantly smaller among physicians who place strong emphasis on physician authority. These patterns suggest that the chatbot moves clinical decisions mainly when physicians are receptive to what patients bring to the visit, and far less when physicians emphasize their own authority.

We next ask whether the effects are concentrated where baseline practice is most intensive.[19] Table 8 examines whether the treatment effects are larger among physicians who express more favorable views toward prescribing specific medications. In the physician survey, we elicit attitudes toward the use of Traditional Chinese Medicine, antibiotics, and opioids, and classify physicians according to whether they report more favorable or more conservative views toward each category. In column (1) of Table 8, the interaction between treatment assignment and a more pro-TCM attitude is negative and statistically significant, indicating that the decline in TCM prescribing is substantially larger among physicians who are more inclined to prescribe TCM. A similar, though imprecisely estimated, pattern appears for antibiotics in column (2). We find no differential effects for opioids, consistent with their low baseline prescribing rates in China.

We then turn to physicians' revealed prescribing behavior prior to the experiment. Specifically, we classify physicians according to whether their prescribing rates for TCM, antibiotics, and opioids between January and May 2025, before the start of the experiment, exceed the median within their department. This measure captures baseline treatment intensity based on actual prescribing patterns rather than self-reported attitudes. Table 9 reports the results. The reduction in medication use is

[19] One potential explanation for heterogeneity in prescribing intensity is financially motivated physician-induced demand (e.g., Gruber and Owings, 1996; Liu et al., 2009; Iizuka, 2012; Lu, 2014; Fang et al., 2021). However, such incentives are limited in our institutional setting. Physicians' salaries and bonuses are not tied to drug sales, and hospitals operate under a zero-markup policy for medications (Yi et al., 2015; Yip et al., 2019; Fang et al., 2021).

significantly larger among physicians with higher baseline prescribing intensity. In particular, the decline in TCM prescribing is concentrated among physicians whose pre-experiment TCM prescribing rates were above the departmental median. A similar pattern appears for antibiotics, while we find no differential effects for opioids, again consistent with their low baseline prescribing rates in China.

Taken together, the heterogeneity indicates that the treatment effects are concentrated where the intervention has the greatest potential to alter decisions. They are larger among physicians who are receptive to patient input, for whom both the reduction in prescribing and the increase in diagnostic testing are more pronounced, and among physicians with the most intensive baseline prescribing, where there is more scope to reduce medication use.

5 Dynamic and Spillover Effects

5.1 Dynamic Effects

Having documented the effects of chatbot access and usage on clinical decisions, we next examine how these effects evolve over time and whether they generate spillovers. To study the temporal dynamics of the intervention, we implement an event-study framework. This approach serves three purposes. First, it provides a diagnostic check on the physician-level randomization by testing for differential pre-trends between *Exposed* and *Unexposed* physicians. Second, it characterizes how outcomes for *Exposed* physicians evolve over the course of the intervention. Third, it allows us to assess whether any effects persist after the formal intervention period ends.

We aggregate the data to the physician-week level and estimate the following specification:

$$Y_{pt} = \alpha + \sum_{k \neq -1} \beta_k \cdot \left(\text{Exposed}_p \times \mathbb{1}\{\text{Week}_t = k\}\right) + \delta_p + \tau_t + \varepsilon_{pt}, \tag{2}$$

where Y_{pt} denotes the outcome for physician p in week t, such as the rate of Traditional Chinese Medicine prescribing or diagnostic testing. The variable Exposed_p equals one for physicians randomized to the *Exposed* group. The indicator $\mathbb{1}\{\text{Week}_t = k\}$ indexes k weeks relative to the intervention start date of June 2, 2025. The coefficient for $k = -1$, corresponding to the week from May 26 to June 1, 2025, is normalized to zero.

The coefficients of interest are $\{\beta_k\}_{k=-12}^{12}$. For $k < -1$, the estimated coefficients capture

differences in outcomes between *Exposed* and *Unexposed* physicians prior to the intervention and provide a test for pre-existing differential trends. For $k \geq 0$, the coefficients trace the dynamic response of outcomes for *Exposed* physicians relative to *Unexposed* physicians. The intervention period extends through day 5 of week $k = 4$; coefficients for subsequent weeks therefore capture post-intervention dynamics. Weeks earlier than $k = -12$ and later than $k = +12$ are binned at the respective endpoints. All specifications include physician fixed effects δ_p, which absorb time-invariant differences across physicians, and week fixed effects τ_t, which control for common temporal shocks. Standard errors are clustered at the physician level to account for serial correlation within physicians over time. Physician-week observations are weighted by the number of patient visits.

Figure 3 presents the results for medication prescribing rates (overall, Traditional Chinese Medicine, antibiotics, and opioids), diagnostic testing, and revisit rates. For all outcomes, we observe no evidence of pre-trends prior to the experiment, suggesting balance between *Exposed* and *Unexposed* physicians. Weeks 0 through 3 correspond to the four full weeks of the intervention period, so the coefficients β_0–β_3 capture the treatment effect and its evolution during the experiment. Because the analysis compares outcomes between *Exposed* and *Unexposed* physicians, the estimated effects are mechanically attenuated. Only half of the patients seen by *Exposed* physicians are assigned access to the chatbot, and take-up among eligible patients is incomplete (approximately 17%). As a result, the magnitudes of the estimates are expected to be small and can be interpreted as roughly one-half of the corresponding intention-to-treat effects and approximately one-tenth of the average treatment-on-the-treated effects.

As shown in Figure 3, we observe clear reductions in overall medication prescribing and Traditional Chinese Medicine prescribing beginning in week 1, while the estimated effects on antibiotic and opioid prescribing are substantially noisier. Starting in week 1, we also observe a clear increase in diagnostic testing rates, along with a noisy and statistically insignificant decrease in revisit rates. While point estimates vary across weeks, including a null effect in week 0, we find no statistically significant evidence that the treatment effects change between week 1 and week 3. The experiment concludes in the middle of week 4. Beginning in week 4, we find no differences in any of these outcomes between *Exposed* and *Unexposed* physicians. This pattern indicates no persistence in physicians' clinical practices following the intervention. Once the experiment ends, the gap between *Exposed* and *Unexposed* physicians fully closes.

5.2 Within-Physician Spillovers

Having established that there are no spillovers to patients who see *Exposed* physicians *after* the experiment ends, we next test for within-physician spillovers *during* the intervention period. Specifically, we examine whether interactions with patients who have access to the chatbot affect outcomes for patients without access who see the same physician. To do so, we adopt the event study framework in equation (2) with one modification. We exclude all visits by patients assigned access to the chatbot. This restriction allows us to compare outcomes for patients without chatbot access who see *Exposed* physicians (*Control* group) with outcomes for patients without chatbot access who see *Unexposed* physicians (*Unexposed* group). If within-physician spillovers or rebound effects are present, we would expect to observe differences in outcomes between these two groups of patients, even though neither group has access to the chatbot.

Appendix Figure A1 reports the results for the same set of clinical outcomes. Across all outcomes, we find no statistically significant differences between patients randomly assigned to the *Control* group and those assigned to the *Unexposed* group. This finding is consistent with the patterns observed in Figure 2. Combined with the absence of persistent effects documented in Figure 3, we are able to conclude that interactions with AI-prepared patients do not generate spillovers to other patients. In particular, physicians do not appear to update their clinical practices in ways that affect patients who do not have access to the chatbot, either contemporaneously or after the intervention ends. This pattern suggests that the effects of the chatbot operate primarily through direct patient use rather than through lasting changes in physician behavior.

From a policy perspective, these results raise concerns about unequal access and uptake. Because chatbot adopters are disproportionately younger, male, and employed, the benefits of generative AI tools may flow primarily to already advantaged groups, potentially widening existing health disparities. Policies aimed at expanding access, improving usability, or targeting underserved populations may therefore be necessary to ensure that generative AI tools benefit a broader patient population.

One potential concern is that exposure to AI-prepared patients may generate spillovers across physicians, for example through informal communication or peer learning. Such spillovers would bias our estimates of persistence and within-physician spillovers toward zero by contaminating

the comparison group if *Unexposed* physicians indirectly update their practice over time. Several features of our setting mitigate this concern. First, physicians conduct consultations independently in separate rooms, limiting opportunities to observe or discuss specific patient interactions. Second, prescribing patterns among *Unexposed* physicians who never interact with treated patients remain stable over time. Third, for across-physician spillovers to drive the within-physician estimates to zero, the magnitude of across-physician learning would need to be comparable to the magnitude of within-physician learning generated by direct exposure to treated patients. We consider across-physician learning of that scale unlikely in our setting. Taken together, these patterns indicate that across-physician spillovers are unlikely to change the qualitative interpretation of our results.

6 Patient Behavior and Physician–Patient Relationship

Having documented changes in clinical decisions, we now examine whether chatbot access also affects patient behavior and perceptions of the consultation. Figure 4 summarizes these outcomes from medical records and the patient survey by treatment status, drawing on both administrative records and the patient survey. Panels (a) through (c) use administrative medical records. Panel (a) reports patient attrition, measured as whether patients who scheduled an appointment ultimately attended their consultation. We find no evidence that access to the chatbot discourages patients from seeing physicians or substitutes for in-person care, as attendance rates are similar across the *Treatment*, *Control*, and *Unexposed* groups. Panels (b) and (c) capture realized post-consultation behavior, measuring whether patients purchased prescribed medications and whether they completed prescribed diagnostic tests following the visit. For both outcomes, we find no statistically meaningful differences across the *Treatment*, *Control*, and *Unexposed* groups. This suggests that access to the chatbot does not materially affect patients' decisions to follow through on physicians' recommendations along these observable dimensions.

Panels (d) through (f) are based on patient survey responses and therefore reflect a more selected sample. While these survey-based measures should be interpreted with caution, they provide insight into how access to the chatbot may have affected the consultation experience. Treated patients report lower overall satisfaction, with 83.3% of respondents reporting being very satisfied, compared with approximately 86% in both the *Control* and *Unexposed* groups. Treated patients also perceive

communication with physicians as less smooth, as reflected in a 2 percentage point reduction in the likelihood of rating the interaction as very smooth. Finally, intended compliance with physicians' recommendations declines substantially among treated patients, with the share reporting an intention to fully comply falling from 90% in the *Control* and *Unexposed* groups to 84.5% in the *Treatment* group. Appendix Table A8 confirms these patterns in regression estimates. Patients with chatbot access report lower satisfaction, less smooth communication with physicians, and lower intended compliance, with the communication and compliance effects statistically significant despite the relatively small sample size.

Taken together, these patterns suggest that while the chatbot does not meaningfully alter observable patient behavior, it may negatively affect patients' perceptions of the clinical encounter and their interactions with physicians. One possibility is that when patients act more knowledgeable, they receive less polite responses from physicians, a pattern documented by Currie et al. (2011). Another possibility is that access to additional health information prior to the visit changes patients' expectations about the consultation, including which questions should be addressed or how much explanation they anticipate from the physician. When these expectations are not fully met, patients may report lower satisfaction or perceive communication as less smooth, even if clinical decisions and follow-through remain largely unchanged. This interpretation is consistent with evidence from Ayers et al. (2023), which shows that in response to patient questions posted on social media, AI chatbot replies are rated more favorably than physician responses overall and on measures of empathy and clarity.[20]

While the patient survey provides insight into the consultation experience from the patient's perspective, it reflects a selected sample of respondents. We therefore complement this evidence with a physician survey that captures the consultation from the physicians' perspective. The physician survey achieves a high completion rate and thus does not suffer from the same selection concerns, although inference is limited by the smaller sample size of physicians rather than visits. Accordingly, we interpret the physician survey results as descriptive and suggestive evidence on potential mechanisms.

Figure 5 summarizes physicians' perceptions of patient behavior along four dimensions, comparing

[20]The survey additionally asks chatbot users to rate the helpfulness of the AI assistant on a five-point scale, from "not helpful at all" to "very helpful." Among respondents, 84 percent rated the chatbot as very helpful and an additional 11 percent as somewhat helpful, with fewer than 1 percent reporting it was not helpful.

responses from physicians in the *Exposed* and *Unexposed* groups. In Panel (a), physicians in the *Exposed* group are more likely to report that patients describe their symptoms clearly, with 24.8% of physicians reporting that patients very clearly describe their symptoms, compared with 19.4% among *Unexposed* physicians. Panel (b) shows a similar pattern for perceived patient understanding of their condition, with 22.9% of *Exposed* physicians reporting great understanding, compared with 19.4% in the *Unexposed* group. Panel (c) indicates smoother perceived physician–patient communication in the *Exposed* group, with 36.7% reporting very smooth communication, relative to 30.6% among *Unexposed* physicians. Taken together, the patient and physician surveys reveal an important divergence in perspectives. From the patient's perspective, access to the chatbot is associated with worse perceived communication and lower satisfaction with the visit, whereas from the physician's perspective, patients appear better prepared and communicate more clearly.

Despite these opposing assessments of communication quality, both patients and physicians report lower adherence or intended compliance with medical advice among treated patients. Panel (d) of Figure 5 shows a 5.7 percentage point reduction in physician-reported patient adherence in the *Exposed* group. This pattern mirrors the patient survey findings and highlights a potential tension between improved patient preparedness and reduced adherence to physicians' recommendations. This is consistent with prior evidence showing that patients with access to expertise exhibit lower adherence (Finkelstein et al., 2022). From a policy perspective, this pattern underscores a potential trade-off: while AI tools may enhance patient understanding and improve aspects of the consultation process, they may also alter authority dynamics in ways that affect adherence, with potential implications for both care delivery and health outcomes.

Appendix Table A9 reports regression estimates. The independent variable, *Share of AI Adopters*, is the fraction of a physician's patients who used the chatbot, which equals zero by construction for *Unexposed* physicians and varies across *Exposed* physicians based on patient take-up. The point estimates are consistent with Figure 5. Physicians with higher patient AI adoption report greater symptom clarity, better patient understanding, smoother communication, and lower patient compliance. However, the estimates are imprecise, with only the clarity and compliance coefficients reaching marginal statistical significance in Panel B. The small sample size of 171 physicians limits statistical power.

As a final sanity check, we elicit physicians' beliefs about the share of their patients who used

generative AI tools prior to consultations during the experimental month. Importantly, physicians were not informed of the experiment or its nature throughout the study period, so these perceptions are formed only through interacting with their patients.[21] Appendix Figure A2 reports the results. *Exposed* physicians report an average perceived patient AI adoption rate of 25.2 percent, compared with 16.2 percent among *Unexposed* physicians, a difference of 8 percentage points consistent with the direction of our experimental design. The perceived rates are considerably higher than the actual take-up recorded in our chatbot usage logs, which is unsurprising given that physician recall is subject to recollection biases and their estimates may also capture patients' use of other AI tools beyond our chatbot. Nonetheless, the gap between *Exposed* and *Unexposed* physicians provides additional confirmation that the treatment assignment meaningfully altered the information environment patients brought into the consultation.

7 Conclusion

This paper provides the first large-scale randomized evidence on how patient access to generative AI affects healthcare delivery in a real-world clinical setting. We show that providing patients with access to a generative AI chatbot prior to outpatient visits meaningfully alters clinical practice. Medication prescribing declines by 4.6 percentage points, with particularly large reductions for Traditional Chinese Medicine and antibiotics, while diagnostic testing increases by 2.7 percentage points, without raising total medical expenditures. We find no evidence of spillovers in physicians' behavior toward patients without chatbot access, indicating that the effects operate primarily through direct patient use rather than persistent changes in physician practice. Because chatbot adopters are disproportionately younger, male, and employed, the absence of spillovers also implies that unequal access to generative AI tools may translate directly into unequal benefits, with the potential to widen existing health disparities.

The specific pattern of clinical change we document, reduced prescribing and increased diagnostic testing, mirrors the directional advice we observe in the conversation logs, which is itself consistent with the defensive, liability-driven guardrails encoded in AI training. The chatbot cautions heavily

[21] In our post-visit patient survey, 80.6% of *Treatment*-group respondents who reported using the chatbot also reported telling their physician about it during the consultation. While survey respondents are a selected subset of treated patients, this disclosure rate offers a plausible channel through which physicians inferred patients' chatbot use without being informed of the experiment.

against medications while recommending diagnostic testing freely, and treated patients appear to carry this direction into their consultations. Consistent with this, the effects are concentrated among physicians who are receptive to patient input and among those who prescribe most intensively at baseline. More broadly, when AI systems are deployed as consumer-facing tools at scale, the norms encoded in their training can propagate into real clinical decisions, with the potential to shift aggregate outcomes such as population-level healthcare utilization.

At the same time, our survey results reveal a tension between the use of generative AI tools and the physician–patient relationship. While physicians report clearer communication and better patient preparation when interacting with AI-assisted patients, patients themselves report lower satisfaction and reduced intended adherence to medical advice. These patterns suggest that generative AI may reshape expectations about clinical encounters and shift the balance of authority within the physician–patient interaction in ways that affect compliance.

Whether these shifts improve welfare is not clear. On one hand, the reductions in prescribing fall disproportionately on Traditional Chinese Medicine and antibiotics, categories long viewed as overprescribed in China, and the additional testing may surface conditions that would otherwise be missed, so the changes could move care toward greater appropriateness. On the other hand, less medication may also withhold beneficial treatment, additional testing imposes costs on patients and the health system, and lower adherence may reflect either healthy scrutiny or the disregard of sound advice. Importantly, the direction of these changes is set by the objectives of those who build and govern the AI, principally the minimization of legal exposure, which need not coincide with the objectives that optimize healthcare delivery.

Taken together, our findings speak to a broader transformation in expert–client markets. Healthcare is a canonical credence good, but it is far from the only one. Legal services, financial advice, and skilled trades share the same underlying information asymmetry that generative AI is now positioned to reduce. Our results suggest that generative AI does more than narrow that asymmetry. The priorities and cautions embedded in AI training travel with the information into real decisions, introducing new frictions in expert–client relationships along the way. While we document this in healthcare, the same mechanism may operate wherever clients consult generative AI before turning to an expert. As people increasingly rely on these tools, from health questions to financial decisions, the design choices of a small number of developers can propagate into decision-making across many

domains of life.

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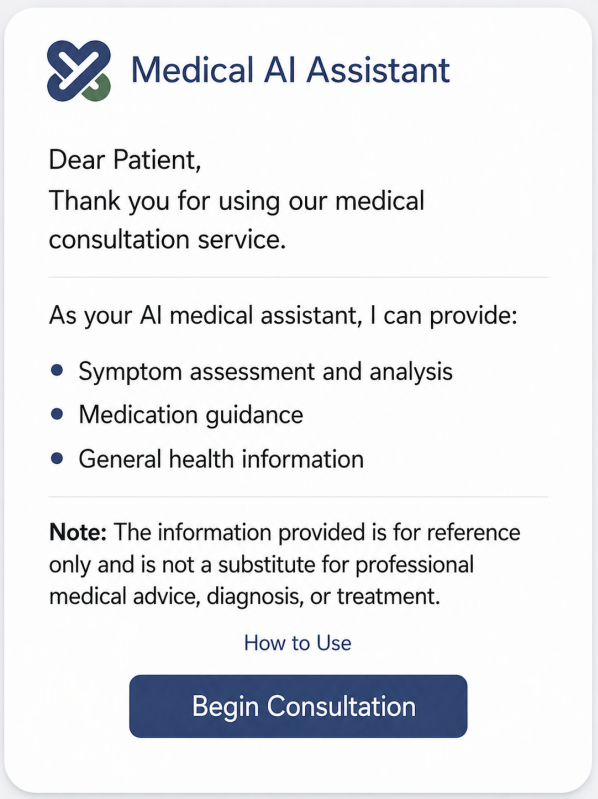
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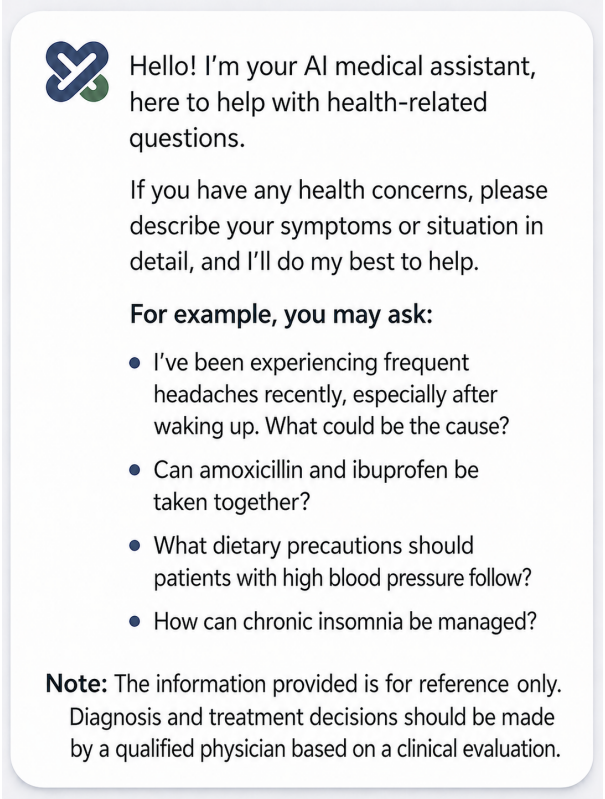
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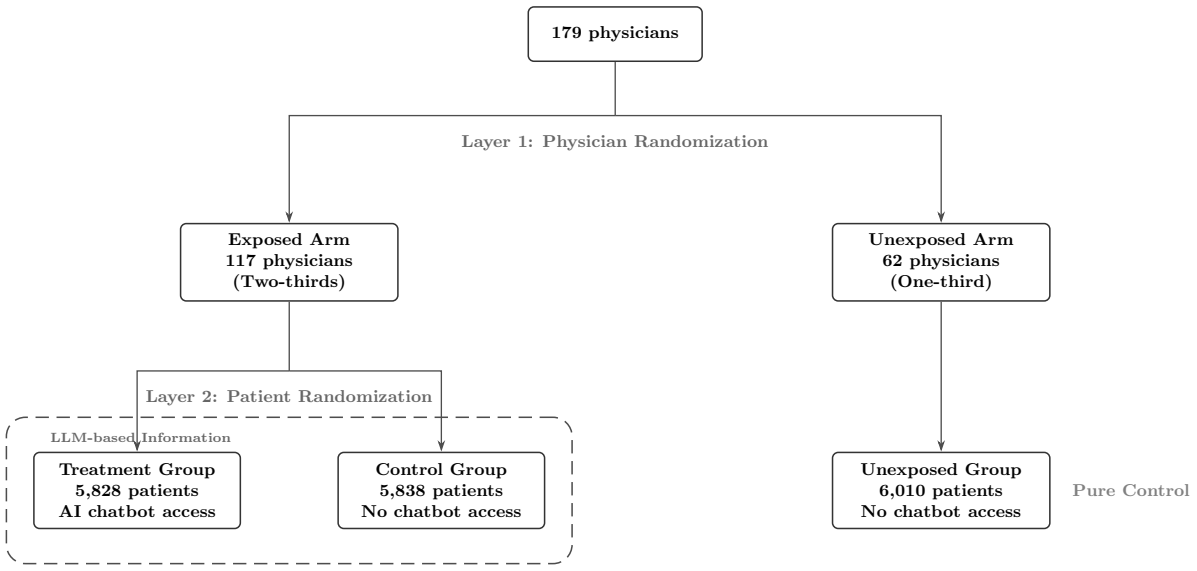
Figures and Tables



(a) Initial Interface

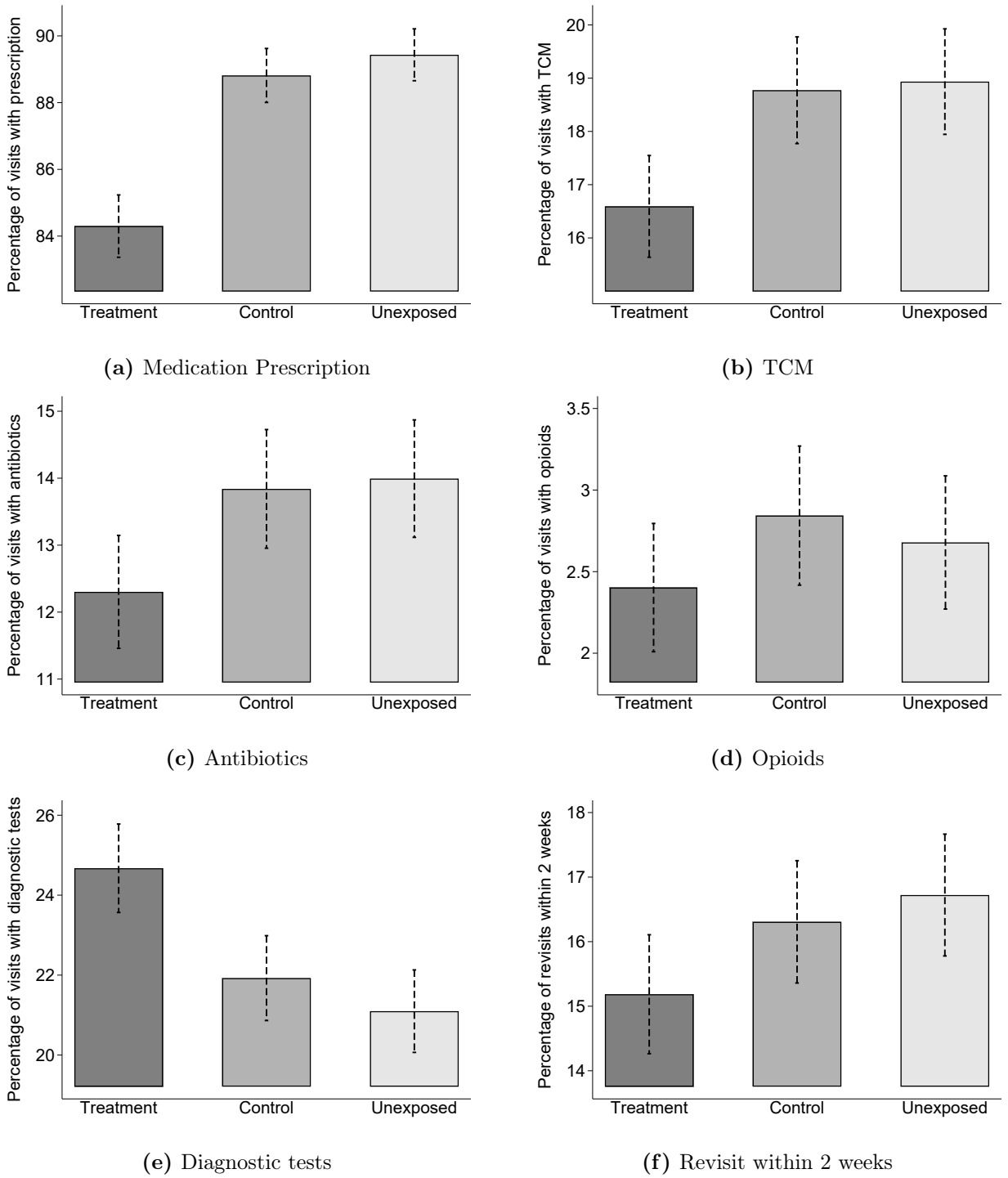


(b) Consultation Interface



(c) Experimental Design

Figure 1. Medical AI Chatbot User Interfaces and Experimental Design Flowchart



(a) Medication Prescription

(b) TCM

(c) Antibiotics

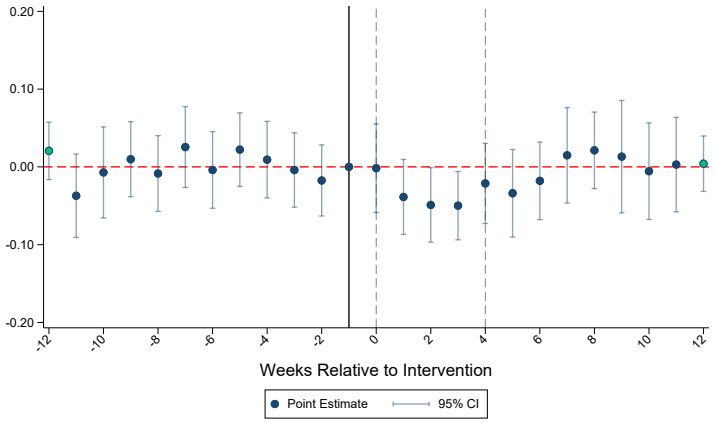
(d) Opioids

(e) Diagnostic tests

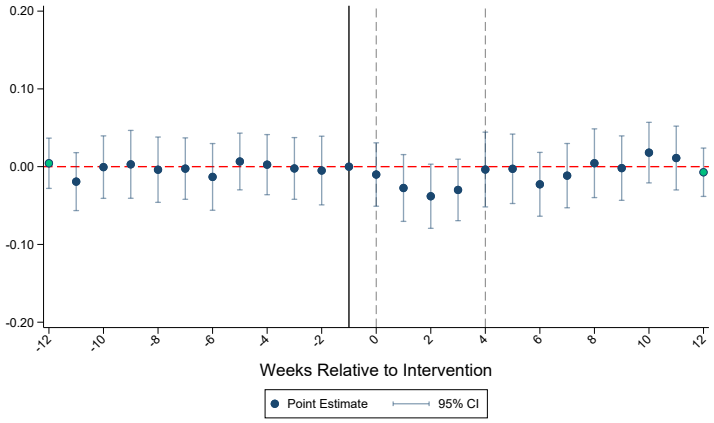
(f) Revisit within 2 weeks

Figure 2. Prescriptions and Clinical Practices by Treatment Status

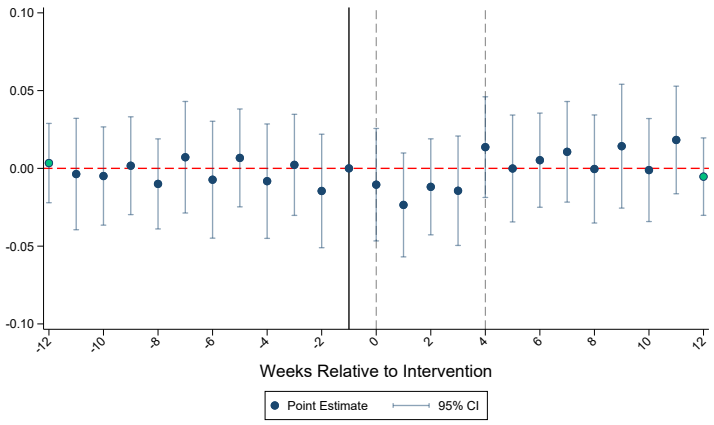
Notes: This figure reports mean clinical outcomes for patients in the *Treatment*, *Control*, and *Unexposed* groups, with 95% confidence intervals (dashed lines).



(a) Medication Prescription

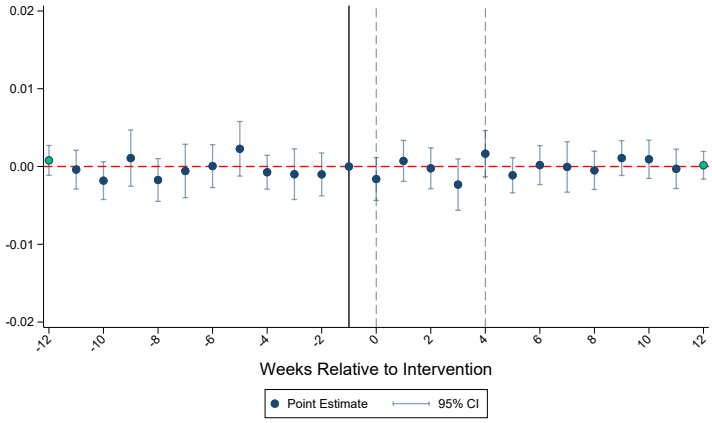


(b) TCM

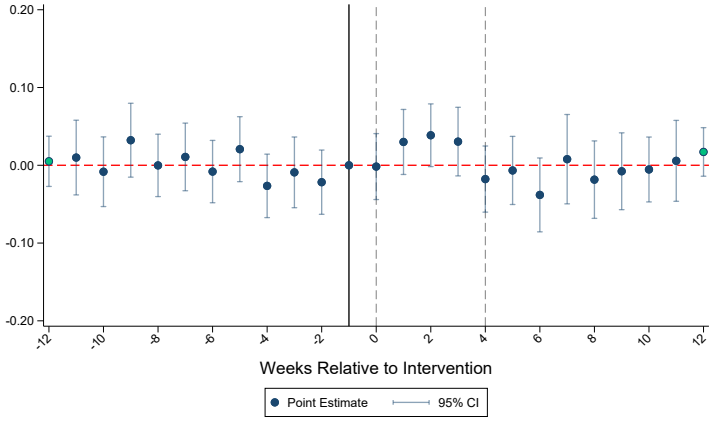


(c) Antibiotics

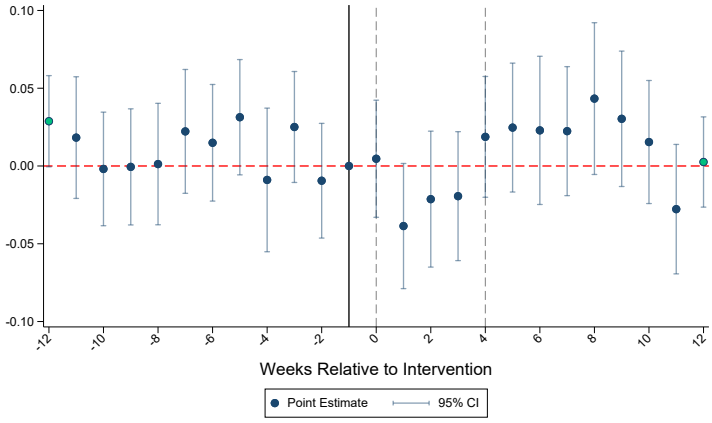
Figure 3. Dynamic Effects of Exposure to Treated Patients on Prescriptions and Clinical Practices



(d) Opioids



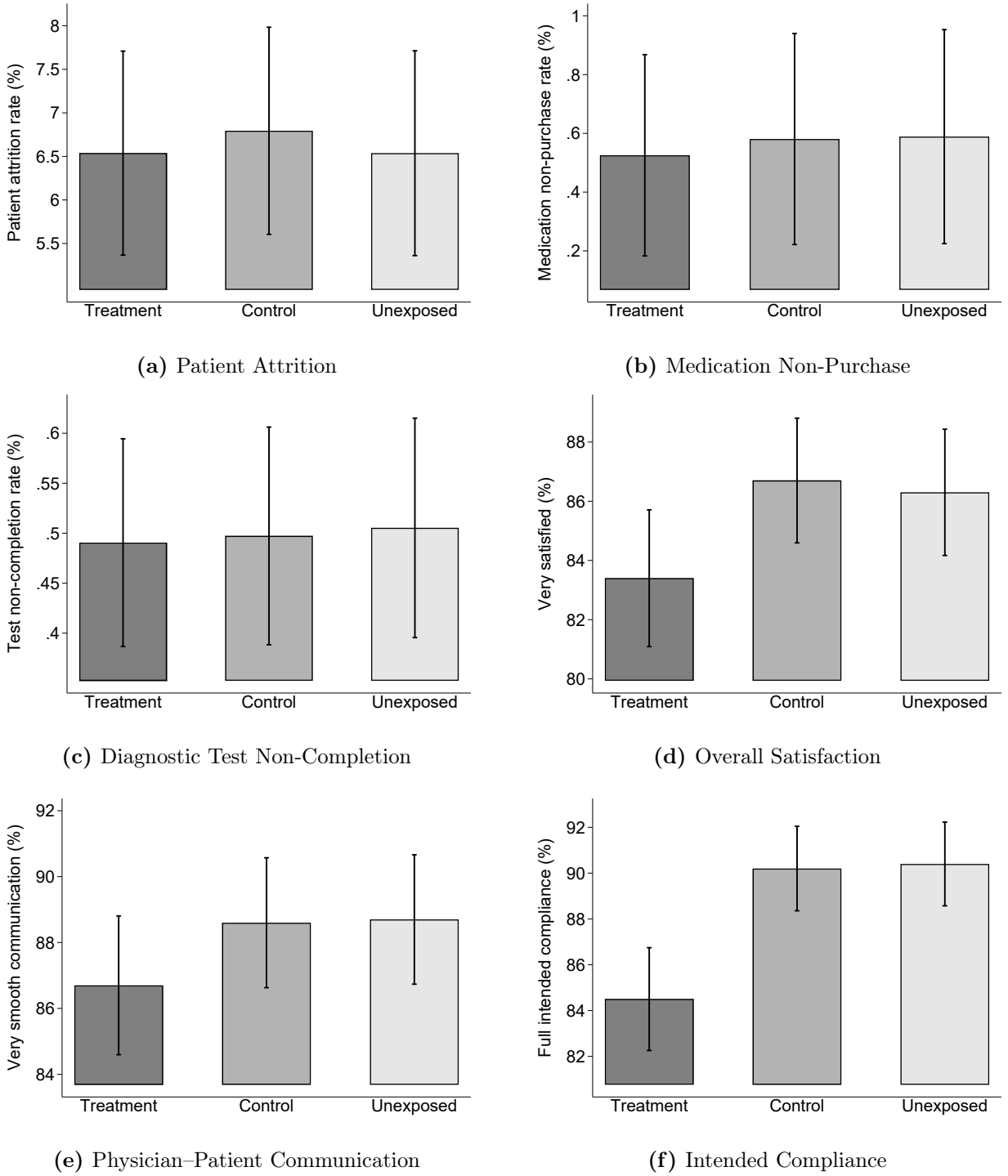
(e) Diagnostic tests



(f) Revisit within 2 weeks

Figure 3. Dynamic Effects of Exposure to Treated Patients on Prescriptions and Clinical Practices (Continued)

Notes: This figure presents the point estimates with 95% confidence intervals from equation (2). Data are aggregated to the physician-week level using all patient visits from 2025, weighted by the number of visits per physician per week. Relative weeks beyond −12 and +12 are grouped at the endpoints. The baseline period is Week −1 (May 26–June 1, 2025). Standard errors are clustered at the physician level.



(a) Patient Attrition

(b) Medication Non-Purchase

(c) Diagnostic Test Non-Completion

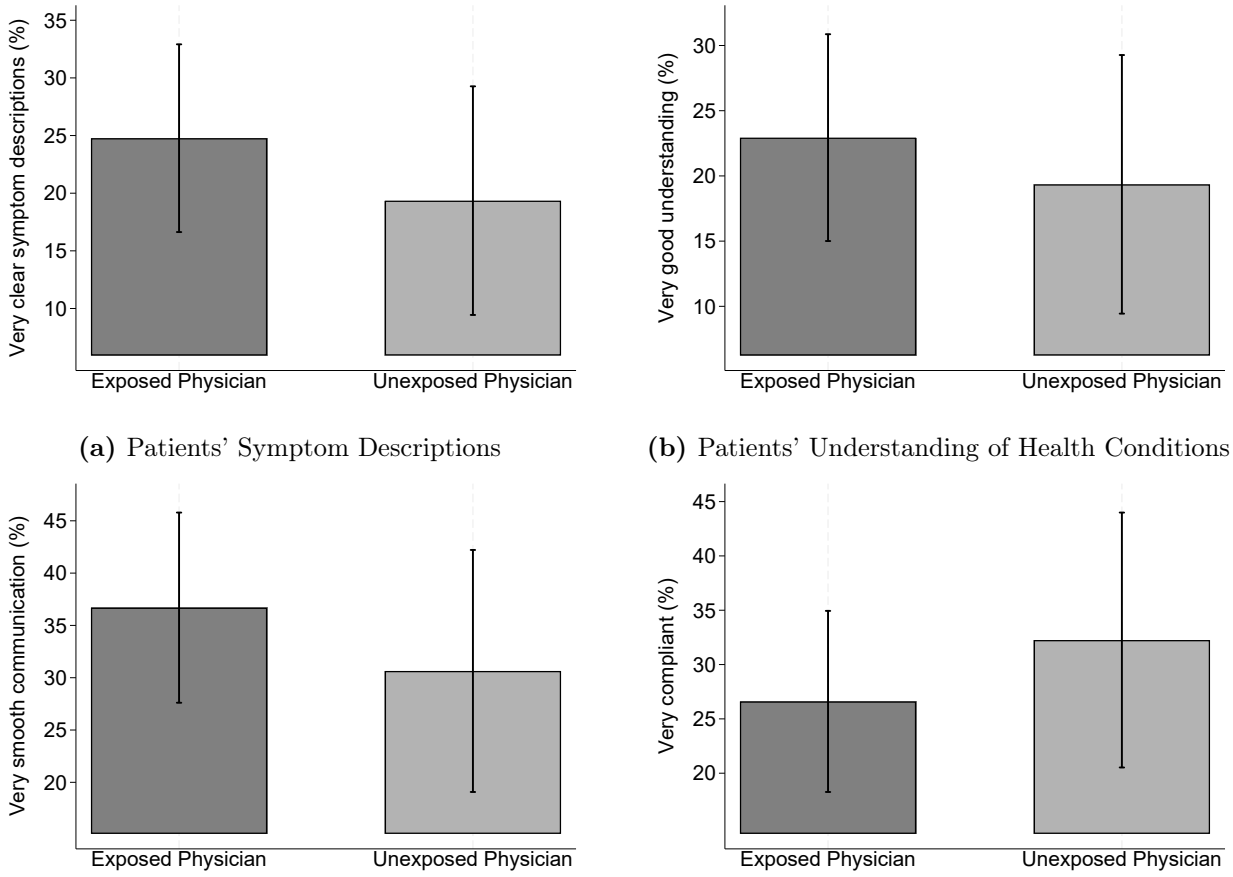
(d) Overall Satisfaction

(e) Physician–Patient Communication

(f) Intended Compliance

Figure 4. Patient Behavior and Perceptions by Treatment Status

Notes: Panels (a)–(c) report outcomes constructed from administrative medical records and capture patient attendance and realized post-consultation behavior. Panels (d)–(f) report outcomes from a post-consultation patient survey, comparing respondents in the *Treatment*, *Control*, and *Unexposed* groups. Percentages denote the share of patients with the indicated outcome or selecting the indicated response category, with 95% confidence intervals (dashed lines).



(a) Patients' Symptom Descriptions

(b) Patients' Understanding of Health Conditions

(c) Patients' Communication with Physicians

(d) Patients' Adherence to Medical Advice

Figure 5. Physicians' Perceptions of Patient Behaviors during Consultations

Notes: This figure reports physicians' survey responses collected after the conclusion of the experiment, comparing physicians randomized to the *Exposed* and *Unexposed* groups. Outcomes reflect physicians' perceptions of patient behavior during consultations. Percentages denote the share of physicians selecting the indicated response category, with 95% confidence intervals (dashed lines).

Table 1. Balance Test: Physician and Patient Characteristics

Panel A: Physician Characteristics

Variables	Exposed Arm		Unexposed Arm		Diff	p-value
	Mean	S.D.	Mean	S.D.		
Age	37.94	8.52	39.48	9.61	−1.54	0.29
Male	0.61	0.49	0.69	0.46	−0.09	0.25
Senior Physician	0.30	0.46	0.29	0.46	0.01	0.90
College Degree or Above	0.91	0.29	0.92	0.27	−0.01	0.76
Specialty: Internal Medicine	0.34	0.48	0.34	0.48	−0.00	0.97
Specialty: Surgery	0.26	0.44	0.23	0.42	0.04	0.56
Specialty: Psychiatry	0.24	0.43	0.27	0.45	−0.04	0.62
Specialty: Emergency	0.05	0.22	0.08	0.27	−0.03	0.47
Specialty: Other Dept.	0.12	0.33	0.11	0.32	0.01	0.89
Physicians	117		62			

Panel B: Patient Characteristics

	Treatment		Control		Unexposed		Treat vs Ctrl		Treat vs Unexp	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Diff	p-value	Diff	p-value
Age	45.36	16.92	45.33	16.93	45.49	17.24	0.02	0.95	−0.15	0.63
Male	0.36	0.48	0.36	0.48	0.36	0.48	−0.00	0.96	0.00	0.93
Occupation: Farmer	0.44	0.50	0.44	0.50	0.44	0.50	0.00	0.98	−0.00	0.97
Occupation: Formally Employed	0.24	0.43	0.23	0.42	0.24	0.43	0.01	0.20	−0.01	0.18
Occupation: Student	0.09	0.29	0.09	0.29	0.09	0.29	−0.00	0.92	0.00	0.89
Occupation: Other	0.07	0.26	0.07	0.26	0.07	0.26	−0.00	0.72	0.00	0.69
Unemployed or Retired	0.16	0.36	0.17	0.37	0.16	0.37	−0.01	0.23	−0.00	0.82
First-time Visit	0.70	0.46	0.70	0.46	0.70	0.46	−0.00	0.95	0.00	0.95
Advance Booking Time (hours)	24.63	27.08	24.90	28.02	24.96	27.59	-0.28	0.55	-0.32	0.48
Patients	5,828		5,838		6,010					

Table 2. Patient–AI Conversation Patterns by Topic

	Mention Rate		AI Attitude (% of AI mentions)			
Topic	Patient	AI	Rec Only	Rec+Caution	Caution Only	Neither
General medication	11.4%	58.9%	19.1%	44.2%	25.5%	11.3%
Diagnostic testing	8.5%	58.2%	94.5%	3.0%	0.3%	2.2%
Traditional Chinese Medicine	0.8%	11.0%	3.8%	3.8%	87.0%	5.3%
Antibiotics	0.1%	18.2%	7.8%	13.4%	74.2%	4.6%

Notes: The sample consists of 1,192 conversation turns from 956 patients with chatbot access. Mention rates are shares of all turns in which the topic appears, identified through keyword matching at the sentence level. Patient mentions are based on the patient message; AI mentions are based on the chatbot's reply. The four AI attitude categories are constructed from two independent binary flags assigned by GPT-4o for each turn in which the AI mentions the topic: whether the AI recommends the treatment or test, and whether it raises any caution or advises against its use. Attitude shares are computed as percentages of turns in which the AI mentions the topic and therefore sum to 100% within each row. A single turn can mention multiple topics, in which case it is classified independently for each topic.

Table 3. Within-Physician Intent-to-Treat Effects on Clinical Practice Patterns

	Dependent Variables					
	Prescribed medication	TCM	Antibiotics	Opioids	Diagnostic tests	Revisit
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No Controls						
Treated	−0.045***	−0.022***	−0.015**	−0.004	0.027***	−0.011*
	(0.006)	(0.007)	(0.006)	(0.003)	(0.008)	(0.007)
Mean	0.87	0.18	0.13	0.03	0.23	0.16
Observations	11,666	11,666	11,666	11,666	11,666	11,666
Panel B: Patient Characteristics & Physician FE						
Treated	−0.046***	−0.022***	−0.015**	−0.004	0.027***	−0.012*
	(0.006)	(0.007)	(0.006)	(0.003)	(0.008)	(0.007)
Patient Char.	Y	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y	Y
Mean	0.87	0.18	0.13	0.03	0.23	0.16
Observations	11,666	11,666	11,666	11,666	11,666	11,666

Notes: This table reports within-physician intent-to-treat estimates of the effect of chatbot access on clinical practice patterns. The sample is restricted to outpatient visits with *Exposed* physicians. Panel A reports estimates without controls; Panel B adds patient characteristics (age, gender, occupation, and an indicator for first visit) and physician fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Within-Physician Intent-to-Treat Effects on Healthcare Expenditures

	Dependent Variables				
	TCM costs (RMB)	WM costs (RMB)	Diagnostic costs (RMB)	Other costs (RMB)	Total costs (RMB)
	(1)	(2)	(3)	(4)	(5)
Panel A: No Controls					
Treated	−1.686*	−5.276*	6.542	0.174	−0.245
	(1.008)	(3.080)	(7.170)	(3.007)	(8.180)
Mean	13.10	64.81	92.69	35.88	206.48
Observations	11,666	11,666	11,666	11,666	11,666
Panel B: Patient Characteristics & Physician FE					
Treated	−1.762*	−5.021*	6.313	−0.002	−0.472
	(0.945)	(2.952)	(5.622)	(3.388)	(7.279)
Patient Char.	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y
Mean	13.10	64.81	92.69	35.88	206.48
Observations	11,666	11,666	11,666	11,666	11,666

Notes: This table reports within-physician intent-to-treat estimates of the effect of chatbot access on expenditures. The sample is restricted to outpatient visits with *Exposed* physicians. Panel A reports estimates without controls; Panel B adds patient characteristics (age, gender, occupation, and an indicator for first visit) and physician fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Instrumental Variable Estimates: Treatment Effects on Clinical Practice Patterns

	Dependent Variables					
	Prescribed medication	TCM	Antibiotics	Opioids	Diagnostic tests	Revisit
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No Controls						
Chatbot Usage	−0.265***	−0.128***	−0.090**	−0.026	0.161***	−0.066*
	(0.037)	(0.041)	(0.037)	(0.017)	(0.046)	(0.039)
Mean	0.87	0.18	0.13	0.03	0.23	0.16
Observations	11,666	11,666	11,666	11,666	11,666	11,666
F-statistic	1200.244					
Panel B: Patient Characteristics & Physician FE						
Chatbot Usage	−0.267***	−0.129***	−0.089**	−0.025	0.161***	−0.070*
	(0.037)	(0.042)	(0.037)	(0.017)	(0.046)	(0.040)
Patient Char.	Y	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y	Y
Mean	0.87	0.18	0.13	0.03	0.23	0.16
Observations	11,666	11,666	11,666	11,666	11,666	11,666
F-statistic	1186.766					

Notes: This table reports within-physician instrumental variable estimates of the effect of chatbot usage on clinical practice patterns, where chatbot usage is instrumented with random assignment to chatbot access. The sample is restricted to outpatient visits with *Exposed* physicians. Panel A reports estimates without controls; Panel B adds patient characteristics (age, gender, occupation, and an indicator for first visit) and physician fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Instrumental Variable Estimates: Treatment Effects on Healthcare Costs

	Dependent Variables				
	TCM costs (RMB) (1)	WM costs (RMB) (2)	Diagnostic costs (RMB) (3)	Other costs (RMB) (4)	Total costs (RMB) (5)
Panel A: No Controls					
Chatbot Usage	−9.884*	−30.933*	38.359	1.023	−1.436
	(5.542)	(17.227)	(33.189)	(19.306)	(42.585)
Mean	13.10	64.81	92.69	35.88	206.48
Observations	11,666	11,666	11,666	11,666	11,666
F-statistic			1200.244		
Panel B: Patient Characteristics & Physician FE					
Chatbot Usage	−10.331*	−29.437*	37.026	0.032	−2.710
	(5.551)	(17.308)	(32.967)	(19.862)	(42.677)
Patient Char.	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y
Mean	13.10	64.81	92.69	35.88	206.48
Observations	11,666	11,666	11,666	11,666	11,666
F-statistic			1186.766		

Notes: This table reports within-physician instrumental variable estimates of the effect of chatbot usage on healthcare expenditures, where chatbot usage is instrumented with random assignment to chatbot access. The sample is restricted to outpatient visits with *Exposed* physicians. Panel A reports estimates without controls; Panel B adds patient characteristics (age, gender, occupation, and an indicator for first visit) and physician fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Heterogeneous Treatment Effects by Physicians' Attitudes

	Dependent variables					
	Prescribed medication	TCM	Antibiotics	Opioids	Diagnostic tests	Revisit
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Physician Openness						
Treated × Openness	−0.069***	−0.037**	−0.017	−0.000	0.087***	−0.031
	(0.017)	(0.019)	(0.016)	(0.007)	(0.021)	(0.023)
Treated	−0.035***	−0.015	−0.011	0.000	0.007	0.004
	(0.007)	(0.008)	(0.007)	(0.003)	(0.009)	(0.009)
Patient Char.	Y	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y	Y
Mean	0.87	0.18	0.13	0.03	0.23	0.16
Observations	11,666	11,666	11,666	11,666	11,666	11,666
Panel B. Physician Authority						
Treated × Authority	0.036**	0.021*	0.023**	0.004	−0.031	0.007
	(0.016)	(0.012)	(0.011)	(0.007)	(0.020)	(0.017)
Treated	−0.068***	−0.031***	−0.026***	−0.003	0.046***	−0.019
	(0.014)	(0.011)	(0.010)	(0.006)	(0.018)	(0.016)
Patient Char.	Y	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y	Y
Mean	0.87	0.18	0.13	0.03	0.23	0.16
Observations	11,666	11,666	11,666	11,666	11,666	11,666

Notes: This table reports heterogeneous treatment effects by physicians' attitudes measured in the post-experiment survey. In Panel A, *Openness* equals one if the physician reported that medical knowledge acquired by patients from external sources is "very helpful" to physicians, and zero otherwise. In Panel B, *Authority* equals one if the physician strongly agreed with the statement "Patients should closely follow physicians' recommendations," and zero otherwise. All regressions control for patient characteristics (age, gender, occupation, and first-visit indicator) and include physician fixed effects. Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8. Heterogeneous Treatment Effects by Physicians' Attitudes Toward Medications

	Dependent Variables		
	TCM	Antibiotics	Opioids
	(1)	(2)	(3)
Treated × Pro-TCM	−0.029**		
	(0.014)		
Treated × Pro-antibiotic		−0.017	
		(0.012)	
Treated × Pro-opioid			−0.001
			(0.007)
Treated	−0.013	−0.009	0.001
	(0.011)	(0.009)	(0.006)
Patient Char.	Y	Y	Y
Physician FE	Y	Y	Y
Mean	0.18	0.13	0.03
Observations	11,666	11,666	11,666

Notes: This table reports heterogeneous treatment effects by physicians' attitudes toward different medications. Pro-TCM equals one if the physician selected "Equal emphasis on TCM and Western medicine" when asked about the relationship between TCM and Western medicine, and zero if the physician selected "Completely Western medicine" or "Western medicine primary, TCM supplementary." Pro-antibiotic equals one if the physician selected "Use is generally appropriate" when asked about antibiotic use in China, and zero if the physician selected "Obviously overused" or "Slightly overused." Pro-opioid equals one if the physician selected "Use is generally appropriate" when asked about opioid analgesic use in China, and zero otherwise. All regressions control for patient characteristics (age, gender, occupation, and an indicator for first visit) and include physician fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

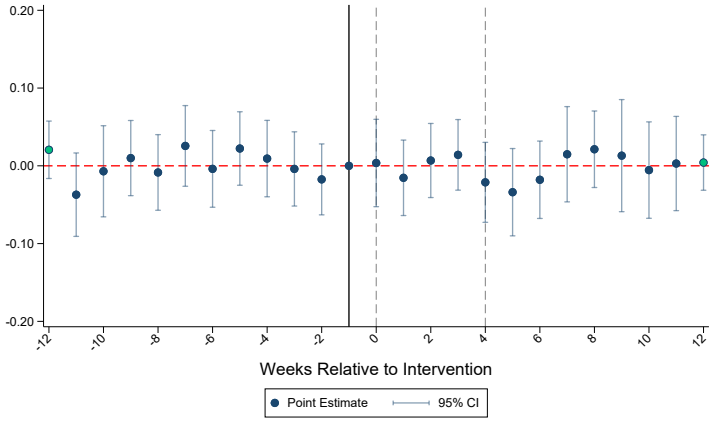
Table 9. Heterogeneous Treatment Effects by Physicians' Baseline Prescribing Intensity

	Dependent Variables		
	TCM	Antibiotics	Opioids
	(1)	(2)	(3)
Treated × High-TCM	−0.023**		
	(0.012)		
Treated × High-antibiotic		−0.019**	
		(0.009)	
Treated × High-opioid			−0.004
			(0.004)
Treated	−0.005	−0.003	0.004
	(0.009)	(0.008)	(0.005)
Patient Char.	Y	Y	Y
Physician FE	Y	Y	Y
Mean	0.18	0.13	0.03
Observations	11,666	11,666	11,666

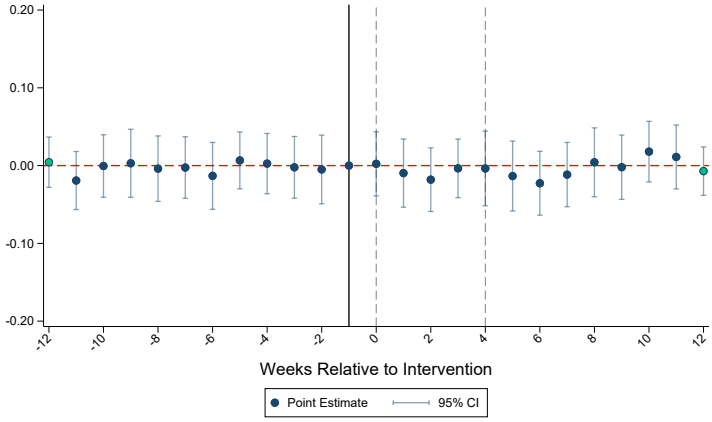
Notes: This table reports heterogeneous treatment effects based on whether a physician has above-median treatment intensity within their department prior to the experiment between January and May 2025. High TCM (High Antibiotic, High Opioid) is an indicator equal to one if the physician's pre-experiment mean prescribing rate for TCM (antibiotics, opioids) exceeds the department median, and zero otherwise. All regressions control for patient characteristics (age, gender, occupation, and an indicator for first visit) and include physician fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

ONLINE APPENDIX

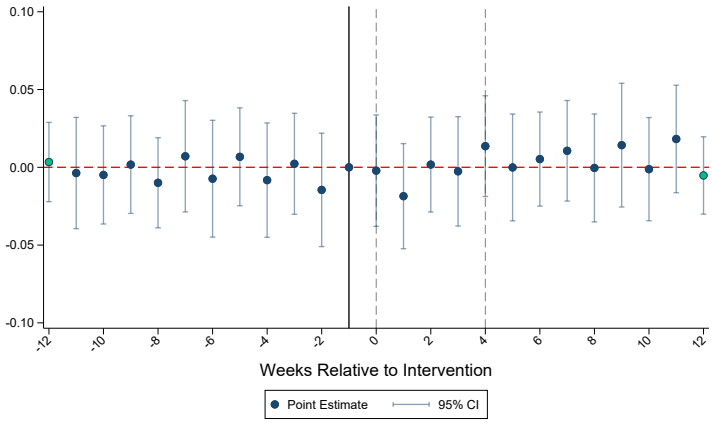
A Additional Figures and Tables



(a) Medication Prescription

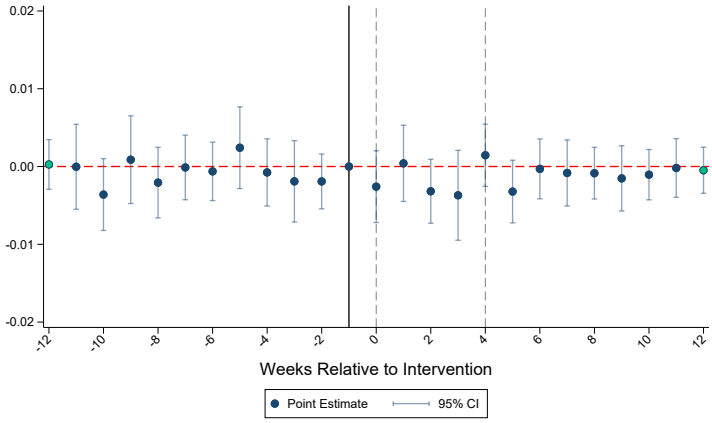


(b) TCM

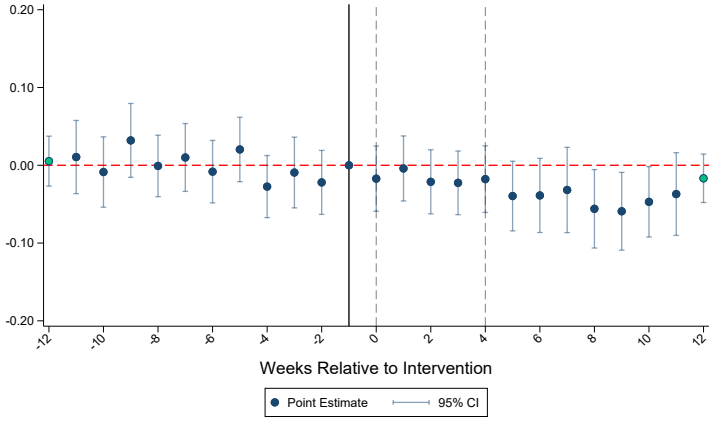


(c) Antibiotics

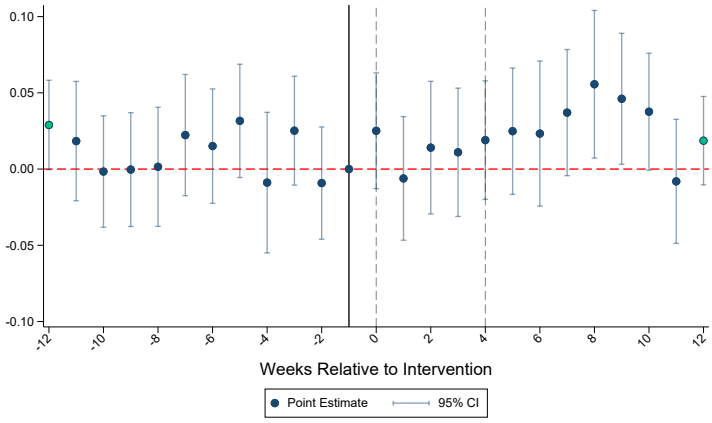
Figure A1. Dynamic Effects of Exposure to Treated Patients on Prescriptions and Clinical Practices, Excluding Treated Patients



(d) Opioids



(e) Diagnostic tests



(f) Revisit within 2 weeks

Figure A1. Dynamic Effects of Exposure to Treated Patients on Prescriptions and Clinical Practices, Excluding Treated Patients (Continued)

Notes: This figure presents the point estimates with 95% confidence intervals from equation (2). Data are aggregated to the physician-week level using patient visits from 2025, comparing those from *Control* group and *Unexposed* group, weighted by the number of visits per physician per week. Relative weeks beyond −12 and +12 are grouped at the endpoints. The baseline period is Week −1 (May 26–June 1, 2025). Standard errors are clustered at the physician level.

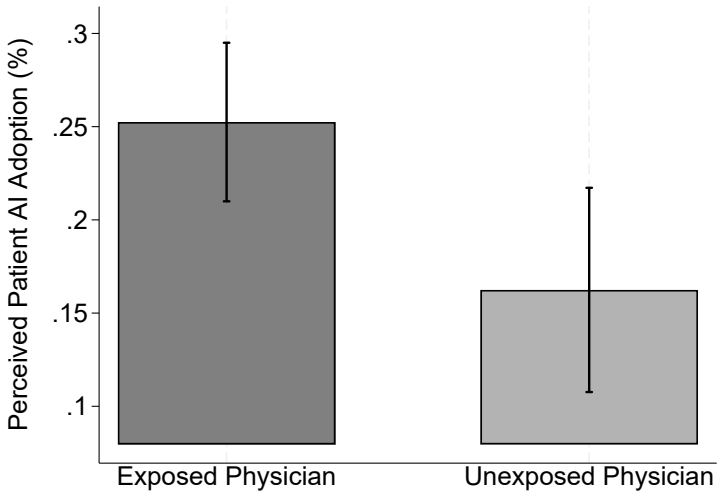


Figure A2. Physicians' Perceived Patient AI Adoption Rate

Notes: This figure reports physicians' survey responses collected after the conclusion of the experiment, comparing physicians randomized to the *Exposed* and *Unexposed* groups. The outcome variable is physicians' perceived share of patients who used generative AI chatbots prior to consultations during the experimental month, with 95% confidence intervals (dashed lines).

Table A1. Effect of Treatment on AI Adoption

	Whether Using AI Consulting Before Visit (1=Yes)	
	(1)	(2)
Treated	0.171***	0.170***
	(0.005)	(0.005)
Patient Characteristics	No	Yes
Observations	11,666	11,666
R-squared	0.093	0.098

Notes: This table reports linear probability estimates of the effect of treatment assignment on AI adoption, using the *Treatment* and *Control* samples. The dependent variable equals one if the patient used the AI chatbot before the visit, and zero otherwise. Column (1) includes only the treatment indicator, while Column (2) additionally controls for patient characteristics, including age, gender, occupation, and dummy for first visit. Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2. Patient Characteristics and AI Usage

	Whether Using AI Consulting Before Visit (1=Yes)			
	(1)	(2)	(3)	(4)
Age	−0.005***	−0.006***	−0.006***	−0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
Male		0.075***	0.055***	0.055***
		(0.009)	(0.012)	(0.012)
Students			−0.001	−0.009
			(0.019)	(0.020)
Farmers			−0.010	−0.008
			(0.013)	(0.013)
Formally Employed			0.067***	0.066***
			(0.013)	(0.014)
Unemployed/Retired			0.024	0.022
			(0.025)	(0.027)
First Visit				0.024**
				(0.010)
Mean	0.171	0.171	0.171	0.171
Observations	5,828	5,828	5,828	5,828

Notes: This table reports estimates from linear probability models examining the relationship between patient characteristics and AI usage. The dependent variable equals one if the patient used AI consulting before the visit, and zero otherwise. The sample is restricted to patients in the treatment group who have access to the chatbot. Columns (1)–(4) sequentially add patient characteristics, including age, gender, student status, occupation, employment status, and first visit status. Robust Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3. Robustness Checks for Intent-to-Treat Effects on Clinical Practice Patterns: Clustered Standard Errors

	Dependent Variables					
	Prescribed medication	TCM	Antibiotics	Opioids	Diagnostic tests	Revisit
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No Controls						
Treated	-0.045^{***}	-0.022^{***}	-0.015^{**}	-0.004	0.027^{***}	-0.011^{*}
	(0.006)	(0.007)	(0.006)	(0.003)	(0.008)	(0.007)
Mean	0.87	0.18	0.13	0.03	0.23	0.16
Observations	11,666	11,666	11,666	11,666	11,666	11,666
Panel B: Patient Characteristics & Physician FE						
Treated	-0.046^{***}	-0.022^{***}	-0.015^{***}	-0.004	0.027^{***}	-0.012
	(0.007)	(0.005)	(0.006)	(0.003)	(0.008)	(0.008)
Patient Char.	Y	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y	Y
Mean	0.87	0.18	0.13	0.03	0.23	0.16
Observations	11,666	11,666	11,666	11,666	11,666	11,666

Notes: This table reports within-physician intent-to-treat estimates of the effect of chatbot access on clinical practice patterns. The sample is restricted to outpatient visits with *Exposed* physicians. Panel A reports estimates without controls; Panel B adds patient characteristics (age, gender, occupation, and an indicator for first visit) and physician fixed effects. Standard errors clustered at physician level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4. Robustness Checks for Intent-to-Treat Effects on Healthcare Expenditures: Clustered Standard Errors

	Dependent Variables				
	TCM costs (RMB) (1)	WM costs (RMB) (2)	Diagnostic costs (RMB) (3)	Other costs (RMB) (4)	Total costs (RMB) (5)
Panel A: No Controls					
Treated	−1.686*	−5.276*	6.542	0.174	−0.245
	(1.008)	(3.080)	(7.170)	(3.007)	(8.180)
Mean	13.10	64.81	92.69	35.88	206.48
Observations	11,666	11,666	11,666	11,666	11,666
Panel B: Patient Characteristics & Physician FE					
Treated	−1.762*	−5.021	6.313	−0.002	−0.472
	(0.999)	(3.080)	(7.229)	(3.108)	(8.304)
Patient Char.	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y
Mean	13.10	64.81	92.69	35.88	206.48
Observations	11,666	11,666	11,666	11,666	11,666

Notes: This table reports within-physician intent-to-treat estimates of the effect of chatbot access on expenditure. The sample is restricted to outpatient visits with *Exposed* physicians. Panel A reports estimates without controls; Panel B adds patient characteristics (age, gender, occupation, and an indicator for first visit) and physician fixed effects. Standard errors clustered at physician level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5. Robustness Checks for Instrumental Variable Estimates for Clinical Practice Patterns: Clustered Standard Errors

	Dependent Variables					
	Prescribed medication	TCM	Antibiotics	Opioids	Diagnostic tests	Revisit
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No Controls						
Chatbot Usage	−0.265***	−0.128***	−0.090**	−0.026	0.161***	−0.066*
	(0.037)	(0.041)	(0.037)	(0.017)	(0.046)	(0.039)
Mean	0.87	0.18	0.13	0.03	0.23	0.16
Observations	11,666	11,666	11,666	11,666	11,666	11,666
First Stage F-statistics	1200.244					
Panel B: Patient Characteristics & Physician FE						
Chatbot Usage	−0.267***	−0.129***	−0.089***	−0.025	0.161***	−0.070
	(0.040)	(0.031)	(0.034)	(0.017)	(0.045)	(0.044)
Patient Char.	Y	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y	Y
Mean	0.87	0.18	0.13	0.03	0.23	0.16
Observations	11,666	11,666	11,666	11,666	11,666	11,666
First Stage F-statistics	1198.901					

Notes: This table reports within-physician instrumental variable estimates of the effect of chatbot usage on clinical practice patterns, where chatbot usage is instrumented with random assignment to chatbot access. The sample is restricted to outpatient visits with *Exposed* physicians. Panel A reports estimates without controls; Panel B adds patient characteristics (age, gender, occupation, and an indicator for first visit) and physician fixed effects. Standard errors clustered at physician level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6. Robustness Checks for Instrumental Variable Estimates for Healthcare Expenditures: Clustered Standard Errors

	Dependent Variables				
	TCM costs (RMB) (1)	WM costs (RMB) (2)	Diagnostic costs (RMB) (3)	Other costs (RMB) (4)	Total costs (RMB) (5)
Panel A: No Controls					
Chatbot Usage	−9.884*	−30.933*	38.359	1.023	−1.436
	(5.542)	(17.227)	(33.189)	(19.306)	(42.585)
Mean	13.10	64.81	92.69	35.88	206.48
Observations	11,666	11,666	11,666	11,666	11,666
First Stage F-statistics			1200.244		
Panel B: Patient Characteristics & Physician FE					
Chatbot Usage	−10.331*	−29.437	37.026	0.032	−2.710
	(5.882)	(18.145)	(42.349)	(18.244)	(48.711)
Patient Char.	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y
Mean	13.10	64.81	92.69	35.88	206.48
Observations	11,666	11,666	11,666	11,666	11,666
First Stage F-statistics			1198.901		

Notes: This table reports within-physician instrumental variable estimates of the effect of chatbot usage on healthcare expenditures, where chatbot usage is instrumented with random assignment to chatbot access. The sample is restricted to outpatient visits with *Exposed* physicians. Panel A reports estimates without controls; Panel B adds patient characteristics (age, gender, occupation, and an indicator for first visit) and physician fixed effects. Standard errors clustered at physician level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7. Robustness Checks for Intent-to-Treat Effects on Clinical Practice Patterns: First-Time Visit Subsample

	Dependent Variables					
	Prescribed medication	TCM	Antibiotics	Opioids	Diagnostic tests	Revisit
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No Controls						
Treated	−0.036***	−0.018**	−0.011	−0.006*	0.036***	−0.008
	(0.008)	(0.008)	(0.007)	(0.004)	(0.009)	(0.008)
Mean	0.81	0.16	0.12	0.04	0.28	0.14
Observations	8,166	8,166	8,166	8,166	8,166	8,166
Panel B: Patient Characteristics & Physician FE						
Treated	−0.037***	−0.018**	−0.011	−0.006	0.036***	−0.009
	(0.008)	(0.008)	(0.008)	(0.004)	(0.009)	(0.008)
Patient Char.	Y	Y	Y	Y	Y	Y
Physician FE	Y	Y	Y	Y	Y	Y
Mean	0.81	0.16	0.12	0.04	0.28	0.14
Observations	8,166	8,166	8,166	8,166	8,166	8,166

Notes: This table reports within-physician intent-to-treat estimates of the effect of chatbot access on clinical practice patterns. The sample is restricted to patients' first-time outpatient visits with *Exposed* physicians. Panel A reports estimates without controls; Panel B adds patient characteristics (age, gender, occupation, and an indicator for first visit) and physician fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8. Effect of Chatbot Access on Patient Perceptions of the Consultation

	Satisfaction (1)	Communication (2)	Compliance (3)
Treated	−0.032	−0.035*	−0.041**
	(0.020)	(0.019)	(0.019)
Patient Char.	Y	Y	Y
Physician FE	Y	Y	Y
Mean	0.86	0.85	0.87
Observations	1,418	1,418	1,418

Notes: This table reports the effect of chatbot access on patient survey responses following the consultation. The dependent variables are binary indicators equal to one if the patient reported (1) being "very satisfied" with the consultation, (2) perceiving physician–patient communication as "very smooth," and (3) intending to "fully comply" with the physician's medical advice. The sample is restricted to survey respondents in the *Treatment* and *Control* groups. All regressions control for patient characteristics (age, gender, occupation, and an indicator for first visit) and include physician fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9. Effect of Patient AI Adoption on Physicians' Perceptions of the Consultation

	Clarity	Understanding	Communication	Compliance
	(1)	(2)	(3)	(4)
Panel A: No Controls				
Share of AI Adopters	0.242	0.228	0.014	−0.215*
	(0.147)	(0.146)	(0.162)	(0.121)
Mean	0.23	0.22	0.35	0.29
Observations	171	171	171	171
Panel B: Physician Characteristics & Department FE				
Share of AI Adopters	0.267*	0.187	0.063	−0.217*
	(0.146)	(0.142)	(0.163)	(0.125)
Mean	0.23	0.22	0.35	0.29
Observations	171	171	171	171

Notes: This table reports the effect of patient AI adoption on physicians' perceptions of the consultation. The dependent variables are binary indicators equal to one if the physician reports that (1) the patient described their symptoms "very clearly"; (2) the patient demonstrated "very good understanding" of their health condition; (3) communication with the patient was "very smooth"; and (4) the patient was "very compliant" with physician instructions. The unit of observation is the physician. *Share of AI Adopters* is the fraction of a physician's patients who used the AI chatbot, equal to zero for *Unexposed* physicians by construction. Panel A includes no controls. Panel B controls for physician characteristics (gender, education, years of experience, and seniority) and includes department fixed effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Analyses of Patient–AI Conversation Logs

This appendix provides additional detail on the analyses the patient–AI conversation logs. The analytic sample contains 1,192 turns from 956 patients. A turn consists of a single patient message and the AI's reply. Most patients (81.5 percent) interact with the chatbot in a single turn; the remaining 18.5 percent have multi-turn conversations, with two-turn conversations accounting for the majority of these. The analysis proceeds in three steps. We first classify each patient message by its intent, in order to characterize what patients ask the chatbot. We then identify, for each conversation turn, which of four clinical topics the patient and the AI discuss. Finally, for each topic the AI discusses, we classify the AI's stance along two dimensions: whether the AI recommends use of the treatment or test, and whether it raises any caution against use.

B.1 Patient Intent

We classify the intent of each patient message into one of eight categories. Five categories cover the medical content of the consultation: symptom inquiries, in which the patient describes symptoms and asks for a diagnosis or cause; test result inquiries, in which the patient shares a lab result and asks for an interpretation; treatment inquiries, in which the patient asks how to manage a condition or which medication to take; test inquiries, in which the patient asks whether to undergo a specific test; and lifestyle inquiries, in which the patient asks about diet, exercise, or daily self-care. Two categories cover the practicalities of obtaining care: care-seeking, in which the patient asks whether, when, or where to see a doctor, and administrative inquiries about cost, insurance, or scheduling. The descriptive shares reported in Section 4.1 combine these last two into a single "logistical questions" share, since both concern how to obtain care rather than its medical content. A residual "other" category collects greetings and uninformative messages.

Classification is performed by GPT-4o-mini at temperature zero. For each message, the model is given the eight category definitions and returns a primary label, defined as the label that best captures the message's main intent, and zero or more secondary labels. We instruct the model to assign secondary labels only when the message explicitly raises a second distinct topic, not when a second topic is merely implied by the primary.

Table B10 reports the distribution of primary intent labels across the 1,192 messages in the

analytic sample, together with a representative example of each. Symptom inquiries account for two-thirds of all messages; treatment inquiries are the next largest category, followed by smaller shares of lifestyle, test, care-seeking, result, and administrative inquiries.

Table B10. Primary Intent Distribution and Examples

Intent	N	%	Example patient message (translated)
Symptom inquiry	795	66.7	"Lately I keep feeling tightness in my chest. It hurts a little when I breathe deeply. It's been about a week."
Treatment inquiry	140	11.7	"Do I need to take any medicine? Can I take Suxiao Jiuxin Wan?"
Lifestyle inquiry	65	5.5	"One more question: can I exercise during this period, or will it make symptoms worse?"
Test inquiry	59	4.9	"My foot is still swollen. Should I get an X-ray?"
Care-seeking	51	4.3	"How long do I have to wait before I can get a dental implant?"
Result inquiry	37	3.1	"I'm a 35-year-old woman. A recent physical showed an elevated AST/ALT ratio of 1.64."
Administrative inquiry	28	2.3	"If I get tested at the CDC, do I have to use my real name? Will there be a record?"
Other	17	1.4	"I haven't had that nasal endoscopy."

Notes: Sample of 1,192 patient messages from 956 patients with chatbot access. Each message is assigned exactly one primary intent label. Examples are translated from the original Mandarin.

B.2 Topic Identification

The remaining analysis examines the clinical content of the conversation. We focus on four topics that correspond to the clinical outcomes studied in the main analyses: general medication (excluding TCM and antibiotics), diagnostic testing, Traditional Chinese Medicine, and antibiotics. For each

turn, and separately for the patient's message and the AI's reply, we record whether each topic is mentioned.

Topic mentions are identified by keyword matching at the sentence level. We split each message into sentences and check whether any sentence contains a keyword associated with the topic. Sentence-level matching, rather than document-level matching, prevents false positives that arise when distantly related terms co-occur in long structured replies. A turn may match multiple topics, in which case it enters each topic's analysis independently.

Two topic-specific refinements are worth noting. For general medication, we exclude any sentence whose match is driven by a TCM keyword, an antibiotic keyword, or a marker for non-pharmacological treatment, so that the residual category captures conventional Western pharmaceuticals without overlapping the TCM and antibiotic categories. For diagnostic testing, we distinguish always-specific test names, which match on their own (for example, complete blood count, CT, or endoscopy), from condition terms such as liver function, which match only when paired with a testing-action verb in the same sentence; this prevents the AI's general references to a clinical condition from being miscoded as references to a test.

Table B11 summarizes the keyword scope for each topic.

B.3 AI Stance

For every turn–topic pair in which the AI mentions a topic, we classify the AI's stance along two dimensions: whether the AI recommends the treatment or test, and whether it raises a caution against use. We treat these as independent binary flags. Clinical guidance often combines both: a passage may recommend acetaminophen for fever above 38.5°C while warning against self-administration of cough suppressants, or recommend physician-supervised use of an antibiotic while discouraging patient-initiated use. Coding the two dimensions separately yields four interpretable cells per topic: recommend without caution, recommend with caution, caution without recommending, and neither.

Classification is performed by GPT-4o at temperature zero. For each turn–topic pair, we extract the topic-matching sentences from the AI reply, concatenate them into a single passage, and submit the passage together with the topic name. The model is instructed to evaluate the two flags only with respect to how the AI frames the specified topic, and to return the dominant stance over the full passage when individual sentences differ.

Table B11. Keyword scope for topic identification.

Topic	Keyword scope
General medication	Sentence contains the generic term for medication or a specific drug name (e.g., ibuprofen, acetaminophen, aspirin, metformin, omeprazole, statins, progesterone); excludes sentences also matching TCM, antibiotic, or non-pharmacological keywords.
Diagnostic testing	Always-specific test names (e.g., complete blood count, CT, MRI, ultrasound, endoscopy, biopsy) match directly; condition terms (e.g., liver function, lipid panel, thyroid function) match only when paired with a testing-action verb in the same sentence.
TCM	Chinese herbal medicine, proprietary Chinese medicines, traditional Chinese medicine practice, herbal decoctions, acupuncture, and tuina massage.
Antibiotics	Generic antibiotic terms and named agents (penicillin, amoxicillin, cephalosporins, azithromycin, erythromycin, levofloxacin, ofloxacin, metronidazole, tinidazole, clarithromycin, roxithromycin, doxycycline, tetracycline). The colloquial Chinese term for "anti-inflammatory medicine," which patients use loosely, is treated as general medication rather than antibiotics.

Three features of the prompt warrant emphasis. First, the prompt specifies that providing dosage, timing, or usage instructions for a treatment counts as recommending it, even when no explicit directive appears, since these instructions carry the same operative meaning as an explicit recommendation. By the same logic, listing tests with diagnostic purposes counts as recommending the tests, and urging the patient to seek care urgently counts as a recommendation rather than a caution. Second, the prompt distinguishes deferring to a physician from recommending physician-supervised use: telling the patient to consult a physician about whether to use a treatment is not coded as a recommendation, while instructing the patient to use a treatment under physician guidance is. Third, the prompt treats negative statements as cautions: stating that a treatment is not needed, not indicated, or not effective for the condition is coded as cautioning, since these statements function as discouragements of use even when the AI does not invoke risk or side effects.

Table B12 reports representative AI replies illustrating each of the main attitude cells.

Table B12. Illustrative classification examples.

Topic	Label	Excerpt from AI reply
General medication	(yes, no)	Fever reduction: medication is generally not needed below 38.5°C; above 38.5°C, acetaminophen (e.g., Tylenol) may be used at the dose indicated on the label.
General medication	(yes, yes)	Do not self-administer strong cough suppressants (e.g., those containing codeine). The following is for reference only; specific use must follow physician guidance. For productive cough, ambroxol (Mucosolvan) may be considered as an expectorant. For fever, acetaminophen (Tylenol) is appropriate when temperature is at least 38.5°C.
General medication	(no, yes)	Lifestyle intervention should be the first line of treatment, rather than rushing to medication. If episodes occur more than twice within a year, or if uric acid remains above 540 μmol/L, the patient should seek hospital care to evaluate whether urate-lowering therapy is needed.
Diagnostic testing	(yes, no)	If fever persists beyond the third day or worsens, please go to the hospital promptly for a complete blood count and other basic tests to determine whether the infection is viral or bacterial.
TCM	(no, yes)	Self-administration of Chinese herbal medicine or proprietary Chinese medicines to "dissolve nodules" is not recommended; routine follow-up should be the main course of action.
Antibiotics	(no, yes)	Self-use of antibiotics is not recommended. If grinding-related tooth pain has reached the pulp, decompression is required; antibiotics cannot relieve intra-pulp pressure and have no effect on the cavity itself.

Notes: Excerpts are translated from the original Mandarin and lightly condensed. The label column reports (*recommends*, *cautions*).