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How Does Generative AI Reshape Chinese Patients' Perceptions of Medical Authority?

Xue Yuan [1], Qiqi Jin [1], Yulong Tang [1], and Jinghong Xu [2,3]

[1] School of Journalism and Communication, Beijing Institute of Graphic Communication, China
[2] School of Journalism and Communication, Beijing Normal University, China
[3] International College, Krirk University, Thailand

Correspondence: Jinghong Xu (123abctg@163.com)

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Abstract

Employing a sequential mixed-methods design combining survey ($N = 607$), interviews ($N = 30$), and digital ethnography, the study traces pathways from technology adoption to clinical interaction and introduces the concept of "algorithm-mediated negotiated authority." Findings indicate that trust in generative AI arises from both perceived technical capability and socially conferred legitimacy, mediated by cognitive load. Health literacy and technology anxiety moderate this process, resulting in unequal empowerment. Authority is dynamically co-constructed as patients strategically introduce AI advice and physicians respond with explanatory, reassertive, or reserved strategies. Theoretically, the study bridges macro-level power critique with micro-behavioral analysis, advancing the "medical gaze" into a "negotiated gaze." It extends technology acceptance models by emphasizing legitimacy construction and cognitive internalization, framing generative AI as a reconstructive force that reshapes clinical communication.

Keywords

algorithmic mediation; doctor–patient communication; generative AI; health communication; medical authority; technology acceptance

1. Introduction

The rise of generative AI (GAI) is redrawing the boundaries of clinical authority. Patients now enter consultations not only with symptoms but armed with algorithmic suggestions that can rival or challenge the physician's judgment.

This shift unsettles medical authority, which Foucault (1973) conceptualized through the "medical gaze"—a power-laden mode of observation granting physicians interpretive dominance over the patient's body. By monopolizing specialized knowledge, physicians assert epistemic authority over illness, creating an information asymmetry that leaves patients little recourse but tacit compliance (Haug & Lavin, 1983). Today, large language models are lowering barriers to medical knowledge at unprecedented scale and speed (Dave et al., 2023; Meskó & Topol, 2023). By rendering specialized terminology into accessible health narratives, GAI challenges the discursive privilege traditionally held by physicians (Lupton, 2012), altering the knowledge barriers that once sustained professional dominance. It also promotes the inclusion of multiple actors and transforms modes of interaction between experts and non-experts (Taddicken & Krämer, 2021).

Despite celebrations of AI democratizing access to evidence and care, the reshaping of authority is more complex than a straightforward redistribution of professional dominance. Patients increasingly turn to GAI for self-triage, becoming active participants in constructing their own health narratives (Traylor et al., 2025; Woods et al., 2025). This tendency is particularly salient in China, where rapid digital adoption meets deeply embedded cultural patterns: strong reliance on institutional authority, high power-distance norms, and distinct doctor–patient dynamics (Hofstede, 2001; Tucker et al., 2015). From JD Health's AI assistant, Kangkang, attracting over 30 million users, to the integration of GAI into auxiliary diagnosis—such technology is visibly reshaping clinical practice. China thus becomes a critical site for observing how algorithmic tools reconfigure professional authority.

This study traces how GAI reshapes Chinese patients' perceptions of medical authority, moving beyond broad theoretical claims to examine the specific mechanisms at work. We employ a sequential mixed-methods design. The logic is cumulative: A large-scale survey identifies key drivers of adoption and trust in GAI; in-depth interviews explore cognitive shifts regarding authority; digital ethnography examines how internalized perceptions surface in real clinical dialogues. By moving from statistical correlation to cognitive interpretation to observable interaction, this design attends to the situated dynamics emerging when algorithmic advice enters clinical encounters.

2. Literature Review

2.1. The Knowledge Monopoly of Traditional Medical Authority

Traditional medical authority rests on the power–knowledge symbiosis described by Foucault (1973, 1977). Physicians secured a monopoly over defining disease and interpreting the body through specialized discourse, clinical rituals, and archival practices. Central to this is the "medical gaze," an observational mode that objectifies patients and decodes their bodies unidirectionally via professional knowledge. This gaze operates in diagnosis and dominates consultation processes, dictating how illness is constructed in clinical communication (Durieux et al., 2025; Waitzkin, 1991).

In China, this authority is reinforced by distinctive cultural foundations. The moralized “benevolent physician” grants inherent ethical authority, while high power-distance means patients are more likely to defer to doctors (Hofstede, 2001; X. Zhang & Sleeboom-Faulkner, 2011). Traditional Chinese Medicine’s emphasis on “syndrome differentiation and treatment” places weight on physicians’ personal experience, with medical judgments embedded in familial collective decision-making (Yan & Yang, 2025). Together, these factors shape a hybrid “professional-relational” authority that is more complex and resilient. Traditional medical authority is thus not merely specialized knowledge but a layered system integrating cognitive monopoly, institutional status, moral legitimacy, and cultural expectations.

2.2. Dual Research Trajectories on Technological Intervention

GAI unsettles clinical authority through two capabilities: translating specialized discourse and equipping patients with independent knowledge resources.

First, GAI renders complex medical terminology into accessible health narratives while providing real-time multilingual support (Ayers et al., 2023; Clusmann et al., 2023; Grewal et al., 2023). This capability challenges the physicians’ long-held monopoly over professional discourse, enabling medical knowledge to flow into the public domain. From a Foucauldian perspective, this lowers the knowledge barriers sustaining the “medical gaze,” potentially equipping patients with a “counter-gaze.”

Second, GAI offers preliminary diagnostic suggestions, treatment comparisons, and evidence summaries (Singhal et al., 2023), enabling users to independently generate, verify, or contest medical judgments. Unlike shared decision-making (SDM), this empowerment originates externally rather than by physician invitation, moving clinical interaction toward a more contested space where competing knowledge sources (algorithmic, experiential, professional) become explicit topics of discussion. Yet this empowerment is unevenly distributed, depending on digital literacy and risking a deepening of existing health inequalities (Timmermans & Kaufman, 2020).

Academic research has evolved along two separate tracks.

The instrumental-rational perspective splits into technology acceptance and cognitive transformation. Studies grounded in technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT) predict adoption through constructs such as perceived technological capability (PTC), perceived ease of use (PEOU), and social influence (SI; Davis, 1989; Venkatesh et al., 2003). These models predict whether patients use GAI but seldom examine how usage reshapes cognitive structures and social relationships (Bagozzi, 2007). The cognitive transformation trajectory draws on cognitive trust (CT; McKnight & Chervany, 2001) and cognitive load (CL; Sweller, 1988) to examine how psychological strain influences trust formation. Its limitation is abstracting psychological mechanisms from socio-cultural contexts. While illuminating micro-level antecedents, this perspective struggles to account for macro-level power shifts.

The macro-critical perspective, rooted in sociology, science and technology studies, and critical theory, builds on Foucault’s power–knowledge analysis. It offers insights into how technology reconfigures established structures of professional authority (Latour, 2005). It excels at structural analysis, tracing the broad contours of authority reconfiguration. But it brackets the psychological mechanisms through which these shifts occur, rarely specifying how reconfiguration unfolds through patients' cognitive processes, trust formation, or communicative actions. The result is a failure to bridge macro-structural change with micro-level behavioral practices.

2.3. Bridging the Gap: Toward an Integrative Perspective

Current understandings remain fragmented: Macro-level critiques trace broad power shifts, while micro-level studies map individual cognitions, yet neither fully explains how authority is actively negotiated in technology-saturated encounters. What is missing is an integrative lens that connects behavior, cognition, and interaction (Leonardi, 2013).

To address this, this study proposes an analytical framework spanning three interconnected levels: technology acceptance, cognitive transformation, and interactive negotiation. This framework is a holistic lens connecting micro-level adoption behaviors, meso-level cognitive shifts, and macro-level clinical interaction where power is negotiated.

The core premise is straightforward: To understand how GAI reshapes medical authority, we must examine not merely whether patients use the technology, but what happens when they do. This requires asking (a) what initially motivates patients to turn to GAI (technology acceptance); (b) how usage reorganizes their cognitive and trust schemas (cognitive transformation); and (c) how these reconfigured cognitions are mobilized in clinical dialogues, setting in motion authority renegotiation (interactive negotiation).

Based on this integrated framework, which positions clinical interaction as the site where macro-structural shifts in authority are negotiated through micro-level discursive practices, the study addresses:

> Primary Research Question (PRQ): How does GAI mediate and reshape medical authority within Chinese doctor–patient relationships, specifically, through its influence on patients' technology acceptance, cognitive transformation, and interactive negotiation?
>
> RQ1 (Technology Acceptance): What factors shape Chinese patients' adoption of GAI for health-related inquiries?
>
> RQ2 (Cognitive Transformation): How does consulting GAI reconfigure patients' perceptions of medical authority—its knowledge base, its social role, its trustworthiness?
>
> RQ3 (Interactive Negotiation): What discursive practices and interaction patterns emerge when patients introduce AI-generated advice during clinical consultations, and how do these micro-processes of negotiations reflect, and further reconfigure, medical authority?

3. Theoretical Framework and Research Hypotheses

The literature review reveals a disconnect: Micro-level research on technology acceptance and cognitive transformation has developed largely independently of macro-level critiques of power, and neither explains how cognitive shifts translate into clinical negotiation. To address RQ1 and RQ2, and to establish antecedents for RQ3, this section develops an integrated "technology acceptance–cognitive transformation dual-path model" (Figure 1). The model traces how patients move from adopting GAI to forming CT, a cognitive capital available for subsequent clinical interactions.

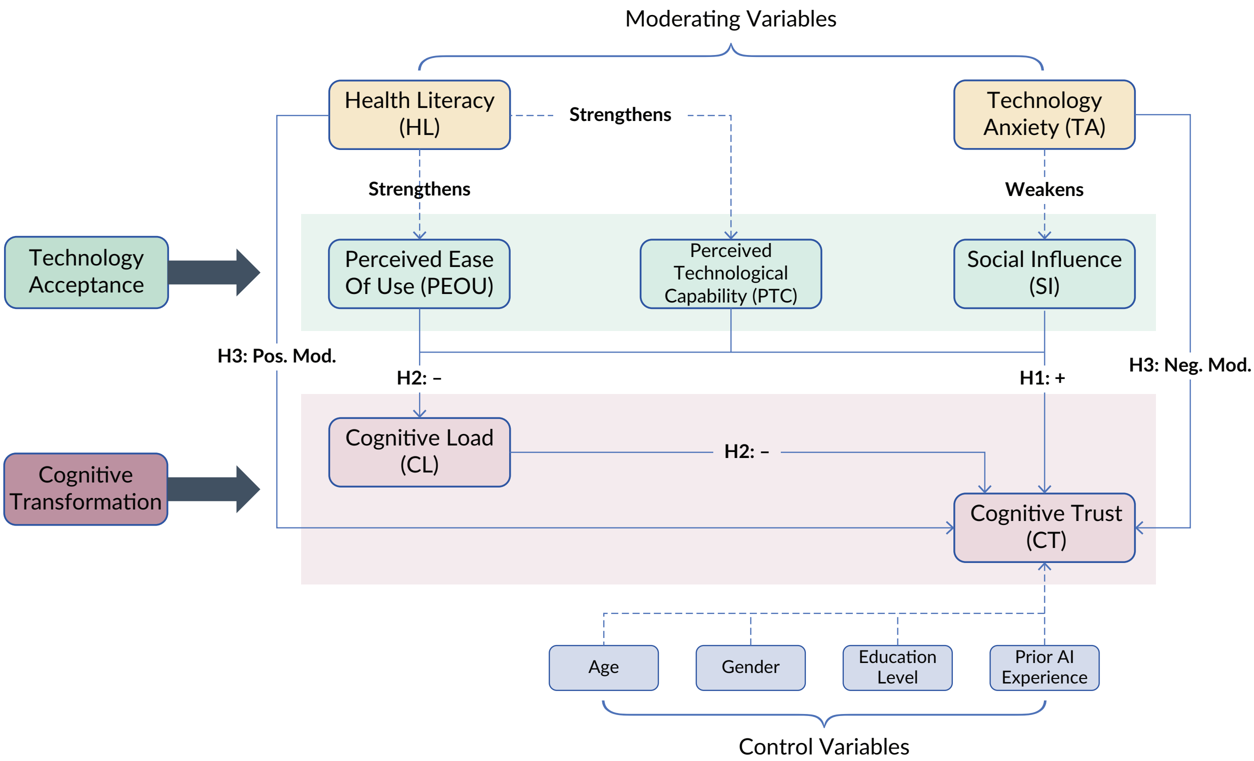

Figure 1. Conceptual model of the quantitative study.

3.1. Overall Model Logic

The model consists of two sequentially linked pathways. The technology acceptance pathway captures the motivations to turn to GAI, behavioral triggers in authority reconfiguration, anchored by PTC, PEOU, and SI. The cognitive transformation pathway opens the psychological "black box" between usage and trust formation, with CL as mediator and CT as endpoint, showing how external technological experiences become internalized resources. These pathways link through CL: technological antecedents → cognitive experience → trust capital. CT, conceptualized as "patient cognitive capital," is not a terminus but a resource patients carry into clinical interactions, shaping their confidence and discursive strategies. This provides the micro-psychological foundation for addressing RQ3.

3.2. The Technology Acceptance Pathway

This pathway extends the TAM to explain what exposes patients to GAI, situated within China's high-context and high-uncertainty medical environment.

PTC adapts the perceived usefulness construct from TAM (Davis, 1989; D. Zhang & Zhao, 2024), referring to users' assessment of GAI's accuracy and coherence. When patients perceive GAI as capable, it challenges physicians' standing as the sole credible knowledge source (Tan & Goonawardene, 2017).

PEOU captures the degree to which a user believes that interacting with the technology requires minimal effort (Davis, 1989; Lee et al., 2025). Intuitive, low-threshold interaction is a prerequisite for broad patient accessibility and sustained cognitive engagement with the technology.

SI refers to the extent to which an individual perceives that significant others (family, peers, or experts) believe they should use the system (Meng & Guo, 2024; Venkatesh et al., 2003). In China's collectivist, high power-distance context (Hofstede, 2001), social network endorsements carry particular weight. When medical authority figures endorse GAI, they grant patients legitimacy, reducing perceived adoption risks (Lawton et al., 2015).

3.3. The Cognitive Transformation Pathway

This pathway addresses how psychological processes mediate between use and stable trust, linking individual cognition to social practice. We conceptualize CL as a micro-level mediator and CT as the internalized resource patients carry into clinical interactions.

CL serves as a key psychological mediator, grounded in cognitive load theory (Sweller, 1988; Sweller et al., 2019). Factors inherent to GAI interaction—information complexity, jargon density, or interface intuitiveness—directly influence extraneous CL (R. E. Mayer & Moreno, 2003). High CL impedes effective information processing and hinders trust formation; low CL facilitates comprehension and knowledge assimilation. CL thus functions as a regulatory mechanism, determining whether technological experience converts into positive cognitive appraisal.

CT is the core outcome variable, trust based on a rational evaluation of an agent's competence, reliability, and professionalism (R. C. Mayer et al., 1995). In the AI context, CT originates from the user's assessment of its technical logic, evidentiary basis, and perceived expertise (Glikson & Woolley, 2020). Conceptualized as internalized trust capital, CT enables patients to move from passive recipients to cognitively equipped participants capable of inquiry and negotiation, thereby contributing to the reconfiguration of medical authority.

3.4. Model Integration

These two pathways form a sequential chain: technology acceptance factors (PTC, PEOU, SI) → influence on CL → CT formation. CT is not a terminus but a precursor, a novel form of "patient capital" patients carry into clinical encounters. When patients equipped with GAI-facilitated CT translate this trust into discursive action, they set in motion algorithm-mediated authority negotiation. Physicians' responsive strategies co-constitute the dynamic (re)production of authority.

This conceptualization bridges individual technology adoption with the social reconstruction of clinical relationships, providing the foundation for examining how internalized trust is mobilized in clinical dialogue (RQ3).

3.5. Boundary Conditions

The dual-path model's strength varies across individuals. Introducing health literacy (HL; Nutbeam, 2000) and technology anxiety (TA; Heinssen et al., 1987) as boundary conditions helps explain why identical technological exposures yield divergent outcomes.

HL refers to the capacity to access, comprehend, evaluate, and apply health information. Higher HL equips individuals to better decode and assess GAI outputs (Nasra et al., 2025). We hypothesize that HL positively moderates the relationship between technology acceptance factors (PTC and PEOU) and CT development. Specifically, the positive effects of PTC and PEOU on CT are stronger for patients with higher HL.

TA refers to apprehension toward using technology, acting as a psychological filter between SI and trust formation. Even in socially supportive environments, individuals with high TA are likely to attenuate the social norms' positive impact due to internal discomfort. We therefore hypothesize that TA negatively moderates the SI–CT relationship. Specifically, the positive effect of SI on CT is weaker for patients with higher TA.

Based on the integrated framework, the study proposes three core hypotheses:

> H1 (Foundational Driving Effect of Technology Acceptance): PTC, PEOU, and SI are positively associated with CT.
>
> H2 (Core Mediating Effect of CL): CL mediates the relationship between technology acceptance factors (PTC, PEOU, SI) and CT, exerting a negative mediating effect.
>
> H3 (Differentiated Moderating Effect of User Characteristics): HL positively moderates the PTC–CT and PEOU–CT relationships (stronger for higher HL). TA negatively moderates the SI–CT relationship (weaker for higher TA).
>
> Control Variables: Age, gender, education, and prior AI experience are included to isolate theoretical constructs. No directional hypotheses are proposed.

4. Method

We adopt an explanatory sequential mixed-methods design. The research unfolds as a three-stage "explanatory cascade": A survey maps statistical patterns; interviews interpret cognitive processes; digital ethnography observes how internalized cognitions surface in clinical interaction. Together, the three stages form an evidentiary chain moving from establishing what relationships exist, to explaining why, and finally to demonstrating how they manifest in practice (Figure 2). The methods are designed not merely to confirm one another but to challenge and refine interpretations across phases. This logic unfolds as follows:

> Stage 1: Quantitative "Mapping"—A large-scale survey identifies key variables influencing trust and delineates their structural relationships.

Stage 2: Qualitative "Interpretation"—In-depth interviews explore the cognitive logics and cultural scripts underlying the statistical patterns, surfacing contradictions where lived experiences diverge from survey trends.

Stage 3: Naturalistic "Observation"—Digital ethnography captures how internalized cognitions are externalized into discursive practices within actual clinical encounters.

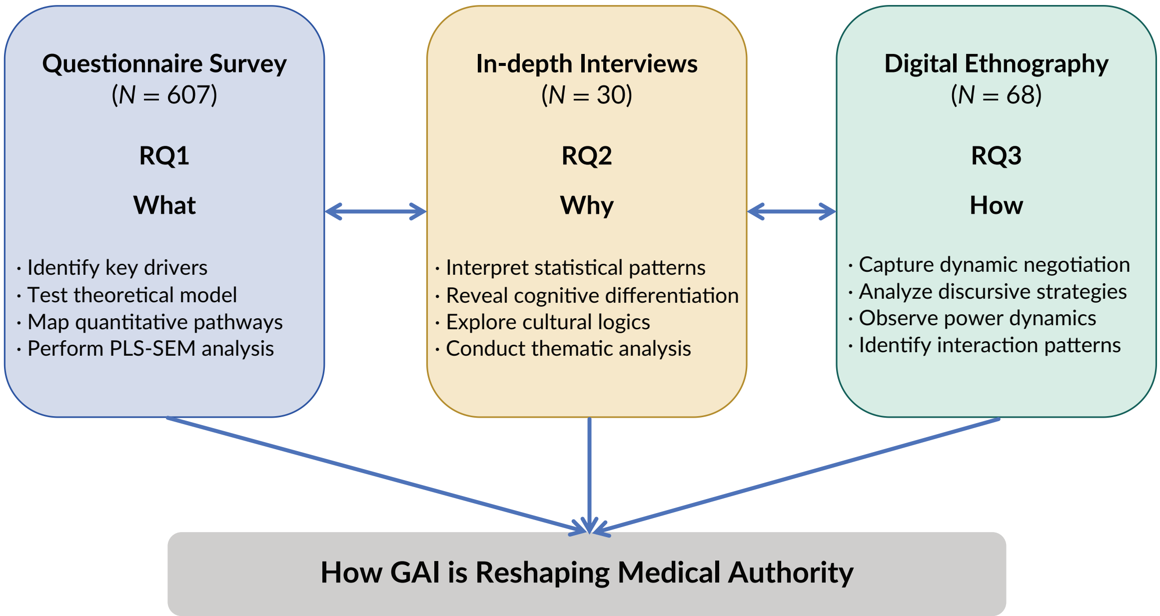

Figure 2. Flowchart of the three-step sequential mixed-methods research design. Note: PLS-SEM = partial least squares structural equation modeling.

4.1. Questionnaire Survey: Mapping Key Drivers and Psychological Pathways

Administered from February to April 2025, an online questionnaire mapped the factors shaping Chinese patients' trust in GAI, identifying precise variables for subsequent investigation.

Following ethical approval, questionnaire links were distributed through the official channels of four Grade A tertiary hospitals in Beijing, Shanghai, and Guangzhou. Recruitment was supplemented by online chronic disease communities and snowball sampling. The final sample of 607 valid respondents consisted primarily of middle-aged and younger adults with higher education levels—a demographic profile consistent with early adopters of digital health technologies (Rogers, 2003).

The survey assessed seven latent variables (PTC, PEOU, SI, CL, CT, HL, and TA) using validated 5-point Likert scales. All items underwent contextual adaptation and pretesting, demonstrating robust reliability (Cronbach's $\alpha > 0.80$). Aligning with their theoretical nature, CL and CT were operationalized as continuous latent variables rather than arbitrary dichotomies (R. E. Mayer & Moreno, 2003; Sweller et al., 2019). The Supplementary File details all measurement items and demographic profiles.

We employed partial least squares structural equation modeling (PLS-SEM) to examine the direct effects of antecedent variables on CT, and used bootstrapping procedures to test the mediating role of CL and the moderating effects of HL and TA. This enabled us to trace how the technology acceptance pathway influences trust through the cognitive transformation pathway (Hair et al., 2019).

4.2. In-Depth Interviews: Interpreting the Cognitive Logic Behind Trust Differentiation

Following the quantitative mapping, this phase sought to open the “black box” of statistical correlations by exploring how the identified drivers are differentially interpreted and internalized across individuals. Using purposive extreme case sampling (Patton, 2015), we selected 15 participants with the highest CT scores (high-trust group, R01–R15) and 15 with the lowest (low-trust group, R16–R30) for semi-structured interviews. Rather than treating CT as a dichotomous category, contrasting polar cases rendered trust formation mechanisms more visible.

Interviews were conducted in May 2025, primarily via WeChat video calls (averaging 45 minutes) with a few face-to-face sessions. All were audio-recorded following explicit informed consent. The iteratively developed protocol was informed by digital ethnographic observations and preliminary quantitative findings, the significance of SI, and the moderating effects of HL and TA. It focused on four dimensions: (a) authority deconstruction and trust construction; (b) cognitive and behavioral processes; (c) sociocultural embeddedness; and (d) power dynamics and relationship reconfiguration.

Transcripts were analyzed using reflexive thematic analysis (Braun & Clarke, 2006, 2019). Two researchers independently generated open codes, which were clustered into themes through constant comparison. Multiple calibration discussions resolved coding discrepancies. Inter-coder reliability (Cohen’s Kappa = 0.82) indicated strong agreement. This phase transformed statistical relationships into narrative logic, revealing how identical drivers generate divergent cognitive schemas through mechanisms such as HL and TA.

4.3. Digital Ethnography: Capturing Authority Negotiated in Clinical Interaction

Building on the preceding phases’ focus on internal cognitive evolution, this phase observed how these cognitions function as “capital” in real social interactions, triggering micro-level reconfigurations. We employed digital ethnography (Kozinets, 2015) on Haodf.com, a leading Chinese online medical platform. We combined real-time observation (January to May 2025) with retrospective historical analysis (dating back to April 2024). With 280,000 registered doctors and 91 million patients served, the platform hosts millions of publicly accessible, text-based consultation records. These archives provide an unobtrusive view into natural patient–physician interactions, making them an ideal context to examine how algorithmic advice shapes authority negotiation.

This study was conducted as “public observation” without automated web crawling. All analyzed texts were publicly accessible, anonymized consultation records (Eysenbach & Till, 2001). Any cited excerpts underwent secondary anonymization.

Employing a hybrid timeframe, researchers analyzed historical records (June to December 2024) to assess community norms, followed by weekly immersive tracking (January to May 2025) that amassed approximately 10,000 public consultations. Text screening adhered to theoretical sampling via predefined keywords (e.g., "AI," "ChatGPT," "AI says"). Following manual integrity reviews, we constructed a final corpus of 68 key threads, achieving theoretical saturation.

Dialogue threads underwent integrated critical discourse and thematic analysis via intensive researcher-led interpretation. Analysis focused on three dimensions: (a) patients' discursive patterns and speech acts; (b) physicians' response typologies; and (c) the ensuing negotiation over epistemic authority. Findings from the preceding quantitative and qualitative phases served as an interpretive framework, tracing how survey-identified drivers (PTC, PEOU, SI) and interview-elucidated cognitive logics (e.g., "relational authority") manifested in actual discourse.

5. Results

We organize the findings to trace how GAI reshapes medical authority: quantitative mapping of technology acceptance (RQ1); qualitative interpretation of cognitive shifts (RQ2); and observational analysis of clinical negotiations (RQ3). These phases form a continuous explanatory chain rather than functioning in isolation.

5.1. Measurement Model Evaluation

We first assessed reliability and validity. All constructs showed high internal consistency, with Cronbach's α and composite reliability ranging from 0.865 to 0.919, exceeding the 0.7 threshold (Table 1). Convergent validity was supported by confirmatory factor analysis: All indicator loadings exceeded 0.60, and average variance extracted (AVE) ranged from 0.562 to 0.693, surpassing 0.50.

Table 1. Reliability and convergent validity of the measurement model.

Construct	Items	Loadings	Cronbach's α	Composite Reliability	AVE
PTC	A1–A5	0.728–0.768	0.865	0.865	0.562
PEOU	B1–B5	0.744–0.808	0.883	0.883	0.603
SI	C1–C5	0.762–0.787	0.883	0.883	0.602
CT	D1–D5	0.772–0.825	0.898	0.898	0.638
CL	E1–E5	0.818–0.861	0.919	0.919	0.693
HL	F1–F5	0.785–0.839	0.907	0.907	0.661
TA	G1–G5	0.782–0.843	0.911	0.911	0.673

The confirmatory factor analysis indicated good model fit: χ^2/df = 1.76, GFI = 0.921, AGFI = 0.908, CFI = 0.969, NFI = 0.931, TLI = 0.965, RMSEA = 0.035. All fit indices met established thresholds, supporting the measurement model's structural validity.

Discriminant validity was confirmed via the Fornell-Larcker criterion (Table 2), as the square root of each construct's AVE exceeded its correlations with other constructs.

Table 2. Discriminant validity assessment (Fornell-Larcker criterion).

	PTC	PEOU	SI	CT	CL	HL	TA
PTC	0.75*						
PEOU	0.353	0.78*					
SI	0.309	0.364	0.78*				
CT	0.331	0.380	0.420	0.80*			
CL	−0.286	−0.290	−0.317	−0.360	0.83*		
HL	0.309	0.334	0.362	0.395	−0.345	0.81*	
TA	−0.268	−0.380	−0.377	−0.416	0.273	−0.370	0.82*

Note: * Represent the square root of the AVE.

5.2. Findings for RQ1: Drivers of and Resistances to Technology Entry

What draws patients to GAI for medical consultations? The survey shows a dual logic: PTC and socially conferred legitimacy, with the latter carrying greater weight. PLS-SEM analysis (Figure 3) indicates that PTC ($\beta = 0.128$, $p < .001$) and PEOU ($\beta = 0.115$, $p < .01$) positively predict CT, confirming instrumental rationality's role in trust formation. SI, however, emerged as the strongest predictor ($\beta = 0.205$, $p < .001$), supporting H1 (Table 3).

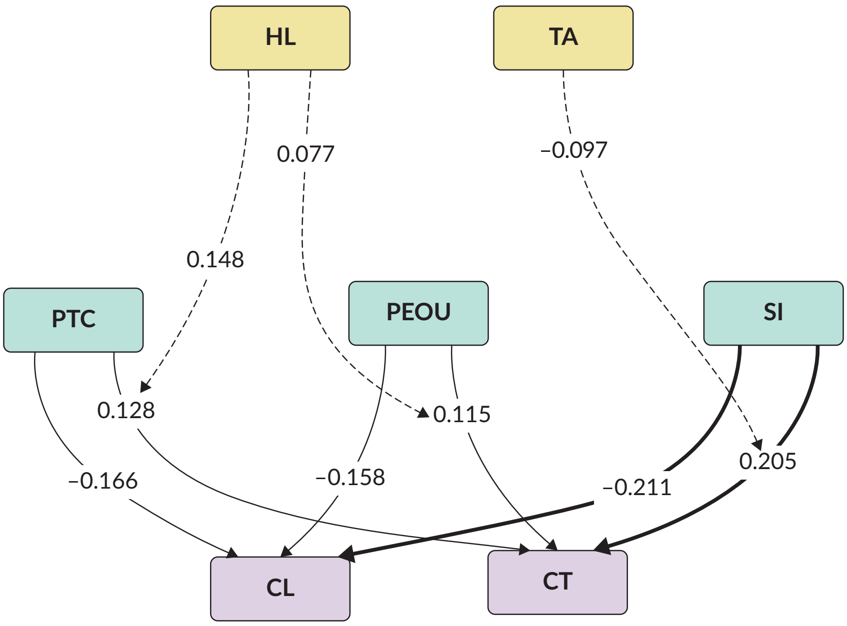

Figure 3. Path analysis results of the structural model.

Table 3. Hypothesis testing results (direct effects).

Hypothesis	Path	β	*t* Statistics	*p* Values	Decision
H1	PTC → CT	0.128	3.647	0.000	Supported
H1	PEOU → CT	0.115	3.009	0.003	Supported
H1	SI → CT	0.205	5.395	0.000	Supported

SI's dominance signals socially conferred legitimacy, a process substantiated by interviews. For high-trust participants, doctor or peer recommendations served as a "risk mitigation strategy" and "legitimacy guarantee." As R05 noted: "My family doctor mentioned I could try this for an initial assessment, which made me feel comfortable." R12 similarly stated: "With a doctor friend endorsing it, I figured it couldn't hurt to try." In these accounts, SI often intersected with PTC, shaping a rational recognition of GAI's "performance-based authority."

Yet interviews revealed a tension invisible in the survey's main effects. For some participants, SI was muted by a more potent logic: "relational authority." These low-trust users emphasized physicians' irreplaceable clinical experience and emotional connection. As R22 argued: "AI only looks at data; it can't match a doctor's clinical experience." Others questioned GAI's technical capability (R19 noted: "My condition requires observation, auscultation, inquiry, and palpation. What does AI know?") or described anxiety-inducing information overload (R21 recounted: "AI presented too many possibilities….I couldn't sleep"). For these patients, the physician's embodied experience and rapport constituted an unreplicable "relational efficacy." R16 affirmed: "I trust my doctor…that sense of security AI can't provide." This emphasis on personal and experiential authority explains why SI's effect weakens where trust in physicians runs deep, a nuance the survey alone could not capture.

Digital ethnography revealed this tension in actual consultations. Patients sometimes introduced AI advice by referencing social endorsements, using phrases like "a doctor friend suggested I check this with AI first." This discursive move used SI to frame their intervention as legitimate.

The mediating role of CL further illuminated this pathway. Mediation analysis (Table 4) showed that all three antecedents significantly reduced CL, indirectly promoting CT (indirect effects = 0.021–0.028, $p < .05$) and supporting H2. This suggests that trust in GAI builds partly by alleviating cognitive burden. Interviews corroborated this: High-trust users described how clear, logical AI explanations reduced confusion (R07), while low-trust users reported anxiety and "information overload" eroding trust (R26). The statistical path from antecedents through CL to CT thus maps onto lived experiences.

Table 4. Mediation analysis results for CL.

Hypothesis	Mediating Path	β	t Statistics	p Values	Decision
H2	PTC → CL → CT	0.022	2.504	0.013	Supported
H2	SI → CL → CT	0.028	2.887	0.004	Supported
H2	PEOU → CL → CT	0.021	2.424	0.016	Supported

In high-stakes medical decision-making, SI provides a socially sanctioned pathway to reduce uncertainty and gain legitimacy. GAI's initial adoption is thus not a simple technical choice but a negotiation between technological and social rationality, mediated by CL and conditioned by pre-existing relational authority.

5.3. Findings for RQ2: Internal Cognitive Reconfiguration

Addressing RQ2, the survey shows that GAI unevenly reshapes patients' perceptions of medical authority, as its effects are systematically moderated by individual characteristics. As Table 5 shows, HL significantly amplifies the positive effects of PTC ($\beta = 0.148$, $p < .001$) and PEOU ($\beta = 0.077$, $p < .05$) on CT, whereas TA dampens the effect of SI on CT ($\beta = -0.097$, $p < .01$). Supporting H3, these findings demonstrate that GAI does not empower patients uniformly; its effects depend on user traits.

Table 5. Results of moderation effect tests.

Hypothesis	Moderating Path	β	*t* Statistics	*p* Values	Decision
H3	HL × PTC → CT	0.148	4.121	0.000	Supported
H3	HL × PEOU → CT	0.077	2.004	0.045	Supported
H3	TA × SI → CT	−0.097	2.685	0.008	Supported

Interviews reveal how these interactions manifest in practice. For high-HL individuals, GAI serves as a deployable resource. R03 described how AI's detailed explanations gave her confidence to engage with her physician on more equal footing: "AI explained the principles...empowered me to question the doctor." HL enabled her to decode complex outputs and manage CL, transforming information into "cognitive capital."

The opposite held for those with low HL or high TA. Complex terminology and probabilistic descriptions imposed heavy CLs, triggering confusion and anxiety. R26's experience was typical: "It listed a bunch of possibilities, and the more I read, the more scared I got." For these users, GAI did not empower but overwhelmed. Rather than equipping them for negotiation, the technology reinforced reliance on traditional physician authority.

Survey data suggest most patients possess the digital skills for positive transformation, with 66.4% rating themselves proficient. Interviews, however, complicate this narrative. Consider R17, an AI engineer who rarely used GAI for health purposes. His caution stemmed not from technical deficits but from a sophisticated knowledge of its limitations. Bandura (2001) argues that self-efficacy builds on past performance and that its absence breeds anxiety and avoidance. However, this case reveals that TA and disengagement need not stem from skill deficits, but from recognizing algorithmic limitations.

Digital ethnographic observations confirmed these divergent paths. Patients like R03, who transformed GAI into cognitive capital, actively introduced AI-generated information and positioned themselves as informed participants. By contrast, those overwhelmed by the experience, like R21, rarely mentioned AI; when they did, they were tentative, often starting with disclaimers. This internal cognitive transformation (or its failure) directly shaped how patients presented in consultations.

These findings carry a broader implication. By equipping resource-rich groups (high HL, low TA) with tools to negotiate authority while potentially marginalizing others, GAI functions as a covert sorting mechanism. Introduced with promises of democratization, the technology may instead reproduce and deepen existing health inequalities (Timmermans & Kaufman, 2020).

5.4. Findings for RQ3: External Interactive Negotiation

The third research question examines the discursive practices and interaction patterns emerging when patients introduce AI-generated advice into consultations. It reveals how trust formed via prior pathways is mobilized as cognitive capital during these encounters, shaping medical authority through micro-level exchanges.

The foundation for these interactions is shaped by survey-revealed trust differentials. ANOVA confirmed significant differences in CT scores across age ($F = 2.818$, $p = 0.038$) and education ($F = 7.215$, $p < 0.001$), with younger (18–30 years) and highly educated respondents reporting higher trust in AI. Interviews further revealed how distinct cognitive schemas—"cognitive capital" (high HL, low TA); "algorithmic authority belief" (high PTC); "relational authority" (deep trust in physicians); and "cognitive anxiety/overload" (high TA, low HL—shape patients' orientations toward both AI and physicians.

Digital ethnography of 68 dialogues on Haodf.com reveals patients strategically translating AI suggestions into concrete speech acts. The resulting typology (Figure 4) systematically mirrors the cognitive schemas, survey drivers, and interview logics identified earlier.

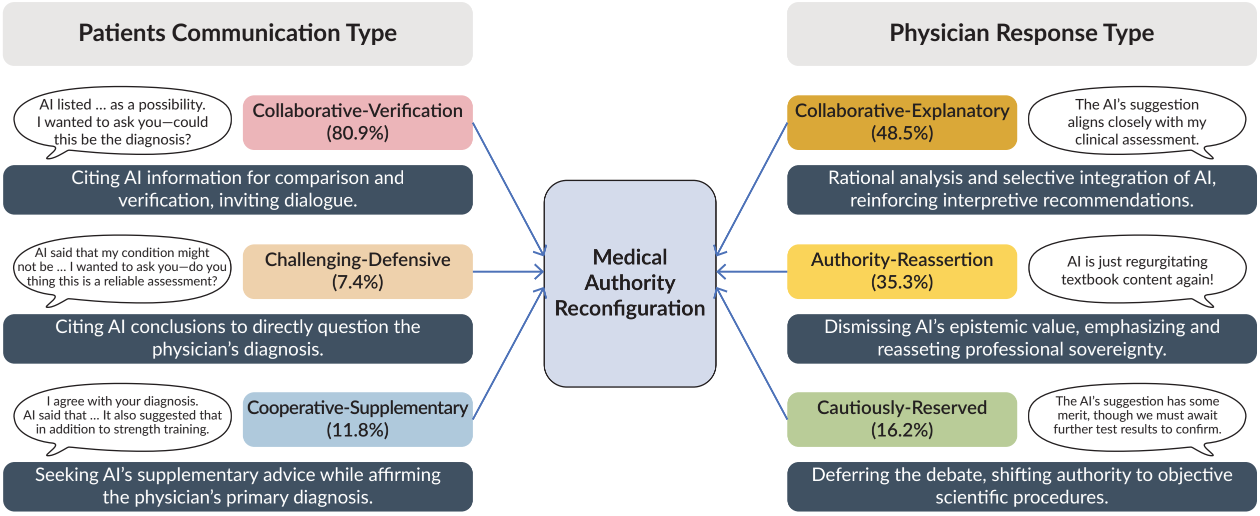

Figure 4. Patient–physician behavioral typology in algorithm-mediated encounters.

First, patients with "cognitive capital" (high HL, low TA) predominantly adopted a "collaborative-verification" stance (80.9%). Their discourse featured paraphrasing AI information, integrating personal health data, and soliciting physician validation. This aligns with survey findings showing PTC and PEOU positively predict CT, and interviews detailing how empowered users convert AI outputs into dialogic resources. R01 (high-trust group) noted: "When a tertiary hospital doctor misdiagnosed my skin rash as eczema, I presented the medical literature links provided by AI and engaged in discussion. This was a form of questioning the doctor." A typical inquiry, "AI mentioned X, but I wanted to ask you: Based on your experience, is that consistent with my situation?", positions the physician as the final arbiter while demonstrating informed patient agency.

Second, patients with "algorithmic authority belief" (high PTC, variable HL) occasionally adopted a "challenging-defensive" strategy (7.4%). Their discourse treated AI outputs as definitive evidence to pressure physicians and contest professional judgment. Figure 5 illustrates a high PTC patient invoking AI's pharmacological knowledge to challenge clinical authority. This reflects survey findings that PTC predicts CT, which, coupled with algorithmic authority belief and limited relational trust, can manifest as a challenging-defensive clinical stance. R03, another high-trust participant, exemplified this orientation: "AI explained the principles in detail...which empowered me to question the doctor." A typical utterance might be, "The AI suggested it could be Y, not X. Are you sure you're not missing something?" Here, the algorithmic voice is granted epistemic weight comparable to, or exceeding, professional authority.

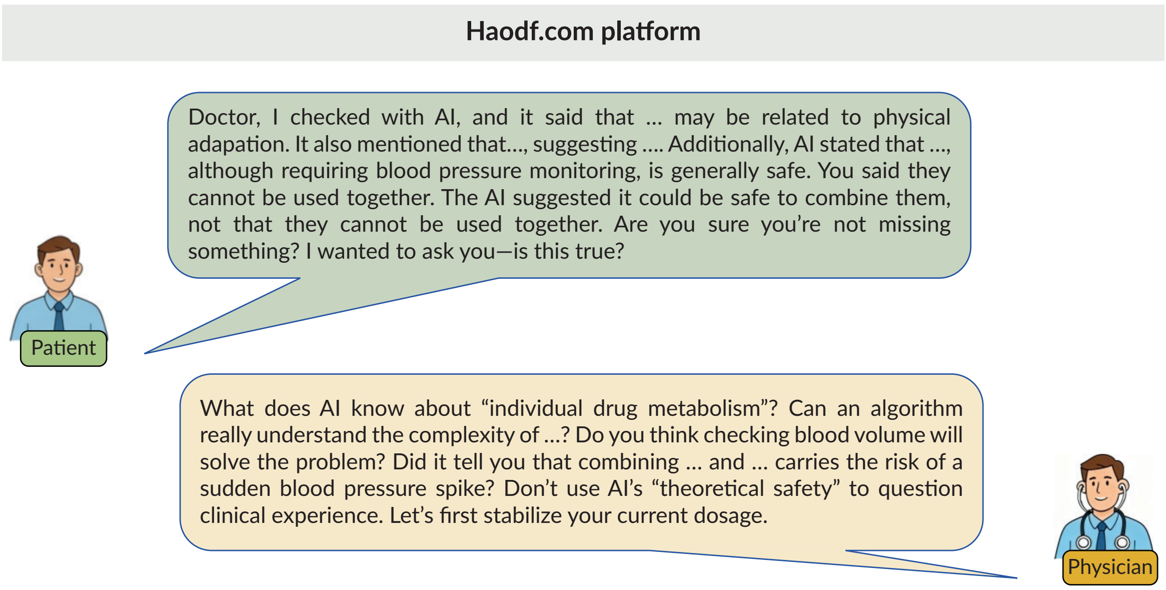

Figure 5. Sample excerpts from doctor–patient dialogues involving AI. Note: A "challenging-defensive" patient (high PTC) questions the physician's clinical judgment based on AI advice, met by an "authority-reassertion" response reaffirming clinical experience.

Third, patients anchored in "relational authority," emphasizing the irreplaceable value of physician experience and personal connection, tended to adopt cooperative stances (collaborative-verification or cooperative-supplementary). Yet, their AI introductions were heavily mitigated: attributed to social sources (e.g., "my sister, a nurse, mentioned this AI"); framed tentatively ("I was just wondering..."); and accompanied by explicit trust reaffirmations ("I'm not questioning your diagnosis at all"). This aligns with interviews where relational trust buffered social endorsement (SI) and moderated behavioral assertiveness. R16 noted: "I trust my doctor...that sense of security AI can't provide."

Fourth, patients experiencing "cognitive anxiety/overload" (high TA, low HL) displayed hesitancy, emotional language, and pleas for authoritative reassurance. When introducing AI, their utterances were often fragmented, reflecting fear ("it scared me") and confusion ("I don't know what to believe"). This corroborates survey findings that high TA dampens SI's effect on CT, alongside interview accounts of information paralysis. R21 recalled: "AI presented too many possibilities....I couldn't sleep all night." In practice, after a brief, anxious mention of AI, such patients often retreated into passive reliance, or physicians misinterpreted this tentative engagement as irrational distrust, escalating tension.

Physician response strategies (Figure 4) mirrored these patient profiles. The "collaborative-explanatory" approach (48.5%) prevailed when physicians perceived patients as knowledgeable and cooperative, a judgment often informed by the patient's education level and ability to paraphrase AI information coherently. The "authority-reassertion" strategy (35.3%) was frequently elicited by challenging-defensive patients or those whose anxious, fragmented introductions were perceived as unwarranted challenges. R22 noted the importance of a physician's perspective: "AI only looks at data; doctors consider the whole clinical picture." The "cautiously-reserved" strategy (16.2%) appeared when physicians faced uncertainty about the AI's source or the patient's intent, deferring to procedural authority (e.g., "Let's wait for the test results") as neutral ground.

These interaction patterns behaviorally enact the cognitive schemas shaped by the moderating effects of HL and TA. Patients who transform AI outputs into cognitive capital (high HL, low TA) gravitate toward collaborative verification. Those with strong algorithmic authority belief (high PTC) may adopt a challenging-defensive stance. Patients anchored in relational authority adopt cooperative stances marked by discursive mitigation. Those burdened by cognitive anxiety (high TA, low HL) engage with AI hesitantly, risking misunderstandings and unproductive interactions. The micro-level discourse thus manifests the psychosocial dynamics captured by our survey and interviews, confirming the value of our mixed-methods design. However, translating cognitive capital into assertive behavior is not always linear, as individual dispositions remain embedded in broader social contexts.

6. Discussion

To understand how GAI reshapes medical authority within doctor–patient relationships, this study traces pathways from technology adoption to clinical interaction. Our findings show a layered process beyond mere disruption or empowerment. We synthesize this evidence into a conceptual framework: “algorithm-mediated negotiated authority,” demonstrating that authority in the AI era is neither absolute nor obsolete, but dynamically co-constructed.

6.1. Theoretical Integration: The “Algorithm-Mediated Negotiated Authority” Framework

6.1.1. The Epistemic Logic of Algorithm-Mediated Negotiation

Rather than simply accepting or rejecting professional judgment, patients engage with it using algorithmic resources that introduce a new epistemic logic into the consultation room. In the traditional physician-dominated model, authority is institutionally conferred and static, with patients expected to defer. Even in SDM, a more progressive paradigm, authority is conditionally shared through a process the physician invites and controls (Edwards & Elwyn, 2009; Elwyn et al., 2012). What remains undisturbed in both is the physician’s epistemic core: the exclusive claim to define and interpret clinical reality.

What we observed diverges from these established patterns. GAI introduces an uninvited participant, a non-human actant equipping patients with a parallel knowledge base (Fraile Navarro et al., 2025) driven by probabilistic pattern recognition rather than clinical training and embodied experience. When patients bring algorithmic insights into consultations, they implicitly challenge how clinical truth is validated. Unlike SDM’s harmonious, invited cooperation, our documented encounters are marked by power tensions and epistemic friction.

This divergence is not merely a matter of degree but of kind, differing systematically from SDM across three dimensions. First, impetus: SDM is physician-invited, opening space for patient choice among reasonable options; conversely, algorithm-mediated negotiation is often uninvited and patient-initiated, introducing external algorithmic knowledge. Second, power relations: SDM operates within a framework where the physician’s epistemic authority remains largely intact and unchallenged, whereas negotiated authority contests this foundation via algorithmic logic. Third, outcomes: SDM aims for collaborative consensus on a treatment path, yet algorithm-mediated negotiation yields more fluid outcomes—reinforced, reconfigured, or fractured authority—marked by epistemic friction rather than tidy consensus.

6.1.2. Three Mechanisms of Authority Reconfiguration

This reconfiguration unfolds through three interconnected mechanisms, each corresponding to a different space in the patient's journey from technology encounter to clinical interaction.

The first mechanism operates in the social space, prior to consultation. For GAI to rival professional authority, it must first be trusted. Trust follows two pathways: technical efficacy (PTC, PEOU) and procedural legitimacy via social endorsement (SI). The primacy of SI reveals a paradox: The algorithm reconfiguring authority depends on the very social networks that sustain it (Greenhalgh et al., 2017). Yet interviews reveal a resilient "relational authority" buffering algorithmic influence, suggesting that authority transitions are negotiated through, rather than against, established social fabrics.

Importantly, while users rely on social fabrics to manage technological uncertainties, the specific "trust brokers" vary cross-culturally. In China's high power-distance, collectivist context, SI emerged as a strong predictor. Extending Meng and Guo (2024), who demonstrated the significance of SI in Chinese healthcare technology adoption, our findings further show that in the specific context of GAI, interpersonal ties, including family, community networks, and increasingly, online patient communities, legitimize risky new tools. Conversely, in individualistic contexts, informal SI carries less weight. In Scandinavian countries, institutional trust runs deep (Trägårdh, 2007); citizens rely on state agencies, not peers, to vet medical innovations. Trust brokerage is outsourced to institutional safeguards, such as official certifications and algorithmic auditability, or to the individual's own functional evaluation (Araujo et al., 2020; Shin, 2021). The mechanism is the same—users need trusted brokers—but the brokers differ: personal networks in one context, institutional authorities in another.

Beyond cultural variations, our data reveal a more universal risk unfolding in the second mechanism: the cognitive space. Here, technological empowerment is subject to a "Matthew effect" (Merton, 1968). Far from democratizing medical expertise, translating GAI exposure into usable cognitive capital is uneven and socially patterned—a covert stratification mechanism (Gero et al., 2025). Individuals with higher HL convert AI outputs into discursive leverage, whereas those with higher TA experience information paralysis, retreating to traditional authority. GAI thus functions as an invisible sorting mechanism, equipping the resource-advantaged to pull further ahead while erecting cognitive barriers for others who fall behind (Mackert et al., 2016). Consequently, merely providing public access to AI tools does not flatten clinical hierarchies. Instead, it reframes "digital divides" beyond mere access, embedding them in cognitive and emotional experiences where pre-existing inequalities in HL and technology comfort are amplified into a wider "cognitive divide." Unlike prior access-focused digital divide research (van Dijk, 2020), our cognitive mechanism reveals a second-order divide: Equal access does not guarantee equal outcomes—HL and TA still stratify users. This extends van Dijk (2020) by showing that cognitive capital, not physical access, is the new axis of differentiation.

The third mechanism, discursive enactment, brings these internalized resources into the clinical space. Digital ethnography shows how authority is negotiated in real time: Patients introduce algorithmic evidence through strategies ranging from collaborative verification to direct challenge; physicians respond with explanatory, reassertive, or reserved tactics. Authority thus emerges as a relational effect, continuously reshaped within the turn-by-turn flow of clinical dialogue. Power is less institutionally conferred than situationally negotiated through the micropolitics of communicative exchange. However, this negotiation remains asymmetrical; physicians retain structural and experiential advantages that constrain this discursive process.

While GAI universally pushes professional authority from unidirectional conferral toward bidirectional negotiation, how patients navigate this inherent asymmetry depends heavily on regional contexts and medical models. In deference-oriented settings such as China, patients use GAI as a subtle instrument to navigate these status disparities, engaging doctors without direct confrontation (Liu et al., 2025). The technology provides cover for questioning within hierarchies that discourage open dissent. In contrast, within the more egalitarian, consumer-oriented medical culture of the United States (Timmermans & Oh, 2010), the negotiation that GAI enables is more overt. Patient autonomy is prioritized, and algorithmic outputs may be used to demand second opinions, challenge clinical decisions, or hold professionals accountable (Tan & Goonawardene, 2017). Ultimately, this underlying shift toward negotiated authority manifests in different communicative registers: careful circumvention in collectivist settings, direct consumerist demands in individualistic ones.

Together, these three mechanisms bridge macro-level critiques of medical power with micro-level analyses of technology use, offering a meso-level account of authority reconfiguration under algorithmic mediation. The explanatory chain—from socially legitimated adoption, through cognitively stratified internalization, to discursively contested enactment—operates as a recursive loop. Each clinical negotiation feeds back into subsequent technology acceptance (reinforcing or weakening SI) and cognitive transformation (deepening or eroding CT). For instance, a dismissive clinical encounter may drive patients back to peer networks or heighten their cognitive anxiety, continuously re-making authority through this ongoing cycle. Yet this recursive process does not produce deterministic outcomes. For instance, R10, despite high CT and HL, remained cautious: "I now only use AI as a 'second opinion.'" This indicates that cognitive capital is strategically deployed or reserved depending on contextual factors such as physician receptivity and condition severity. Consequently, "algorithm-mediated negotiated authority" is not a straightforward product of individual psychological profiles but a situated accomplishment, shaped by the interplay between what patients bring into the consultation and what unfolds within it.

6.2. Theoretical and Practical Implications

6.2.1. Advancing Theoretical Paradigms

Having sketched the framework, we now consider how it engages with and extends three core theoretical traditions.

6.2.1.1. From "Disciplinary Gaze" to "Negotiated Gaze"

Our findings suggest GAI enables a form of "counter-gazing," where patients use algorithmic data to challenge the physician's interpretive monopoly. This transforms rather than ends the medical gaze, dispersing power into a more complex, dialogic field. Clinical authority must now be sustained by managing multiple competing gazes: the physician's expertise, the data-driven logic, and the patient's experiential narrative (Lupton, 2017; Ruckenstein & Schüll, 2017). Authority depends less on monopolistic knowledge control and more on discursive skills to integrate, reframe, or rebut the algorithmic "voice." We term this emergent form a "negotiated gaze" to capture its dynamic, contested character. This reframing provides a micro-foundation for power analysis, demonstrating that algorithms are new "actants" within power networks, reconfiguring the traditional "power–knowledge" nexus (Bucher, 2018; Coeckelbergh, 2020). The negotiated gaze is not a refutation of Foucauldian insight but its situational extension. Importantly, this negotiation signals resilience rather than the erosion of professional authority. Through strategies such as "collaborative-explanatory" responses, physicians actively incorporate AI-generated knowledge into their frameworks, reasserting their epistemic gatekeeping role. Power adapts: When challenged by a new actant, it mutates into a dialogic form while its institutional foundations remain intact. Ultimately, this dialectic both challenges and reconsolidates medical authority.

6.2.1.2. From "Intention to Adopt" to "Legitimacy Construction"

While traditional models (TAM/UTAUT) effectively explain low-risk, efficiency-driven adoption, in the high-stakes context of medical decision-making, SI functions not merely as a subjective norm but as a strategy for social risk sharing and securing procedural legitimacy. This explains its heightened predictive power: When stakes are high, social legitimacy outweighs perceived usefulness alone. To understand how external adoption translates into stable internal trust, we integrated cognitive load theory, addressing the "black box" problem in technology acceptance research (Benbasat & Barki, 2007). CL emerges as a central explanatory variable in trust formation, clarifying the empirical paradox that patients with similar perceptions of AI's usefulness arrive at different trust levels. This variance stems from the unseen cognitive labor required to reconcile algorithmic output with personal understanding, shifting the focus from predicting whether a tool is used to mapping how its use internalizes and reshapes cognitive and social relationships.

6.2.1.3. From "Channel" to "Reconstructive Force"

GAI functions not as a neutral communication "channel" but as a mediating force whose inherent logic of immediacy, data-driven reasoning, and dialogic capacity restructures the "grammar" of institutionalized doctor–patient interaction (Couldry & Hepp, 2016). With the integration of GAI, the clinical encounter shifts from information transmission to the negotiation of meaning and power (Stivers & Timmermans, 2020). By introducing a quasi-autonomous "voice" that both parties must orient to, GAI expands the traditional dyad into a triangular negotiation space. For health communication research, this implies moving beyond "how to persuade" toward "how to facilitate constructive negotiation" (Epstein & Street, 2011). Extending mediatization theory into professional institutions, this framework shows how media logic embeds itself in core relational structures (Hepp, 2020). Beyond infrastructural shifts such as teleconsultations, the mediatization of medicine now reaches into the epistemology of clinical practice, reshaping how knowledge is sourced, validated, and contested between experts and laypersons.

6.2.2. Practical Implications

Beyond scholarship, our findings inform practice. Recognizing that patients may arrive with AI-generated "cognitive capital" enables clinicians to reframe potentially adversarial encounters as collaborative sense-making. Communication training should equip physicians with strategies to acknowledge, critically engage with, and integrate algorithmically sourced patient knowledge rather than dismissing it as a threat.

For AI developers, the stratified effects of HL and TA necessitate design features that reduce CL for vulnerable populations, including plain-language summaries, visual explanations, and a tiered information architecture that allows users to control output depth and complexity. Such adaptations are essential for GAI to fulfill its democratizing potential rather than widening the "cognitive divide." For policymakers, uncritical GAI deployment risks exacerbating rather than mitigating health inequalities. Targeted interventions must address not only access but also cognitive and emotional barriers.

7. Conclusion

Through a sequential mixed-methods exploration, this study shows how GAI reshapes medical authority in China. Findings indicate a chain reaction: GAI fosters hybrid legitimacy blending technical efficacy with socially endorsed procedural authority; its empowering effects are constrained by resource disparities, moderated by HL and TA; and clinical encounters transform into algorithm-mediated negotiations where authority is co-constructed through discursive exchange.

Theoretically, the study bridges macro-level power critique with micro-behavioral analysis, advancing the "medical gaze" into a "negotiated gaze." It extends TAM by emphasizing legitimacy construction and cognitive internalization, framing GAI as a reconstructive force that reshapes clinical communication. Practically, our findings offer actionable guidance for clinicians, AI developers, and policymakers to foster constructive rather than adversarial negotiation and to prevent GAI from exacerbating existing health inequalities.

This study has limitations. Its cross-sectional design offers a snapshot of a rapidly evolving phenomenon, and the sample may underrepresent older or less digitally engaged patients. The digital ethnography focuses on online, text-based consultations, leaving offline nonverbal dynamics unexamined. Moreover, the study centers on patient perspectives, leaving physicians' psychological adaptation underexplored. Future research should track longitudinally how authority models stabilize or remain fluid; conduct cross-cultural comparisons across healthcare systems; and design interventions, such as communication training and platform features, that foster constructive negotiation.

Ultimately, recognizing these intertwined technological and cognitive mechanisms is essential for the future trajectory of professional institutions. Clarifying how professional authority is being redefined in the algorithmic age will not only guide equitable AI integration in healthcare but also provide a critical blueprint for mitigating emerging digital inequalities across other high-stakes knowledge domains globally.

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Supplementary Material

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About the Authors

Xue Yuan is a lecturer at the School of Journalism and Communication, Beijing Institute of Graphic Communication. Her research interests include health communication, digital media studies, and media sociology.

Qiqi Jin is a postgraduate student at the School of Journalism and Communication, Beijing Institute of Graphic Communication. Her research interests include digital media, health communication, and popular cultural studies.

Yulong Tang is an associate professor in the School of Journalism and Communication, Beijing Institute of Graphic Communication. His research interests include digital health, privacy protection, and social media technologies.

Jinghong Xu is a professor at the School of Journalism and Communication, Beijing Normal University. He is also an adjunct professor at the International College, Krirk University, Bangkok, Thailand. His research interests include new media and internet governance, health communication, intercultural communication, film and television studies, and game research.