INTERNATIONAL JOURNAL OF BUSINESS AND MANAGEMENT SCIENCES (ISSN: 2693-3500)
VOL.06 ISSUE11 (2026)

Research Article

Healthcare Affordability and Service Utilization: An Empirical Assessment of Consumer Perspectives

Shubham Naresh Bhoir

Assistant Manager, Volo Health Services, RH No.9, Villa Delphine, Opp Infant Jesus School, Mahada Colony Ambarnath East 421501

Received: 23 October 2026
Revised: 30 October 2026
Accepted: 04 November 2026
Published: 10 November 2026

DOI: 10.55640/ijbms-06-11-01
Page No: 01-09

Copyright: © 2026 Authors retain the copyright of their manuscripts, and all Open Access articles are disseminated under the terms of the Creative Commons Attribution License 4.0 (CC-BY), which licenses unrestricted use, distribution, and reproduction in any medium, provided that the original work is appropriately cited.

Abstract

This study explores the connection between healthcare affordability and utilization, considering consumer perspectives within the dynamics of healthcare financing and GenAI adoption. Due to increasing cost-sharing approaches and financial barriers, consumers' behaviour is shifting toward underutilization of needed services due to information asymmetries and financial toxicity. This research, following a quantitative cross-sectional design and employing 400 participants, explores constructs of affordability, accessibility, trust, personalization, technology, and data privacy concerns. Internal reliability was proven high by the analysis of the data, while the descriptive analysis showed quite positive consumer attitudes in terms of all variables. Correlation analysis shows strong positive relationships between affordability, quality, accessibility, and trust that positively influence the adoption of healthcare. Affordability appears as a critical construct that influences the decision to use the healthcare service, and this research proves that consumer perspectives strongly moderate the adoption of technologies including GenAI.

Keywords: Healthcare Affordability, Service Utilization, Consumer Perceptions, Generative AI, Data Privacy, Accessibility, Trust, Financial Toxicity.

INTRODUCTION

Healthcare financing has been changing in advanced economies over the last two decades. For the last two decades, health systems in advanced economies have experienced a "structural change" in the mechanisms that drive the financing of healthcare. There have been significant increases in formal coverage rates via universal coverage mandates and subsidized exchange models, but financial burden has increasingly shifted towards individual consumers [1]. Growth of cost-sharing mechanisms, particularly the introduction of high deductibles, co-insurance rates, and limiting access to pharmacies [2][3], has changed how consumers engage with the health care enterprise [4][5]. This shift was, in part, based on consumer-directed healthcare theory: that there is a positive relationship between consumer incentives to accept first-dollar liability and market discipline [6], the reduction of moral hazard, and the reduction of price insensitivity for elective services. But there is some new empirical evidence that offers a very negative corollary: consumers are not necessarily looking for high-value, low-cost services, but rather are “buying up” all services, even some of the most critical preventive services, chronic disease monitoring, and associated services for the symptoms of acute conditions [7].

Figure 1 depicts the expansion of India’s hospital market between 2020 and 2034, combining historical data with forecasted projections. The market size begins at USD 135.99 billion in 2020 and rises to USD 198.42 billion by 2025, reflecting a strong upward trajectory in the initial phase. From 2026 onward, the forecasted values continue this growth pattern, with the market expected to reach USD 364.55 billion by 2034. The orange growth line emphasizes the consistency of this upward trend, suggesting that the sector is poised for long-term expansion. Overall, the visualization highlights a nearly threefold increase in market size over the 14 years, underscoring the structural drivers of healthcare demand in India, such as demographic changes, rising medical needs, and sustained investment in hospital

infrastructure.



Fig. 1.Growth Trajectory of India's Hospital Market from 2020 To 2034

The term 'financial toxicity' was initially used in oncology to refer to the psychological, financial, and physical burden caused by a high patient burden on health care costs. High and/or low out-of-pocket thresholds create a situation in which basic healthcare becomes a "discretionary consumer good" for low- and middle-income families, causing the agonizing trade-offs between physical health and a variety of basic household security (e.g., housing, food, emergency savings) [8][9].

However, the basic concept of consumer-driven health care that an increased out-of-pocket risk encourages consumers to act as smart, price-sensitive buyers – contradicts more and more with the actual behavior of consumers in real-life medical settings [10][11]. Instead of carefully searching the health care system in order to choose cost-efficient providers, people often show what can be called "blunt price sensitivity [12]." As a result of increased deductibles and unpredictable cost sharing, consumers simply decrease their utilization of care irrespective of the type of services they use. This applies both to screening, chronic condition control, and even early treatment of some acute diseases. This indiscriminate approach results from a major information mismatch: patients frequently lack the necessary price clarity, administrative direction, and clinical acumen to differentiate between low-value discretionary services and high-value essential services [13]. Financial disincentives turn routine medical advice into a frightening financial risk [14][15].

A. Problem Statement

Even with continuous healthcare reform efforts and insurance programs, healthcare costs have remained a major obstacle to healthcare accessibility. Most of the literature on the topic has focused mainly on measurable aspects, while very little attention has been given to consumers' perceptions of healthcare costs.

B. Research Objectives

- To assess the impact of the perception of healthcare affordability on healthcare service use.
- To analyze the impact of having health insurance on healthcare affordability.
- To study the impact of healthcare access on healthcare utilization.
- To explore the association between healthcare quality and healthcare utilization.
- To measure the mediating impact of consumer trust between healthcare affordability and healthcare utilization.

C. Research Questions

- Does affordability affect healthcare utilization?
- Does having health insurance make healthcare more affordable to people?
- Is there a connection between healthcare quality and healthcare utilization?
- Does accessibility lead to increased healthcare utilization?
- Does trust play a mediator role between affordability and utilization?

II. LITERATURE REVIEW

It is evident from the literature that affordability is a critical determinant of healthcare access. Financial constraints prevent preventive services and create delays in seeking care. Higher out-of-pocket costs have remained a significant concern amid increasing coverage programs [16].

A. Price Elasticity and Healthcare Service Utilization

Price elasticity of demand is the degree of responsiveness of the demand for a product or service as its price changes. Price elasticity in health care describes the responsiveness of demand for health care services to a change in price, or

how much a person's behavior changes in response to a change in the price of a health care service. Healthcare is generally seen as a necessity, as its demand is relatively inelastic. Consumer goods are not considered a necessity; the relative elasticity of demand depends on the product and the individual. But sometimes, the cost of preventive care, routine consultations, diagnostic tests, and elective procedures is more sensitive [17].

Consumers' willingness and ability to use health care services are directly affected by the cost of health care. For consumers, especially those with low incomes, increases in consultation fees, medication costs, diagnostic tests or the cost of a hospital stay may cause them to delay seeking care, reduce the number of visits and/or avoid preventive care. Therefore, increased health care costs may lead to lower levels of health care use and over time, to worse health. Consumers view the price elasticity of their response to a health care service treatment depending on income, insurance coverage, health state, and perceived need for treatment. Consumers who have comprehensive health insurance or higher incomes tend to be less sensitive to health care price changes, while those without health insurance or lower incomes tend to be more sensitive. So, price elasticity can be used to understand the role of financial barriers in people's use of health services and to design policies that enhance the affordability and equity of health services [18][19].

B. Moral Hazard in Healthcare

Moral hazard occurs when individuals increase consumption of healthcare services because they are protected from full payment through health insurance. This is because covered individuals may not worry much about the expense of treatments since they only have to pay a portion of the expenses [20]. They will end up using more healthcare services than those not insured. Moral hazard in healthcare economics is broadly classified into two categories:

Ex ante moral hazard: Individuals may engage in risky health practices because they will receive insurance payments for future treatment costs.

Ex post moral hazard: Individuals may utilize more healthcare services after they become insured due to a reduction in costs.

From the point of view of healthcare costs, moral hazard implies better financial access due to insurance cover, but also more consumption of healthcare services. However, empirical studies show that for many developing nations, an increase in usage after the adoption of insurance arises from previously underutilized health services. Thus, moral hazard must be taken into account with caution, taking into consideration the presence of healthcare services, socio-economic factors, and consumer health conditions [21].

C. Concept of Behavioral Unawareness

Behavioral unawareness occurs when individuals do not make rational healthcare choices because they are unaware of healthcare costs, their health insurance benefits, preventive care options or healthcare services. Unlike moral hazard that arises out of financial protection, behavioral unawareness emanates from information gaps, cognitive biases and low health literacy [22]. Many healthcare consumers underutilize healthcare services either due to lack of understanding of the significance of preventive care, misunderstanding of health insurance policies, fear of unexpected costs or overestimation of treatment costs. Some may be unable to use healthcare services because they do not know about available financial aid for services or symptoms [23].

Behavioral unawareness is very pertinent in a developing healthcare system, where low health literacy, lack of awareness of governmental insurance schemes and cost visibility hinder the utilization of healthcare services. This problem can be addressed through consumer education and increase of price visibility [24].

1) Conceptual Framework and Hypothesis development

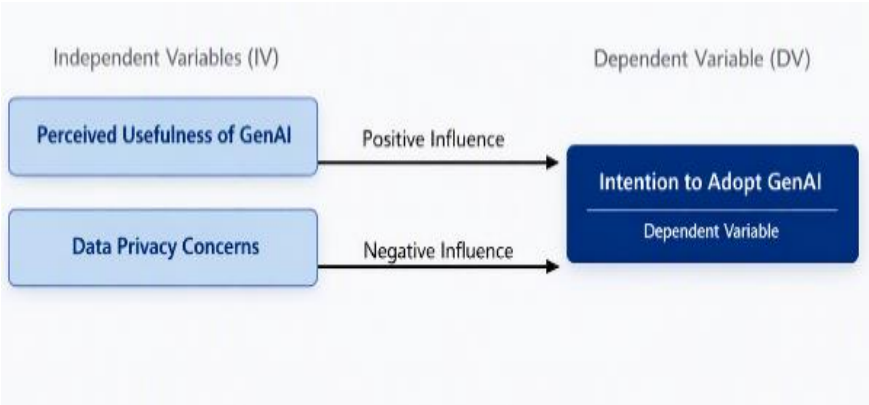


Fig. 2. Conceptual Framework

The Framework shows the Figure 2 conceptual model of the research by showing how the dependent and independent variables are related. In this case, the dependent variable is “intention to adopt generative artificial intelligence

(GenAI)," while the two independent variables include "Perceived Usefulness of Generative Artificial Intelligence (GenAI)" and "Data Privacy Concerns [25]." The two arrows in the diagram show the direction of the relationship between the dependent and independent variables, such that the relationship is expected to be positive for one and negative for the other.

Hypothesis Development

- H1: Perceived Usefulness of GenAI and Intention to Adopt GenAI: The term "perceived usefulness" relates to healthcare practitioners' confidence in the impact that Generative Artificial Intelligence (GenAI) will have on their clinical performance, decision-making, productivity, and positive patient outcomes [26]. Perceived usefulness was recognized as the most effective predictor of individuals' willingness to embrace new technologies formulated by Davis (1989). When healthcare professionals realize that GenAI will make their clinical documentation easier, aid in diagnosis and treatment planning, decrease administrative burden, and promote patient-centered care, they tend to form a positive attitude towards it.However, recent research has revealed that AI technology makes people more efficient through the automation of repetitive tasks, evidence-based clinical decision-making, and giving healthcare professionals more time to interact with patients. As users perceive the technology as more useful, there is a growing likelihood of incorporating it into healthcare practice. Thus, usefulness becomes a motivation behind adopting GenAI [27].
- H2: Data Privacy Concerns and Intention to Adopt GenAI: Data privacy concerns relate to fear among health care professionals about data collection, storage, processing, dissemination, and the security of patients' data by Generative Artificial Intelligence. Health care data are very sensitive and are governed by stringent ethical and legal standards. Therefore, fears about unauthorized access, cybersecurity, data breaches, algorithm abuse, and non-compliance with privacy laws may lower trust in AI technology in health care [28].

III. RESEARCH METHODOLOGY

In this study, a quantitative cross-sectional research methodology was used to explore consumer perceptions about Generative Artificial Intelligence (GenAI) in healthcare. Descriptive and correlational research methodologies were used to examine the associations between different factors that affect perceptions towards GenAI [29]. Primary data was collected by distributing a structured questionnaire only once at a point in time. In other words, a cross-sectional design was used, as it helped explore respondents' opinions regarding the association between the study variables. The target population included individuals who had knowledge of health care services and usage of Artificial Intelligence. In all, 400 valid responses were used for the analysis. The sample was made up of people with varied demographics in terms of gender, age group, education level, occupation, income, geographic location, and experience with AI.

In this research, the deductive research methodology was used to test the association between the study variables. Hypotheses were formed based on different literature and theoretical concepts. Primary data were collected using a structured questionnaire consisting of two sections [30].

The first part of the questionnaire collected information about the demographic variables such as gender, age, educational qualifications, profession, monthly income, place of living, and prior experience with Artificial Intelligence among the participants.

The second part of the questionnaire collected respondents' perceptions about fourteen important constructs regarding the adoption and acceptance of Generative Artificial Intelligence (GenAI) in healthcare. These constructs included Improved Health Outcomes, Convenience and Accessibility, Empowerment through Personalization, Technological Sophistication, Market Competition, Government Approval, Social Influences, Brand Image, Media Influence, Data Privacy Concerns, Uncertainty and Trust in Artificial Intelligence, Digital Divide, Human Touch Preferences, and Cost Issues.

IV. RESULTS AND DISCUSSION

The Results and Discussion section will contain the empirical findings of this research grounded on the data gathered from the respondents. It involves analyzing and interpreting the statistical output to identify the characteristics of the respondents, determine the validity of the measurement instrument, analyze the distribution of the research variables, and determine the relationship among the research constructs. The findings are analyzed in accordance with the research objectives and previous literature for their relevance in adopting and accepting the use of GenAI in healthcare [31].

TABLE I. RELIABILITY STATISTICS

Reliability Statistics	
Cronbach's Alpha	N of Items
991	14

Table I This table shows the internal consistency of the scale using Cronbach's Alpha. The coefficient value of .991 shows very high reliability, as it means that all 14 items in this scale have very strong interrelationships and consistently measure the same construct. As regards the reliability analysis, any value above .90 is regarded as excellent, and this nearness to 1 shows negligible measurement error. On the other hand, this high alpha may indicate redundancy, as it can imply that some items are too similar and do not provide unique information. In conclusion, this result shows that the instrument is very reliable in measuring the intended construct.

A. Frequency Table

The Frequency Table shows the distribution of responses across variable categories. It displays the frequency of each category, its percentage of the overall sample, its valid percentage after eliminating missing instances, and the cumulative percentage that adds up across categories until 100%. This section explains how the sample is separated by gender, age, or other demographic or survey data. It helps readers rapidly analyze the dataset and spot trends or imbalances in response distribution[32].

Figure 3 shows the demography and experience of respondents in terms of gender, age, education level, occupation, monthly income, residential area, and prior experience in using AI. Most respondents are male (215), followed by female (182), and the smallest category is other (3). As for the age structure of the respondents, most are aged 26-35 years (135) and 18-25 years (125). As for educational attainment, the highest number of respondents holds a graduate degree (144) and a postgraduate degree (106). In addition, the least educated category includes people who have only a high school education (46) and a PhD (25). Regarding occupation, most respondents work as private employees (189), followed by business professionals (112) and government employees (57). Concerning monthly income, the highest number of respondents earn between ₹25,000 - ₹50,000 (133), while the smallest number earn more than ₹100,000 (42). As for residential area, most of the respondents live in urban areas (172). Besides, respondents also live in semi-urban areas (126) and rural areas (102). In the last category, most respondents have prior experience in AI (250), while 150 respondents do not have prior experience.

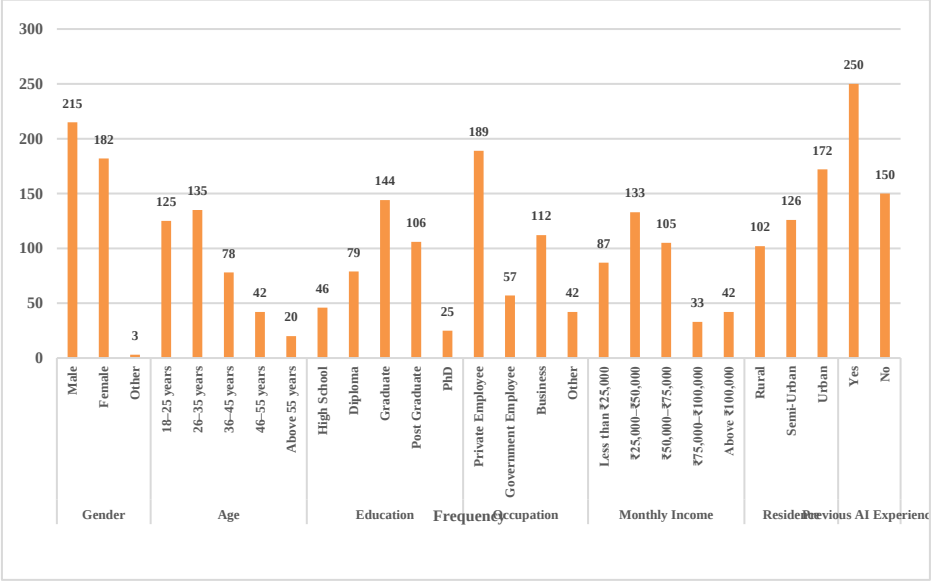


Fig. 3. Demographic and Experiential Profile of Respondents

B. Descriptive Statistics

The values of Minimum, Maximum, Mean, and Standard Deviation are essential descriptive statistics parameters that help describe the characteristics of a dataset. The minimum value defines the smallest observation made, while the maximum is the largest, thus determining the range of the dataset. The mean determines central tendency by calculating the average value of all observations, which becomes a representative value of the dataset. Standard Deviation helps in understanding how spread out the values are from the mean, whereby a low standard deviation implies that observations are clustered around the mean, while a high standard deviation means that they are far from the mean [33].

TABLE II. DESCRIPTIVE STATISTICS OF RESPONDENTS' PERCEPTIONS ACROSS KEY VARIABLES

Descriptive Statistics				
	Minimum	**Maximum**	**Mean**	**Std. Deviation**
Improved Health Outcomes	2	5	3.49	.794
Convenience and Accessibility	2	5	3.51	.792
Empowerment Through Personalization	2	5	3.49	.790

Technological Sophistication	2	5	3.49	.804
Market Competition	2	5	3.48	.816
Government Endorsement	2	5	3.49	.784
Social Influence	2	5	3.52	.812
Brand Reputation	2	5	3.49	.826
Media Coverage	2	5	3.48	.816
Concerns About Data Privacy	2	5	3.51	.815
Uncertainty and Trust in AI	2	5	3.50	.834
Digital Divide	2	5	3.51	.805
Preference for Human Touch	2	5	3.52	.817
Cost Concerns	2	5	3.52	.799

Table II shows Descriptive Statistics of key variables and provides a description of the distribution of responses on the variables such as better health results, convenience, personalization, technology use, market competition, governmental approval, social influence, reputation of a company, media publicity, worries about privacy, trust in AI, digital divide, preference for the human touch, and cost concerns. The minimum and maximum values for each variable represent the lowest and highest possible scores achieved during the analysis and show that responses ranged from 2 to 5. All the mean values (3.48 - 3.52) show that the respondents had a moderately positive opinion about the variables under analysis. The standard deviation (.784 - .834) shows low variability among the respondents' answers; thus, there is no extreme discrepancy in their opinions.

C. Correlations

In statistics, correlation is a measure of the degree of association between two variables. The correlation coefficient is given by 'r' and is a number ranging between -1 and +1. A correlation coefficient of +1 implies a positive relationship between two variables (where an increase in one implies an increase in the other). On the other hand, a correlation coefficient of -1 shows a negative relationship (an increase in one implies a decrease in the other). A correlation coefficient of zero implies no relationship between the variables [34].

TABLE III. CORRELATION MATRIX OF KEY VARIABLES

Correlations														
	IHO	CAN	ETP	TS	MC	GEND	SI	BR	MCV	CADP	UTAI	DD	PLHT	CC
IHO	1													
CAN	.905**	1												
ETP	.897**	.884**	1											
TS	.879**	.889**	.882**	1										
MC	.894**	.898**	.875**	.891**	1									
GEND	.898**	.898**	.887**	.895**	.907**	1								
SI	.892**	.902**	.879**	.885**	.888**	.892**	1							
BR	.903**	.903**	.885**	.896**	.891**	.903**	.893**	1						
MCV	.894**	.898**	.875**	.891**	1.000**	.907**	.888**	.891**	1					
CADP	.900**	.889**	.885**	.892**	.878**	.889**	.894**	.904**	.878**	1				
UTAI	.890**	.892**	.881**	.891**	.891**	.889**	.886**	.903**	.891**	.890**	1			
DD	.893**	.893**	.868**	.885**	.876**	.878**	.886**	.888**	.876**	.886**	.890**	1		
PLHT	.904**	.906**	.888**	.890**	.877**	.900**	.897**	.896**	.877**	.893**	.893**	.884**	1	
CC	.880**	.886**	.880**	.888**	.878**	.876**	.885**	.899**	.878**	.878**	.893**	.887**	.882**	1
**. Correlation is significant at the 0.01 level (2-tailed).														

Table III above: The correlation table gives us an idea about the degree of relationship between the various variables used in the study, which includes improved health outcome, convenience and accessibility, customization, technology, market competition, government approval, social influence, brand reputation, media coverage, data privacy concern, AI acceptance, digital divide, preference for human touch, and cost concern. All the coefficients have been found to be positive and very high (greater than .87), thus showing a strong relationship amongst the different variables. For instance, the correlation coefficient between convenience and accessibility (CAN) and improved health outcome (IHO) is .905, which means that when perceptions about CAN increase, perceptions of IHO also improve. Likewise, MC and MCV have a perfect correlation (1.000) in this dataset, meaning that they move together perfectly. Double asterisks (**) signify that all correlations are statistically significant at the 0.01 level, thus making sure that none of these relationships is accidental.

V. COMPLEXITIES IN MEASURING CONSUMER PERCEPTIONS

Some of the issues that this research ran into included the following: measuring consumer perceptions, since consumer attitudes towards the affordability and adoption of AI within the healthcare sector involve numerous intersecting

influences such as socio-economic position, culture, previous experience with the healthcare system, etc [35]. This issue was complicated by the fast pace of change in the healthcare and technology industry, where policy changes, market fluctuations and the emergence of new AI technologies may affect people's perceptions much quicker than research can document, leading to potential obsolescence of findings. It was also difficult for the study to combine the breadth of the subject (the numerous constructs of the problem like affordability, accessibility, trust, personalization, etc.) and the depth of analysis since the latter would require more time and resources to be spent on each factor. Moreover, multicollinearity among numerous interrelated variables made the statistical analysis difficult, as it was hard to single out the role of each construct. Information asymmetry was another challenge faced by the research [36].

VI. FUTURE RESEARCH

For future research, longitudinal designs should be considered in order to analyze changes in consumer perceptions and healthcare utilization over time, which would aid in understanding the cause-and-effect relationships better. Increasing the sample size by including larger populations and populations from other socio-economic and geographic areas would improve the validity of the results. Researchers might also adopt mixed methods, using both quantitative and qualitative methodologies (for example, combining surveys with in-depth interviews) to better understand consumer perceptions and attitudes. Comparative research is also needed for future studies in other countries, particularly by comparing developed and developing countries and analyzing differences in the use of AI in healthcare due to varying infrastructures.

VII. CONCLUSION

This study stresses the importance of healthcare service affordability as a factor affecting consumer behaviour and service adoption. Results have shown that factors such as affordability, accessibility, and trust considerably affect the way people use healthcare services, whereas issues such as data protection, cost, and the digital divide considerably moderate the technology adaptation process of Generative AI. This paper shows that consumers have moderate and fairly positive attitudes toward key constructs, though their decision-making process is hindered by limitations, including financial and informational barriers. High intercorrelations between variables indicate interrelations among affordability, quality, accessibility, and trust. Overall, the current study offers empirical evidence supporting the assumption that affordability is still a crucial factor in health care service adoption and should be taken into account when designing policies, implementing technologies, and delivering services.

REFERENCES

1. Joon, S. A. Pahune, S. S. S. Neeli, and B. Boddu, “A Robust Artificial Intelligence-Based Financial Forecasting System to Enhance Accuracy with Machine Learning Algorithms,” in Proceedings of the Second International Conference on Advanced Computing and Systems, Springer Nature Switzerland, 2026, pp. 522–533. doi: 10.1007/978-3-032-20253-6_40.
2. P. Chandra Shekhar, “Next-Gen Test Automation in Life Insurance: Self-Healing Frameworks,” Int. J. Sci. Res. Eng. Manag., vol. 5, no. 7, pp. 1–13, 2021, doi: 10.55041/IJSREM9554.
3. R. Snehamrutha, “Patient Engagement Strategies in Community Pharmacies and their Effect on Vaccination Uptake and Medication Synchronizations,” ESP J. Eng. Technol. Adv., vol. 3, no. 3, pp. 163–173, 2023, doi: 10.56472/25832646/JETA-V3I7P120.
4. Chaudhuri et al., “A theory of change roadmap for universal health coverage in India.,” Front. Public Heal., vol. 10, p. 1040913, Dec. 2022, doi: 10.3389/fpubh.2022.1040913.
5. S. Ragaupathy and M. Mittal, “Next-Generation Crm In Healthcare: The Role of AI, Predictive Analytics, And Patient Journey Mapping,” Int. J. Cust. Relatsh. Manag., vol. 4, no. 2, pp. 1–24, Jul. 2025, doi: 10.34218/IJCRM_04_02_001.
6. S. Kukar, “Explainable AI Models for Transparent and Ethical Customer Relationship Management Decision,” in 2026 IEEE 2nd International Conference on Secure IoT, Assured and Trusted Computing (SATC), Houston, TX, USA: IEEE, Mar. 2026, pp. 1–7. doi: 10.1109/SATC69565.2026.11542554.
7. S. L. Barber, L. Lorenzoni, and P. Ong, Price Setting and Price Regulation in Health Care. OECD, 2019. doi: 10.1787/ed3c16ff-en.
8. S. R. Chanthati, “Enterprise Generative AI Financial Architecture,” 2025. doi: 10.5281/zenodo.18372222.
9. F. J. Hlubocky, D. Cella, and C. K. Daugherty, “Financial Toxicity Has Never Been More Important in Cancer Care: How Do We Measure It?,” JCO Oncol. Pract., vol. 21, no. 1, pp. 52–56, Jan. 2025, doi: 10.1200/OP.24.00162.
10. M. Mittal, “The Transformative Role of CRM Systems in Modern Healthcare: Bridging the Provider Patient Gap,” Int. J. Multidiscip. Res., vol. 6, no. 6, pp. 1–9, November-December, 2024.
11. R. Lingam, “Integrating Trustworthiness Into the AI Lifecycle (Trustworthiness),” in AI Safety and Preventing Harm in AI Systems, IGI Global Scientific Publishing, 2026, pp. 213–248. doi: 10.4018/979-8-3373-6935-8.ch008.

12. L. K. Wiles et al., "Consumer engagement in health care policy, research and services: A systematic review and meta-analysis of methods and effects.," PLoS One, vol. 17, no. 1, p. e0261808, Jan. 2022, doi: 10.1371/journal.pone.0261808.

13. H. Najim, K. A. M. Al-sharhanee, I. M. Al-Joboury, D. Kanellopoulos, V. K. Sharma, and M. Y. Hassan, "An IoT Healthcare System With Deep Learning Functionality for Patient Monitoring," Int. J. Commun. Syst., vol. 38, no. 4, pp. 1–15, October, 2024, doi: 10.1002/dac.6020.

14. N. Fusco, B. Sils, J. S. Graff, K. Kistler, and K. Ruiz, "Cost-sharing and adherence, clinical outcomes, health care utilization, and costs: A systematic literature review," J. Manag. Care Spec. Pharm., vol. 29, no. 1, pp. 4–16, Jan. 2023, doi: 10.18553/jmcp.2022.21270.

15. R. Palwe, "Adaptive human: AI decision support for high-stakes financial advice," Int. J. Comput. Artif. Intell., vol. 6, no. 2, pp. 385–392, Jul. 2025, doi: 10.33545/27076571.2025.v6.i2e.226.

16. J. Yadav, S. Devi, M. N. Singh, N. Manchanda, and Moradhawaj, "Health care utilization and expenditure inequities in India: Benefit incidence analysis," Clin. Epidemiol. Glob. Heal., vol. 15, p. 101053, May 2022, doi: 10.1016/j.cegh.2022.101053.

17. M. Lin, L. Ma, and C. Ying, "Matching daily home health-care demands with supply in service-sharing platforms," Transp. Res. Part E Logist. Transp. Rev., vol. 145, p. 102177, Jan. 2021, doi: 10.1016/j.tre.2020.102177.

18. D. R. Singh, R. K. Sah, B. Simkhada, and Z. Darwin, "Potentials and challenges of using co-design in health services research in low- and middle-income countries.," Glob. Heal. Res. Policy, vol. 8, no. 1, p. 5, Mar. 2023, doi: 10.1186/s41256-023-00290-6.

19. S. Pareek, "Testing Approaches in Life Insurance: Accelerated and Fluid-less Underwriting Amidst Data-Driven Dynamics," Int. J. Sci. Res. Publ., vol. 14, no. 11, pp. 8–10, Nov. 2024, doi: 10.29322/IJSRP.14.11.2024.p15503.

20. L. Einav and A. Finkelstein, "Moral Hazard in Health Insurance: What We Know and How We Know It," J. Eur. Econ. Assoc., vol. 16, no. 4, pp. 957–982, Aug. 2018, doi: 10.1093/jeea/jvy017.

21. Q. Cheng et al., "Determinants of healthcare utilization under the Indonesian national health insurance system - a cross-sectional study.," BMC Health Serv. Res., vol. 25, no. 1, p. 48, Jan. 2025, doi: 10.1186/s12913-024-11951-8.

22. M. Graf, J. R. Baumgardner, U. Neumann, I. P. Brewer, J. W. Chou, and A. M. Fendrick, "Economic Evidence on Cost Sharing and Alternative Insurance Designs to Address Moral and Behavioral Hazards in High-Income Health Care Systems: A Systematic Review," J. Mark. Access Heal. Policy, vol. 12, no. 4, pp. 342–368, Nov. 2024, doi: 10.3390/jmahp12040027.

23. Ghosh, "Delaying factors influencing the maternal health care disparities in developing countries: A scoping review," Women Health, vol. 65, no. 4, pp. 340–375, Apr. 2025, doi: 10.1080/03630242.2025.2486985.

24. İ. Gün and S. Söyük, "The serial mediation effect of perceived quality and customer satisfaction on the relationship between trust and repurchase intention: a research on private health insurance owners," BMC Health Serv. Res., vol. 25, no. 1, p. 257, Feb. 2025, doi: 10.1186/s12913-025-12269-9.

25. R. Palwe and A. Kumar, "Redefining usability in the age of generative AI: Towards a new evaluation paradigm," Int. J. Comput. Artif. Intell., vol. 6, no. 2, pp. 155–163, Jul. 2025, doi: 10.33545/27076571.2025.v6.i2b.193.

26. Warrier and K. Abhilash, "Autonomous Agentic AI for Clinical Workflow Orchestration: Self-Managing Healthcare Operations," in 2025 6th International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS), Bengaluru, India: IEEE, 2025, pp. 1450–1457, December. doi: 10.1109/ICICNIS66685.2025.11315712.

27. S. Navale and B. Bhamare, "Artificial Intelligence in Healthcare: Transforming the Future of Medicine," Int. J. Latest Technol. Eng. Manag. Appl. Sci., vol. 14, no. 13, pp. 62–65, Oct. 2025, doi: 10.51583/IJLTEMAS.2025.1413SP014.

28. Warrier, "Machine Learning-Enhanced Data Quality Validation for Electronic Health Record Integration," Int. J. Sci. Technol., vol. 11, no. 1, pp. 1–8, Feb. 2020, doi: 10.71097/IJSAT.v11.i1.8387.

29. Q. Wu, J. Tian, and Z. Liu, "Exploring the usage behavior of generative artificial intelligence: a case study of ChatGPT with insights into the moderating effects of habit and personal innovativeness," Curr. Psychol., vol. 44, no. 9, pp. 8190–8203, May 2025, doi: 10.1007/s12144-024-07193-w.

30. S. T. Fife and J. D. Gossner, "Deductive Qualitative Analysis: Evaluating, Expanding, and Refining Theory," Int. J. Qual. Methods, vol. 23, Jan. 2024, doi: 10.1177/16094069241244856.

31. Herwanis, M. Alianur, Maulida, and K. Nasir, "Quantitative Research: Data Collection and Data Analysis for Beginner Researcher in Discussion," Educompassion J. Integr. Pendidik. Islam dan Glob., vol. 2, no. 1, pp. 1–18, Feb. 2025, doi: 10.63142/educompassion.v1i3.88.

32. Tawakuli, B. Havers, V. Gulisano, D. Kaiser, and T. Engel, "Survey:Time-series data preprocessing: A survey and an empirical analysis," J. Eng. Res., vol. 13, no. 2, pp. 674–711, Jun. 2025, doi: 10.1016/j.jer.2024.02.018.

33. P. Mishra, C. Pandey, U. Singh, A. Gupta, C. Sahu, and A. Keshri, "Descriptive statistics and normality tests for statistical data," Ann. Card. Anaesth., vol. 22, no. 1, p. 67, 2019, doi: 10.4103/aca.ACA_157_18.

34. P. Schober, C. Boer, and L. A. Schwarte, "Correlation Coefficients: Appropriate Use and Interpretation," Anesth. Analg., vol. 126, no. 5, pp. 1763–1768, May 2018, doi: 10.1213/ANE.0000000000002864.

35. Q. Dai et al., "Attitudes, Perceptions, and Factors Influencing the Adoption of AI in Health Care Among Medical Staff: Nationwide Cross-Sectional Survey Study," J. Med. Internet Res., vol. 27, p. e75343, Aug. 2025, doi: 10.2196/75343.

36. M. A. Rahman, E. Victoros, J. Ernest, R. Davis, Y. Shanjana, and M. R. Islam, "Impact of Artificial Intelligence (AI) Technology in Healthcare Sector: A Critical Evaluation of Both Sides of the Coin," Clin. Pathol., vol. 17, Jan. 2024, doi: 10.1177/2632010X241226887.