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ARTIFICIAL INTELLIGENCE IN HEALTHCARE: ACCEPTANCE, UTILIZATION, AND CHALLENGES AMONG MEDICAL PROFESSIONALS IN THE PHILIPPINES

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Abstract

Artificial Intelligence (AI) represents a paradigm-shifting force in global healthcare, offering critical solutions to clinical and administrative burdens; however, in low- and middle-income countries (LMICs) such as the Philippines, its translation into clinical practice remains structurally and culturally constrained. This study investigates the determinants of AI acceptance, utilization, and challenges among medical professionals in the Philippines using an extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework incorporating Perceived Risk and Trust. A cross-sectional explanatory research design was conducted among 384 physicians and nurses from tertiary healthcare institutions in Metro Manila, with structural equation modeling and hierarchical multiple regression used to examine the relationships among Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Risk, Trust, Behavioral Intention, and Actual Utilization. Findings revealed a substantial acceptance-utilization gap, characterized by high Perceived Risk ($M = 3.97$, $SD = 0.75$), moderate Behavioral Intention ($M = 3.61$, $SD = 0.74$), and low Actual Utilization ($M = 2.88$, $SD = 0.80$). The extended model explained 64.9% of the variance in Behavioral Intention and 55.4% in Actual Utilization. Trust was significantly suppressed by Perceived Risk ($\beta = -0.3129$, $p < 0.001$) but emerged as the strongest predictor of Behavioral Intention ($\beta = 0.3292$, $p < 0.001$), while Facilitating Conditions exerted a strong direct effect on Actual Utilization ($\beta = 0.3032$, $p < 0.001$). These findings indicate that although Filipino medical professionals are receptive to AI, systemic deficits in data interoperability, institutional policies, digital infrastructure, and ethical guidance hinder meaningful adoption. Healthcare institutions should therefore transition from ad hoc AI adoption toward structured, competency-based training, strengthened digital infrastructure, and localized ethical guidelines that reflect contextual values such as *pakikiramdam*.

Keywords: *Artificial Intelligence; Technology Acceptance Model; UTAUT; Healthcare Digitization; Healthcare Policy; Philippines; Clinical Decision Support Systems.*

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Introduction

Background of the Study

Global Perspective

The contemporary global healthcare sector is grappling with an existential structural crisis characterized by escalating service demand, soaring operational costs, and a severely depleted and overburdened workforce. Key factors driving this strain include rapidly aging demographic profiles, an increasing epidemiological burden of chronic non-communicable diseases, and widespread clinician burnout. The World Health Organization projects a global shortfall of approximately 11 million healthcare workers by 2030, highlighting a systemic vulnerability that threatens the delivery of safe and equitable care.

Against this backdrop, Artificial Intelligence (AI) has emerged as a disruptive technological intervention capable of reforming clinical medicine and public health capacity. Clinicians worldwide are increasingly turning to machine learning algorithms, natural language processing platforms, and computer vision systems to optimize disease detection, customize clinical treatment pathways, and automate repetitive administrative tasks.

Yet this rapid technological transition is marked by a significant governance lag: clinicians are adopting AI-based systems at a pace that far outstrips the development of regulatory frameworks, exposing healthcare systems to substantial legal, ethical, and clinical risks.

Regional Perspective

Within Southeast Asia, the landscape of digital health and clinical AI adoption is highly heterogeneous, reflecting the deep socioeconomic disparities that define the region. High-income countries, most notably Singapore, have successfully leveraged advanced machine learning models to streamline hospital resource management, automate pathological diagnostics, and deploy interactive conversational bots for patient triage.

In contrast, lower-middle-income countries (LMICs) such as Indonesia, Thailand, and Vietnam are still in the early stages of establishing foundational digital health frameworks. Across these developing healthcare systems, the deployment of clinical AI is severely restricted by deficient physical infrastructure, fragmented health information systems, and a lack of standardized, localized clinical registries.

Consequently, while regional dialogues in wealthier nations focus on technical sophistication and advanced integration, discussions in LMICs center heavily on establishing basic acceptance of technology, securing data privacy, and mitigating algorithmic biases stemming from underrepresented training data.

National Perspective

The Philippines presents a unique national environment for healthcare AI, shaped by historical resource constraints, a fragmented, devolved healthcare structure, and landmark legislative mandates. The passage of the Universal Health Care (UHC) Act in 2019 (Republic Act No. 11223) legally committed the state to providing comprehensive, equitable, and affordable health services to all Filipinos while eliminating out-of-pocket financial barriers.

However, achieving the objectives of the UHC Act is severely hampered by a persistent shortage of medical professionals, an uneven distribution of clinical staff across the archipelago, and geographical barriers to service delivery in remote provincial areas. To bridge these equity gaps, the Philippine government has positioned digital health technologies as critical pillars of national development.

The Department of Trade and Industry (DTI) launched the National AI Strategy Roadmap 2.0 (NAISR 2.0) in July 2024 to position the country as a regional hub for AI innovation. Under this framework, the Department of

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Science and Technology (DOST) has committed substantial funding to upskilling initiatives and clinical R&D, and has established the Center for AI Research (CAIR) to pioneer localized AI solutions for healthcare, disaster response, and agricultural sustainability.

Concurrently, the Department of Health (DOH) has deployed automated tools, such as the AI-powered KIRA health chatbot and predictive data-collection dashboards, to optimize triage services and monitor hospital bed capacity in real time.

Local Perspective

At the operational level within Philippine hospitals, the practical implementation of AI is highly fragmented and characterized by "shadow adoption". In large tertiary public and private teaching hospitals in Metro Manila, such as the Philippine General Hospital, clinical documentation remains a major driver of professional burnout, consuming hours of a clinician's shift.

To reclaim their time, frontline physicians and nurses are increasingly utilizing consumer-grade generative AI tools ad hoc to transcribe clinical notes and compile health summaries. However, the vast majority of these clinicians operate with little to no guidance from their employers, using tools without secure institutional interfaces or formal data governance policies.

This unguided adoption introduces substantial clinical risks, including algorithmic hallucinations and potential breaches of patient data privacy.

Furthermore, while urban medical centers explore these advanced tools, provincial primary care facilities continue to struggle with basic internet connectivity, a lack of digitized records, and limited technical support. This digital divide threatens to exacerbate pre-existing health disparities between urban metropolises and rural peripheries.

Empirical Research Gap

Despite a surge in regional interest in digital health, a critical empirical gap remains in understanding how medical professionals in developing healthcare systems transition from technological awareness to the sustained, safe, and effective use of clinical AI. While the Unified Theory of Acceptance and Use of Technology (UTAUT) has been widely used to predict general software adoption, standard models fail to capture the high-stakes, ethically complex environment of clinical decision-making. Specifically, existing literature has largely failed to model how clinical risk perceptions, data privacy anxieties, and professional trust interact to influence actual technology usage in LMICs.

Quantitative research evaluating these structural pathways in the Philippines remains virtually non-existent, with most local literature limited to qualitative essays, student surveys, or general organizational assessments. This study addresses these deficiencies by constructing and statistically validating an extended UTAUT model that integrates Perceived Risk and Trust as critical structural mediators, applied specifically to the unique socio-cultural, clinical, and regulatory realities of the Philippine healthcare system.

Formal Problem Statement

Filipino medical professionals are caught between severe operational demands and a highly constrained, rapidly evolving digital healthcare environment. Although national mandates and institutional frameworks promote AI integration, actual clinical utilization remains low and highly uneven. Frontline clinicians must navigate the technical limitations of AI, such as diagnostic inaccuracy and data privacy concerns, alongside deep socio-cultural anxieties, including the potential erosion of humanistic values like *pakikiramdam* (empathetic attunement).

Without systematic empirical data clarifying the structural drivers of and barriers to AI acceptance, healthcare administrators, educational institutions, and state policymakers cannot design effective, safe, and culturally

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aligned integration strategies. This leads to wasted technological investments, increased clinical exposure to privacy breaches, and a worsening of healthcare delivery disparities.

Research Objectives

This study aims to achieve the following specific research objectives:

1. To measure the prevailing levels of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Risk, Trust, Behavioral Intention, and Actual Utilization of AI among medical professionals in the Philippines.

2. To evaluate the statistical influence of traditional UTAUT predictors (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions) and Perceived Risk on professional Trust in healthcare AI.

3. To determine the structural impacts of these core variables and Trust on clinicians' Behavioral Intention to adopt AI.

4. To identify the primary determinants of Actual Utilization of AI in daily clinical practice.

5. To systematically document the primary operational, ethical, and systemic challenges restricting the safe integration of AI in Philippine clinical environments.

Research Questions

To address the research objectives, this study seeks to answer the following research questions:

1. What are the descriptive levels (means and standard deviations) of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Risk, Trust, Behavioral Intention, and Actual Utilization among the surveyed Filipino medical professionals?

2. To what extent do Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Perceived Risk predict professional Trust in clinical AI tools?

3. To what extent do these primary constructs and Trust predict the Behavioral Intention of medical professionals to utilize AI?

4. How do Facilitating Conditions, Trust, and Behavioral Intention predict the Actual Utilization of healthcare AI in Philippine clinical settings?

5. What are the key systemic, regulatory, and ethical challenges reported by medical professionals regarding the institutional deployment of AI?

Operational Hypotheses

Based on the theoretical integration of the extended UTAUT model, the following null hypotheses were tested:

- **$H_0$1**: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, and Perceived Risk do not significantly predict professional Trust in clinical AI systems.

- **$H_0$2**: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Risk, and Trust do not significantly predict the Behavioral Intention of medical professionals to adopt AI.

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- **H_03**: Facilitating Conditions, Trust, and Behavioral Intention do not significantly predict the Actual Utilization of AI in clinical practice.

Systemic Boundaries and Delimitations of the Research

This study is limited to medical professionals, specifically licensed physicians and registered nurses, who are actively engaged in clinical practice within tertiary healthcare institutions in the National Capital Region (NCR), Philippines. Tertiary hospitals were selected because they represent the primary centers of digital healthcare modernization and early-stage AI tool deployment in the country.

The structural model focused exclusively on the cognitive and perceptual constructs of the extended UTAUT framework, specifically modeling Perceived Risk and Trust, and did not examine peripheral clinical indicators or economic cost-benefit metrics. Data collection was cross-sectional, capturing professional perceptions during a specific regulatory transition period in 2026, and did not evaluate longitudinal changes in technology adoption behavior.

Societal and Institutional Significance

This study holds significant value for multiple stakeholder groups. For **policymakers** at the Department of Health (DOH), Department of Science and Technology (DOST), and Department of Information and Communications Technology (DICT), this research provides empirical data to refine the National AI Strategy Roadmap 2.0, ensuring that national technological investments are aligned with the actual readiness of clinical implementers.

For **hospital administrators and clinical leaders**, these findings offer a clear diagnostic tool to identify structural bottlenecks in local infrastructure and to design targeted upskilling initiatives that transition clinicians from ad hoc use to safe, auditable AI practices.

For **medical educators**, the empirical validation of clinical AI literacy requirements supports the ongoing redesign of medical and nursing curricula, helping integrate data stewardship and algorithmic bias evaluation into core competencies.

Finally, for **system developers and ethical researchers**, this study introduces a culturally grounded quantitative framework that highlights the necessity of designing clinical systems that respect and support personal human touch, relational trust, and clinical judgment.

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Review of Related Literature

Theoretical Underpinnings of Technology Acceptance

The conceptualization of technology acceptance has historically evolved from the Technology Acceptance Model (TAM) to the Unified Theory of Acceptance and Use of Technology (UTAUT). TAM, developed by Davis, established that perceived usefulness (PU) and perceived ease of use (PEOU) are the primary determinants of technological adoption.

In 2003, Venkatesh et al. synthesized these constructs into the UTAUT framework, introducing four core determinants: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). While UTAUT exhibits high explanatory power in stable corporate settings, its direct application to healthcare AI is limited due to the high-stakes, ethically complex nature of medical practice.

Unlike standard software, clinical AI tools interact directly with patient welfare, patient privacy, and professional liability, introducing unique psychological dynamics.

To address these limitations, this study extends the baseline UTAUT model by integrating two critical psychological constructs: **Perceived Risk** and **Trust**. Perceived Risk captures the multi-dimensional anxieties of clinicians, including diagnostic errors, algorithmic hallucinations, data privacy leaks, and potential job displacement. Trust is the essential psychological mechanism that enables clinicians to rely on complex, often opaque "black-box" technology with confidence.

By modeling Perceived Risk as a direct inhibitor of Trust and Behavioral Intention, and positioning Trust as a central mediator, this extended model provides a more robust, clinically relevant framework for predicting AI adoption in developing healthcare systems.

Thematic Analyses of AI in Contemporary Medicine

Clinical Workflow Efficiency and the Documentation Crisis

The integration of AI into clinical practice is driven primarily by the need to optimize administrative efficiency and combat clinician burnout. Historically, clinical documentation has been identified as a leading source of professional fatigue, with clinicians identifying it as their most time-consuming task. Recent global findings indicate that up to 88% of medical professionals view charting and paperwork as their primary administrative burden.

To address this, the deployment of ambient clinical AI scribes and automated transcription tools has accelerated, with studies reporting that regular AI usage is becoming standard in many international practices. However, an unguided transition has occurred: a significant majority (83%) of clinicians report using these tools without formal policy or employer guidance, raising critical concerns about patient data security and the potential erosion of clinical judgment.

Infrastructural Disparities and Systemic Bottlenecks in LMICs

While high-income countries focus on the sophistication of AI integration, low- and middle-income countries (LMICs) face severe foundational challenges. In Southeast Asia, the adoption of clinical AI is severely bound by "Facilitating Conditions," which capture the availability of hardware, local IT support, and internet connectivity. Research in private and public hospitals in Indonesia and Thailand reveals that technology adoption remains highly uneven, particularly in rural settings.

The transition from traditional paper-based charting to electronic medical records (EMRs) remains incomplete, creating a highly fragmented data environment that prevents the standardized deployment of clinical decision

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support systems. Furthermore, a pronounced training deficit exists; while frontline clinicians express interest in AI-enabled tools, very few receive formal institutional training, which severely limits potential productivity gains and return on investment.

Ethical, Legal, and Regulatory Landscapes in the Philippines

The deployment of clinical AI in the Philippines operates within a rapidly evolving regulatory environment. The fundamental legal anchor is the Data Privacy Act of 2012 (Republic Act No. 10173), which protects individual personal information across all processing systems.

To address emerging AI-driven risks, the National Privacy Commission (NPC) released Advisory No. 2024-04 on December 19, 2024, providing explicit guidelines on applying data privacy principles to AI systems. These advisories mandate that healthcare organizations, acting as Personal Information Controllers (PICs), must observe absolute transparency, perform mandatory Privacy Impact Assessments (PIAs), integrate privacy-by-design, and establish robust human-in-the-loop override mechanisms to prevent automated decision-making from violating patient rights.

Concurrently, the Food and Drug Administration (FDA) of the Philippines has drafted specialized guidelines for Medical Device Software (MDSW), classifying AI-enabled diagnostic instruments as high-risk technologies that require rigorous validation.

These regulatory developments are supported by legislative initiatives in Congress, including House Bill No. 57 (instituting the National Artificial Intelligence Code) and House Bill No. 2827, which seek to establish central regulatory bureaus to monitor algorithmic bias, prevent job displacement, and mandate continuous upskilling programs for workers.

Socio-Cultural Dynamics and the Empathetic Core of Care

Beyond technical and regulatory parameters, the integration of clinical AI must navigate deep socio-cultural patterns. In the context of Philippine medicine, the clinician-patient relationship is built on relational trust and mutual understanding.

As Gozum discusses, the rapid mechanization of clinical decision-making risks displacing essential Filipino cultural values such as pakikiramdam—an intuitive, empathetic attunement that allows clinicians to perceive unspoken patient needs, fears, and hesitations.

AI models are highly proficient at processing structured clinical data, but they lack the capacity to experience *kapwa* (shared identity) or interpret the clinical silences and subtleties that Filipino physicians navigate in their practice.

Consequently, there is a risk that clinical decision-making could become overly technocratic, sidelining the holistic, relational, and spiritual aspects of healing.

Therefore, researchers emphasize that AI must be designed and deployed not as a replacement for clinical presence, but as a supportive tool that enhances the humanistic dimensions of care.

Formulation of the Integrated Conceptual Model

To evaluate these dynamic forces, this study constructs an integrated conceptual model that extends the UTAUT framework. In this model, Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) are posited as positive predictors of professional Trust in AI, while Perceived Risk (PR) is modeled as a primary negative determinant. Trust in AI (TR) is positioned as a key psychological mediator, directly influencing clinicians' Behavioral Intention (BI) alongside PE, EE, SI, and PR.

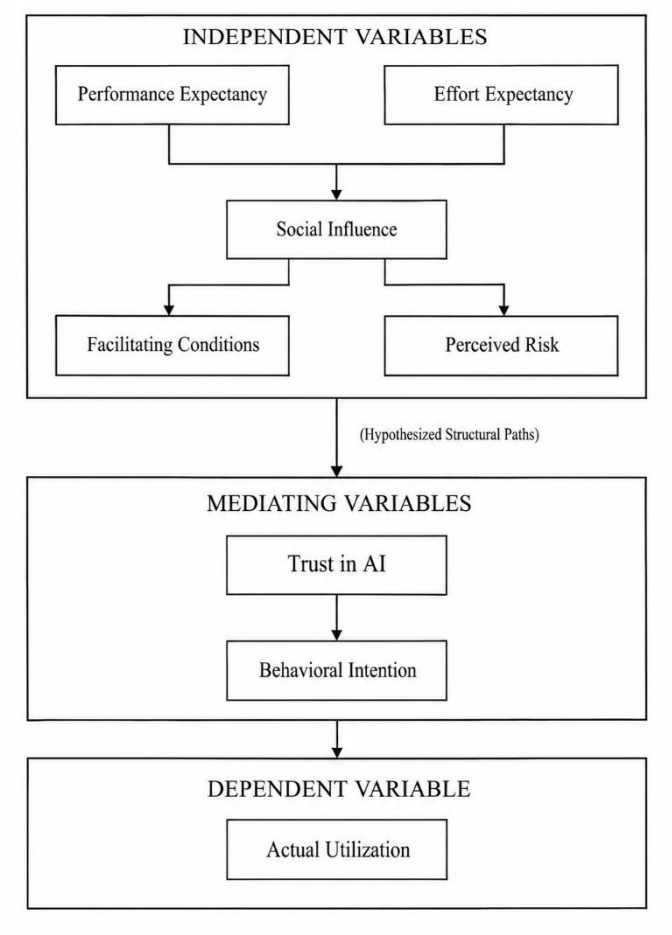
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Finally, Actual Utilization (AU) is predicted directly by Behavioral Intention (BI) and Facilitating Conditions (FC). This direct pathway from FC to AU is critical for capturing the physical and infrastructural bottlenecks that define the Philippine healthcare setting.

ASCII Conceptual Framework Diagram

The conceptual framework is represented in the following ASCII path diagram, mapping the structural pathways tested in this study:



Research Hypotheses

- **H_a1**: Performance Expectancy positively predicts professional Trust in healthcare AI systems.
- **H_a2**: Effort Expectancy positively predicts professional Trust in healthcare AI systems.
- **H_a3**: Social Influence positively predicts professional Trust in healthcare AI systems.
- **H_a4**: Facilitating Conditions positively predict professional Trust in healthcare AI systems.
- **H_a5**: Perceived Risk negatively predicts professional Trust in healthcare AI systems.
- **H_a6**: Trust in AI positively predicts the Behavioral Intention of medical professionals to adopt AI.
- **H_a7**: Performance Expectancy positively predicts the Behavioral Intention of medical professionals to adopt AI.

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- **H_a8**: Effort Expectancy positively predicts the Behavioral Intention of medical professionals to adopt AI.
- **H_a9**: Social Influence positively predicts the Behavioral Intention of medical professionals to adopt AI.
- **H_a10**: Facilitating Conditions positively predict the Behavioral Intention of medical professionals to adopt AI.
- **H_a11**: Perceived Risk negatively predicts the Behavioral Intention of medical professionals to adopt AI.
- **H_a12**: Behavioral Intention positively predicts the Actual Utilization of AI in clinical practice.
- **H_a13**: Facilitating Conditions positively predict the Actual Utilization of AI in clinical practice.
- **H_a14**: Trust in AI positively predicts the Actual Utilization of AI in clinical practice.

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Research Design and Procedures

Research Paradigm and Design

This study is rooted in the post-positivist research paradigm, utilizing an empirical, quantitative, cross-sectional explanatory research design. Structural regression and pathway analysis were deployed to model and evaluate the predictive relationships established by the extended UTAUT framework. This design is appropriate because it allows simultaneous evaluation of multiple independent predictors, mediating pathways, and direct effects in a high-stakes clinical context.

Empirical Settings and Locale

The study was conducted in tertiary healthcare institutions located within the National Capital Region (NCR), Philippines. The NCR was selected as the research locale because it represents the epicenter of healthcare technology integration, hosting the country's leading public and private teaching hospitals where initial AI deployments and digital health programs are concentrated.

Population, Sampling Strategy, and Sample Size Calculation

The target population comprised licensed medical doctors and registered nurses actively engaged in clinical practice in tertiary hospital settings in Metro Manila. To ensure rigorous statistical power, the minimum sample size was computed using Cochran's sample size formula for infinite populations:

$$n = \frac{Z^2 \bullet p \bullet q}{e^2}$$

Where:

- Z represents the standard normal deviation at a 95% confidence interval (Z = 1.96).
- p represents the estimated proportion of the attribute in the population (p = 0.50, maximizing sample size requirement).
- q is defined as 1 - p (q = 0.50).
- e represents the acceptable margin of error (e = 0.05).

The computation yielded:

$$n = \frac{(1.96)^2 \bullet (0.50) \bullet (0.50)}{(0.05)^2} = 384.16$$

Thus, a sample size of N = 384 respondents was targeted and successfully achieved. A stratified purposive sampling technique was used to ensure balanced representation across clinical cadres (physicians and nurses) and hospital types (public and private).

Operational Survey Instrument

Data were collected using a highly structured, self-administered questionnaire adapted from Venkatesh et al. and modified to include healthcare-specific risk and trust items. The instrument comprised 32 items, evaluated on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

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Content Validity and Reliability Diagnostics

The research instrument was evaluated and approved by a panel of five academic and clinical experts, yielding a Scale-Content Validity Index (S-CVI/UA) of 0.92, indicating high content validity. A pilot study was conducted with 30 clinical practitioners to evaluate instrument reliability. The internal consistency of the items was evaluated using Cronbach's alpha coefficient (α). The validation metrics for the final study (N = 384) demonstrated high reliability across all constructs, with Cronbach's alpha values ranging from 0.894 to 0.932:

- Performance Expectancy: $\alpha = 0.894$
- Effort Expectancy: $\alpha = 0.909$
- Social Influence: $\alpha = 0.895$
- Facilitating Conditions: $\alpha = 0.918$
- Perceived Risk: $\alpha = 0.919$
- Trust in AI: $\alpha = 0.916$
- Behavioral Intention: $\alpha = 0.919$
- Actual Utilization: $\alpha = 0.932$

Step-by-Step Data Collection Protocol

Following ethical approvals, institutional permission was secured from the hospital directors of the selected tertiary facilities. The research instrument was developed as an online survey on a secure platform, while paper questionnaires were provided to departments with restricted access to devices. Data collection was conducted over a five-month period in 2026.

Prior to survey administration, participants were provided with a brief explanatory video that defined key concepts and applications of clinical AI (such as machine-learning diagnostics, ambient scribes, and triage bots) to establish a baseline understanding. Informed consent was obtained electronically or in person by all participants prior to unlocking the survey items.

Stringent Ethical Safeguards

The research protocol was reviewed and approved by the Institutional Review Board (IRB) of the coordinating universities. The study strictly adhered to the ethical principles of the Declaration of Helsinki and the National Ethical Guidelines for Health and Life Sciences Research. To ensure complete compliance with the Data Privacy Act of 2012 (Republic Act No. 10173) and NPC Advisory No. 2024-04, no personally identifying information was collected. Anonymity was maintained through a dual-key institutional coding system. Participants were informed of their absolute right to withdraw from the study at any stage without negative consequences. All research data were stored in an encrypted database accessible only to the principal investigators.

Statistical Treatments and Mathematical Formulations

The statistical analysis of the quantitative data was executed using SPSS version 28.0 and AMOS version 28.0. Descriptive statistics, including frequencies, percentages, mean scores ($\bar{x}$), and standard deviations (SD), were computed to outline the sample demographics and construct profiles. The dataset's normality was assessed using skewness and kurtosis analyses, with all values falling within the acceptable limits of [-1.0, +1.0].

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To evaluate the structural pathways and test the hypotheses, a series of hierarchical ordinary least squares (OLS) multiple regression analyses was performed:

Model 1

Predicting the mediating variable Trust (TR) using UTAUT constructs and Perceived Risk:

$$TR = \beta_0 + \beta_1 PE + \beta_2 EE + \beta_3 SI + \beta_4 FC + \beta_5 PR + \varepsilon_1$$

Model 2

Predicting Behavioral Intention (BI) using all antecedents and Trust:

$$BI = \alpha_0 + \alpha_1 PE + \alpha_2 EE + \alpha_3 SI + \alpha_4 FC + \alpha_5 PR + \alpha_6 TR + \varepsilon_2$$

Model 3

Predicting the final dependent variable Actual Utilization (AU) using Facilitating Conditions, Trust, and Behavioral Intention:

$$AU = \gamma_0 + \gamma_1 FC + \gamma_2 TR + \gamma_3 BI + \varepsilon_3$$

Comparative Analyses

To evaluate demographic differences across cadres and age groups, independent-samples t-tests and one-way Analysis of Variance (ANOVA) were performed.

The t-test statistic was computed using:

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{{s_1}^2}{n_1} + \frac{{s_2}^2}{n_2}}}$$

The ANOVA F-ratio was evaluated using:

$$F = \frac{MS_{between}}{MS_{within}} = \frac{\frac{SS_{between}}{k-1}}{\frac{SS_{within}}{N-k}}$$

The statistical significance of all models was evaluated at the 95% confidence level ($\alpha = 0.05$). Multicollinearity was evaluated using Tolerance and Variance Inflation Factors (VIF), with all VIF values falling below 3.0, indicating no multicollinearity concerns.

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Results

Demographic and Professional Characteristics of the Cohort

The demographic profile of the N = 384 healthcare respondents is detailed in Table 1, providing a comprehensive distribution of age, sex, clinical profession, hospital sector, years of experience, and prior AI training exposure.

Table 1. ***Demographic Characteristics of the Respondents (N = 384)***

Demographic Variable	Category	Frequency (n)	Percentage (%)
Age Group	Under 28 years	96	25.0%
	28–35 years	144	37.5%
	36–45 years	88	22.9%
	Above 45 years	56	14.6%
Sex	Female	211	54.9%
	Male	173	45.1%
Profession	Clinical Physician	180	46.9%
	Registered Nurse	204	53.1%
Hospital Type	Public Tertiary Hospital	200	52.1%
	Private Tertiary Hospital	184	47.9%
Years of Experience	Less than 5 years	84	21.9%
	5–10 years	156	40.6%
	11–20 years	92	24.0%
	More than 20 years	52	13.5%
Prior AI Training	Received Formal Training	78	20.3%
	No Formal Training	306	79.7%

The demographic analysis shows a highly active, mid-career professional cohort, with over 60% of the sample aged 35 or under, and a balanced split between physicians (46.9%) and nurses (53.1%). Notably, a severe training deficit is evident: only 20.3% of practicing professionals reported receiving any formal institutional training in clinical artificial intelligence tools, suggesting that the vast majority navigate these technologies on an ad hoc basis.

Descriptive Baseline Evaluation of Key Constructs

The descriptive profiles of the eight key variables are detailed in Table 2, which highlights the means, standard deviations, and internal consistency statistics.

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Table 2. ***Descriptive Statistics and Reliability Metrics for the Study Constructs (N = 384)***

Construct	Mean ($\bar{x}$)	Standard Deviation (SD)	Cronbach's Alpha (α)
Performance Expectancy (PE)	3.84	0.66	0.894
Effort Expectancy (EE)	3.66	0.73	0.909
Social Influence (SI)	3.51	0.66	0.895
Facilitating Conditions (FC)	3.15	0.81	0.918
Perceived Risk (PR)	3.97	0.75	0.919
Trust in AI (TR)	3.30	0.71	0.916
Behavioral Intention (BI)	3.61	0.74	0.919
Actual Utilization (AU)	2.88	0.80	0.932

The descriptive results highlight a significant structural and psychological mismatch. Medical professionals recognized the high utility and productivity potential of AI, resulting in a strong Performance Expectancy score ($\bar{x}$ = 3.84). However, this cognitive acceptance is countered by high levels of Perceived Risk ($\bar{x}$ = 3.97), indicating severe ethical, security, and safety anxieties.

Furthermore, Facilitating Conditions scored the lowest among all baseline predictors ($\bar{x}$ = 3.15), exposing a severe lack of infrastructural and policy support in Philippine tertiary hospitals. This combination of low systemic support and high-risk perception directly limits the translation of high willingness to adopt ($\bar{x}$ = 3.61) into actual routine clinical use, resulting in a low Actual Utilization score ($\bar{x}$ = 2.88).

Bivariate Correlation Matrix

To establish the preliminary relationships between the variables, a Pearson product-moment correlation matrix was computed, as detailed in Table 3.

Table 3. ***Inter-Construct Correlation Matrix (N = 384)***

Variable	PE	EE	SI	FC	PR	TR	BI	AU
PE	1.000							
EE	0.567**	1.000						
SI	0.371**	0.247**	1.000					
FC	0.420**	0.508**	0.249**	1.000				
PR	-0.229**	-0.281**	-0.133**	-0.221**	1.000			
TR	0.568**	0.494**	0.323**	0.464**	-0.485**	1.000		
BI	0.646**	0.594**	0.432**	0.537**	-0.394**	0.692**	1.000	

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AU	0.515**	0.434**	0.314**	0.596**	-0.238**	0.552**	0.693**	1.000

Note. Correlation is significant at the 0.01 level (2-tailed).

The correlational metrics demonstrate a strong, highly significant relationship between the constructs. Behavioral Intention exhibits its strongest positive relationship with Trust ($r = 0.692$, $p < 0.01$) and Performance Expectancy ($r = 0.646$, $p < 0.01$), confirming that trust and perceived productivity are central to clinician willingness.

Notably, Actual Utilization is strongly correlated with Behavioral Intention ($r = 0.693$, $p < 0.01$) and Facilitating Conditions ($r = 0.596$, $p < 0.01$), confirming that the physical availability of technical infrastructure and clear hospital guidelines directly determine whether clinicians routinely use AI in their clinical work.

Hierarchical Regression Modeling: Drivers of Professional Trust

The first regression model examined the predictors of professional Trust (TR). The model demonstrated high explanatory power, explaining 50.8% of the total variance in clinical trust ($R^2 = 0.508$, Adj. $R^2 = 0.501$, $F(5, 378) = 78.04$, $p < 0.001$). The detailed coefficient outputs are structured in Table 4.

Table 4. ***Model 1 Regression Outputs: Predictors of Trust in AI (TR)***

Predictor Variable	Unstandardized Coefficient (b)	Standard Error (SE)	Standardized Coefficient (β)	t-statistic	p-value
Constant	1.9887	0.266	—	7.473	< 0.001
Performance Expectancy (PE)	0.3536	0.050	0.326	7.047	< 0.001
Effort Expectancy (EE)	0.1002	0.046	0.103	2.162	0.031
Social Influence (SI)	0.0941	0.042	0.088	2.243	0.025
Facilitating Conditions (FC)	0.1586	0.038	0.179	4.177	< 0.001
Perceived Risk (PR)	-0.3129	0.036	-0.330	-8.705	< 0.001

The analysis reveals that Performance Expectancy ($\beta = 0.326$, $t = 7.047$, $p < 0.001$) and Perceived Risk ($\beta = -0.330$, $t = -8.705$, $p < 0.001$) are the primary drivers of clinician Trust. Effort Expectancy, Social Influence, and Facilitating Conditions also exert statistically significant positive effects on Trust.

Therefore, the first null hypothesis ($H_0 1$) is rejected, confirming that both traditional UTAUT drivers and risk perceptions are critical determinants of professional trust in AI.

Hierarchical Regression Modeling: Determinants of Behavioral Intention

The second model evaluated the drivers of clinicians' Behavioral Intention (BI) to adopt AI, incorporating the mediating pathway of Trust. The model demonstrated strong predictive power, accounting for 64.9% of the variance in behavioral willingness ($R^2 = 0.649$, Adj. $R^2 = 0.644$, $F(6, 377) = 116.4$, $p < 0.001$). The results are presented in Table 5.

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Table 5. ***Model 2 Regression Outputs: Predictors of Behavioral Intention (BI)***

Predictor Variable	Unstandardized Coefficient (b)	Standard Error (SE)	Standardized Coefficient (β)	t-statistic	p-value
Constant	0.2080	0.250	—	0.830	0.407
Performance Expectancy (PE)	0.2583	0.047	0.230	5.509	< 0.001
Effort Expectancy (EE)	0.1712	0.041	0.169	4.181	< 0.001
Social Influence (SI)	0.1715	0.037	0.154	4.621	< 0.001
Facilitating Conditions (FC)	0.1383	0.034	0.151	4.052	< 0.001
Perceived Risk (PR)	-0.0857	0.035	-0.087	-2.477	0.014
Trust in AI (TR)	0.3292	0.045	0.317	7.285	< 0.001

The regression findings identify Trust as the most powerful direct driver of Behavioral Intention ($\beta = 0.317$, $t = 7.285$, $p < 0.001$), followed closely by Performance Expectancy ($\beta = 0.230$, $t = 5.509$, $p < 0.001$) and Social Influence ($\beta = 0.154$, $t = 4.621$, $p < 0.001$). Effort Expectancy, Facilitating Conditions, and Perceived Risk also remain statistically significant predictors.

Consequently, the second null hypothesis ($H_0 2$) is rejected, confirming that Trust serves as a vital psychological mechanism and a primary driver of professionals' willingness to adopt AI.

Regression Path Analysis: Predictors of Actual Utilization

The final regression model investigated the immediate determinants of Actual Utilization (AU) of AI in clinical settings. The model successfully explained 55.4% of the total variance in actual technology use in the wards ($R^2 = 0.554$, Adj. R^2 = 0.550, $F(3, 380) = 157.2$, $p < 0.001$). The predictive coefficients are summarized in Table 6.

Table 6. ***Model 3 Regression Outputs: Predictors of Actual Utilization (AU)***

Predictor Variable	Unstandardized Coefficient (b)	Standard Error (SE)	Standardized Coefficient (β)	t-statistic	p-value
Constant	-0.2376	0.150	—	-1.588	0.113
Facilitating Conditions (FC)	0.3032	0.041	0.304	7.387	< 0.001
Trust in AI (TR)	0.0959	0.054	0.085	1.767	0.078
Behavioral Intention (BI)	0.5118	0.055	0.471	9.333	< 0.001

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The model results show that Behavioral Intention exerts the strongest positive direct influence on Actual Utilization ($\beta = 0.471$, $t = 9.333$, $p < 0.001$), followed closely by Facilitating Conditions ($\beta = 0.304$, $t = 7.387$, $p < 0.001$).

Crucially, the direct effect of Trust on Actual Utilization is not statistically significant at the 95% confidence level ($\beta = 0.085$, $t = 1.767$, $p = 0.078$), indicating that Trust operates almost entirely indirectly through the development of Behavioral Intention.

Because Facilitating Conditions and Behavioral Intention exert highly significant structural pathways, the third null hypothesis ($H_0 3$) is rejected.

Comparative Demographic Analyses: Cadre Differences (Physicians vs. Nurses)

To evaluate potential differences in technological engagement across clinical cadres, an independent-samples t-test was conducted to compare physicians (n = 180) and nurses (n = 204) in their levels of Actual Utilization (AU).

Table 7. *Independent-Samples t-Test: Actual Utilization by Professional Cadre*

Professional Cadre	n	Mean ($\bar{x}$)	SD	t-statistic	df	p-value
Clinical Physician	180	3.02	0.78	3.204	382	0.001
Registered Nurse	204	2.76	0.81			

The comparative analysis reveals a statistically significant difference in Actual Utilization between professional cadres ($t(382) = 3.204$, $p = 0.001$). Clinical physicians exhibited a significantly higher level of AI utilization ($\bar{x} = 3.02$) compared to registered nurses ($\bar{x} = 2.76$).

This difference indicates that early-stage healthcare AI deployment in Philippine tertiary facilities is highly concentrated in diagnostic and therapeutic decision-support systems and drug-interaction engines, which primarily fall within the clinical scope of medical doctors.

Comparative Demographic Analyses: Generational Cohort Differences

To investigate generational influences on technological engagement, a one-way Analysis of Variance (ANOVA) was performed to compare Actual Utilization (AU) across the four defined age groups.

Table 8. ***One-Way ANOVA: Actual Utilization across Age Groups***

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Square (MS)	F-ratio	p-value
Between Groups	15.68	3	5.227	8.452	< 0.001
Within Groups	235.03	380	0.618		
Total	250.71	383			

The ANOVA results reveal a highly significant effect of age on the Actual Utilization of clinical AI ($F(3, 380) = 8.452$, $p < 0.001$). Post-hoc Tukey HSD tests confirmed that the youngest cohort (Under 28 years, $\bar{x} = 3.12$, SD = 0.75) utilized AI tools at a significantly higher rate than both the 36–45 age group ($\bar{x} = 2.72$, SD = 0.82) and the oldest cohort (Above 45 years, $\bar{x} = 2.58$, SD = 0.85).

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This finding highlights a distinct generational divide within the healthcare workforce; younger, digital-native clinicians exhibit a much higher baseline readiness to integrate AI applications into their daily workflows, despite a widespread lack of formal institutional training.

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Discussion

Detailed Interpretation of Structural Pathways

The structural evaluation of the extended UTAUT model reveals several critical insights regarding how Filipino medical professionals adopt healthcare AI. The descriptive results show a distinct mismatch in readiness: clinicians display strong cognitive appreciation for the clinical utility of AI (PE Mean = 3.84) and a moderate willingness to adopt these tools (BI Mean = 3.61).

However, actual routine utilization remains low (AU Mean = 2.88), suppressed by severe infrastructural deficits (FC Mean = 3.15) and highly elevated anxieties about security, ethical, and clinical risks (PR Mean = 3.97).

The hierarchical regression analyses expose the unique dynamics of this acceptance-utilization gap. Model 1 reveals that Trust is not a static construct but is dynamically balanced by two primary forces: the cognitive pull of expected clinical utility ($\beta = 0.326$) and the powerful negative push of perceived professional risk ($\beta = -0.330$).

In the high-stakes environment of Philippine tertiary medicine, clinicians will not trust an AI application simply because it is technically advanced; they must be confident that the tool is clinically safe, ethically compliant, and legally secure.

In Model 2, Trust is identified as the single strongest direct driver of Behavioral Intention ($\beta = 0.317$), outperforming all traditional UTAUT variables. This finding highlights a critical psychological mechanism: for clinical decision support systems, diagnostic machine learning models, and automated triage applications, trust is the primary bridge that converts cognitive recognition of utility into actual professional willingness.

Clinicians must navigate complex clinical scenarios with highly opaque ("black-box") algorithms; trust is the essential factor that makes clinicians feel secure in relying on automated outputs.

Crucially, Model 3 exposes a significant structural bottleneck. While Trust is the primary driver of Behavioral Intention, its direct path to Actual Utilization is not statistically significant ($p = 0.078$) when behavioral willingness and facilitating conditions are controlled for. This indicates a profound "trust-utilization paradox." Trust is necessary to establish the psychological willingness to adopt AI, but trust alone cannot trigger routine use unless supported by adequate technical infrastructure, interoperable EMR systems, and clear institutional policies.

The powerful direct influence of Facilitating Conditions on Actual Utilization ($\beta = 0.304$) confirms that systemic, organizational support is a critical bottleneck in the Philippine health system.

Clinicians may be willing to adopt AI, but they are prevented from doing so by slow digital connectivity, fragmented, non-interoperable databases, and the complete absence of clear hospital policies.

Integration with Regional and Global Literatures

These results align with and extend recent empirical studies across regional and global contexts. The finding that documentation is a key driver of adoption aligns with the 2026 global clinical consensus survey, which identified charting and administrative transcription as the most time-consuming professional burdens that drive rapid, ad hoc AI use.

Furthermore, the high-risk perception observed in this study (PR Mean = 3.97) matches the global finding that approximately 68% of frontline clinicians identify algorithmic hallucinations, diagnostic inaccuracy, and lack of transparency as primary clinical concerns.

Within the ASEAN context, the significant influence of Facilitating Conditions as a bottleneck in the path to actual utilization mirrors recent digital health evaluations in Indonesia and Thailand. Research in Indonesian public and

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private hospitals confirms that while clinicians demonstrate highly positive attitudes toward electronic medical records and automated analytics, adoption is uneven due to infrastructural differences and a persistent training deficit in remote areas.

This study confirms these regional patterns, demonstrating that the Philippine "training deficit" (79.7% of surveyed clinicians reported receiving zero formal AI upskilling) directly limits clinical productivity.

Theoretical Implications

This study offers several important contributions to the theoretical literature on technology acceptance in healthcare. By successfully extending the UTAUT framework to include Perceived Risk and Trust, this study provides a more comprehensive, clinically sensitive model of technology acceptance in high-risk professional environments.

The empirical validation of the extended model demonstrates that standard UTAUT constructs are insufficient to predict AI acceptance in healthcare; trust acts as a vital psychological mediator that must be integrated to capture how clinicians evaluate and adopt opaque algorithmic recommendations.

Importantly, the non-significant direct pathway from Trust to Actual Utilization ($p = 0.078$) introduces a key refinement to the theory. This finding shows that the cognitive transition from trust to utilization is not a direct path but is fully mediated by behavioral willingness and strictly bounded by facilitating conditions.

In resource-constrained LMICs, standard assumptions of technology acceptance models must be modified: facilitating conditions must be modeled not merely as an influence on behavioral intention, but as a critical direct predictor of actual utilization to capture the real-world impact of physical infrastructure deficits.

Practical and Operational Implications

For clinical operations and hospital management, these findings highlight the urgent need to shift from ad hoc technology adoption to structured, institutional upskilling frameworks. With the study revealing that nearly 80% of practicing medical professionals utilize AI without any formal training, healthcare institutions are highly exposed to significant risks of data breaches, clinical errors, and professional liability.

Hospital administrators must proactively address this training deficit by instituting structured, tiered capacity-building programs, similar to the Department of Health's Data Management Roadshow. These upskilling programs must move beyond generic "tool training" to establish core clinical competencies in AI literacy, teaching clinicians how to critically evaluate algorithmic outputs, identify bias and drift, document human-AI decision pathways, and execute manual overrides when recommendations conflict with clinical judgment.

Furthermore, hospitals must focus on building highly user-friendly, intuitive digital interfaces. If a system is difficult to navigate or poorly integrated with the hospital’s primary electronic health record, busy clinicians will quickly reject the technology.

Therefore, healthcare institutions should actively involve practicing doctors and nurses in co-creating and piloting clinical AI tools to ensure seamless integration into real-world workflows.

Unexpected Findings and Cultural Dialectics

A particularly striking and unexpected statistical result is the relatively weak direct negative impact of Perceived Risk on Behavioral Intention ($\beta = -0.087$, $p = 0.014$), compared to its massive negative impact on professional Trust ($\beta = -0.330$, $p < 0.001$). This statistical mismatch reveals a unique "pragmatic cognitive dissonance" among Filipino healthcare workers: despite harboring intense anxieties regarding data security, algorithmic inaccuracy, and professional displacement, clinicians remain willing to adopt AI tools.

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This pragmatic tolerance of risk is a direct consequence of severe professional burnout and a critical workforce shortage; clinicians are so heavily burdened by administrative tasks that they are willing to accept technological risks if they believe the tools can provide immediate relief.

However, this pragmatic acceptance is deeply constrained by complex socio-cultural factors. As Gozum discusses, the rapid mechanization of clinical decision-making threatens to displace *pakikiramdam*—the deeply embedded Filipino cultural practice of empathetic attunement, intuitive listening, and nonverbal understanding that lies at the core of the patient-physician relationship in the Philippines.

While an AI system can optimize diagnostic variables rapidly, it cannot replicate the nuanced communal dynamics of *kapwa* (shared identity) or navigate the quiet silences that Filipino clinicians routinely interpret in family-centered care.

Therefore, clinicians experience a profound dialectical tension: they value AI as a tool to automate administrative work and reclaim their clinical hours, yet they remain deeply anxious that overreliance on algorithms could reduce patient care to mere data processing, undermining the relational, humanistic, and spiritual core of Filipino healing.

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Conclusion

Summary of Findings

This study has successfully mapped and statistically evaluated the structural relationships that govern AI acceptance, utilization, and challenges among medical professionals in the Philippines. The findings show that while Filipino clinicians demonstrate strong cognitive readiness (PE Mean = 3.84) and moderate willingness (BI Mean = 3.61) to use AI to address operational burnout, actual utilization remains low (AU Mean = 2.88).

This clinical acceptance-utilization gap is driven by a combination of weak facilitating conditions (FC Mean = 3.15) and highly elevated perceived risk anxieties (PR Mean = 3.97) regarding patient data privacy and clinical safety.

The structural regression analyses validated the extended UTAUT framework, showing that:

1. Professional trust is dynamically balanced by expected clinical utility and perceived risk.

2. Trust is the primary direct driver of behavioral intention, acting as the essential psychological bridge that makes clinicians feel secure in adopting opaque algorithms.

3. Facilitating conditions act as a critical direct predictor of actual utilization, highlighting that physical, organizational, and regulatory infrastructure are essential to translate professional willingness into routine practice.

4. Trust does not directly drive actual utilization, but operates almost entirely indirectly through the establishment of behavioral intention, highlighting the critical role of structural support systems.

Theoretical and Conceptual Contributions

The primary theoretical contribution of this study is the integration of Perceived Risk and Trust as critical pathways within the UTAUT model, applied directly to the high-stakes clinical environment of an emerging health system. The empirical results demonstrate that standard technology acceptance models are inadequate for healthcare AI; trust must be modeled as a central mediator, and facilitating conditions must have a direct pathway to actual utilization to capture the real-world challenges of resource-constrained settings.

Furthermore, this study introduces a culturally sensitive conceptual framework that addresses the structural tension between global algorithmic optimization and essential localized clinical values such as *pakikiramdam*.

Practical and Policy Contributions

At the practical level, this study exposes a critical "training gap": nearly 80% of practicing medical professionals utilize AI tools ad hoc without formal institutional upskilling, exposing health systems to significant clinical, ethical, and legal liabilities.

This research provides a clear roadmap for hospital administrators to transition from unstructured, risky technological adoption to secure, auditable, and competency-based integration.

For policymakers, these findings provide empirical evidence to support the implementation of the National AI Strategy Roadmap 2.0, highlighting the need to build robust, interoperable local databases and clear regulatory sandboxes to foster safe, inclusive, and culturally aligned clinical AI deployment.

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Recommendations

Recommendations for National Policymakers

To establish a secure, equitable, and innovation-friendly environment for clinical AI, national policymakers must execute several urgent interventions:

1. **Enact Enforceable AI Governance Legislation**: The Philippine Congress should accelerate the approval of pending bills, such as House Bill No. 57 (the National Artificial Intelligence Code) and House Bill No. 2827, to establish the Bureau of Artificial Intelligence Systems (BAIS) as a centralized regulatory authority. This legislation must mandate clear risk-based classifications for clinical software, establish liability allocation protocols, and mandate compliance audits.

2. **Issue Specific Clinical AI Regulations**: The Food and Drug Administration (FDA) of the Philippines must finalize its draft circular on medical device software (MDSW). This circular should establish clear criteria for the pre-market approval, post-market monitoring, and change-control plans of adaptive clinical algorithms, providing developers and healthcare providers with a stable regulatory pathway.

3. **Formulate Culturally Aligned Ethical Guidelines**: The Department of Health (DOH), in coordination with the National Privacy Commission (NPC), should issue standardized ethical guidelines that reflect both strict data privacy principles and essential cultural values. These guidelines must define the boundaries of automated decision-making, ensure patients' right to an explanation, and mandate human-in-the-loop oversight to prevent the erosion of empathetic clinical care and *pakikiramdam* in medicine.

4. **Fund Local Clinical Data Repositories**: The Department of Science and Technology (DOST) must invest in establishing secure, high-quality, and localized databases under programs such as the Democratized Intelligent Model Exchange Repository (DIMER). Funding must be targeted toward building representative registries that minimize algorithmic bias and ensure that AI clinical outputs are validated specifically for the demographic and epidemiologic realities of the Filipino population.

Recommendations for Hospital Administrators and Clinical Practitioners

To ensure patient safety and maximize operational efficiency, hospital leaders and clinical practitioners should:

1. **Implement Competency-Based AI Training**: Healthcare institutions must transition from ad-hoc usage to structured clinical training. Administrators should establish mandatory, competency-based AI literacy programs integrated into residency and nursing education. This curriculum must go beyond basic tool training, teaching clinicians how to perform bias screening, interpret statistical probabilities, detect model drift, and document human-AI decision pathways.

2. **Establish Dedicated Institutional AI Ethics Boards**: Tertiary hospitals should establish multidisciplinary committees—comprising clinical specialists, medical ethicists, data protection officers, and patient advocates—to review and approve the local deployment of clinical AI applications. These boards must review local Privacy Impact Assessments (PIAs) and ensure that all deployments adhere to strict transparency and fairness guidelines.

3. **Deploy Enterprise-Grade AI Interfaces**: Hospital administrators must actively eliminate "shadow adoption" by procuring secure, enterprise-grade AI tools that feature end-to-end data encryption. Contract language with technology vendors must explicitly guarantee complete compliance with NPC Advisory No. 2024-04, ensuring that no patient health data is utilized for external model training without explicit consent.

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4. **Ensure Active Clinical Co-Creation**: Clinical practitioners must actively participate in the development and validation of digital health tools. Clinicians should advocate for intuitive, user-friendly interface designs that minimize cognitive fatigue, and assert their clinical authority to ensure that AI serves as a supportive tool that enhances, rather than replaces, humanistic care.

Recommendations for Medical and Nursing Educational Institutions

To prepare the future healthcare workforce for an increasingly digitized environment, educational institutions must:

1. **Embed Structured AI Literacy in the Curriculum**: The Commission on Higher Education (CHED) and university boards must revise medical and nursing curricula to include structured medical informatics and artificial intelligence competencies. AI literacy must be treated as a core clinical competency, with hands-on training built into student simulation labs.

2. **Design AI-Integrated Clinical Assessments**: Medical educators must transition from ad-hoc AI exposure to principled, auditable educational practices. Objective Structured Clinical Examinations (OSCEs) must be designed to assess students' clinical judgment and safety protocols when utilizing AI-assisted diagnostic tools and retinal imaging devices.

3. **Invest in Tiered Faculty Development**: Universities must establish tiered training and mentorship programs to build AI confidence among senior clinicians and medical faculty, ensuring they can effectively supervise and critique students' AI-assisted clinical reasoning.

Recommendations for Healthcare AI Researchers

To advance the scientific understanding of AI in medicine, researchers should:

1. **Conduct Longitudinal Performance Appraisals**: Future research must utilize longitudinal designs to evaluate the long-term impact of clinical AI on actual diagnostic accuracy, clinical error rates, and patient outcomes in low-resource environments.

2. **Investigate the Patient and Community Perspective**: Researchers should investigate patient trust, acceptability, and ethical perceptions regarding AI-mediated care, especially in rural and indigenous communities in the Philippines.

3. **Engage in Interdisciplinary Co-Design**: Researchers must foster collaborative partnerships between data scientists, clinical practitioners, cultural anthropologists, and legal experts to develop ethical-by-design, culturally aligned AI tools.

Practical Implications

The empirical findings of this study have direct, practical implications for the daily operations of clinical medicine in the Philippines. First, the data reveal that clinical documentation and transcription represent the most critical administrative burdens driving professional burnout. In practice, this means that hospital procurement strategies should prioritize acquiring secure, ambient AI clinical scribes and natural language processing tools to automate charting, enabling doctors and nurses to redirect their clinical time from computer screens back to direct patient interaction.

However, to execute this shift safely, healthcare institutions cannot outsource technology governance to third-party vendors. In practice, hospitals must establish structured clinical protocols that mandate manual, human-in-the-loop review and verification of all AI-generated medical records before signature. Clinicians must be trained

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to recognize algorithmic hallucinations and verify dosage recommendations, maintaining complete accountability for the final clinical decisions.

Furthermore, because digital connectivity is highly uneven in the Philippines, clinical AI tools must be designed with offline-capable or low-bandwidth features to ensure they can be safely utilized in provincial primary care units without causing system failures.

Policy Implications

From a policy perspective, the results highlight a critical misalignment between national AI ambitions and institutional regulatory readiness. The Department of Trade and Industry's National AI Strategy Roadmap 2.0 cannot achieve its industrial goals unless the Department of Health actively builds matching digital health policies. State agencies must collaborate to establish a unified regulatory sandbox system that allows developers to safely test innovative AI systems under real-world clinical conditions while maintaining strict privacy and ethical oversight.

Furthermore, this study highlights that compliance with data privacy regulations is an urgent institutional requirement. Every hospital deploying clinical AI must perform a comprehensive Privacy Impact Assessment (PIA) in strict alignment with NPC Advisory No. 2024-04.

National health insurance frameworks, such as PhilHealth, must integrate AI auditability standards into their accreditation requirements, ensuring that any healthcare facility that uses automated analytics to process billing or medical records has demonstrable security measures, secure data minimization policies, and clear human-in-the-loop override systems.

Limitations of the Study

This study is subject to several important limitations that must be acknowledged. First, the cross-sectional design captures professional perceptions and technological adoption behaviors at a single point in time, preventing the evaluation of long-term behavioral changes or direct causal relationships as AI technologies continue to evolve. Second, the sample was drawn exclusively from tertiary healthcare institutions within Metro Manila. While Metro Manila represents the primary center of healthcare modernization in the Philippines, this urban focus may limit the generalizability of the findings to rural and provincial healthcare settings, where digital infrastructure, internet connectivity, and technical resources are significantly more constrained.

Third, the quantitative self-reporting methodology may introduce common-method and social desirability biases, particularly in self-reported scores of actual utilization and risk perceptions.

Finally, while the extended UTAUT model explained a substantial proportion of the variance in behavioral intention and actual utilization, it did not examine other contextual moderating variables, such as generational differences among clinicians, hospital-specific procurement dynamics, or the direct impact of patient-side technological attitudes on clinical adoption.

Future Research Directions

Building on the findings and limitations of this study, several productive avenues for future research are identified. First, future studies should utilize longitudinal explanatory research designs to track how clinicians' trust, risk perceptions, and actual utilization patterns evolve over time as formal AI policies and training programs are institutionalized. Second, there is a critical need to replicate this structural model in primary and secondary healthcare settings across rural and provincial regions of the Philippines, enabling a comparative evaluation of how geographical and infrastructural disparities affect digital technology acceptance.

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Third, future research should integrate the patient and community perspective into the acceptance model. Investigating how Filipino patients perceive AI-mediated diagnostics, automated triage bots, and algorithmic decision support systems will provide vital insights to balance clinical efficiency with public trust and cultural acceptability.

Finally, future studies should focus on quantitatively evaluating localized clinical databases and generative models. Examining how training algorithms on local Filipino medical registries affects diagnostic accuracy, reduces algorithmic bias, and minimizes diagnostic error rates will provide developers and clinical leaders with the scientific evidence needed to build safer, more equitable, and highly inclusive healthcare AI systems.

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