

Factors Influencing Adoption of Large Language Models in Health Care: Mixed-Methods Study of Health Care Professionals and Patients in China

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Table of Contents

Original Manuscript.....	5
Supplementary Files.....	37
Figures	38
Figure 1.....	39
Figure 2.....	40
Figure 3.....	41
Figure 4.....	42
Figure 5.....	43
Figure 6.....	44
Figure 7.....	45
Figure 8.....	46
Multimedia Appendixes	47
Multimedia Appendix 1.....	48
Multimedia Appendix 2.....	48
Multimedia Appendix 3.....	48
Multimedia Appendix 4.....	48
Multimedia Appendix 5.....	48
Multimedia Appendix 6.....	48
Multimedia Appendix 7.....	48
Multimedia Appendix 8.....	48
Multimedia Appendix 9.....	48
Multimedia Appendix 10.....	48
Multimedia Appendix 11.....	48
TOC/Feature image for homepages	49
TOC/Feature image for homepage 0.....	50

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Abstract

Background: Large language models (LLMs) such as ChatGPT are rapidly reshaping information management in health care by transforming how knowledge is accessed, communicated, and applied. However, their adoption in sensitive domains raises unresolved concerns regarding trust, privacy, and equity, especially in low- and middle-income countries with varying levels of digital readiness and institutional safeguards.

Objective: This study aimed to examine the factors influencing adoption intent of LLMs among health care professionals (HCPs) and patients/caregivers (PCs) in China, with particular focus on trust, information behavior, and socio-technical readiness.

Methods: We conducted a multicenter mixed-methods study across five tertiary hospitals, surveying 240 HCPs and 480 PCs and conducting semi-structured interviews with 30 participants. Quantitative analyses included logistic regression, random forest, and XGBoost models, supplemented with SHAP-based interpretability. Qualitative data were analyzed thematically to identify role-specific expectations and concerns.

Results: Trust, perceived usefulness, and digital readiness emerged as the strongest facilitators of LLM adoption, while privacy concerns, limited literacy, and socioeconomic disadvantage were significant barriers. Predictive models achieved strong performance (AUC = 0.83–0.96), with trust consistently identified as the central predictor across user groups. Qualitative findings highlighted distinct perspectives: HCPs emphasized workflow integration and accountability, whereas PCs prioritized plain-language comprehensibility and emotional reassurance.

Conclusions: LLM adoption in health care depends less on technical performance than on managing trust, information behaviors, and socio-technical contexts. These findings extend information management theory by positioning socio-technical readiness as a critical construct and highlight that trust and ethical concerns outweigh demographic factors. Practically, the study points to the need for trust-centered, role-sensitive system design, inclusive digital literacy strategies, and governance frameworks that promote accountability and equitable participation.

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Original Manuscript

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Abstract

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Conclusions: LLM adoption in health care depends less on technical performance than on managing trust, information behaviors, and socio-technical contexts. These findings extend information management theory by positioning socio-technical readiness as a critical construct and highlight that trust and ethical concerns outweigh demographic factors. Practically, the study points to the need for trust-centered, role-sensitive system design, inclusive digital literacy strategies, and governance frameworks that promote accountability and equitable participation.

Keywords: Large Language Models (LLMs), Socio-technical Readiness, Knowledge Management, Information Behavior, Trust and Governance

Introduction

The rapid advancement of large language models (LLMs), such as ChatGPT and other generative artificial intelligence (AI) tools, has opened new opportunities in the management and use of information across multiple sectors, including health care¹⁻⁴. These models, trained on vast datasets of biomedical literature and clinical texts, are increasingly capable of performing tasks that fundamentally reshape the way information is accessed and applied—such as explaining medical concepts, summarizing patient records, supporting decision-making, and facilitating communication between patients and professionals⁵⁻¹⁰. Their accessibility, versatility, and potential for integration into organizational workflows highlight LLMs as a significant force in transforming information practices, with implications for efficiency, equity, and engagement¹¹.

In the field of information systems, the integration of LLMs into enterprise and knowledge management systems is shown to optimize data processing and automate business workflows, marking a new era of intelligent data capabilities¹². Research in knowledge management has documented how generative AI enhances knowledge transfer, decision-making efficiency, and operational effectiveness through improved content creation and knowledge dissemination^{13,14}. In the realm of information systems research, generative AI has been identified as a transformative

technology with profound societal and organizational implications—calling for reevaluation of research agendas and considering its evolving influence on business and social systems¹⁵. Additionally, LLMs are being deployed to support knowledge workers, streamlining complex tasks through natural language interfaces and enabling new kinds of workflow integration^{16,17}.

However, the integration of LLMs into sensitive domains such as health care raises critical questions for information management theory and practice. Concerns about accuracy, data privacy, transparency, embedded biases, and accountability are by no means resolved, reflecting broader challenges in governing AI-augmented information systems. Information management research emphasizes that the governance of information artifacts in high-stakes environments must address these socio-technical risks at multiple levels—from technology design to organizational oversight^{18,19}. Importantly, successful adoption of LLMs depends not only on technical performance but also on stakeholder perceptions and acceptance. Multi-stakeholder research shows that trust, explainability, equity, and human oversight play central roles in determining whether an AI system is perceived as credible and useful by different user groups^{20,21}. Understanding how healthcare professionals (HCPs) and patients/caregivers (PCs) assess usefulness, trustworthiness, and risk is essential—not only to ensure that LLMs enhance information use and knowledge exchange but also to prevent them from reinforcing existing inequalities or mistrust²².

Previous studies in high-income contexts have begun to explore how clinicians interact with AI-generated information. However, limited evidence exists from low- and middle-income countries (LMICs), where factors like digital literacy, information trust, and institutional readiness critically shape technology adoption. A systematic scoping review highlights that AI initiatives in LMIC healthcare—such as clinical decision support and chatbots—face persistent challenges, including reliability, user-friendliness, context misalignment, and distrust of AI systems²³.

Specifically in China, the socio-economic diversity between urban and rural regions suggests that attitudes toward LLMs may vary significantly. Insights from information management research emphasize the digital divide in LMICs, pointing to disparities not merely in access but in digital capacity, health literacy, and socio-technical support systems^{24,25}. Therefore, examining LLM adoption in China becomes an inquiry not just into technology implementation, but into information behavior and management within complex socio-cultural and infrastructural contexts²⁶.

Against this backdrop, this study investigates how HCPs and PCs in China perceive and anticipate the use of LLMs in health care. By employing a multicenter mixed-methods design, we aim to identify both opportunities and challenges related to the management of information flows, trust, and knowledge creation. The findings contribute to the broader field of information

management by offering empirical insights into how emerging AI technologies are understood and negotiated by different user groups, thereby informing theory on technology adoption, as well as guiding ethical and effective strategies for implementation in LMIC health care systems.

Methods

Study Design and Setting

We conducted a multicenter, cross-sectional mixed-methods study across five tertiary hospitals located in four provinces of China-Guangdong, Hunan, Jiangxi, and Guizhou-between August 2024 and March 2025. The study sites included both academic medical centers and regional tertiary hospitals. These institutions were purposively selected to represent diverse regional levels of economic development and digital infrastructure, thereby providing a heterogeneous context for examining how LLMs are perceived and adopted as information tools in health care.

The study employed a mixed-methods design, integrating a structured quantitative survey with qualitative semi-structured interviews. This design enabled us to examine both generalizable patterns and nuanced perspectives regarding HCPs and PCs trust, readiness, and willingness to use LLMs.

Participant Recruitment

HCPs were eligible if they were licensed physicians or registered nurses actively involved in outpatient or inpatient care. PCs were eligible if they were aged 18 years or older, receiving care at the hospital during the study period, and able to provide informed consent.

A total of 240 HCPs and 480 PCs were enrolled through purposive sampling across the five hospitals. **Table 1** summarizes the sociodemographic and professional characteristics of HCPs (e.g., role, department, years of experience, attitudes toward digital tools), while **Table 2** presents PCs' demographic features (e.g., age, gender, education, digital literacy, perspectives on AI-assisted interpretation). These structured datasets informed both quantitative analyses and the purposive selection of participants for qualitative inquiry.

Data Collection Instruments

The overall study flow is illustrated in **Figure 1**. Two parallel questionnaires were designed for HCPs and PCs (**Tables S1–S2**). The instruments were informed by established theoretical frameworks in information systems research, particularly the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Core constructs included: 1. Perceived usefulness (expected benefits of LLMs for information tasks); 2. Trust and perceived ease of use (confidence in reliability and accessibility of LLM outputs); 3. Behavioral intention (willingness to use LLMs in information-seeking or communication scenarios); 4. Facilitating conditions (e.g., privacy concerns, legal accountability, digital infrastructure).

Ethical dimensions such as fairness, transparency, and accountability were incorporated to reflect sociotechnical risks documented in prior research. Items were measured using five-point Likert scales, complemented by an open-ended question to capture additional concerns. The instruments underwent expert review, pilot testing, and iterative refinement to ensure content validity, linguistic clarity, and cultural appropriateness.

Questionnaires were administered on-site using paper forms or electronically via secure QR code-based survey tools, depending on local facility logistics and participant preference. Trained research assistants provided support when needed, particularly for older participants or those with limited digital literacy.

Qualitative Interviews

To capture richer insights into information-related perceptions and concerns, we conducted semi-structured interviews with a purposive subsample of 15 HCPs and 15 PCs, selected to ensure diversity in demographics, institutional background, and digital literacy. Interviews were conducted either in person or via secure audio/video platforms, lasting approximately 30–45 minutes.

The interview guide focused on four domains: 1. Perceived benefits of LLMs for health information use; 2. Concerns related to trust, accuracy, and data privacy; 3. Expectations for accountability and ethical safeguards; 4. Anticipated changes in patient-provider information interaction.

All interviews were audio-recorded with informed consent, transcribed verbatim, and anonymized. Data were analyzed using inductive thematic analysis. Two researchers independently coded transcripts, followed by axial coding to identify categories and themes. Discrepancies were resolved by consensus. Coding was managed using RQDA and Excel.

A hierarchical coding framework was iteratively developed, enabling thematic depth and cross-case comparison. To visualize information patterns, we generated word clouds, bar plots of thematic frequency, and Sankey diagrams mapping participant groups to themes. These visualizations supported interpretation of how trust, readiness, and willingness intersect with user roles and contexts.

Quantitative and Predictive Analyses

Quantitative analyses were performed using Python (v3.12) and R (v4.3). Descriptive statistics were reported as means (SD) for continuous variables and frequencies (%) for categorical variables. Group differences were assessed using chi-square tests and independent-sample t-tests as appropriate.

To identify determinants of adoption intent, we estimated multivariable logistic regression (LR) models, controlling for demographic and contextual covariates. To complement regression, two

machine learning approaches—random forest (RF) and extreme gradient boosting (XGBoost)—were implemented to explore nonlinear patterns and improve prediction of willingness to use LLMs. Model training employed stratified sampling (70% training, 30% validation), with five-fold cross-validation applied to reduce overfitting.

Model performance was assessed primarily through discrimination (area under the receiver operating characteristic curve, AUC) and calibration (Brier score, calibration plots). While conventional clinical decision-making metrics (e.g., decision curve analysis) were not central to this study, additional evaluation measures such as F1 score, precision, recall, and accuracy were included to examine classification quality. Variable importance rankings and Shapley Additive Explanation (SHAP) values were used to enhance interpretability, highlighting the most influential factors shaping adoption intent (e.g., digital literacy, trust, privacy concerns). An overview of the statistical modeling and analytical procedures is provided in **Figure S1**.

Ethics approval and consent to participate

This study was approved by the institutional review boards (IRBs) or ethics committees of all participating hospitals. All participants provided written informed consent prior to participation. Participation was voluntary, and respondents were assured of the confidentiality and anonymity of their data. This study was conducted in accordance with the Declaration of Helsinki and relevant local ethical guidelines.

Results

Participant Characteristics

A total of 720 individuals participated, comprising 240 HCPs and 480 PCs (**Table 1** and **Table 2**). Among HCPs, two-thirds were physicians (66.2%) and one-third nurses (33.8%), with an average age of 39.9 years (SD = 6.5) and 9.9 years (SD = 4.8) of clinical experience. Participants were drawn from diverse departments, with representation from internal medicine, surgery, intensive care, and emergency care. Almost half (48.8%) reported frequent use of digital tools, and 69.2% were already aware of LLMs, though only 36.7% had prior experience using them.

PCs were evenly distributed by gender (50.4% male), with a mean age of 50.1 years (SD = 12.6). Educational attainment varied considerably: 25.2% had only primary schooling or below, while 15.0% held a bachelor's degree or higher. Frequent digital tool use was reported by 46.5%, and about half (51.5%) had heard of LLMs, though only 26.0% had ever used them. These characteristics reflected broad heterogeneity in digital readiness and information familiarity across both user groups.

Group Differences in Perceptions of LLMs

Perceptions of LLMs varied significantly between HCPs and PCs. On a five-point Likert scale, HCPs

rated perceived usefulness higher (2.98 vs 2.61, $P < 0.001$) and expressed stronger privacy concerns (3.23 vs 2.72, $P < 0.001$). Trust in LLMs, however, was comparable between groups (3.09 vs 2.83, $P = 0.195$). These results suggest that professionals view LLMs as potentially valuable but remain cautious about risks, while patients and caregivers perceive fewer benefits but also fewer risks (**Figure S2**).

Correlates of Adoption Willingness

Among HCPs, willingness to adopt LLMs was positively associated with prior awareness and use, frequent digital tool use, AI/informatics training, higher trust, and perceived usefulness (all $P < 0.05$). In contrast, privacy concerns and uncertainty about legal accountability reduced willingness (**Table 3**).

Among PCs, willingness was more strongly shaped by socio-demographic and contextual factors: higher education level, better regional economic conditions, and frequent digital tool use were all associated with stronger adoption intent (all $P < 0.001$). Trust and perceived usefulness were again positive predictors, while privacy concerns acted as deterrents. Unlike HCPs, prior LLM exposure was not a significant factor for PCs (**Table 4**).

Independent Predictors from Multivariate Modeling

Multivariable logistic regression highlighted both common and distinct predictors across groups.

For HCPs, adoption was most strongly predicted by trust (OR = 3.78, $P < 0.001$), prior use (OR = 5.61, $P < 0.001$), and clarity regarding legal responsibility (OR = 1.56, $P = 0.021$). Privacy concerns and infrequent digital tool use were negative predictors (**Table S3; Figure 2A**).

For PCs, trust dominated as the single strongest determinant (OR = 36.34, $P < 0.001$), alongside perceived usefulness (OR = 2.01, $P < 0.001$). Lower education, infrequent digital tool use, and disadvantaged economic background significantly reduced adoption likelihood (**Table S4; Figure 2B**).

These results underscore that attitudinal and informational readiness factors (trust, usefulness, digital literacy) are more predictive of willingness than static demographic variables.

Model Performance and Interpretability

Across LR, RF, and XGBoost, predictive performance was strong, with AUCs ranging from 0.83–0.85 among HCPs and 0.93–0.96 among PCs. Classification metrics (precision, recall, F1 score) confirmed robustness across models (**Figures 3-5, Figures S3-S4, Table 5 and Tables S5-S8**).

Interpretability analyses (SHAP values) consistently identified trust in LLMs as the most influential predictor of adoption across both groups. Among HCPs, prior use, legal clarity, and digital tool use also ranked highly. For PCs, education and regional economic status were more prominent,

reflecting underlying disparities in digital readiness. Demographic and institutional factors (e.g., age, department, hospital type) had minimal predictive power.

Marginal Effects and Interaction Patterns

Marginal effects analysis confirmed that trust in LLMs exerted the strongest positive effect on adoption across both groups, while privacy concern consistently deterred adoption. Among HCPs, prior use amplified the effect of trust, whereas among PCs, education and digital literacy had stronger moderating roles. Interaction effects were limited but indicated that combinations such as trust $\times$ legal clarity (for HCPs) and usefulness $\times$ prior exposure (for PCs) enhanced adoption intent (**Figures 6–7, Figures S5–S9**).

Qualitative Insights

Semi-structured interviews (n = 30) revealed eleven thematic categories providing depth to the survey findings (**Figure 8**).

HCPs emphasized risks and responsibilities, focusing on concerns about misinformation, privacy, and institutional accountability. They also stressed the need for structured onboarding, training, and workflow integration.

PCs prioritized accessibility and comprehensibility, particularly among participants with lower digital literacy. Themes such as plain-language explanations, conversational interaction, and support for understanding medical information emerged strongly.

Across both groups, trust surfaced repeatedly as the foundation for adoption, while digital readiness shaped whether users perceived LLMs as beneficial or burdensome. Thematic co-occurrence analyses highlighted that risk-related concerns were often tied to calls for oversight and institutional safeguards. PCs' adoption intent was more closely tied to communication benefits, while HCPs' intent was more closely tied to efficiency and professional utility.

Discussion

Principal Findings

This study provides one of the first mixed-methods investigations into how HCPs and PCs evaluate LLMs as information resources in health contexts. By integrating predictive modeling with qualitative insights, we identified trust, digital readiness, and perceived usefulness as the most consistent facilitators of adoption willingness. Barriers included privacy concerns, low digital literacy, and structural inequalities. These results confirm that adoption of generative AI cannot be understood solely as a technical process but must be approached as a sociotechnical information management challenge, where individual attitudes, organizational readiness, and socio-economic context intersect to shape technology uptake.

Trust as a Central Determinant

Across both quantitative models and qualitative narratives, trust consistently emerged as the strongest determinant of users' willingness to adopt LLMs. This aligns with foundational TAM extensions, which establish trust as a significant influence on perceived usefulness and behavioral intention^{27,28}.

From an information systems perspective, trust is not a monolithic construct but is composed of multiple dimensions—including trust in the technology itself and trust in the provider or institution^{29,30}. For HCPs, trust was rooted in institutional validation, professional training, and confidence in the reliability of AI-generated outputs. In contrast, PCs anchored their trust in the clarity, transparency, and reassurance offered by LLM-mediated communication.

Importantly, trust was shown to be iterative and relational, developing over repeated exposure rather than instantaneously. This dynamic, role-dependent conception of trust resonates with findings in human–computer interaction that emphasize the evolving nature of trust in intelligent systems^{31,32}.

These insights underscore the necessity of understanding trust as a multi-faceted, context-sensitive construct in information systems research. For implementation, it suggests that organizations should actively build and sustain trust through transparent design, institutional support, and contextualized user experiences, rather than treating trust as a singular or static variable.

Perceived Usefulness and Role-Specific Information Needs

Perceived usefulness significantly influenced willingness to adopt LLMs, aligning with the foundational principles of the TAM—it represents the degree to which an individual believes that using a particular system would enhance their performance³³⁻³⁵. However, the operational meaning of usefulness varied across user groups, reflecting distinctive role-specific information practices.

For HCPs, usefulness manifested in tangible enhancements to documentation efficiency, workflow integration, and knowledge retrieval, resonating with prior studies emphasizing task performance benefits in professional settings³⁶.

In contrast, PCs framed usefulness around comprehensibility: they valued plain-language explanations, auditory interaction, and simplified medical information. This perspective echoes findings from health communication research that demonstrate how plain-language materials significantly improve comprehension and engagement, especially among low-literacy users^{37,38}.

These divergent interpretations highlight that effective deployment of LLMs must be contextually adaptive—recognizing that the perceived value of an information system is co-defined by the user's role, their level of information literacy, and their communicative needs. As such, a “one-size-fits-all” implementation risks undermining both user engagement and long-term adoption.

Barriers: Privacy, Literacy, and the Digital Divide

Despite widespread interest, significant barriers continue to hamper the adoption of LLMs as information tools in healthcare. Privacy concerns consistently reduced willingness to adopt across both HCPs and PCs, reflecting broader anxieties around data security, accountability, and ownership in information systems. This aligns with established findings highlighting the critical need to balance utility and trust in digital information environments³⁹.

Among HCPs, concerns were particularly focused on liability and auditability; among PCs, fears centered on data misuse. These insights mirror findings that privacy literacy directly influences online information-sharing behavior, with lower privacy awareness reducing engagement⁴⁰.

Moreover, digital divides played a central role in shaping adoption trajectories. Participants with low education, limited digital literacy, or from disadvantaged regions showed significantly lower willingness to engage with LLMs. Qualitative interviews further revealed that low-literacy participants often required structured onboarding or intergenerational support to interact with these systems. These observations extend the concept of the digital divide beyond mere access, aligning with IS research that frames digital inequality as a composite of infrastructure, skills, and participation disparities^{39,40}. In health-specific contexts, the digitization of healthcare in LMICs further illustrates how connectivity, literacy, and local readiness jointly shape equitable adoption²⁴.

Together, these findings suggest that true equity in LLM-driven information environments requires comprehensive strategies that address not only access but also privacy empowerment and inclusive design, ensuring that vulnerable users are not left behind in the AI-enabled transformation of healthcare.

Theoretical Contributions

This study contributes to information management theory in several ways.

First, it extends adoption models such as TAM and UTAUT by empirically demonstrating that trust and ethical risk outweigh demographic factors in shaping adoption intent for AI-driven information tools. This aligns with recent advances emphasizing the importance of trust and perceived risk in technology acceptance contexts, particularly for AI or generative tools—extending beyond traditional predictors like performance expectancy or effort expectancy^{41,42}.

Second, it introduces socio-technical readiness as a critical construct—capturing how digital literacy, institutional support, and privacy concerns jointly influence information behaviors. This concept is increasingly recognized as essential in understanding adoption of emerging technologies, where technical readiness alone is insufficient without corresponding social system alignment⁴³⁻⁴⁵.

Third, the findings highlight the multi-dimensional nature of information use, where the same

technology offers distinct value propositions depending on user roles and contexts—pointing to the need for adaptive system design and role-based evaluation in information management. This reflects a broader theoretical shift toward contextually grounded, socio-technical frameworks rather than one-size-fits-all models.

Collectively, these contributions support a broader agenda for sociotechnical information systems research, emphasizing equity, governance, and the co-construction of trust—reinforcing that effective information tools require integration of social factors, institutional policies, and technological affordances rather than standalone technical performance.

Practical and Policy Implications

From a practical standpoint, the findings of this study point to several priorities for the responsible deployment of LLMs as information systems. Trust must be intentionally designed and managed through transparent interfaces, verifiable outputs, and institutional endorsement. Prior research has emphasized that explainable and trustworthy AI systems are essential for user acceptance and sustained engagement³¹.

Equally important is role-sensitive design, since healthcare professionals demand workflow integration and accountability frameworks, while patients and caregivers benefit more from accessible language, multimodal interfaces, and reassurance mechanisms. This aligns with information systems research emphasizing that system value is contingent on matching technologies to user roles and contexts⁴⁶.

At the same time, bridging the digital divide is critical to prevent exclusion. Accessibility-by-design—through multilingual support, simplified interfaces, and targeted training for low-literacy users—should be treated as a foundational design imperative. Evidence shows that the digital divide in AI use is not only about infrastructure, but also about literacy and socio-technical support systems, requiring intentional interventions to foster equitable participation²⁵.

Finally, policy and governance frameworks must evolve to clarify liability, privacy protection, and data sovereignty. Without institutional safeguards—such as oversight mechanisms, accountability structures, and AI-aware governance—adoption will remain fragile and uneven. These concerns mirror broader debates in information management and AI ethics, where multi-level governance and regulatory clarity are seen as prerequisites for sustainable adoption^{47,48}.

Limitations and Future Research

Several limitations should be noted. First, although trust consistently emerged as the strongest determinant of LLM adoption intent, the underlying dimensions—such as institutional endorsement, interface design, and peer influence—remain underexplored. IS research has shown that trust in

technology is multi-faceted, incorporating both individual and institutional trust components, but these dynamics have not been fully disentangled in this context^{47,49}.

Second, the study focused on willingness rather than actual usage behavior, leaving the intention–behavior gap unexplored. Information systems research emphasizes that stated behavioral intention often does not translate into actual use, especially over time, highlighting a need for longitudinal and intervention-based research⁵⁰.

Third, our analysis was conducted within the Chinese context, which presents unique socio-economic and regulatory conditions. Cross-cultural comparisons would enhance the study's generalizability and allow for better understanding of how societal norms and governance environments shape technology acceptance.

Finally, broader ethical and cultural considerations—including algorithmic bias, informed consent, and localized norms—were not deeply examined. Future research should engage with such issues from an information management perspective, integrating them into AI governance and system design to ensure inclusive and ethically grounded adoption.

Conclusion

This study underscores that adopting LLMs in health care is less about technical capacity and more about information management dynamics—trust, information behavior, and equity in digital readiness. By situating LLM adoption within established frameworks of technology acceptance and information use, we demonstrate both theoretical and practical implications for the field. For researchers and practitioners, the challenge lies not only in improving model performance but in designing trustworthy, inclusive, and role-sensitive information environments. Only through attention to these factors can generative AI be integrated responsibly and sustainably into health care and beyond.

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Figure legends

Figure 1. Overview of the study design, methods, and analytical framework.

Figure 2. Multivariate logistic regression models identifying predictors of willingness to adopt large language models (LLMs). (A) for healthcare professionals (HCPs). (B) for patients/caregivers (PCs).

Figure 3. Discriminative and calibration performance of logistic regression, random forest, and XGBoost models in predicting willingness to adopt large language models (LLMs). (A) ROC curves for healthcare professionals (HCPs). (B) ROC curves for patients/caregivers (PCs). (C) Calibration curves with 10-bin error bars for HCPs. (D) Calibration curves with 10-bin error bars for PCs.

All models were evaluated using stratified 5-fold cross-validation and a held-out validation set. The diagonal line in calibration plots indicates perfect calibration.

Figure 4. Model interpretability and cross-model agreement in predicting LLM adoption willingness among healthcare professionals (HCPs).

(A–B) SHAP bar plot (A) and beeswarm plot (B) for logistic regression. (C–D) SHAP bar plot (C) and beeswarm plot (D) for random forest. (E–F) SHAP bar plot (E) and beeswarm plot (F) for XGBoost. (G) Heatmap of feature importance rank consistency across the three models. (H) Overlap in top 3, 5, and 7 ranked features across models. (I) Kendall's tau rank correlation matrix assessing agreement in feature importance rankings across models.

Figure 5. Model interpretability and cross-model agreement in predicting large language models (LLMs) adoption willingness among patients/caregivers (PCs).

(A–B) SHAP bar plot (A) and beeswarm plot (B) for logistic regression. (C–D) SHAP bar plot (C) and beeswarm plot (D) for random forest. (E–F) SHAP bar plot (E) and beeswarm plot (F) for XGBoost. (G) Heatmap of feature importance rank consistency across the three models. (H) Overlap in top 3, 5, and 7 ranked features across models. (I) Kendall's tau rank correlation matrix assessing agreement in feature importance rankings across models.

Figure 6. Marginal effects of key predictors on willingness to adopt large language models (LLMs) among healthcare professionals (HCPs).

(A) Interaction between Trust in LLMs and Prior Use of LLMs. (B) Interaction between Trust in LLMs and Receipt of AI/Informatics Training. (C) Interaction between Prior Use of LLMs and Perceived Usefulness. (D) Interaction between Prior Use of LLMs and Privacy Concern. (E) Interaction between Perceived Usefulness and Privacy Concern. (F) Interaction between Prior Use of LLMs and Clarity on Legal Responsibility.

Figure 7. Marginal effects of key predictors on willingness to adopt large language models (LLMs) among patients/caregivers (PCs).

(A) Interaction between Trust in LLMs and Prior Use of LLMs. (B) Interaction between Trust in LLMs and Prior awareness of LLMs. (C) Interaction between Trust in LLMs and Low Education Level (Primary school or below). (D) Interaction between Prior Use of LLMs and Perceived Usefulness. (E) Interaction between Prior Use of LLMs and Privacy Concern. (F) Interaction between Privacy Concern and Education level (High school).

Figure 8. Thematic structure, key subthemes, and motivational patterns shaping willingness to adopt large language models (LLMs) across healthcare professionals (HCPs) and patients/caregivers (PCs).

(A) Theme frequency distribution. (B) Subtheme word cloud. (C) Top 20 subthemes in HCPs. (D) Top 20 subthemes in PCs. (E) Subtheme co-occurrence in HCPs. (F) Subtheme co-occurrence in PCs. (G) Motivational pathways for LLM adoption (Sankey).

Figure S1. Overview of statistical modeling and analytical procedures.

Figure S2. Group comparisons of trust, perceived usefulness, and privacy concerns related to large language models (LLMs).

Figure S3. Comparative clinical utility of large language models (LLMs) adoption prediction models based on cumulative incremental accuracy (CIA) and net reclassification improvement (NRI).

(A–B) CIA curves across decision thresholds in healthcare professionals (HCPs) and patients/caregivers (PCs), demonstrating relative model performance in identifying true positives. (C–D) NRI analyses for HCPs and PCs, highlighting the added value of the random forest (RF) model compared to logistic regression (LR) and XGBoost.

Figure S4. Calibration assessment of large language models (LLMs) adoption prediction models across user groups using Hosmer–Lemeshow (HL) plots.

(A–B) HL plots for healthcare professionals (HCPs) across logistic regression (LR), random forest (RF), and XGBoost models. (C–D) HL plots for patients/caregivers (PCs) across LR, RF, and XGBoost models, showing calibration performance and deviations from perfect prediction.

Figure S5. Interaction effects of key predictors on willingness to adopt large language models

(LLMs) among healthcare professionals (HCPs).

(A) Trust in LLMs $\times$ Prior Use of LLMs. (B) Trust in LLMs $\times$ AI or Informatics Training. (C) Prior Use of LLMs $\times$ Perceived Usefulness. (D) Prior Use of LLMs $\times$ Privacy Concern. (E) Perceived Usefulness $\times$ Privacy Concern. (F) Prior Use of LLMs $\times$ Clarity on Legal Responsibility.

Figure S6. Interaction effects of key predictors on willingness to adopt large language models (LLMs) among patients/caregivers (PCs).

(A) Trust in LLMs $\times$ Prior Use of LLMs. (B) Trust in LLMs $\times$ Prior Awareness of LLMs. (C) Trust in LLMs $\times$ Low Education Level (Primary School or Below). (D) Prior Use of LLMs $\times$ Perceived Usefulness. (E) Prior Use of LLMs $\times$ Privacy Concern. (F) Privacy Concern $\times$ Education Level (High School).

Figure S7. Sensitivity analysis of predictor perturbations in healthcare professionals (HCPs).

(A–C) Probability distribution shifts in logistic regression, random forest, and XGBoost models when Trust in LLMs is perturbed. (D–F) Heatmaps of model performance changes (Δ Proba, Δ AUC, Δ LogLoss) across top predictors.

Figure S8. Sensitivity analysis of predictor perturbations in patients/caregivers (PCs).

(A–C) Probability distribution shifts in logistic regression, random forest, and XGBoost models when Trust in LLMs is perturbed. (D–F) Heatmaps of model performance changes (Δ Proba, Δ AUC, Δ LogLoss) across top predictors.

Figure S9. Decision curve analysis (DCA) comparing clinical utility of predictive models for LLM adoption across user groups.

(A) Net benefit curves for logistic regression, random forest, and XGBoost in healthcare professionals (HCPs). (B) Net benefit curves for the same models in patients/caregivers (PCs).

Figure 1



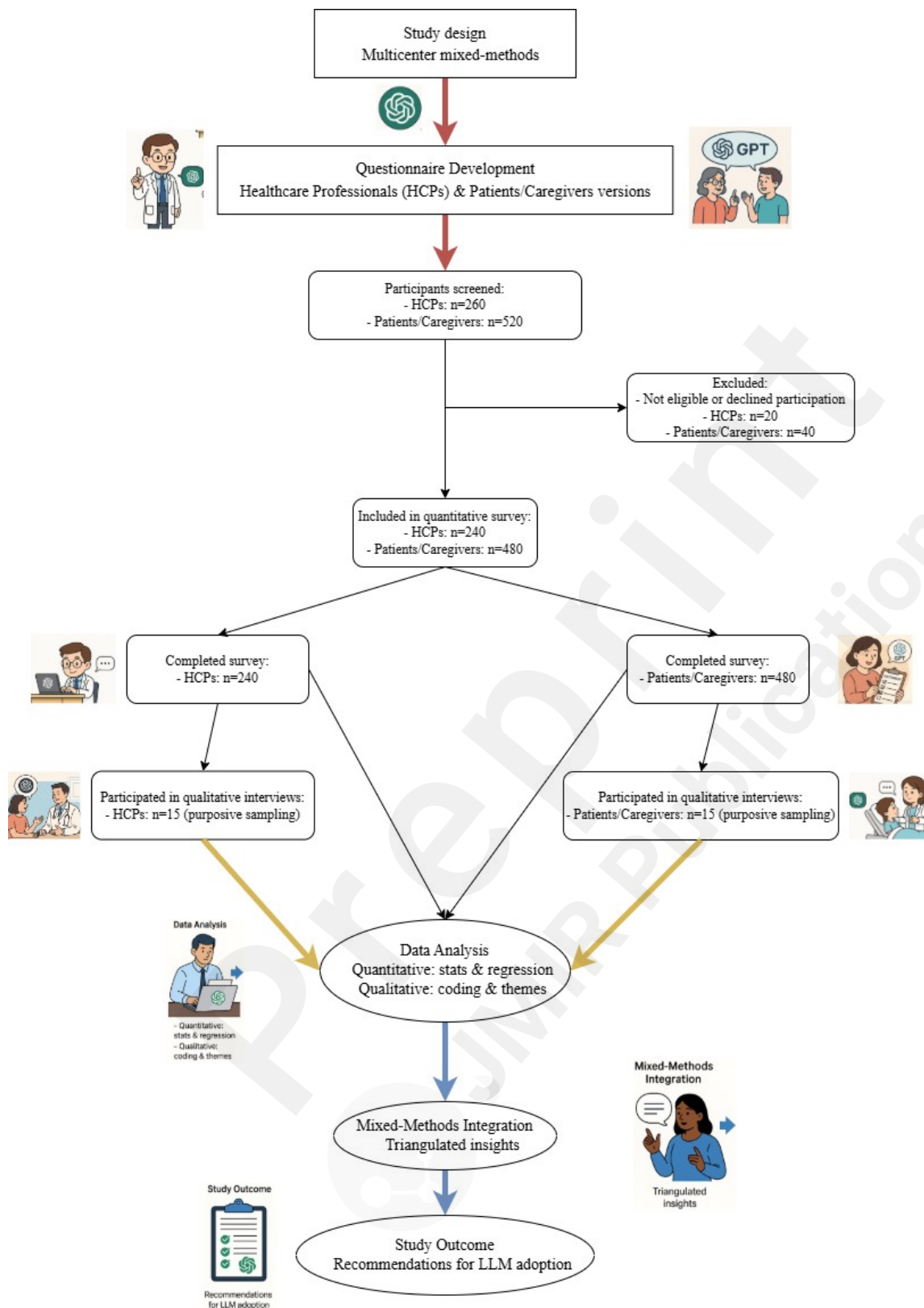


Figure 2

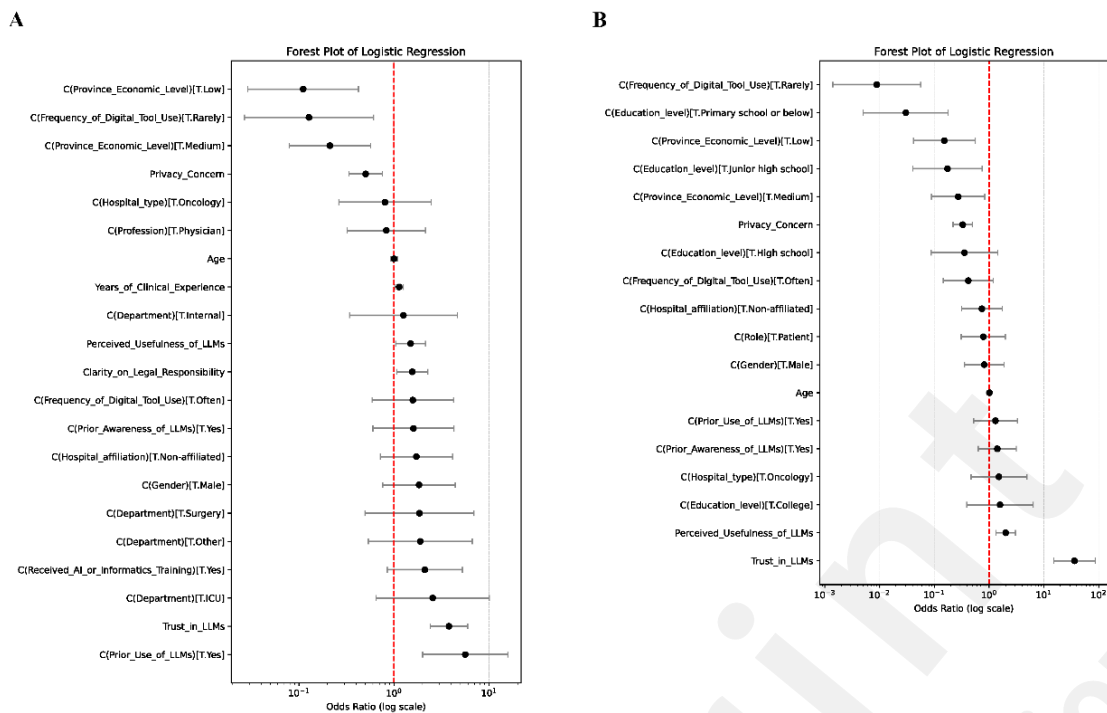


Figure 3

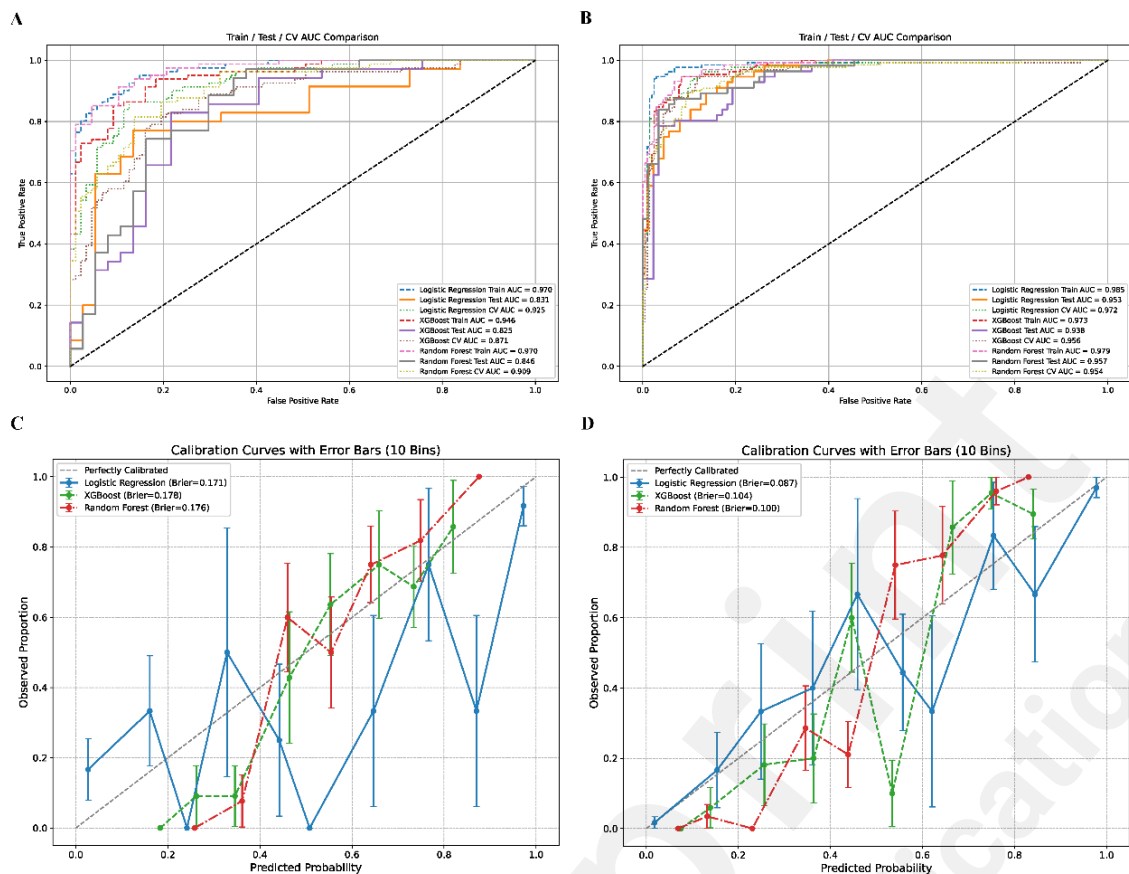


Figure 4

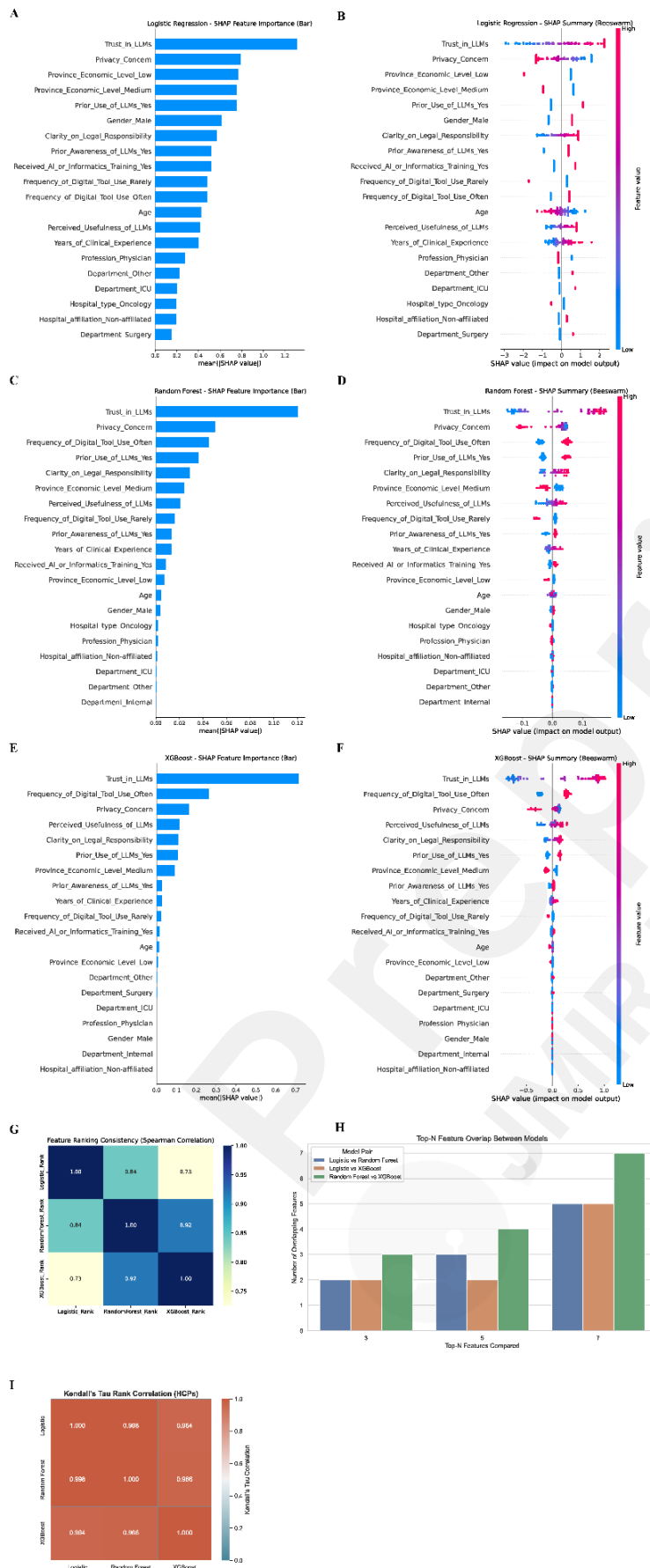


Figure 5

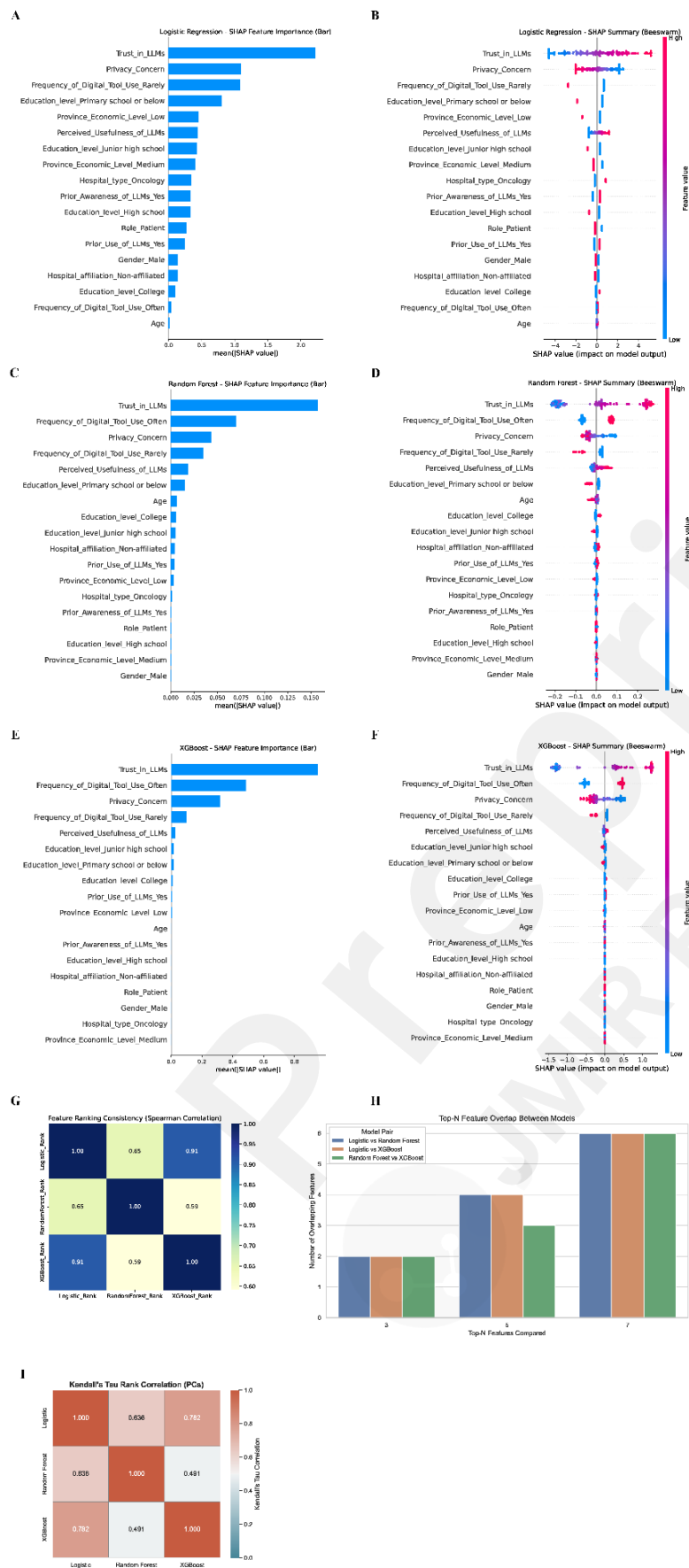


Figure 6

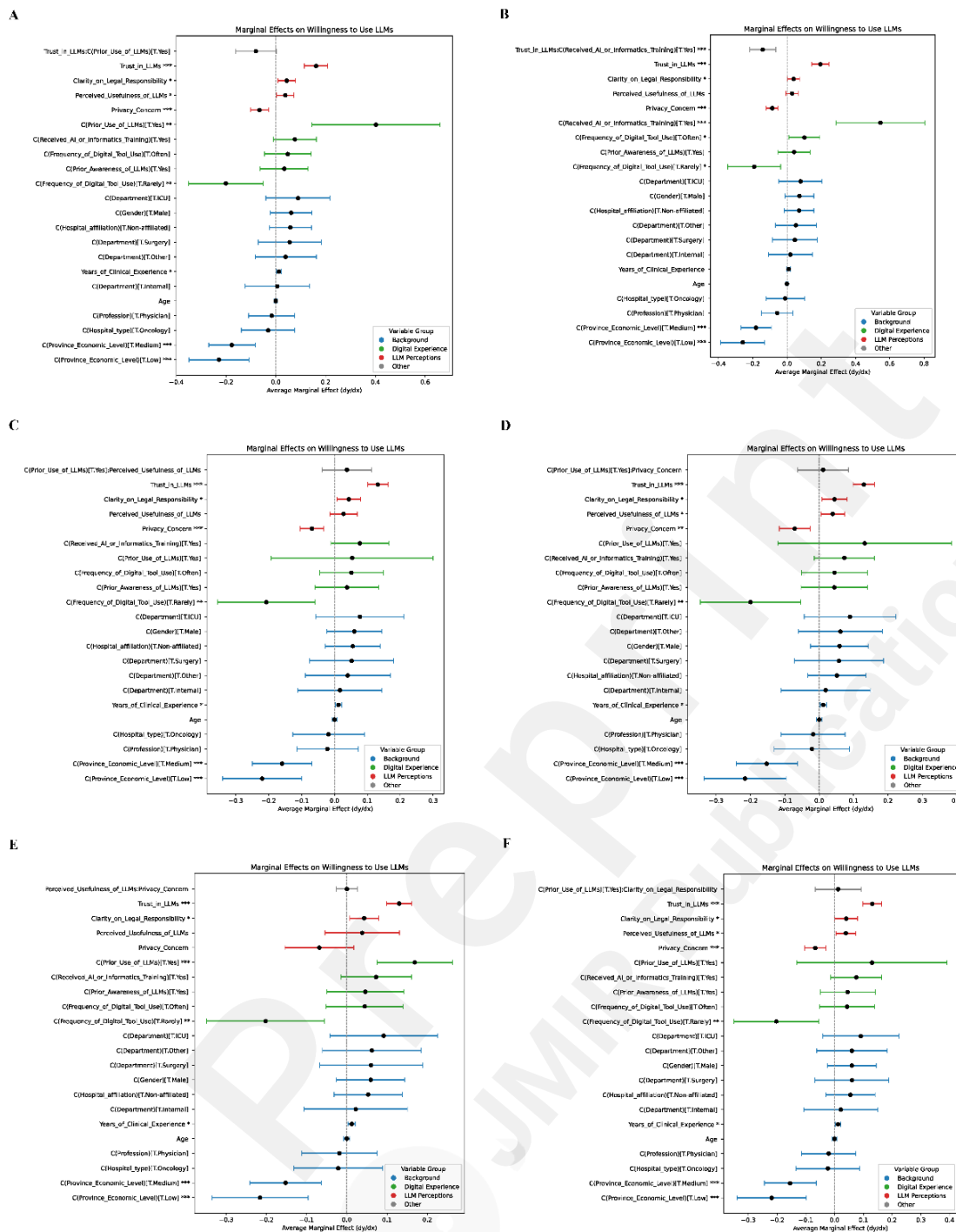


Figure 7

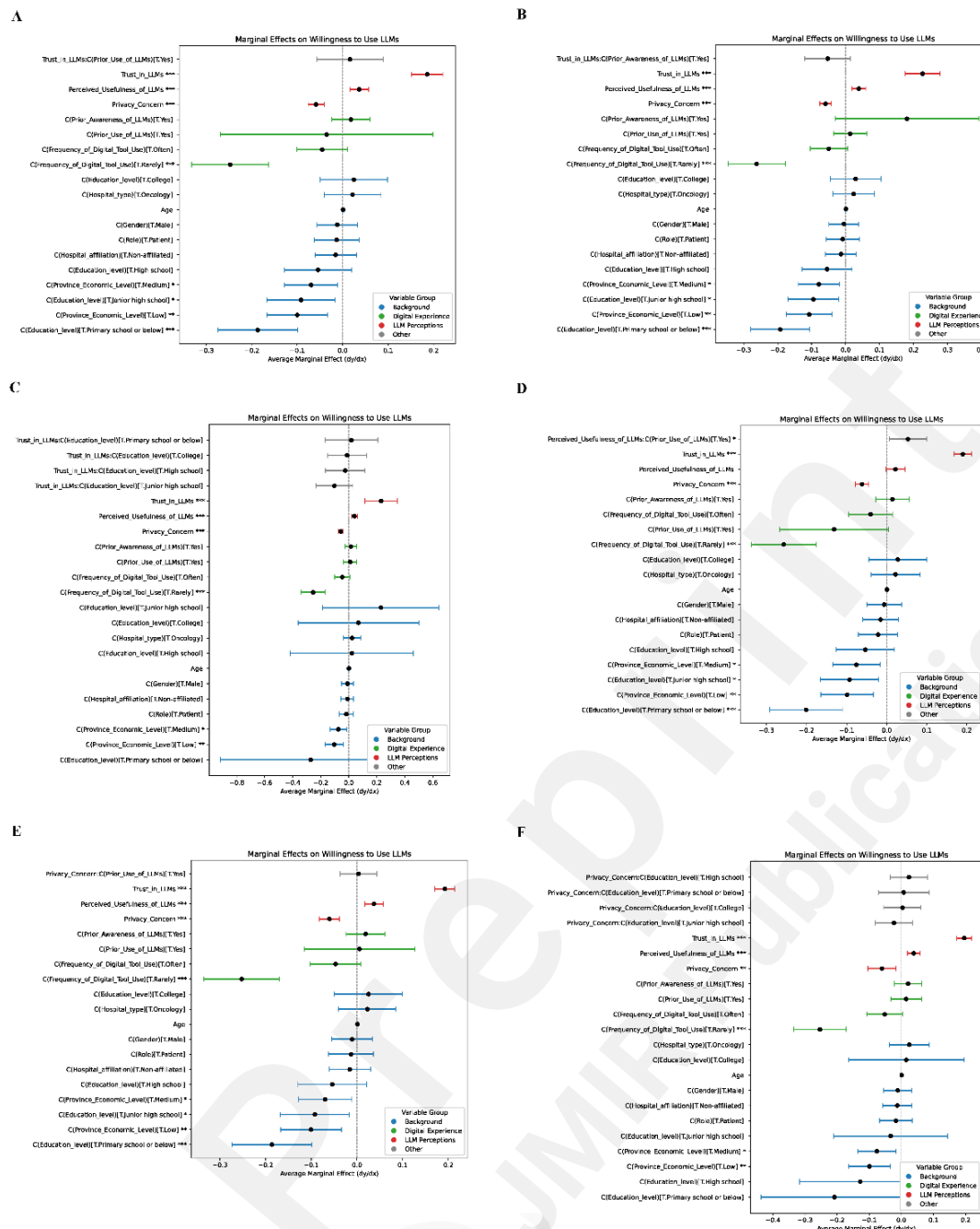


Figure 8

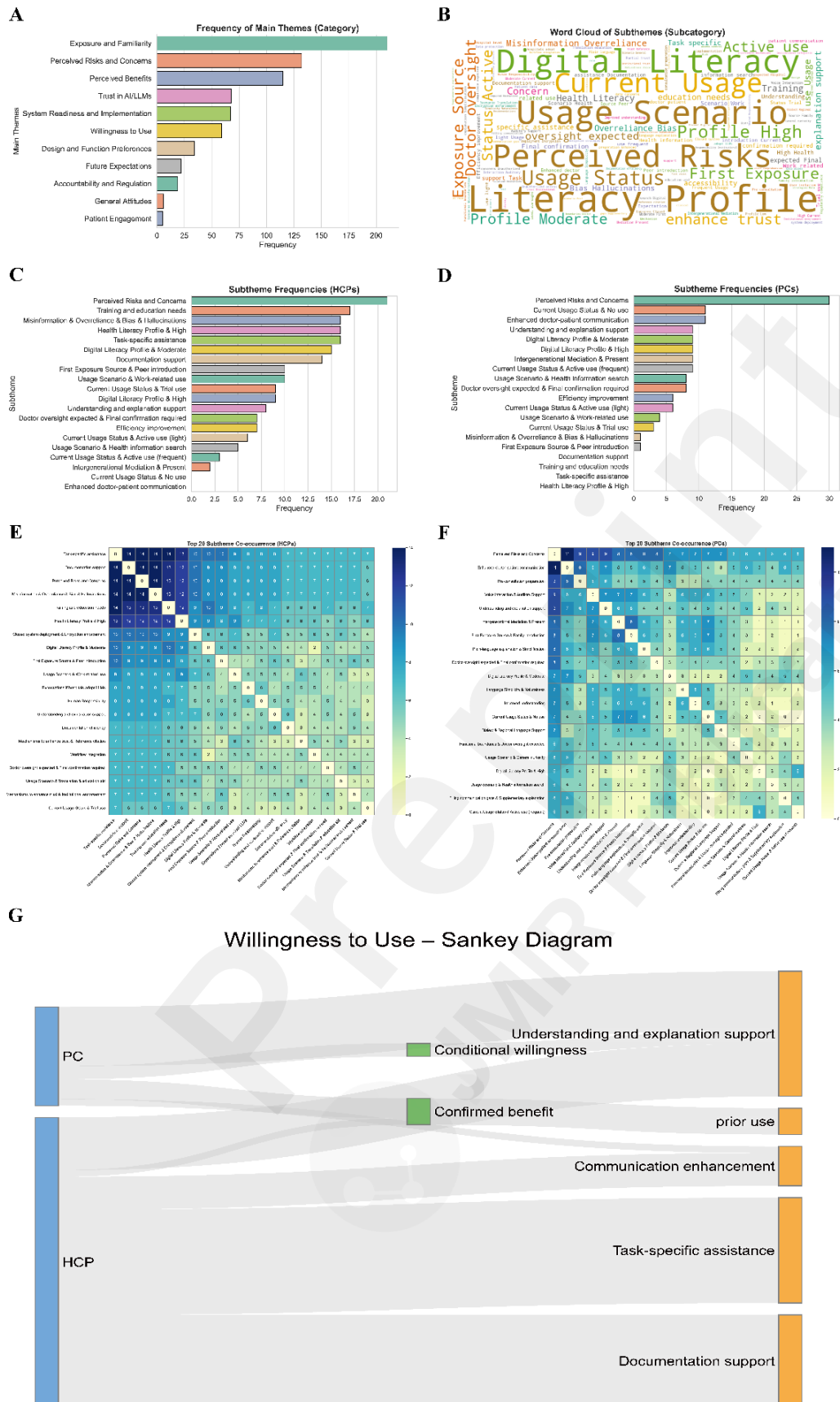


Table 1. Characteristics of healthcare professionals.

Variable	Healthcare professionals (n=240)
Gender	
- Male	141 (58.8%)
- Female	99 (41.3%)
Age (mean $\pm$ SD)	39.90 $\pm$ 6.48
Profession	
- Physician	159 (66.2%)
- Nurse	81 (33.8%)
Years of clinical experience	9.92 $\pm$ 4.81
Department	
- Internal medicine	54 (22.5%)
- Surgery	41 (17.1%)
- ICU	47 (19.6%)
- Emergency	60 (24.0%)
- Other	38 (15.8%)
Hospital affiliation	
Non-affiliated	101 (42.1%)
Affiliated	139 (57.9%)
Hospital type	
Oncology	44 (18.3%)
General	196 (81.7%)
Province economic level	
Low	46 (19.2%)
Medium	101 (42.1%)
High	93 (38.7%)
Frequency of digital tool use	
Rarely	38 (15.8%)
Occasionally	85 (35.4%)
Often	117 (48.8%)
Prior awareness of LLMs	
Yes	166 (69.2%)
No	74 (30.8%)
Prior use of LLMs	
Yes	88 (36.7%)
No	152 (63.3%)
Received AI or informatics training	
Yes	92 (38.3%)
No	148 (61.7%)
Trust in LLMs (1 to 5), (mean $\pm$ SD)	3.09 $\pm$ 1.21
Perceived usefulness (1 to 5), (mean $\pm$ SD)	2.98 $\pm$ 1.25
Privacy concerns (1 to 5), (mean $\pm$ SD)	3.23 $\pm$ 1.33
Clarity on legal responsibility (1 to 5), (mean $\pm$ SD)	3.11 $\pm$ 1.32

Table 2. Characteristics of patients/caregivers.

Variable	Patients/Caregivers (n=480)
Gender	
- Male	242 (50.4%)
- Female	238 (49.6%)
Age (mean $\pm$ SD)	50.08 $\pm$ 12.62

Role	
- Patient	360 (75.0%)
- Caregiver	120 (25.0%)
Education level	
- Primary school or below	121 (25.2%)
- Junior high school	100 (20.8%)
- High school	96 (20.0%)
- College	91 (19.0%)
- Bachelor or above	72 (15.0%)
Hospital affiliation	
Non-affiliated	197 (41.0%)
Affiliated	283 (59.0%)
Hospital type	
Oncology	94 (19.6%)
General	386 (80.4%)
Province economic level	
Low	88 (18.3%)
Medium	202 (42.1%)
High	190 (39.6%)
Frequency of digital tool use	
Rarely	95 (19.8%)
Occasionally	162 (33.7%)
Often	223 (46.5%)
Prior awareness of LLMs	
Yes	247 (51.5%)
No	233 (48.5%)
Prior use of LLMs	
Yes	125 (26.0%)
No	355 (74.0%)
Trust in LLMs (1 to 5), (mean $\pm$ SD)	2.83 $\pm$ 1.22
Perceived usefulness (1 to 5), (mean $\pm$ SD)	2.61 $\pm$ 1.14
Privacy concerns (1 to 5), (mean $\pm$ SD)	2.72 $\pm$ 1.29

Table 3. Univariate correlations of LLMs adoption among healthcare professionals.

Variable	Willing	Unwilling/uncertain	P-value
Gender			0.927
- Male	69	72	
- Female	47	52	
Profession			0.712
- Physician	75	84	
- Nurse	41	40	
Department			0.751
- Internal medicine	27	27	
- Surgery	22	19	
- ICU	22	25	
- Emergency	25	35	
- Other	20	18	

Hospital affiliation			0.137
Non-affiliated	55	46	
Affiliated	61	78	
Hospital type			0.938
Oncology	22	22	
General	94	102	
Province economic level			< 0.001
Low	11	35	
Medium	34	59	
High	71	30	
Frequency of digital tool use			< 0.001
Rarely	5	33	
Occasionally	36	49	
Often	75	42	
Prior awareness of LLMs			< 0.001
Yes	93	73	
No	23	51	
Prior use of LLMs			
Yes	56	32	
No	60	92	
Received AI or informatics training			0.030
Yes	53	39	
No	63	85	
Age (mean $\pm$ SD)	39.52 $\pm$ 6.41	40.25 $\pm$ 6.55	0.382
Years of clinical experience	10.69 $\pm$ 5.10	9.20 $\pm$ 4.43	0.017
Trust in LLMs (1 to 5), (mean $\pm$ SD)	3.20 $\pm$ 1.22	2.78 $\pm$ 1.26	0.011
Perceived usefulness (1 to 5), (mean $\pm$ SD)	3.70 $\pm$ 1.11	2.52 $\pm$ 1.02	< 0.001
Privacy concerns (1 to 5), (mean $\pm$ SD)	2.82 $\pm$ 1.20	3.62 $\pm$ 1.33	< 0.001
Clarity on legal responsibility (1 to 5), (mean $\pm$ SD)	3.41 $\pm$ 1.29	2.84 $\pm$ 1.29	< 0.001

Table 4. Univariate correlates of LLMs adoption among patients/caregivers.

Variable	Willing	Unwilling/uncertain	P-value
Gender			0.547
- Male	98	144	
- Female	89	149	
Role			0.787
- Patient	142	218	
- Caregiver	45	75	
Education level			< 0.001
- Primary school or below	19	86	
- Junior high school	28	66	
- High school	40	65	
- College	58	45	
- Bachelor or above	42	31	
Hospital affiliation			0.886
Non-affiliated	78	119	
Affiliated	109	174	
Hospital type			0.462
Oncology	33	61	
General	154	232	

Province economic level			< 0.001
Low	23	67	
Medium	97	61	
High	67	165	
Frequency of digital tool use			< 0.001
Rarely	4	90	
Occasionally	24	138	
Often	159	65	
Prior awareness of LLMs			0.177
Yes	102	140	
No	85	153	
Prior use of LLMs			0.118
Yes	91	120	
No	96	173	
Age (mean ± SD)	49.50 ± 11.99	50.45 ± 13.02	0.410
Trust in LLMs (1 to 5), (mean ± SD)	3.02 ± 1.18	2.36 ± 1.04	< 0.001
Perceived usefulness (1 to 5), (mean ± SD)	3.97 ± 0.70	2.10 ± 0.88	< 0.001
Privacy concerns (1 to 5), (mean ± SD)	2.21 ± 1.77	3.04 ± 1.25	< 0.001

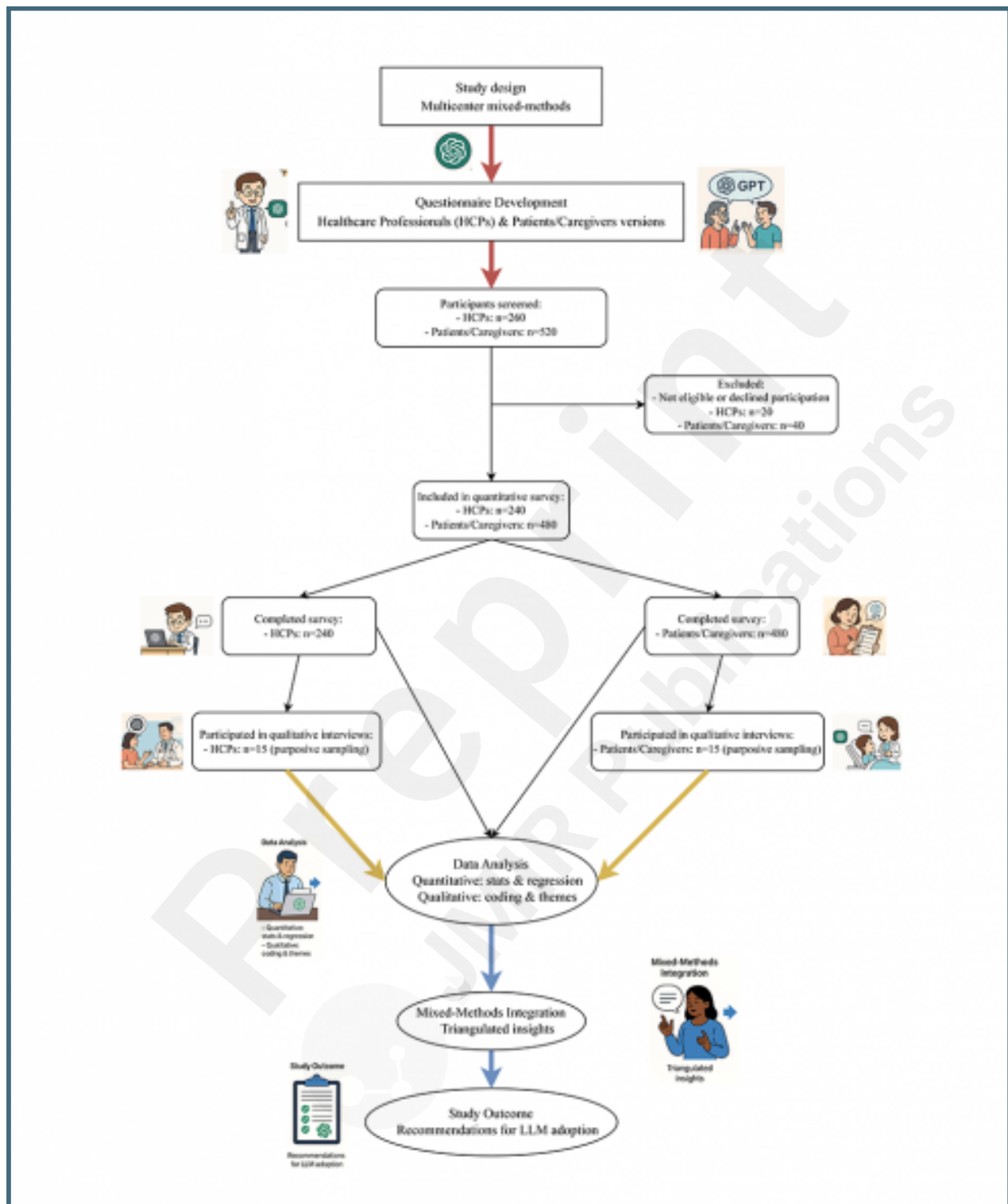
Table 5. Pairwise DeLong test results for AUC comparison across models (HCPs and PCs).

Model 1	Model 2	AUC 1	AUC 2	ΔAUC	P-value
Healthcare Professionals (HCPs)					
Logistic Regression	XGBoost	0.831	0.825	0.006	0.898
Logistic Regression	Random Forest	0.831	0.846	−0.015	0.699
XGBoost	Random Forest	0.825	0.846	−0.022	0.296
Patients/Caregivers (PCs)					
Logistic Regression	XGBoost	0.953	0.938	0.014	0.329
Logistic Regression	Random Forest	0.953	0.957	−0.004	0.775
XGBoost	Random Forest	0.938	0.957	−0.018	0.019

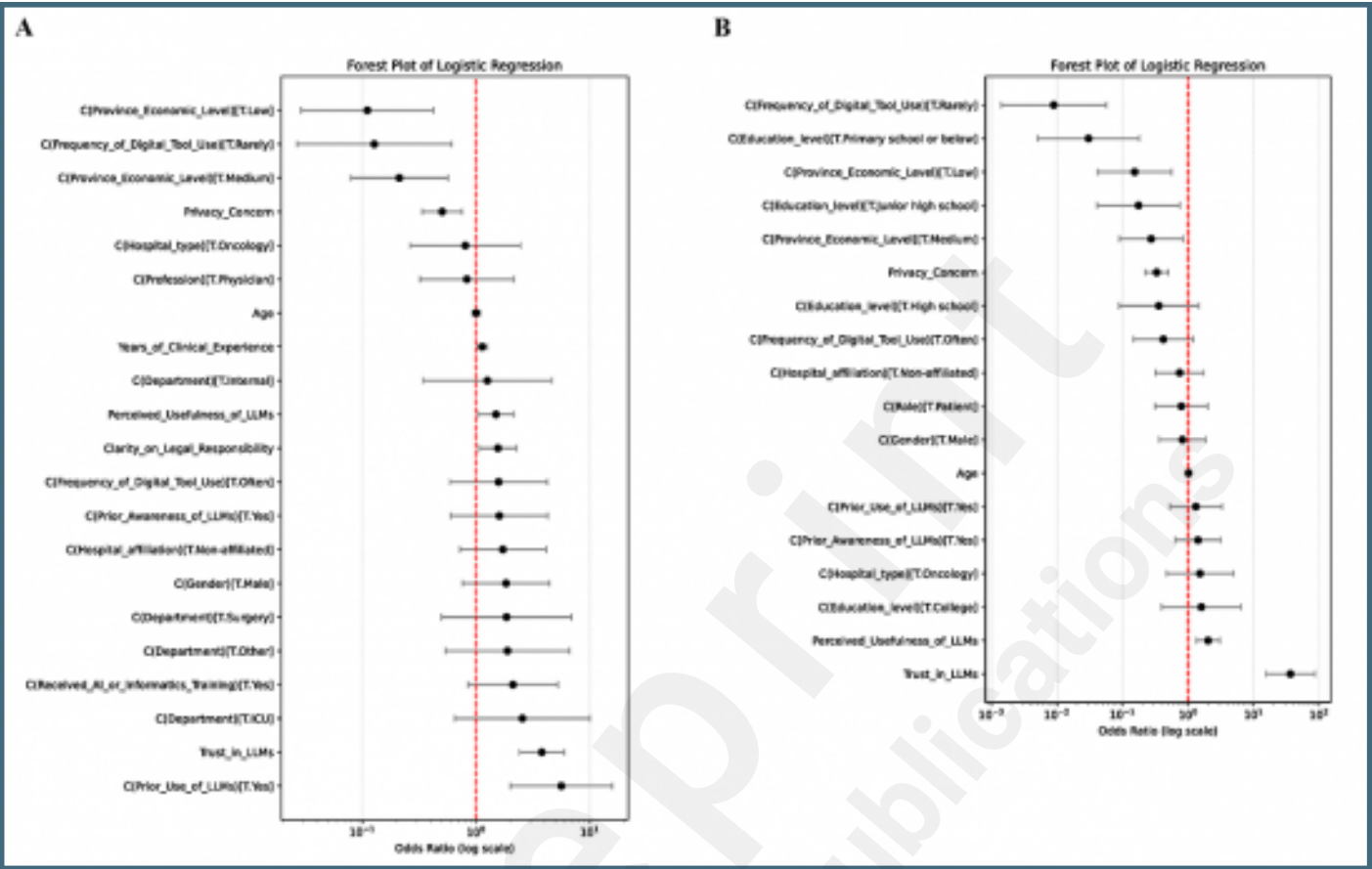
Supplementary Files

Figures

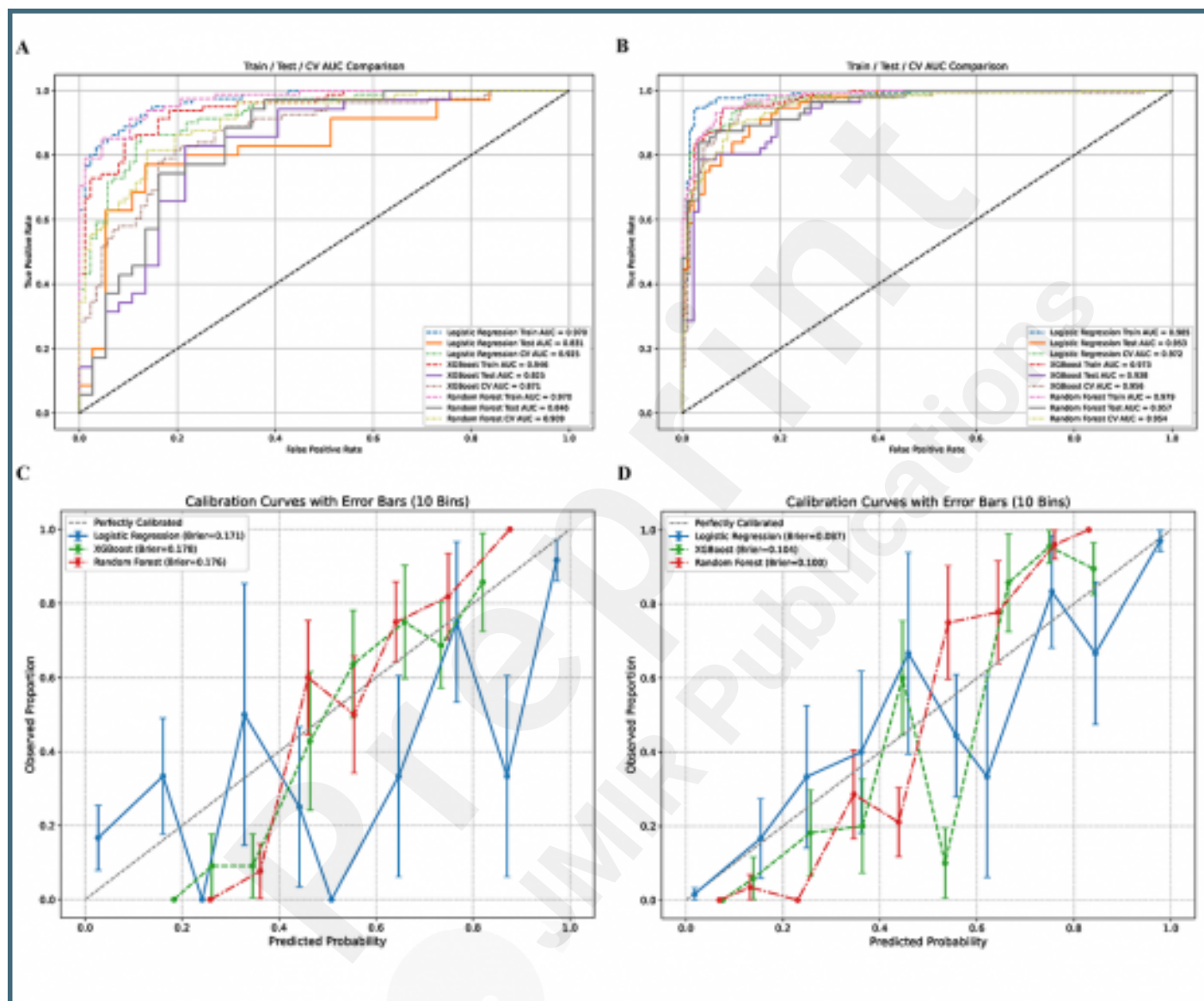
Overview of the study design, methods, and analytical framework.



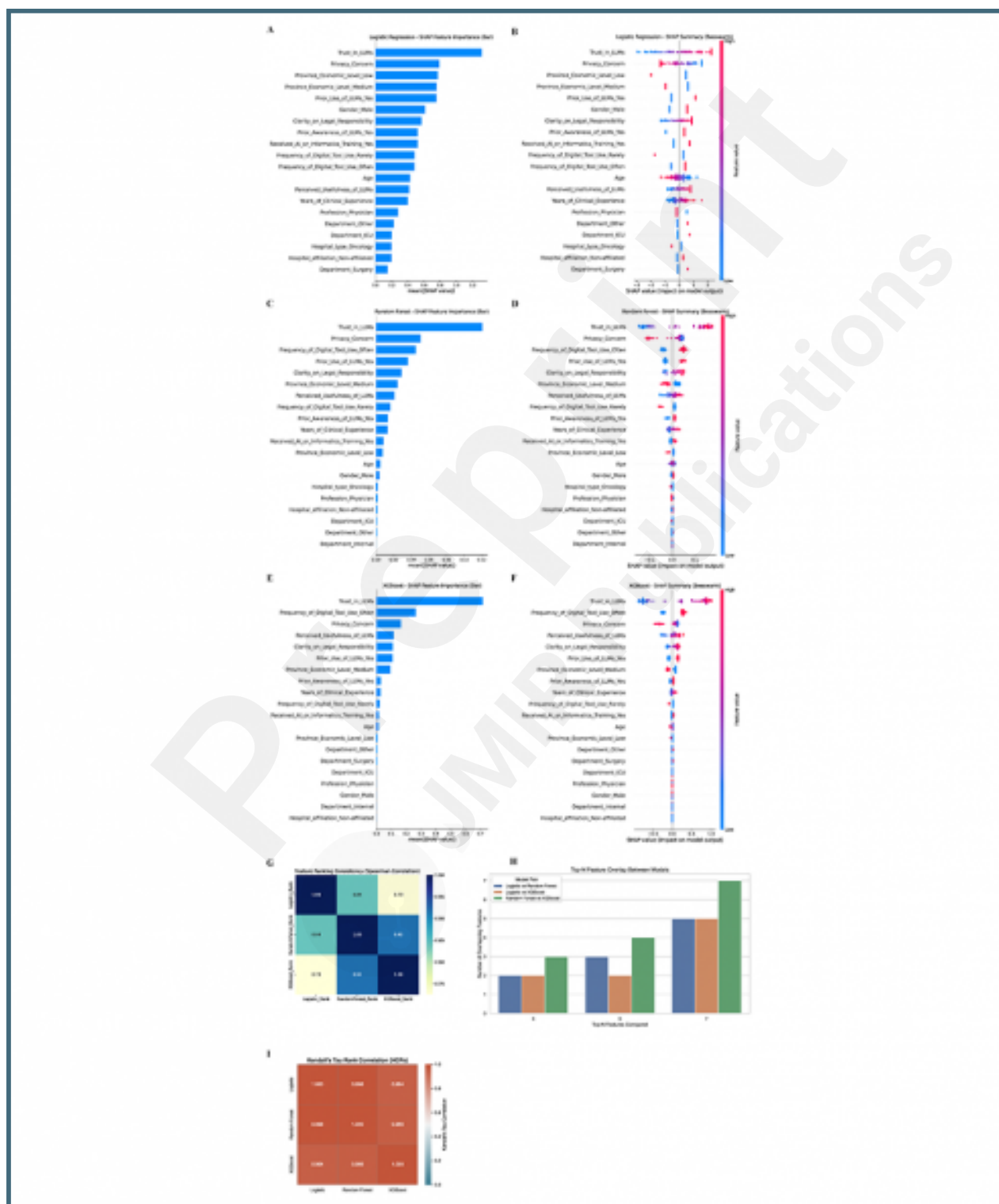
Multivariate logistic regression models identifying predictors of willingness to adopt large language models (LLMs). (A) for healthcare professionals (HCPs). (B) for patients/caregivers (PCs).



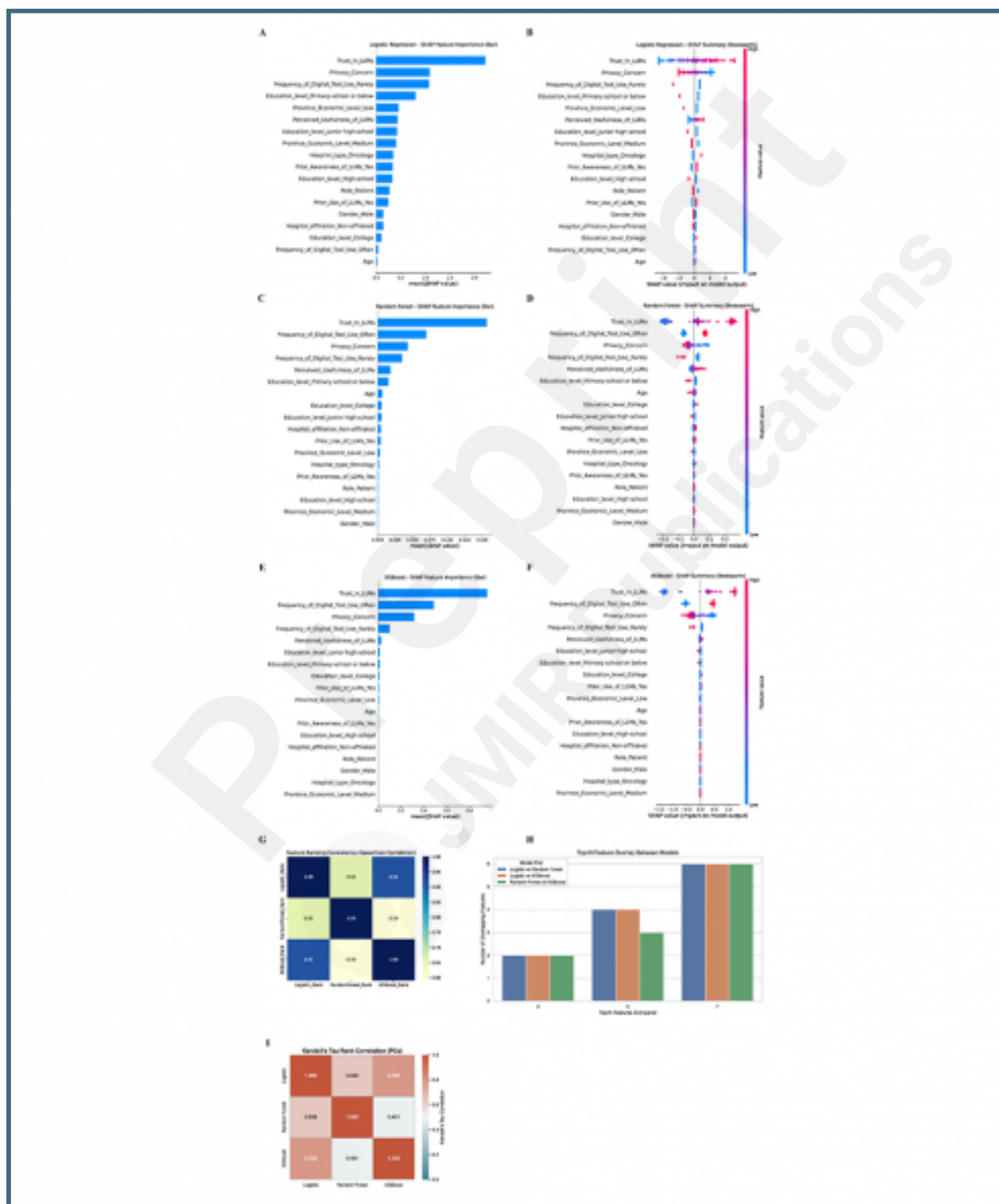
Discriminative and calibration performance of logistic regression, random forest, and XGBoost models in predicting willingness to adopt large language models (LLMs). (A) ROC curves for healthcare professionals (HCPs). (B) ROC curves for patients/caregivers (PCs). (C) Calibration curves with 10-bin error bars for HCPs. (D) Calibration curves with 10-bin error bars for PCs. All models were evaluated using stratified 5-fold cross-validation and a held-out validation set. The diagonal line in calibration plots indicates perfect calibration.



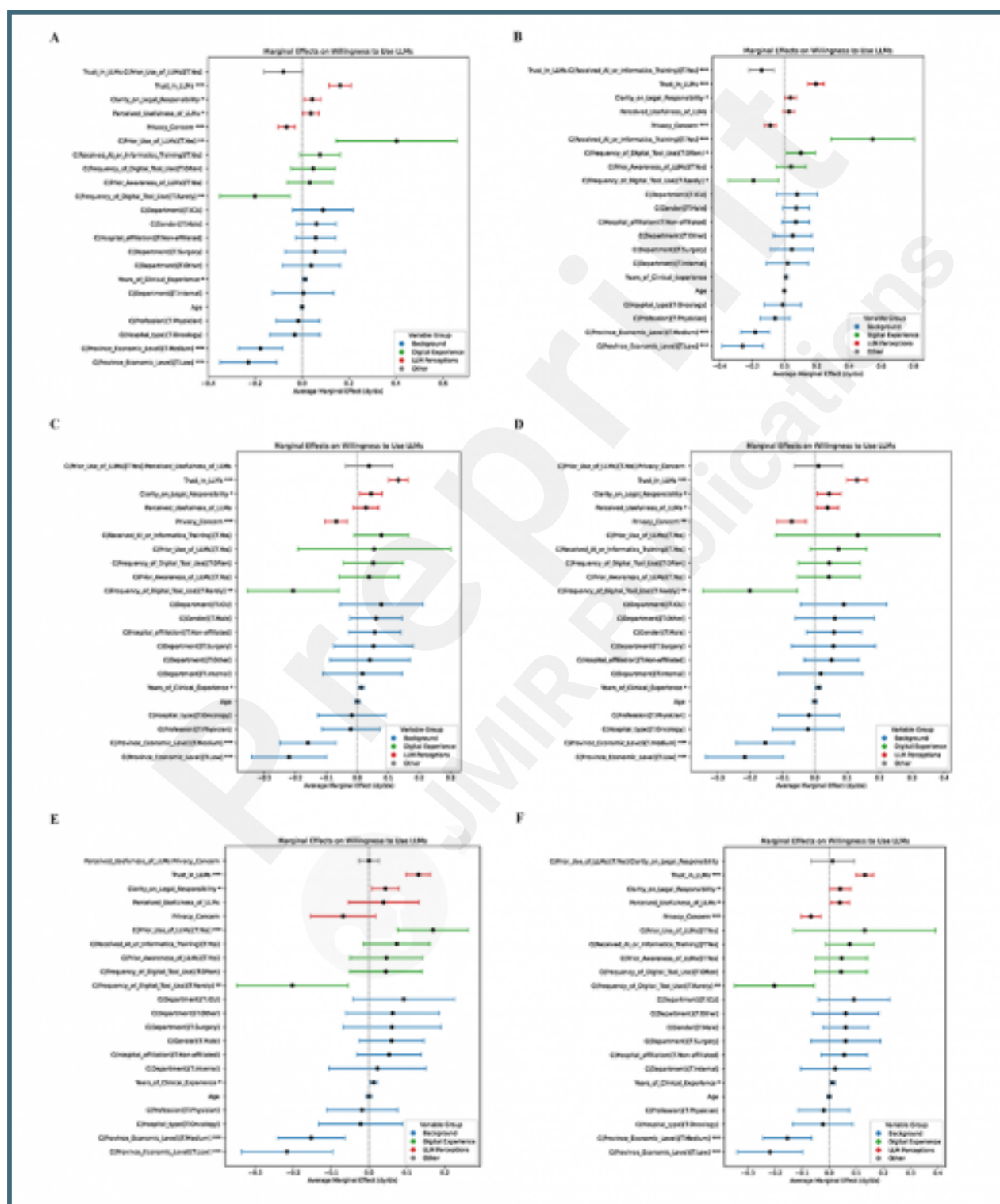
Model interpretability and cross-model agreement in predicting LLM adoption willingness among healthcare professionals (HCPs). (A–B) SHAP bar plot (A) and beeswarm plot (B) for logistic regression. (C–D) SHAP bar plot (C) and beeswarm plot (D) for random forest. (E–F) SHAP bar plot (E) and beeswarm plot (F) for XGBoost. (G) Heatmap of feature importance rank consistency across the three models. (H) Overlap in top 3, 5, and 7 ranked features across models. (I) Kendall's tau rank correlation matrix assessing agreement in feature importance rankings across models.



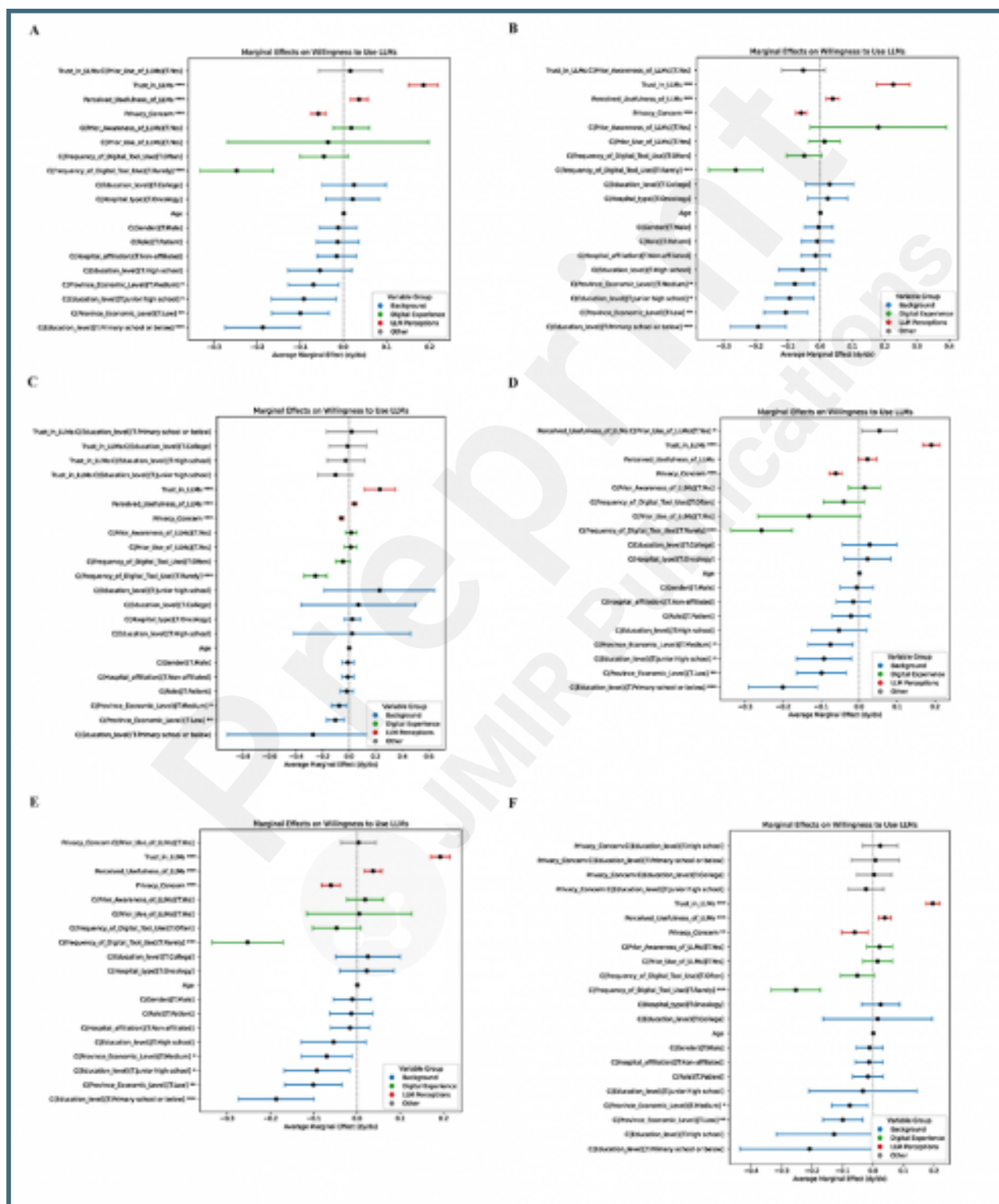
Model interpretability and cross-model agreement in predicting large language models (LLMs) adoption willingness among patients/caregivers (PCs). (A–B) SHAP bar plot (A) and beeswarm plot (B) for logistic regression. (C–D) SHAP bar plot (C) and beeswarm plot (D) for random forest. (E–F) SHAP bar plot (E) and beeswarm plot (F) for XGBoost. (G) Heatmap of feature importance rank consistency across the three models. (H) Overlap in top 3, 5, and 7 ranked features across models. (I) Kendall's tau rank correlation matrix assessing agreement in feature importance rankings across models.



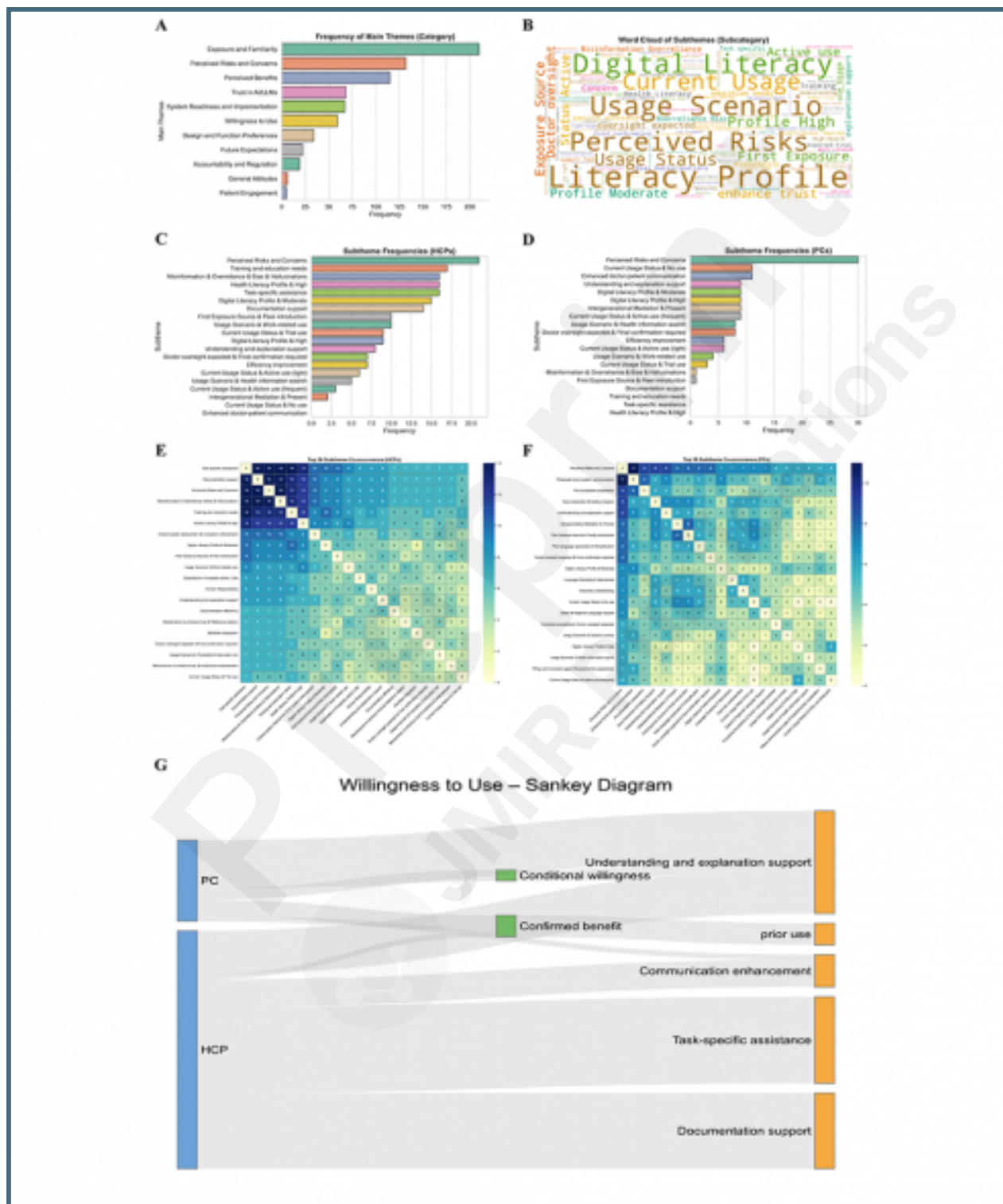
Marginal effects of key predictors on willingness to adopt large language models (LLMs) among healthcare professionals (HCPs). (A) Interaction between Trust in LLMs and Prior Use of LLMs. (B) Interaction between Trust in LLMs and Receipt of AI/Informatics Training. (C) Interaction between Prior Use of LLMs and Perceived Usefulness. (D) Interaction between Prior Use of LLMs and Privacy Concern. (E) Interaction between Perceived Usefulness and Privacy Concern. (F) Interaction between Prior Use of LLMs and Clarity on Legal Responsibility.



Marginal effects of key predictors on willingness to adopt large language models (LLMs) among patients/caregivers (PCs). (A) Interaction between Trust in LLMs and Prior Use of LLMs. (B) Interaction between Trust in LLMs and Prior awareness of LLMs. (C) Interaction between Trust in LLMs and Low Education Level (Primary school or below). (D) Interaction between Prior Use of LLMs and Perceived Usefulness. (E) Interaction between Prior Use of LLMs and Privacy Concern. (F) Interaction between Privacy Concern and Education level (High school).



Thematic structure, key subthemes, and motivational patterns shaping willingness to adopt large language models (LLMs) across healthcare professionals (HCPs) and patients/caregivers (PCs). (A) Theme frequency distribution. (B) Subtheme word cloud. (C) Top 20 subthemes in HCPs. (D) Top 20 subthemes in PCs. (E) Subtheme co-occurrence in HCPs. (F) Subtheme co-occurrence in PCs. (G) Motivational pathways for LLM adoption (Sankey).



Multimedia Appendixes

Overview of statistical modeling and analytical procedures.

URL: <http://asset.jmir.pub/assets/7aa6ce79acb6aa500f3cb8d5ffb16d29.pdf>

Group comparisons of trust, perceived usefulness, and privacy concerns related to large language models (LLMs).

URL: <http://asset.jmir.pub/assets/0d4f204c900e7fe01c449726a1fcfa67.pdf>

Comparative clinical utility of large language models (LLMs) adoption prediction models based on cumulative incremental accuracy (CIA) and net reclassification improvement (NRI). (A–B) CIA curves across decision thresholds in healthcare professionals (HCPs) and patients/caregivers (PCs), demonstrating relative model performance in identifying true positives. (C–D) NRI analyses for HCPs and PCs, highlighting the added value of the random forest (RF) model compared to logistic regression (LR) and XGBoost.

URL: <http://asset.jmir.pub/assets/4a69091e39cdc5da6a4fc42c15868071.pdf>

Calibration assessment of large language models (LLMs) adoption prediction models across user groups using Hosmer–Lemeshow (HL) plots. (A–B) HL plots for healthcare professionals (HCPs) across logistic regression (LR), random forest (RF), and XGBoost models. (C–D) HL plots for patients/caregivers (PCs) across LR, RF, and XGBoost models, showing calibration performance and deviations from perfect prediction.

URL: <http://asset.jmir.pub/assets/81b4895777b43abdeb9b9e7884964f5f.pdf>

Interaction effects of key predictors on willingness to adopt large language models (LLMs) among healthcare professionals (HCPs). (A) Trust in LLMs × Prior Use of LLMs. (B) Trust in LLMs × AI or Informatics Training. (C) Prior Use of LLMs × Perceived Usefulness. (D) Prior Use of LLMs × Privacy Concern. (E) Perceived Usefulness × Privacy Concern. (F) Prior Use of LLMs × Clarity on Legal Responsibility.

URL: <http://asset.jmir.pub/assets/8ea776385969efd23860346a6db54d77.pdf>

Interaction effects of key predictors on willingness to adopt large language models (LLMs) among patients/caregivers (PCs). (A) Trust in LLMs × Prior Use of LLMs. (B) Trust in LLMs × Prior Awareness of LLMs. (C) Trust in LLMs × Low Education Level (Primary School or Below). (D) Prior Use of LLMs × Perceived Usefulness. (E) Prior Use of LLMs × Privacy Concern. (F) Privacy Concern × Education Level (High School).

URL: <http://asset.jmir.pub/assets/1a658fc5500c8deb71b23ec9ba6e777f.pdf>

Sensitivity analysis of predictor perturbations in healthcare professionals (HCPs). (A–C) Probability distribution shifts in logistic regression, random forest, and XGBoost models when Trust in LLMs is perturbed. (D–F) Heatmaps of model performance changes (?Proba, ?AUC, ?LogLoss) across top predictors.

URL: <http://asset.jmir.pub/assets/41a4aa76507ea7d84876fc533c58965c.pdf>

Sensitivity analysis of predictor perturbations in patients/caregivers (PCs). (A–C) Probability distribution shifts in logistic regression, random forest, and XGBoost models when Trust in LLMs is perturbed. (D–F) Heatmaps of model performance changes (?Proba, ?AUC, ?LogLoss) across top predictors.

URL: <http://asset.jmir.pub/assets/40d8b6e7c57192a2c48461dde2aaa847.pdf>

Decision curve analysis (DCA) comparing clinical utility of predictive models for LLM adoption across user groups. (A) Net benefit curves for logistic regression, random forest, and XGBoost in healthcare professionals (HCPs). (B) Net benefit curves for the same models in patients/caregivers (PCs).

URL: <http://asset.jmir.pub/assets/44fd57e31f5de567f944767e1451290b.pdf>

Due to the system requirement that figures be uploaded in PNG format, the resolution of the figures embedded in the main manuscript may not be optimal. Therefore, high-resolution versions of all figures have been provided here as supplementary files for editorial and review purposes. These high-resolution files can be used for publication quality if needed.

URL: <http://asset.jmir.pub/assets/56798fcafa9ce316731793e49ba33bf3.pdf>

Supplementary Tables All supplementary tables (Table S1, Table S2, ...) have been consolidated into a single Microsoft Word document for ease of reference. This file contains the full set of supplementary tables referenced in the manuscript.

URL: <http://asset.jmir.pub/assets/92c286279de50738def0b284af8a83bd.docx>

TOC/Feature image for homepages

A simplified icon-style feature image has been created to represent the theme of trust in AI adoption in health care. This image is intended for use as the TOC/Feature image for the homepage display.

