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Separating Technology and Trust: A Survey Analysis of Patients' Attitudes toward AI-Assisted Healthcare Decision-Making

R. Sugumar*

Professor, Institute of CSE, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Thandalam, Chennai, India.

ABSTRACT

The integration of artificial intelligence (AI) and Internet of Things (IoT) technologies is fundamentally transforming healthcare delivery from hospital-centric to people-centered models. While AI demonstrates significant potential in improving diagnostic accuracy and enabling predictive disease management, important challenges persist regarding ethical considerations, social trust, data privacy, and equitable access across diverse populations. This research significance despite technological advances, comprehensive frameworks addressing AI transparency, social trust, and ethical implications in healthcare remain underdeveloped. This study addresses critical gaps by examining consumer perspectives on AI-assisted clinical decision support (AI-CDS) systems, focusing on perceived benefits, risks, and factors influencing acceptance across demographic segments. These statistical methods and measures were implemented using IBM SPSS 27.0 software for analyzing the survey data on attitudes toward AI-CDS systems. Data were collected through structured online surveys from 442 participants across diverse demographic backgrounds in the United States. The questionnaire assessed nine key dimensions including AI-CDS knowledge, trust, and ease of use, bias concerns, and willingness to follow recommendations using validated five-point Likert scales. Statistical analysis employed descriptive statistics, chi-square tests, and one-sample t-tests. The results respondents demonstrated moderate, neutral attitudes toward AI-CDS across all dimensions (means 3.02-3.18). Education level significantly influenced understanding and comfort with AI systems, while income affected approval needs and bias concerns. Healthcare provider status and clinical documentation experience emerged as crucial factors shaping trust and acceptance. Successful AI-CDS implementation requires addressing trust deficits through experiential learning, robust regulatory frameworks, and maintaining human-AI collaboration in healthcare decision-making.

Keywords: Artificial Intelligence in Healthcare, Clinical Decision Support Systems (AI-CDS), Patient Trust and Acceptance.

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INTRODUCTION

The healthcare sector is on the verge of a technological revolution, with artificial intelligence (AI) and Internet of Things (IoT) technologies fundamentally reshaping traditional care delivery models. The shift from hospital-centric systems to people-centric, data-driven healthcare environments represents a paradigm shift in how medical services are conceptualized, delivered, and evaluated. The integration of AI in healthcare has demonstrated significant potential in improving diagnostic accuracy, with its application in breast cancer screening significantly reducing human detection errors. Meanwhile, IoT-enabled ubiquitous sensing capabilities are enabling predictive disease management through continuous monitoring of physiological parameters. This integration of AI, IoT, and cyber-physical systems (CPS) is not just incremental progress, but a fundamental reimagining of healthcare delivery, promising improved patient outcomes, reduced healthcare costs, and improved access. However, this technological change presents important challenges, including ethical considerations, social trust factors, data privacy concerns, and the need for equitable healthcare access across diverse populations. [1-5]

The existing literature reveals several dimensions of AI and IoT integration in healthcare. AI in medical diagnostics:

Corresponding Author: R. Sugumar, Professor, Institute of CSE, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Thandalam, Chennai, India.

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Research demonstrates the effectiveness of AI in medical information technology, particularly in improving diagnostic accuracy and quality of patient care. Breast cancer screening application shows the potential of AI to reduce human errors, even though ethical frameworks and social trust mechanisms are still underdeveloped [6]. Person-centered healthcare systems: The evolution from hospital-centric to person-centered models emphasizes disease prediction and personal well-being management through the ubiquitous sensing capabilities of IoT devices, enabling proactive rather than reactive healthcare interventions [7]. Pandemic response and data management: The COVID-19 pandemic accelerated the digitalization of healthcare, highlighting both opportunities and challenges in patient data management, consent protocols, and sharing of de-identified data for collaborative purposes [8]. This experience underscores the importance of robust data governance structures in crisis situations. Cyber-Physical Systems Integration: CPS technologies combine physical sensing, communication, control, and networking with computational elements to create seamless healthcare monitoring ecosystems with transformative potential across multiple sectors including manufacturing, transportation, and agriculture [9]. Chronic Disease Prediction: Using lifestyle data, AI-driven predictive models represent emerging approaches to managing chronic diseases, addressing the significant $750 billion annual healthcare costs caused by nutrition-related conditions. This preventive approach is consistent with global shifts toward comprehensive health indicators [10].

Dr. Kakulavaram et al. has been published in the Journal of Business Intelligence and Data Analytics with the 2024 study titled *“Intelligent Healthcare Decisions Leveraging WASPAS for Transparent AI Applications,”* which introduces a transparent and explainable artificial intelligence framework for healthcare decision-making using the WASPAS (Weighted Aggregated Sum Product Assessment) multi-criteria decision-making methodology. The research demonstrates how complex healthcare choices—such as evaluating treatment strategies, operational healthcare processes, and resource optimization—can be ranked objectively by integrating weighted clinical, operational, and performance parameters into an explainable AI-driven decision model. By emphasizing transparency, interpretability, and auditability, the study directly addresses the limitations of black-box AI in medical environments and establishes a scalable, regulation-ready framework that strengthens clinical trust, improves decision accuracy, and supports accountable adoption of AI in real-world healthcare systems. [11]. Physiological monitoring systems: IoT-enabled sensing devices that capture physiological data such as skin temperature, respiratory rate, heart rate, and blood pressure through context-aware middleware architectures enable real-time health monitoring and server-based data analytics [12]. Machine learning in disease prediction: Machine learning methods, particularly decision trees (DT), deep space autoencoder (DSAE), and support vector machines (SVM), show significant potential in improving chronic kidney disease (CKD) prediction models, enabling early detection and home-based diagnostic approaches [13].

Despite significant progress, important gaps in literature persist. First, while demonstrating AI technology effectiveness in diagnostics, comprehensive frameworks addressing ethical implications, social trust, and AI transparency are lacking [14]. Second, integrating SDOH factors into AI-driven healthcare access systems requires deeper investigation, particularly regarding equitable implementation for vulnerable populations. Third, existing studies have focused primarily on patient health literacy levels and technical skills rather than their differential engagement with AI-driven healthcare decisions [15]. Fourth, the scalability and interoperability of IoT-based physiological monitoring systems across different healthcare settings are under-explored [16]. Finally, longitudinal studies examining real-world implementation outcomes, cost-effectiveness, and long-term patient

Table 1: Independent variable

Variable	*Response Options*
Name	*Open response*
Age	Under 20; 21–35; 35–40; 41–55; 56 Above
Gender	Male; Female; Other
Level of education	Less than high school; High school diploma or GED; Associate degree; Bachelor’s degree; Master’s degree; Doctoral degree; Other
Annual household income	Less than 1,00,000; 1,00,000 – 3,00,000; 5,00,000 – 7,00,000; 7,00,000 – 10,00,000; More than 10,00,000
Healthcare visits in the past 12 months	0 times; 1–2 times; 3–5 times; 6–10 times; More than 10 times
Medical situations where participant feels comfortable with AI-assisted decision support	Routine check-ups; Diagnostic imaging interpretation; Cancer diagnosis; Treatment planning for chronic conditions; Emergency care decisions; Surgical planning; Medication recommendations; Mental health assessment; None of the above
Most trusted source of information about AI medical devices with CDS	Personal physician; Medical specialists; Government health agencies (FDA, CDC); Academic researchers; Patient advocacy groups; Technology companies; Healthcare facilities; News media; Others

acceptance of AI-IoT integrated healthcare systems are notably lacking, limiting evidence-based policy formulation and widespread adoption strategies. [17-20]

Objective

We are examining the perceived benefits and risks of AI medical devices with clinical decision support (CDS) features from consumers' perspectives.

METHODOLOGY

These statistical methods and measures were implemented using IBM SPSS 27.0 software for analyzing the survey data on attitudes toward AI-CDS systems.

Data Sources

Primary data for this study were collected through a structured online survey questionnaire distributed to participants from diverse demographic backgrounds. The study captured key variables including age, gender, educational attainment, annual household income, and healthcare utilization patterns as measured by provider visits in the previous 12 months. Multiple-choice questions assessed participants' comfort levels with AI-assisted clinical decision support in various clinical situations and identified their most trusted sources of information regarding AI medical devices with CDS capabilities. To ensure adequate sample representation across demographic segments, data collection was conducted over a period, and a convenience sampling method was used to enable a comprehensive analysis of attitudes toward AI integration in healthcare decision-making.

Data Collection

Data collection was conducted through self-administered questionnaires distributed both online and offline during the research period. The questionnaire consisted of two main sections: demographic profile questions capturing respondent characteristics (age, gender, education level, annual household income, and healthcare use frequency) and nine constructs measuring attitudes toward AI-CDS using validated Likert-scale statements. Respondents rated each statement on a 5-point scale (1=strongly disagree to 5=strongly agree), assessing dimensions including AI-CDS knowledge, need for consent, operational understanding, trust, ease of use, bias concerns, willingness to follow recommendations, trust in supervision, value of human-AI collaboration, and impact on patient-provider relationship. Data quality was ensured through pilot testing, clear instructions, and voluntary informed consent. The collected data underwent rigorous exhaustive tests before statistical analysis using IBM SPSS 27.0 software, using descriptive statistics, correlation analysis, chi-square tests, and reliability estimate to examine the relationships between demographic variables and AI-CDS acceptance factors.

Table 2: Dependent variables and responses

Variable (Short Form)	*Response Options*
I am familiar with AI-powered Clinical Decision Support (CDS) systems used in healthcare. (AI-CDS Knowledge)	Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree.
AI-CDS systems should require approval from regulatory bodies before clinical use. (Need for AI-CDS Approval)	Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree.
I am aware that AI-CDS systems analyze patient data to provide recommendations to doctors (Understanding AI-CDS Function)	Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree.
I trust AI-CDS systems to provide accurate medical recommendations. (Confidence in AI-CDS)	Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree.
I would be comfortable with my doctor using an AI-CDS system to help diagnose my condition (Ease with AI-CDS Use)	Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree.
I am concerned that AI-CDS systems might be biased against certain groups of patients. (Worry About AI-CDS Bias)	Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree.
I would accept treatment recommendations that were partly based on AI-CDS system analysis. (Willingness to Follow AI-CDS)	Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree.
I trust that current regulations are sufficient to ensure the safety of AI-CDS systems. (Faith in AI-CDS Oversight)	Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree.
I believe the combination of human expertise and AI-CDS systems provides better care than either alone. (Value of Human + AI)	Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree.
Whether AI medical devices could reduce the personal connection between patients and doctors. (AI Effect on Rapport)	Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree.

Note. All variables were measured using a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree)

Table 3: Characteristics of participants in the AI-CDS cognitive study

Characteristics	*Frequency*	*Percentage (%)*
Age		
Under 20	71	16.1
21-35	173	31.1
35-40	68	15.4
41-55	81	18.3
56 Above	49	11.1
Gender		
Male	202	45.7
Female	187	42.3
Other	53	12.9
Level of education		
Less than high school	63	14.3
High school diploma or GED	77	17.4
Associate degree	38	8.6
Bachelor's degree	126	28.5
Master's degree	75	17
Doctoral degree	46	10.4
Other	17	3.8
Annual household income		
Level of education Less than 1,00,000	76	17.2
1,00,000 –3,00,000	131	29.6
5,00,000 – 7,00,000	91	20.6
7,00,000 – 10,00,000	101	22.9
More than 10,00,00,000	43	9.7

RESULTS AND DISCUSSION

Table 3 shows this analysis presents a demographic profile of 442 respondents from a study examining attitudes toward AI-assisted medical decision support. The sample was diverse in terms of age, gender, education, and income levels. Respondents were divided into five age groups, with the highest concentration in the 21-35 age range (31.1%), which ranges from young to middle-aged individuals who are more technologically savvy and open to digital health innovations. The 41-55 age group comprised 18.3% of the sample, while 20- and 35-40-year-olds comprised 16.1% and 15.4%, respectively. The smallest segment was 56 years and older (11.1%), indicating that the study may slightly underrepresent the older population, which is a significant consumer of healthcare.

Table 4 shows the descriptive statistics reveal moderate attitudes towards AI-assisted clinical decision support (AI-CDS) across all dimensions, with means ranging from 3.02 to 3.18 on a 5-point scale. "AI-CDS knowledge" scored highest (M=3.18), while "AI-CDS approval requirement" scored lowest (M=3.02). High standard deviations (1.165-1.383) indicate considerable variation in respondents' opinions, indicating mixed general perceptions regarding AI integration in healthcare decision-making.

Table 5 shows the chi-square analysis examines the relationships between demographic factors (education level and annual household income) and ten dimensions of attitudes toward AI-assisted clinical decision support (AI-CDS). Results reveal distinct patterns of association for each demographic variable. Nonsignificant associations: Education level was not significantly associated with consent requirements, dependency concerns, willingness to follow AI recommendations, trust in supervision, evaluation of human-AI collaboration, or effects on the patient-provider relationship. This suggests that these attitudes may be shaped by personal values or experiences rather than formal education.

Table 6 shows the position of healthcare provider primarily influences trust levels, while direct experience with medical documentation systems shapes knowledge, understanding, bias concerns, and willingness to trust AI. This difference suggests that professional role creates trust differences, but genuine system interaction is essential to developing nuanced understanding and informed approaches. Healthcare organizations should prioritize experiential learning opportunities with AI systems to build informed user bases. Being a healthcare provider does not guarantee comfort with AI; rather, practical exposure through documentation tools or similar applications helps develop the knowledge and critical perspective necessary for effective AI-CDS adoption. Training programs should emphasize practical experience over theoretical knowledge alone.

Table 7 shows the all dimensions show highly significant results (p=0.000), with t-values ranging from 47.369 to 49.618 and degrees of freedom (df) ranging from 441. These robust statistics indicate that the findings are unlikely to have occurred by chance, providing strong confidence in the reliability of the results across all measured approaches. The 95% confidence intervals for all dimensions are narrow and relatively consistent (ranging from approximately 0.25-0.29 units), indicating accurate estimates with minimal sampling error. Notably, several lower bounds approach or fall slightly below 3.0 (Need for Recognition: 2.90; Value of Human + AI: 2.91; Trust: 2.92), indicating that while the averages are slightly positive, substantial portions of the sample hold neutral or slightly negative views.

Figure 1 shows that**,** illustrates respondents' perceptions regarding whether they trust current regulations to adequately ensure the safety of AI-CDS systems. The distribution of responses shows a broad spread across the scale, with a noticeable clustering around the mid-range values. The mean score of 3.08 and standard deviation of 1.316 indicate that participants generally hold a neutral position, neither strongly trusting nor distrusting existing regulatory frameworks. While a segment of respondents demonstrates confidence in the ability of current regulations to safeguard AI-enabled clinical decision tools, an equally sizable portion remains uncertain or skeptical. The variation in responses highlights ongoing concerns about regulatory

Table 4: Descriptive Statistics

	N	*Range*	*Minimum*	*Maximum*	*Sum*	*Mean*		*Std. Deviation*	*Variance*
	Statistic	*Statistic*	*Statistic*	*Statistic*	*Statistic*	*Statistic*	*Std. Error*	*Statistic*	*Statistic*
AI-CDS Knowledge	442	4	1	5	1407	3.18	0.055	1.165	1.356
Need for AI-CDS Approval	442	4	1	5	1336	3.02	0.063	1.314	1.727
Understanding AI-CDS Function	442	4	1	5	1384	3.13	0.064	1.354	1.833
Confidence in AI-CDS	442	4	1	5	1347	3.05	0.062	1.313	1.723
Ease with AI-CDS Use	442	4	1	5	1394	3.15	0.064	1.336	1.786
Worry About AI-CDS Bias	442	4	1	5	1351	3.06	0.064	1.34	1.795
Willingness to Follow AI-CDS	442	4	1	5	1383	3.13	0.064	1.353	1.831
Faith in AI-CDS Oversight	442	4	1	5	1361	3.08	0.063	1.316	1.733
Value of Human + AI	442	4	1	5	1344	3.04	0.064	1.348	1.817
AI Effect on Rapport	442	4	1	5	1377	3.12	0.066	1.383	1.912

Table 5: Chi-square analysis showing significant interactions in Level of education and Annual household income

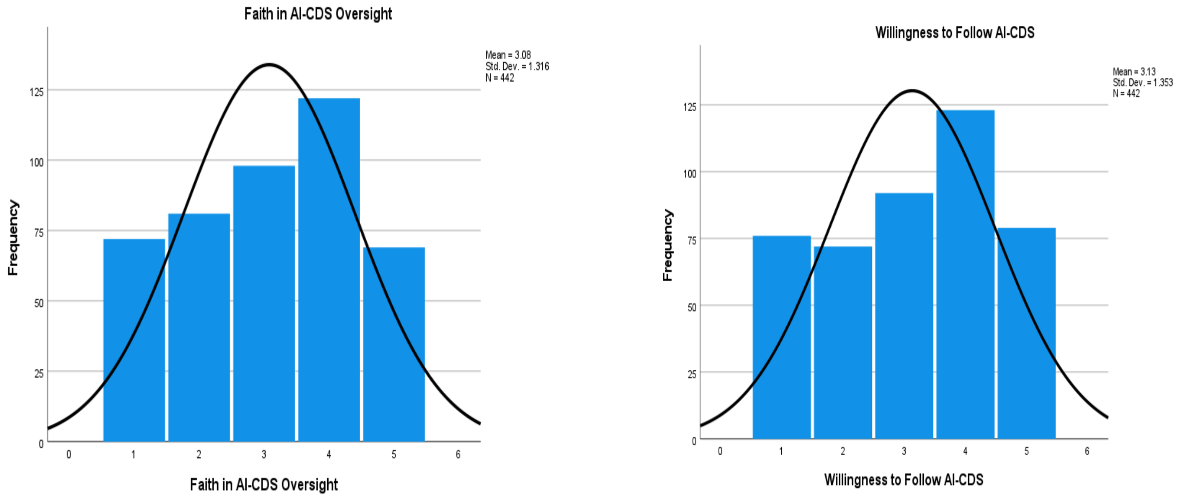
	Level of education			*Annual household income*		
	chi square value	*p value*	*interference*	*chi square value*	*p value*	*interference*
AI-CDS Knowledge	35.953	0.055	Significant	24.729	0.075	Non-significant
Need for AI-CDS Approval	33.638	0.091	Non-significant	36.603	0.002	Significant
Understanding AI-CDS Function	39.777	0.023	Significant	21.508	0.16	Non-significant
Confidence in AI-CDS	36.334	0.051	Significant	23.858	0.093	Non-significant
Ease with AI-CDS Use	36.967	0.044	Significant	55.234	0	Significant
Worry About AI-CDS Bias	27.834	0.267	Non-significant	33.361	0.007	Significant
Willingness to Follow AI-CDS	32.653	0.112	Non-significant	29.723	0.019	Non-significant
Faith in AI-CDS Oversight	34.299	0.079	Non-significant	34.79	0.004	Significant
Value of Human + AI	33.899	0.086	Non-significant	27.23	0.039	Significant
AI Effect on Rapport	27.039	0.303	Non-significant	22.461	0.129	Non-significant

Table 6: Chi-square analysis showing significant interactions of Healthcare provider and Clinical Documentation Support

	Healthcare provider			*Clinical Documentation Support*		
	chi square value	*p value*	*interference*	*chi square value*	*p value*	*interference*
AI-CDS Knowledge	26.228	0.051	Significant	46.746	0.045	Significant
Need for AI-CDS Approval	25.856	0.056	Significant	82.951	0	Non-significant
Understanding AI-CDS Function	21.557	0.158	Non-significant	60.733	0.002	Significant
Confidence in AI-CDS	53.791	0	Significant	34.64	0.343	Non-significant
Ease with AI-CDS Use	17.066	0.381	Non-significant	40.898	0.135	Non-significant
Worry About AI-CDS Bias	16.446	0.422	Non-significant	54.236	0.008	Significant
Willingness to Follow AI-CDS	24.345	0.082	Non-significant	55.11	0.007	Significant
Faith in AI-CDS Oversight	24.349	0.082	Non-significant	42.232	0.107	Non-significant
Value of Human + AI	23.87	0.092	Non-significant	36.38	0.272	Non-significant
AI Effect on Rapport	25.229	0.066	Non-significant	43.319	0.087	Non-significant

Table 7: One-sample t-test results for One-sample T-test analysis comparing the AI-CDS the neutral center point (test value = 3.0)

	t	*df*	*Sig. (2-tailed)*	*Mean Difference*	*95% Confidence Interval of the Difference*	
AI-CDS Knowledge	57.464	441	.000	3.183	3.07	3.29
Need for AI-CDS Approval	48.351	441	0	3.023	2.9	3.15
Understanding AI-CDS Function	48.622	441	0	3.131	3	3.26
Confidence in AI-CDS	48.805	441	0	3.048	2.92	3.17
Ease with AI-CDS Use	49.618	441	0	3.154	3.03	3.28
Worry About AI-CDS Bias	47.964	441	0	3.057	2.93	3.18
Willingness to Follow AI-CDS	48.609	441	0	3.129	3	3.26
Faith in AI-CDS Oversight	49.176	441	0	3.079	2.96	3.2
Value of Human + AI	47.426	441	0	3.041	2.91	3.17
AI Effect on Rapport	47.369	441	0	3.115	2.99	3.24



a)

b)

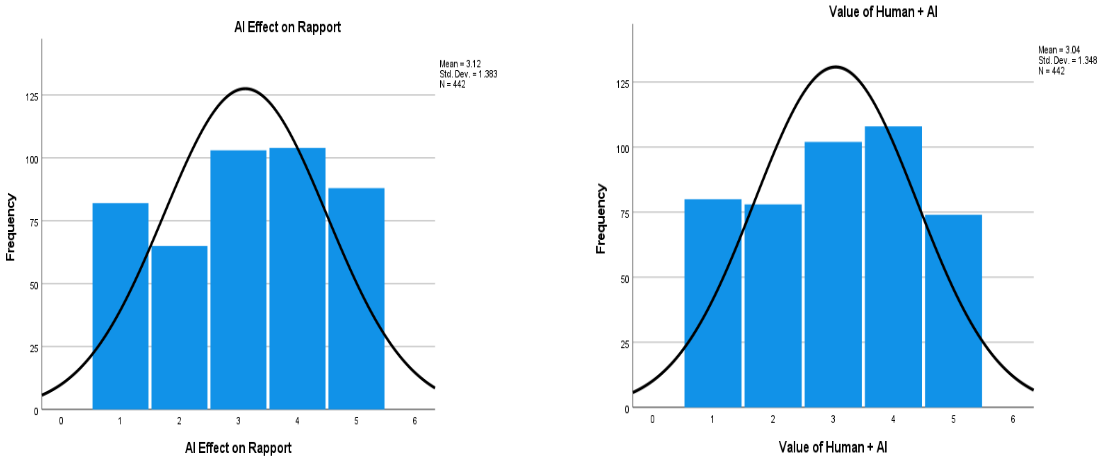
Figure 1: a) Faith in AI-CDS Oversight, b) Willingness to Follow AI-CDS

adequacy, transparency, and oversight as AI continues to evolve in healthcare.

Figure 2 shows that, A illustrates respondents' opinions on whether AI medical devices will reduce personal interactions between patients and doctors. The distribution appears to be relatively balanced, with responses spread across the scale but showing some concentration around the midpoints. This indicates that many participants have moderate opinions rather than strong agreement or disagreement. The mean score of 3.12 and standard deviation of 1.383 indicate a generally neutral stance, with significant variation in opinions. While some respondents expressed concern that AI could reduce human interactions in medical care, a nearly equal proportion were pessimistic or unsure.

P-P Plot in AI-CDS Knowledge

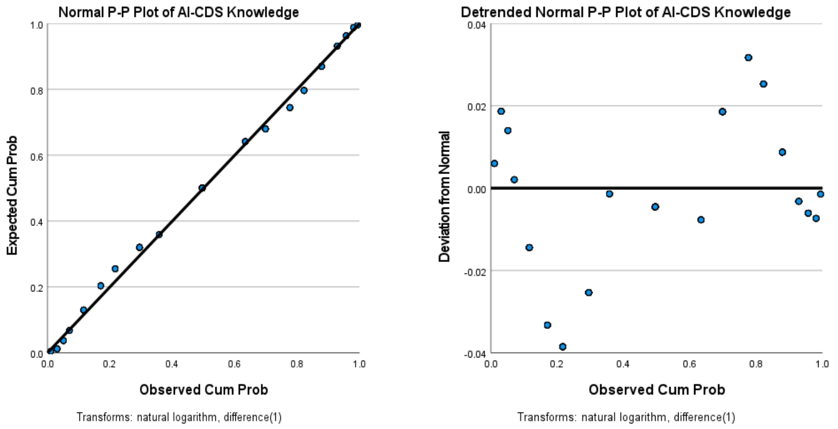
Figure 3 shows that Normal P–P Plot assessing the distribution of AI-CDS Knowledge after applying a natural logarithm transformation and first-difference adjustment. The plotted points lie closely along the diagonal reference line, indicating good alignment between the observed cumulative probabilities and those expected under a normal distribution. Only minor deviations are visible at the extreme ends of the plot, suggesting that the transformed AI-CDS Knowledge data approximate normality reasonably well. This visual evidence supports the suitability of the transformed variable for statistical analyses that assume normally distributed data, such as regression or parametric hypothesis testing.



a)

b)

Figure 2: a) AI Effect on Rapport b) Value of Human + AI



a)

b)

Figure 3: a) Normal Q-Q Plot and b) Detrended Normal P-P Plot for "AI-CDS Knowledge"

CONCLUSIONS

This study examined consumer perceptions of AI-powered clinical decision support (CDS) systems through a survey of 442 diverse participants across the United States. The research revealed moderate levels of acceptance across all dimensions measured, with mean scores ranging from 3.02 to 3.18 on a 5-point Likert scale, indicating cautiously optimistic attitudes toward AI integration in healthcare decision-making. Findings indicate that consumers have moderate knowledge of AI-CDS systems (M=3.18) and show reasonable comfort with their use in clinical settings (M=3.15). Specifically, respondents recognized the value of human-AI collaboration (M=3.04), suggesting that combining human expertise with AI capabilities can improve the quality of care. However, relatively high standard deviations across all constructs (1.165-1.383) reveal considerable heterogeneity in consumer attitudes, reflecting diverse perspectives within the population. Chi-square analysis identified significant demographic patterns influencing AI-CDS acceptance. Educational attainment significantly influenced understanding of AI-CDS functionality (p=0.023), trust in AI-CDS (p=0.051), and ease of use of AI-CDS (p=0.044). Annual household income showed significant associations with consent requirements (p=0.002), ease of use (p<0.001), dependency concerns (p=0.007), supervision trust (p=0.004), and assessment of human-AI collaboration (p=0.039). Critically, healthcare provider status primarily influenced trust levels (p<0.001), while direct experience with medical record systems influenced knowledge (p=0.045), understanding (p=0.002), dependency awareness (p=0.008), and willingness to follow AI recommendations (p=0.007). These findings emphasize that experiential learning with AI systems fosters informed perspectives and nuanced understanding, rather than theoretical knowledge alone. Healthcare organizations should prioritize direct exposure to AI-CDS technologies through training programs that emphasize practical interactions over abstract concepts. To ensure equitable AI-CDS adoption, policymakers should address identified disparities in income and education levels. Furthermore, establishing transparent regulatory frameworks and addressing bias concerns are essential to fostering societal trust. Future research should conduct longitudinal studies that examine real-world implementation outcomes, cost-effectiveness analyses, and long-term patient acceptance patterns to guide evidence-based healthcare innovation policies that balance technological advancement with ethical responsibility and equitable access.

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