The Development of Humanities and Social Sciences, 2026, 2(1), 87-100
https://doi.org/10.71204/vs0xng32

The Role of Artificial Intelligence Applications in Enhancing Healthcare Professionals' Performance in the Context of "Internet Plus Healthcare"

Yingnuo Qi [1,*]

[1] School of medical humanities and hospital management, Wenzhou Medical University, WenZhou 325000, China

[*] **Corresponding Author**
Yingnuo Qi

675477963@qq.com

Received: 6 February 2025 / Accepted: 10 March 2026 / Published online: 12 March 2026

Abstract

Against the backdrop of the deepening national strategy of "Internet Plus Healthcare," artificial intelligence technology is reshaping healthcare service models. As core users of AI, healthcare professionals' job performance has become a critical issue requiring urgent exploration. Existing research primarily focuses on AI's improvement of patient treatment outcomes, while the impact on healthcare professionals' performance lacks systematic analysis. This study constructs a conceptual framework integrating multiple pathways linking AI understanding and trust, Job performance, and Presenteeism, grounded in the Technology Acceptance Model, Social Technological Systems Theory, and Resource Conservation Theory. The findings indicate that AI' s performance-enhancing effects on healthcare workers are conditional and complex, requiring cognitive empowerment as a prerequisite, workflow optimization as a vehicle, and physical and mental health safeguards as a foundation. This research provides theoretical grounding and practical guidance for human resource management in the era of smart healthcare.

Keywords: Artificial Intelligence; Healthcare Workers; Job Performance; Internet Plus Healthcare; Presenteeism

1. Introduction

With the deepening implementation of the "Healthy China 2030" Plan Outline and the continuous advancement of the Digital China strategy, "Internet Plus Healthcare" has become a key driver for development in China's healthcare sector. As the pivotal technology spearheading this transformation, artificial intelligence is being increasingly applied in medical imaging recognition, clinical decision support, and intelligent health management. Driven by policy, AI technology is transitioning from pilot exploration to large-scale implementation. By the end of

2024, over 500 tertiary hospitals nationwide had deployed AI-assisted diagnosis systems, covering more than 20 clinical specialties,including cardiology,oncology,and ophthalmology (China Digital Healthcare Development Report, 2024).

However, technological proliferation has not automatically translated into improved job performance among healthcare workers. The WHO's Global Strategy on Digital Health (2020-2025) notes that introducing digital technologies may alter the nature of healthcare workers' tasks. Without scientifically designed human-machine collaboration protocols, such technologies may instead increase cognitive load and risk occupational burnout (World Health Organization, 2021). Similar challenges have emerged in domestic hospital practices: After implementing the DeepSeek large model, Wenzhou Medical University First Affiliated Hospital saw significant improvements in imaging report efficiency. However, initial resistance from medical staff resulted in an adoption rate of less than 60% (Wenzhou Municipal Health Commission, 2024). An evaluation report on 289 AI application cases in Guangdong Province revealed that departments with low technical comprehension achieved only one-third of the performance improvement seen in departments with high comprehension (Southern Network, 2024).

These phenomena reveal a core issue: the effectiveness of AI technology heavily depends on the medical staff's understanding, trust, and ability to effectively integrate the technology. Based on this, this study constructs an integration model of AI application influencing medical staff performance within the "Internet Plus Healthcare" context. It analyzes the moderating role of cognitive factors and the mediating role of physical and mental health factors, providing policy insights to address the challenge of "technology application—performance improvement."

2. Current State of Research

2.1. International Research Progress

International research on AI applications in healthcare has developed into a relatively comprehensive system. Regarding technical efficacy, Esteva et al. (2017) demonstrated in their natural study that deep learning algorithms achieve diagnostic accuracy comparable to dermatologists in skin cancer classification tasks, rather than replacing physicians.

Regarding healthcare worker job performance, the Individual Job Performance Questionnaire (IJPQ) developed by Koopmans et al. (2014) has become a mainstream measurement tool. It categorizes performance into three major modules: task performance, situational performance, and counterproductive behaviors, providing a standardized framework for subsequent research.

Regarding cognitive mediation effects, Davis's (1989) Technology Acceptance Model (TAM) revealed the decisive role of perceived usefulness and perceived ease of use in technology adoption.

2.2. Current State of Domestic Research

Domestic research exhibits a pattern of "policy-driven, practice-first" development. A series of reports by the Health Development Research Center of the National Health Commission traced the evolution of AI healthcare policies from 2018 to 2014, noting that China has established a comprehensive policy chain encompassing "central top-level design — local pilot implementation—industry standardization" (Health Development Research Center of the National Health Commission, 2023). Notably, the "Opinions on Further Improving the Healthcare Service System" (2023) first incorporated AI-assisted diagnosis as a core indicator for capacity building in primary healthcare institutions.

The Wenzhou practice offers a typical example. Data from the Wenzhou Health Information Center indicates that since the launch of the "Health Cloud Screening" project in July 2023, the AI-assisted diagnosis platform has been integrated into 739 public medical institutions across the city. It has completed nearly 7 million impact analyses, reducing the average time to issue impact reports from 30 minutes to 5 minutes (Wenzhou Municipal People's Government, 2024). An evaluation report by Hu et al. (2024) indicates that after connecting to the MaaS platform, primary healthcare institutions saw a 12.3% increase in diagnostic accuracy. However, healthcare workers'job satisfaction exhibited a U-shaped trajectory—initially declining due to unfamiliarity with the technology, then significantly rebounding as proficiency grew.

Perception studies among medical staff reveal complexity. Liu (2023) surveyed 15 tertiary hospitals in Beijing, finding that while 78.6% of physicians acknowledged AI improved diagnostic efficiency, 63.2% expressed concern that overreliance could lead to clinical reasoning deterioration.

2.3. Research Review and Entry Points

Synthesizing existing literature, this study identifies three key gaps: First, while foreign research offers mature theoretical frameworks, most studies are grounded in market-driven healthcare systems, limiting their explanatory power for China's policy-driven model. Second, domestic research emphasizes macro-policy drivers and tends to focus on AI's technical efficacy, neglecting humanistic impacts — particularly long-term tracking of AI's effects on healthcare workers'physical and mental health. Third, integrated research on moderating and mediating mechanisms remains largely unexplored.

This study constructs an integrated "technology-cognition-performance-health" model within the institutional context of "Internet Plus Healthcare," focusing on:

(1) How AI understanding and trust moderate the conversion of technological efficacy;

(2) How Presenteeism mediates the relationship between AI application and performance;

(3) How policy contexts shape these causal pathways.

This framework responds to international calls for humanistic care in digital health while aligning with China's "new quality productive forces" development strategy, which emphasizes "revolutionary technological breakthroughs and innovative allocation of production factors" (Xi Jinping, 2024).

3. Theoretical Foundation

3.1. Technology Acceptance Model (TAM)

The TAM model proposed by Davis (1989) provides the cognitive foundation for this study. This model posits that users' acceptance of information technology is determined by perceived usefulness and perceived ease of use, which in turn influence attitudes toward use and behavioral intentions. In the medical AI context, "perceived usefulness"manifests as whether medical personnel believe AI can enhance diagnostic accuracy and reduce work time; "perceived ease of use" reflects the simplicity of the system's interface and the level of learning required.

This study extends TAM to include two dimensions: AI understanding and AI trust. Understanding emphasizes the depth of cognitive insight into algorithmic logic, while trust focuses on recognition of technological reliability. This extension aligns with healthcare's high-risk characteristics—merely ease of use is insufficient to drive medical adoption of AI technology; trust grounded in deep understanding is crucial.

3.2. Socio-Technical Systems Theory

This theory emphasizes bidirectional interaction between technical and social systems, positing that optimal performance arises from synergistic optimization rather than isolated technological advancement (Trist & Bamforth, 1951). Medical AI applications disrupt traditional socio-technical equilibrium in clinical practice. While technical systems introduce automated decision-making, social systems must adapt role divisions, accountability frameworks, and communication patterns. The World Health Organization (2021) states that AI healthcare applications must adhere to a "human-centered"principle, ensuring technological design aligns with healthcare professionals' practical needs.

This study operationalizes the theory as a mediating effect on job performance—AI enhances overall performance by optimizing workflows and promoting team collaboration. However, delayed adjustments in the social system may trigger role conflicts and foster counterproductive behaviors.

3.3. Conservation of Resources Theory (COR)

COR posits that individuals possess motivations to conserve and acquire resources, with resource depletion leading to work stress and burnout (Hobfoll, 1989). AI applications exert a double-edged impact on healthcare workers: while AI can replace repetitive tasks and conserve cognitive resources, system learning and algorithmic monitoring may introduce new time pressures and psychological burdens. Presenteeism is a classic manifestation of resource depletion. It refers to reduced work efficiency due to health issues without actual absence.

This study introduces COR theory to explain how AI indirectly impacts job performance through Presenteeism: when AI applications increase resource consumption, healthcare workers' Presenteeism due to working while ill intensifies, leading to declining rather than improving performance. This perspective addresses the limitation of traditional research focusing solely on usage.

3.4. Job Performance Theory

Koopmans et al. (2014) structured job performance into three dimensions: task performance, situational performance, and counterproductive behavior. Task performance measures the quality and efficiency of core medical duties; situational performance encompasses peripheral behaviors like assisting colleagues and maintaining team cohesion; counterproductive behavior includes violations and passive resistance. AI applications impact these dimensions differently. For instance, imaging AI directly enhances task performance but has a limited effect on context performance—which requires interpersonal interaction—and may even trigger counterproductive behaviors if poorly designed.

This study employs overall performance as a composite metric, reflecting both technological efficacy and its socio-psychological side effects.

4. Research Model and Theoretical Proposition

Based on the aforementioned theories, this study constructs an integrated model (as shown in Figure 1). This model integrates four theoretical pillars with policy scenario elements to form a four-pathway integrated framework. Its construction follows a nested logic of "macro-level context — meso-level behavior — micro-level cognition," with each element undergoing a three-stage validation process: theoretical deduction—policy verification—practical alignment.

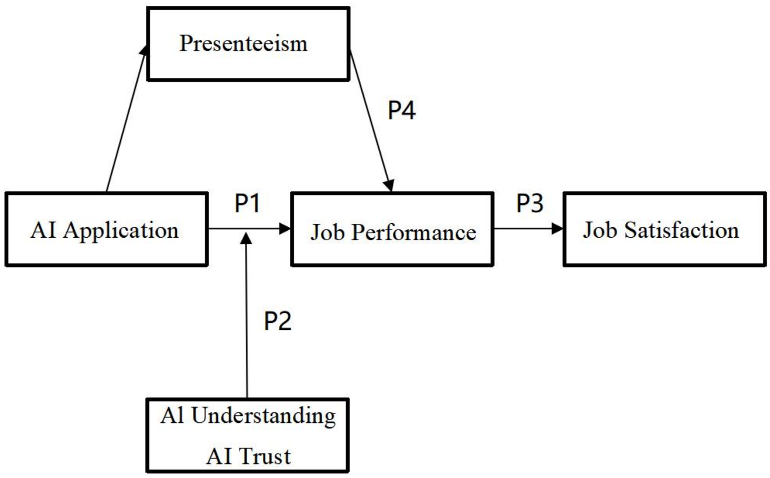

Figure 1. Research Model Framework Diagram

4.1. Theoretical Derivation of Primary Effect Pathways

AI application enhances healthcare professionals' performance through task automation and decision support. Task automation aligns with the Pareto improvement principle by delegating repetitive physician tasks to AI, thereby freeing resources for higher-value workflows. Specifically, AI automates functions such as image analysis, intelligent pre-consultation, and treatment recommendation to reduce repetitive workloads, improve decision accuracy, and directly optimize task performance. Simultaneously, time freed by AI can be redirected toward patient communication and continuing education, indirectly improving situational performance.

The Reference Guidelines for AI Application Scenarios in the Healthcare Industry prioritize intelligent medical imaging diagnosis as its primary application, explicitly targeting efficient and precise imaging-assisted diagnosis (National Health Commission, 2024). Practical data from Wenzhou indicate that AI has increased imaging report efficiency by 80% and improved diagnostic accuracy by 12.3% (Wenzhou Municipal People's Government, 2024). This supports the main effect direction from both policy and practical perspectives.

Simultaneously, this effect follows the diminishing returns law of technological maturity. According to Brynjolfsson's S-curve theory, AI applications experience learning costs during the initial phase (0–6 months), potentially showing short-term performance declines; enter a rapid growth phase during maturity (6–18 months); and exhibit diminishing marginal returns in the stabilization phase (after 18 months) (Brynjolfsson & McElheran, 2016). Based on this, the theoretical proposition is put forward:

P1: Artificial intelligence applications exert a positive impact on healthcare professionals' job performance.

4.2. Theoretical Derivation of the Cognitive Moderation Pathway

Main Effects of AI Understanding and AI Trust Regulation. While traditional TAM models simplify cognition to subjective perception, this study proposes — based on Dual-Process Theory — that physicians' understanding of AI involves both System 2 processing (slow, understanding-based) and System 1 processing (fast, intuition-based). Only when healthcare professionals deeply comprehend AI decision logic and establish trust are they more likely to proactively adopt and integrate AI recommendations, leading to more significant performance improvements. Conversely, performance gains are constrained if understanding is lacking and execution is merely passive, or if excessive trust leads to blind reliance.

This pathway also aligns with Qualitative Comparative Analysis (QCA) logic: understanding and trust are dual necessary conditions. Low understanding + high trust = blind reliance, where physicians may overlook obvious AI errors; high understanding + low trust = excessive defensiveness, where physicians reject reasonable AI suggestions; only the dual-high state enables critical adoption—leveraging AI advantages while maintaining clinical decision-making authority.

The Guiding Principles for Classifying Medical AI Software Products (2021) mandate that decision-support AI must provide rationale explanations, effectively enforcing regulatory-level enhancement of AI comprehension (National Medical Products Administration, 2021). The Opinions on Further Improving the Healthcare Service System propose leveraging information technology while emphasizing enhanced personnel training, reflecting a policy intent that prioritizes both technology and cognition (State Council General Office, 2023). Based on this, we propose:

P2: Healthcare professionals' understanding and trust in AI positively mediate the relationship between AI application and job performance, meaning higher levels of understanding and trust yield stronger positive impacts of AI on performance.

4.3. Theoretical Derivation of the Performance Mediating Pathway

Job performance mediates the relationship between AI application and job satisfaction. According to Self-Determination Theory, job performance influences job satisfaction through two factors: competence fulfillment and autonomy maintenance. If AI enhances performance, physicians gain a sense of competence, thereby increasing satisfaction. However, if AI dominates decision-making, reducing physicians to AI operators and diminishing their sense of autonomy, job satisfaction may decline.

Social-technical systems theory indicates that technological efficacy must be transformed into long-term attitudes through socio-psychological experiences. If AI applications genuinely enhance performance, medical personnel gain a sense of accomplishment and professional value, thereby increasing job satisfaction. However, if AI leads to role ambiguity or skill devaluation, satisfaction may decline even with short-term performance gains. Performance serves as the critical bridge connecting objective technological efficacy and subjective work experiences.

The National Administration of Traditional Chinese Medicine's Operational Manual for Performance Evaluation of Tertiary Public Traditional Chinese Medicine Hospitals (2024 Edition) incorporates healthcare worker satisfaction as a performance metric, reflecting the policy logic linking performance and job satisfaction. Based on this, we propose:

P3: Job performance mediates the relationship between artificial intelligence application and healthcare workers' job satisfaction.

4.4. Theoretical Derivation of Health Depletion Pathways

Presenteeism exerts a negative mediating effect between AI application and job performance. Based on the Loss Spiral principle from COR theory, if AI applications increase cognitive load, monitoring pressure, or trigger technological anxiety without timely compensation, they will deplete healthcare workers' physical and mental resources. This exacerbates Presenteeism, thereby undermining job performance. Presenteeism serves as a behavioral signal of resource depletion — where clinicians remain present but exhibit insufficient cognitive resources. This manifests as repeated verification of AI outputs, decision hesitation, and diminished communication efficiency. This application reveals latent risks in AI deployment.

To refine the theoretical framework of depletion mechanisms, this study proposes a three-stage depletion hypothesis:

Stage 1 depletion occurs during the technical learning phase (1 – 3 months), primarily consuming energy resources and disrupting healthcare workers' self-time management; Second-level depletion occurs during the adaptation conflict phase (3–12 months), primarily consuming psychological resources and affecting healthcare workers' psychological and interpersonal dimensions; Third-level depletion emerges in the deep integration phase (after 12 months). If AI continues to iterate, healthcare workers face lifelong learning pressures, impairing their output demand dimension.

However, this negative mediating effect is conditional—not all AI applications lead to health depletion. When technology design is user-centered, organizational support is robust, and individual agency is strong, the Gain Spiral of COR is activated. AI then conserves resources by reducing repetitive tasks, leading to decreased absenteeism.

The "Opinions on Further Improving the Healthcare Service System" specifically emphasizes strengthening the sharing, exchange, and security framework for health big data after enhancing service accessibility, implying a dual focus on data security and personnel protection (State Council General Office, 2023). The "Guidelines for Pricing Items like Radiological Examinations"prohibit duplicate billing, which protects patients but deprives hospitals of funds to compensate physicians for additional workloads, indirectly exacerbating resource depletion (National Healthcare Security Administration, 2023). Based on this, we propose:

P4: Presenteeism mediates negatively between AI application and healthcare workers' performance, meaning AI adoption may reduce performance by increasing Presenteeism.

The model integration logic is as follows. Four pathways form a complete "technology-cognition-behavior-psychology"chain. P1 represents the direct effect of technological empowerment; P2 reveals how cognitive factors amplify or suppress technological effects; P3 and P4, respectively, demonstrate performance's dual-edged role—both an output of technological efficacy and a precursor to satisfaction; influenced by health status while also impacting health resource depletion. This model incorporates health depletion variables into the AI performance research framework, aligning with the World Health Organization's advocacy for humanistic care in digital health.

5. Model Rationality Analysis

5.1. Theoretical Self-Consistency Argument

5.1.1. Balanced Bidirectional Effects

The primary positive empowerment effect P1 and the negative counteracting health impairment effect P4 create tension. This model avoids simplistic linear judgments, instead revealing a dynamic equilibrium where the net effect = empowerment effect−impairment effect. This aligns with dialectical logic and reflects the complexity of AI application practices. The coexistence of gain spirals and loss spirals in COR theory provides the theoretical foundation for this equilibrium.

5.1.2. Threshold Regulation as Gatekeeper

P2, as a moderator, functions as a "transformation threshold." It explains why identical AI systems yield vastly different outcomes across departments and hospitals—not due to inferior AI technology, but inadequate AI understanding and trust. This design centers individual agency, avoiding technological determinism.

5.1.3. The Pivotal Role of Performance Perception

P3 treats performance as both a dependent and an independent variable, embodying the bidirectional adaptation principle of socio-technical systems theory. Performance is not merely an objective output but a subjectively constructed meaning. Physicians evaluate AI value through performance assessments, thereby determining the depth of subsequent adoption. This forms a feedback loop: “AI application → performance perception → attitude adjustment → subsequent application.”

5.1.4. The Indispensable Role of Health Variables

Most AI studies overlook the health dimension, yet the WHO Global Strategy on Digital Health explicitly warns that technology may increase burden (World Health Organization, 2021). This model addresses this theoretical gap by incorporating Presenteeism as a core mediator, embodying a “people-centered” value orientation.

5.2. Discussion on Practical Applicability

The following discusses the applicable scenarios for this model.

Policy-Driven Adoption: The model is particularly suited to explain China’s top-down promotion model from top-level design to grassroots implementation, where the cognitive adjustment variable can be understood as the last mile in policy execution.

Period of Rapid Technological Iteration: Resource depletion in COR theory is especially pronounced in scenarios with frequent AI model updates. This model can predict performance fluctuations across different stages. Primary Healthcare Capacity Enhancement Projects: This model strongly explains cloud-sharing platforms like Wenzhou’s MaaS platform, where primary care physicians’ comprehension and trust serve as critical success factors.

The following discusses scenarios where this model may not apply.

Fully voluntary adoption: If physicians have complete autonomy over AI usage, P2’s moderating effect may diminish, with main effects becoming more direct.

Highly mature and stable technology: When AI achieves extremely high accuracy and becomes an industry standard, the P4 health depletion pathway may disappear.

Non-clinical roles: Designed for medical personnel, the model requires variable adjustments for applicability to administrative, logistical, or other non-clinical positions.

6. Model-Based Policy Implications

6.1. Cognitive Empowerment Policies

Establish mandatory standards for medical AI explainability. Drawing from the EU AI Act’s requirement for high-risk AI systems to be explainable, it is recommended that China revise policies defining medical AI product classifications. Mandate that AI-assisted diagnostic tools provide decision heatmaps or feature weight maps.

Incorporate AI literacy into the credit system for physician standardized training. The National Health Commission should add a mandatory module on medical AI collaboration to the “Content and Standards for Resident Standardized Training,” with corresponding assessments.

6.2. Performance Incentive Policies

Optimize AI collaboration metrics in performance evaluations. The state should revise the “Public Hospital Performance Evaluation Manual” to introduce an AI performance bonus under personnel expenditure indicators. Hospitals must allocate a fixed proportion of efficiency gains from AI directly to frontline physicians as rewards. This prevents hospitals from monopolizing technological dividends while physicians experience a lack of gain.

Establish a performance-satisfaction linkage monitoring system for AI applications. Require tertiary hospitals to publish quarterly reports on digital healthcare humanities, concurrently tracking four metrics: AI utilization rate, performance improvement rate, medical staff satisfaction, and SPS-6 Presenteeism scores. When performance improves but satisfaction declines, initiate specialized assessments on technological humanism to investigate issues such as excessive AI monitoring or overburdening training.

6.3. Health Protection Policies

Establish occupational health risk assessment systems for AI applications. In accordance with the Occupational Disease Prevention and Control Law, the National Health Commission should issue guidelines on occupational health protection for medical AI use. Hospitals must conduct SPS-6 Presenteeism surveys before deploying AI to identify high-risk individuals and provide humanistic care measures.

Establish mental health leave for AI users. Drawing from innovation leave models in high-tech enterprises, hospitals should grant monthly mental health leave to clinicians using AI for over 4 hours daily. This time may be allocated for technical learning, stress management, or simple rest, directly compensating for resource depletion as outlined in COR theory.

7. Conclusions and Contributions

7.1. Core Findings

The impact of AI applications on healthcare workers’ performance represents a dynamic equilibrium between empowerment and attrition. The main effect P1 indicates the objective existence of technological dividends, yet P4 reveals that health attrition may offset some gains. This implies that net technological benefits = objective empowerment - subjective attrition, necessitating dual-pronged policy interventions.

Cognitive factors act as gatekeepers for translating technological efficacy. Understanding and trust are not supplementary but essential conditions. This overturns the simplistic notion that technological advancement equals performance improvement, establishing cognitive precedence as a theoretical foundation.

Performance perception serves as the pivotal link between objective technology and subjective attitudes. P3’s mediating effect indicates that AI enhances satisfaction both through performance improvement and by directly influencing satisfaction. This suggests managers must ensure clinicians perceive both performance gains and technological respect alongside professional autonomy.

Health attrition represents the hidden cost of AI adoption. P4 translates WHO's macro-level warnings into measurable mediating variables, transforming humanistic care from a technological slogan into an actionable, assessable management metric.

7.2. Theoretical Contributions

Establishes an integrated "technology-cognition-performance-health" framework that synthesizes classic theories (TAM, socio-technical systems, COR) while contextualizing them for medical AI settings.

Introduces Presenteeism into technology performance research, expanding occupational health psychology's scope. While traditional research focuses on absence rates, this model reveals that on-duty inefficiency impacts AI performance conversion more significantly than absence, offering new directions for employee health management.

Theoretical refinement based on policy-driven practices contributes a Chinese sample to localized digital health research. China's policy model of "top-level design—local innovation—grassroots implementation" contrasts sharply with Western market-driven approaches, and this model captures this institutional uniqueness.

7.3. Model Limitations and Pathways for Further Validation

As a theoretical construct, this model candidly acknowledges the following limitations:

Boundary conditions remain inadequately defined. Factors such as the differential impact of AI types, the moderating role of hospital IT infrastructure levels, and the contingency effects of departmental cultural characteristics require validation through qualitative comparative analysis or stratified regression in subsequent studies.

Insufficient dynamic evolution. The model employs a static cross-sectional framework, failing to depict performance curve changes at 1, 3, or 5 years post-AI implementation. Longitudinal tracking studies could analyze performance trajectories over time.

Given these limitations, subsequent field research in hospitals could provide robust validation. For instance, selecting multiple hospitals of varying tiers across different cities for an 18-month tracking study—collecting data every six months—could validate the S-curve effect.

The ultimate vision of this research is to advance the development of a human-centered smart healthcare theory. Technology should not serve as a substitute or monitor for physicians, but rather as a collaborator and enabler. This necessitates sustained theoretical attention to human-centered technology design, institutional humanistic care, and the protection of physicians' professional autonomy. Only through such approaches can "Internet Plus Healthcare" truly achieve the unity of technological revolution and humanistic care, thereby fulfilling the proposition that new-quality productive forces "are driven by innovation and are essentially advanced productive forces" (Xi, 2024).

Author Contributions:

Conceptualization, methodology,formal analysis, resources, data curation, writing—original draft preparation,writing—review and editing,,supervision, project administration:Yingnuo Qi. All authors have read and agreed to the published version of the manuscript.

Funding:

This research received no external funding.

Institutional Review Board Statement:

Not applicable.

Informed Consent Statement:

The study did not involve humans.

Data Availability Statement:

Not applicable.

Acknowledgments:

I would like to express sincere gratitude to the supervisor for their invaluable guidance and insightful suggestions throughout the research. Special thanks are also extended to the university for providing a favorable academic platform and research resources. It is hoped that the findings of this study can serve as a modest reference for relevant research and practice, and further in-depth exploration will be carried out in subsequent work.

Conflict of Interest:

The author declare no conflict of interest.

References

Brayfield, A. H., & Rothe, H. F. (1951). An index of job satisfaction. Journal of Applied Psychology, 35(5), 307–311.

Brynjolfsson, E., & McElheran, K. (2016). The rapid adoption of data-driven decision-making. American Economic Review, 106(5), 133–139.

Central South University News. (2025). Xiangya Hospital completes China's first localized deployment of AI middle platform in medical system. https://news.csu.edu.cn/info/1003/160858.htm

China Digital Healthcare Development Report. (2024). Blue book on China's digital healthcare development 2023–2024. Social Sciences Academic Press.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. Nature, 542(7639), 115–118.

General Office of the CPC Central Committee, & General Office of the State Council. (2023). Opinions on further deepening reforms to promote the healthy development of the rural healthcare system. https://www.gov.cn/zhengce/2023-02/23/content_5742938.htm

General Office of the State Council. (2018). Opinions on promoting the development of "Internet plus healthcare." https://www.gov.cn/zhengce/content/2018-04/28/content_5286645.htm

General Office of the State Council. (2023a). Guiding opinions on comprehensively advancing the construction of tightly-integrated county-level healthcare communities. https://www.gov.cn/zhengce/zhengceku/202312/content_6923447.htm

General Office of the State Council. (2023b). Opinions on further improving the healthcare service system. https://www.gov.cn/zhengce/2023-03/23/content_5748063.htm

Hobfoll, S. E. (1989). Conservation of resource caravans and engaged settings. Journal of Occupational and Organizational Psychology, 82(1), 116–122.

Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., Wang, Y. (2017). Artificial intelligence in healthcare: Past, present, and future. Stroke and Vascular Neurology, 2(4), 230–243.

Koopmans, L., Bernaards, C., Hildebrandt, V., van der Beek, A., & van Buuren, S. (2014). Development of an individual job performance questionnaire. Journal of Occupational and Environmental Medicine, 71(1), 118–125.

Lerner, D., Amick, B. C., Rogers, W. H., Malspeis, S., Bungay, K., & Cynn, D. (2001). The work limitations questionnaire. Medical Care, 39(1), 72–85.

Liu, X., Wang, Y., Wang, Y., & Zhang, Y. (2023). Physician acceptance of artificial intelligence in medical imaging: A cross-sectional study in China. Journal of Medical Internet Research, 25, e45678.

Liu, X., Zhang, K., & Wang, B. (2023). Investigative study on the impact of artificial intelligence-assisted diagnostic systems on physicians' clinical decision-making. China Hospital Management, 43(5), 67–71.

Moran, D., Jia, S., & Zhang, Y. (2022). The dark side of AI in healthcare: A study on physician burnout and job stress. International Journal of Medical Informatics, 165, 104832.

National Health Commission. (2022). Clinical application management specifications for artificial intelligence-assisted treatment technologies (2022 edition).

National Health Commission. (2023). China digital healthcare development report 2023. People's Medical Publishing House.

National Health Commission. (2024). Reference guidelines for artificial intelligence application scenarios in the health sector. https://www.nhc.gov.cn/guihuaxxs/c100133/202411/3dee425b8dc34f739d63483c4e5c334c.shtml

National Healthcare Security Administration. (2023). Guidelines for pricing items in radiological examinations.

National Medical Products Administration. (2021). Guiding principles for classifying medical software products based on artificial intelligence. https://www.beijing.gov.cn/zhengce/zhengcefagui/qtwj/202204/t20220408_2669468.html

Southern Network. (2024). Injecting new momentum into healthcare services: Guangdong implements 289 “AI+” application cases. https://www.nfnews.com/content/z6L5vkVGoe.html

State Administration of Traditional Chinese Medicine. (2024). Operational manual for performance evaluation of national tertiary public traditional Chinese medicine hospitals (2024 edition). https://www.nhc.gov.cn/yzygj/c100068/202403/6544f999d39a4e9a955f8248b582c0ae/files/1732873690528_37083.pdf

Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting. Human Relations, 4(1), 3–38.

Wenzhou Municipal Health Commission. (2024). MaaS medical AI integration platform interfaces cover entire city.

Wenzhou Municipal People’s Government. (2024). Witnessing the new landscape of smart and convenient healthcare in Wenzhou.

World Health Organization. (2021). Global strategy on digital health 2020–2025. WHO Press.

Xi, J. (2024). Developing new quality productive forces is an intrinsic requirement and key focus for promoting high-quality development. China Government Online. https://www.gov.cn/yaowen/liebiao/202405/content_6954761.htm

Zhang, K., Li, M., & Chen, J. (2024). Reconstructing physician professional identity in the digital healthcare era. Medicine and Society, 37(2), 12–18.