Research Article

Quantifying Healthcare Consumers' Perspectives: An Empirical Study of the Drivers and Barriers to Adopting Generative AI in Personalized Healthcare

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Abstract

This study empirically examines the drivers and barriers of adoption of Generative AI (GenAI) in personalized healthcare from the perspective of healthcare consumers. A quantitative analysis was conducted on a sample of 376 healthcare consumers, defined broadly to include individuals and their families or caregivers who interact with healthcare services. The research employed machine learning multiclass classification methods, correlation analysis, and a probabilistic ordered regression model. The data set consisted of 376 observations with 15 features, which was preprocessed, imputed for missing values, and analyzed using StratifiedKFold with 10 folds. The performance of each model was evaluated based on accuracy, Area Under the Curve (AUC), recall, precision, F1 score, Kappa, Matthews Correlation Coefficient (MCC), and execution time. The results showed that Linear discriminant analysis (LDA) emerged as the top-performing model with an accuracy of 95.09%, AUC of 99.68%, and an execution time of only 0.038 seconds. The study also revealed significant correlations between variables and GenAI adoption, highlighting Digital Divide as the most influential factor with a negative correlation of -0.123504. Feature importance analysis from the LDA model indicated that Understanding and Trust in AI Systems, Convenience and Accessibility, and Improved Health Outcomes were among the top influencers. In Logistic Regression and Random Forest models provided Digital Divide consistently appear as a significant barrier to adopt GenAI based healthcare services. A probabilistic ordered regression analysis further elucidated the impact of these variables on adoption willingness. It showed that approximately 89.26% of the variability in willingness to adopt GenAI was explained by the independent variables, with Digital Divide, Convenience and Accessibility, and Understanding and Trust in AI Systems being statistically significant. The overall findings of the study show that the adoption of GenAI in personalized healthcare is primarily driven by its potential to improve health outcomes, increase accessibility and convenience, and provide personalized care. Barriers such as data privacy concerns, trust issues, and digital divide must be addressed to facilitate wider adoption. The study highlights the need for healthcare providers and policymakers to focus on these key areas to enhance the acceptance and effectiveness of GenAI-based healthcare services.

Keywords: Consumer Adoption, Data Privacy, Generative AI, Healthcare Accessibility, Machine Learning, Personalized Healthcare, Technology Trust

Introduction

Anyone who is currently using, has used in the past, or will use health care services in the future, along with their family members and caregivers, is considered a health consumer. The conceptualization of individuals who engage with healthcare services as *health consumers* represents a shift from the traditional term 'patient'. This designation includes not only those who directly receive medical care but also their family members and caregivers, thereby acknowledging the broader spectrum of individuals involved in health-related decision-making processes. The evolution of this terminology reflects a deeper recognition of the active role individuals play in their healthcare journey, showing their agency in making informed decisions in concert with healthcare professionals. This shift in nomenclature from 'patient' to 'health consumer' signifies a more collaborative approach to healthcare, wherein individuals are seen as partners in the management and direction of their health outcomes. It acknowledges the complexities of healthcare decision-making, where individuals must know information, weigh various treatment options, and consider the implications of these decisions on their overall well-being and quality of life.

The term 'healthcare consumer', however, is subject to significant debate and criticism within the academic discourse. Richard Titmuss, in his seminal work in 1968, challenged the notion of equating healthcare services with commodities in the private market [1]. He contested the assumptions underpinning this comparison by delineating thirteen distinct characteristics that set medical care apart from other market goods. This critique was foundational in highlighting the unique nature of healthcare, which encompasses complex ethical, social, and emotional dimensions that transcend conventional market dynamics. Similarly, Stacey's characterization of the healthcare consumer as a 'sociological misconception' in 1976 further illuminates the contentious nature of this term [2]. These critiques emphasize the intrinsic differences between healthcare and other market commodities, arguing that reducing healthcare to a consumerist framework overlooks the nature of medical care.

The overlap of being a 'citizen' and a 'consumer' in healthcare makes the discussion more complex. Health consumer groups, who are often involved in advocacy and lobbying, have a dual role that goes beyond typical consumer behavior. They function at the intersection of individual healthcare needs and wider social and policy issues, showing a citizenship aspect that is more than just using services. This mix of consumer and citizen roles in healthcare highlights a complicated situation where people are not just looking after their own health needs, but also taking part in a bigger conversation about healthcare policies, access, and fairness. The actions of these groups underline the connection between personal health experiences and shared community duties, questioning the clear divide between consumer and citizen. This view suggests a deeper understanding of those who use health services, seeing them as active players in both their own health and the larger arena of healthcare policy and change.

Generative Artificial Intelligence (AI) models represent a significant advancement in unsupervised machine learning. These models distinguish themselves from earlier generative models such as Restricted Boltzmann Machines, Deep Belief Networks, and Deep Boltzmann Machines. The primary limitation of these earlier models lies in their constrained generalization capabilities, a critical aspect in the broader application of machine learning techniques. Generative Adversarial Networks (GANs), introduced by Goodfellow et al. in 2014 operate through a novel framework involving two neural networks in a competitive setting: a generator and a discriminator [3], [4]. The generator's role is to create data that mimics the real dataset as closely as possible, while the discriminator's task is to differentiate between the generator's output and actual data. This adversarial process enhances the generative model's ability to produce highly realistic and varied data.

Another significant advancement in generative AI is the introduction of Transformer models, as elucidated in the seminal paper "*Attention Is All You Need*" by Vaswani et al. in 2017 [5]. Transformers represent a departure from the traditional neural network architectures that relied on recurrent or convolutional layers. Instead, they utilize attention mechanisms, focusing on the concept of self-attention. This mechanism allows the model to weigh different parts of an input sequence differently when generating the output sequence. The flexibility and efficiency of Transformers have made them particularly effective in handling sequential data, leading to substantial improvements in tasks such as language understanding and generation.

Generative AI models stand out from traditional rule-based or deterministic AI systems due to their capability to produce new, original content that isn't directly encoded in their design. Their distinctive feature is the generation of outputs that resemble the style, tone, or structure of the provided inputs, distinguishing them from conventional AI approaches. This inherent capability of generative AI models has substantial implications. Thoughtfully designed and responsibly developed, these models can enhance human capabilities in various information management domains. They can provide support in decision-making processes, facilitate knowledge retrieval, enhance question-answering systems, improve language translation accuracy, and enable the automatic generation of reports or computer code.

Table 1. Characteristics, advancements, and implications of Generative Artificial Intelligence (AI) models

Aspect	Earlier Generative Models (e.g., Restricted Boltzmann Machines)	Generative Adversarial Networks (GANs)	Transformer Models
Introduction	Pre-2014	2014 (Goodfellow et al.) [3]	2017 ("Attention Is All You Need") [5]
Architecture	Typically involved layers with restricted connections	Two neural networks in adversarial setting (generator and discriminator)	Utilizes attention mechanisms, especially self-attention
Generalization Capabilities	Constrained; limited in handling complex data patterns	Enhanced ability to produce realistic and varied data	Superior in processing long-range dependencies and contextual understanding
Primary Function	Learning data distributions in a limited scope	Generating data mimicking real datasets; Discriminating between real and generated data	Efficient handling of sequential data; Language understanding and generation
Advancements	Fundamental in early machine learning	Introduced a novel framework for generative models	Marked a departure from recurrent and convolutional architectures
Implications	Limited scope in application due to generalization constraints	Potential enhancement in various information management domains	Substantial improvements in tasks requiring contextual understanding
Applications	Basic pattern recognition and data modeling	Data generation, decision support, knowledge retrieval	Language translation, automatic report and code generation
Data Analysis Capability	Basic pattern identification with constraints	Analyzing vast data, identifying patterns, suggesting informed decisions	Superior in handling and interpreting large, complex datasets

Generative AI models can analyze vast quantities of data, identify patterns, and suggest informed decisions based on the data. This capability is used in fields where data is abundant and complex, such as finance, healthcare, and scientific research. In these domains, the ability to quickly synthesize and interpret large datasets can lead to more accurate and timely decisions. In language translation and report generation, generative AI models can produce high-quality, contextually accurate translations and reports. This is achieved by understanding the language and the specific requirements of the task at hand. This ability not only increases efficiency but also ensures that the output is of a high standard, maintaining the integrity of the original content.

The first notable characteristic of Generative AI that catalyzes its rapid advancement pertains to its remarkable user-friendliness. Tools powered by GenAI exhibit a low threshold for user expertise, with their effectiveness enhancing as users become adept at crafting effective prompts. This ease of use is a significant factor behind the rapid adoption of these technologies. The ability of GenAI to assist in various tasks, such as document drafting, software coding, and graphic creation, using simple English prompts, has led to its widespread utilization among knowledge workers. This widespread adoption occurred even without formal institutional backing, demonstrating the innate appeal and utility of GenAI tools in diverse professional contexts.

The second aspect accelerating the adoption of GenAI is its software-based delivery model. Unlike Electronic Health Records (EHRs) [6], [7], which necessitated substantial investments in hardware and a fundamental transformation in healthcare workflows, GenAI can be seamlessly integrated into existing computing systems. This attribute starkly contrasts with the implementation challenges encountered in healthcare, where EHR adoption required significant restructuring. Concurrently, the emergence of a robust venture capital-funded ecosystem of healthcare startups, many of which rapidly integrated GenAI into their solutions post the release of GPT, further exemplifies the versatility and rapid incorporation of GenAI in addressing varied healthcare challenges.

The third characteristic is the advancement in application programming interfaces (APIs) and plug-in technologies. These developments facilitate a more integrated interaction between Electronic Health Records (EHRs) and GenAI applications developed by third parties. Despite EHR vendors traditionally dominating the digital landscape in healthcare, the progression in API and plug-in technology is paving the way for a more streamlined integration of third-party GenAI applications with existing EHR systems. This development is prompting EHR vendors to integrate GenAI into their offerings proactively, in a bid to stay competitive and leverage the capabilities of GenAI. This integration represents a strategic move by EHR vendors to maintain relevance in a rapidly evolving digital healthcare environment where GenAI is becoming increasingly influential.

The fourth factor contributing to the rapid evolution of Generative AI lies in its rapid iterative improvement cycles, a critical element in mitigating the productivity paradox historically associated with new technologies. GenAI's capacity for self-improvement with minimal human intervention is a defining feature. Early issues with large language models, such as factual inaccuracies (termed "hallucinations"), racial and ethnic biases, and inappropriate outputs, have been significantly addressed within months of their identification.

Rationale of the study

This research is motivated the rapid pace at which AI technologies are being integrated into healthcare systems and the profound impact they can have on patient care and health outcomes.

Primarily, the study is motivated by the recognition that healthcare consumers – encompassing individuals, families, and caregivers interacting with healthcare services – are central to the successful implementation and utilization of GenAI in personalized healthcare. Their perspectives, concerns, and acceptance levels are critical determinants of how effectively these technologies are adopted and integrated into healthcare practices. Without a clear understanding of these factors, the potential benefits of GenAI in healthcare may not be fully realized.

There is a gap in existing research regarding the specific drivers and barriers affecting GenAI adoption in healthcare from a consumer viewpoint. While there is extensive research on the technical and clinical aspects of AI in healthcare, there is a relative lack of empirical studies focusing on consumer perspectives. This study aims to fill this gap by employing a quantitative analysis to examine the factors that influence healthcare consumers' willingness to adopt GenAI-based services. Understanding the variables that facilitate or impede GenAI adoption can guide healthcare providers, policymakers, and technology developers in crafting strategies that address these factors, leading to more effective, efficient, and consumer-aligned healthcare services.

Methods

This study followed established literature such as [8]–[15] on technology adoption selected 14 features for investigating the adoption of GenAI-based healthcare services. These features are divided into two categories: 9 drivers (table 2) and 5 barriers (table 3), each represented through Likert-scale questionnaire items (tables

4 and 5). The initial phase involved distributing the questionnaire to 1200 healthcare consumers. However, the response rate was moderate, with only 408 completed questionnaires received. After a thorough examination of these responses and the removal of those with missing values, the usable sample was narrowed down to 376 participants.

The primary variable of interest, *'Adoption'*, is categorized into three classes: 1) Unwilling to adopt GenAI-based healthcare services, 2) Undecided, and 3) Willing to adopt. To analyze this variable, 16 different multiclass machine learning algorithms were applied.

Table 2. feature definitions (drivers)

Variable (Driver)	Definition
Improved Health Outcomes (IHO)	The potential enhancement in health outcomes resulting from the application of AI-driven medical insights and diagnostics.
Convenience and Accessibility (CNA)	The increased ease and reduced barriers in accessing healthcare services, facilitated by AI technology, especially significant in remote or underserved areas.
Empowerment Through Personalization (ETP)	The enhancement of patient care and decision-making through AI-driven personalized healthcare solutions, fostering a more tailored and individualized approach to treatment and care.
Technological Sophistication (TS)	The advanced and complex nature of AI technology employed in healthcare, contributing to improved efficiency, accuracy, and capabilities in medical services.
Market Competition (MC)	The competitive dynamics among healthcare service providers utilizing AI technologies, influencing the quality, innovation, and pricing of healthcare services.
Government Endorsement (GE)	The support or promotion of AI in healthcare by governmental bodies, which can lend credibility and foster trust in these technologies among consumers.
Social Influence (SI)	The impact of social networks, peer opinions, and community trends on shaping individuals' decisions and attitudes towards adopting AI in healthcare.
Brand Reputation (BR)	The perceived credibility and trustworthiness of AI technology and healthcare service providers, influenced by their brand name and market reputation.
Media Coverage (MCV)	The role of media in shaping public perception and awareness of AI in healthcare, influencing consumer knowledge, opinions, and acceptance of these technologies.

The Likert-scale questionnaire items designed to assess the drivers of AI adoption in healthcare from the consumers' perspective are formulated to capture the attitudes and perceptions that influence patient decisions. These items address several key areas: Improved Health Outcomes (IHO), Convenience and Accessibility (CNA), Empowerment Through Personalization (ETP), Technological Sophistication (TS), Market Competition (MC), Government Endorsement (GE), Social Influence (SI), Brand Reputation (BR), and Media Coverage (MCV).

Table 3. Feature definitions (barriers)

Variable (Barrier)	**Definition**
Concerns About Data Privacy (CADP)	Apprehensions regarding the security and confidentiality of personal health information in AI healthcare systems, emphasizing risks of data misuse and privacy breaches [16].
Understanding and Trust in AI Systems (UTAI)	The lack of comprehension and confidence in AI technology's ability to effectively and safely manage health issues, reflecting skepticism about its reliability and effectiveness.
Digital Divide (DD)	The inequality in access to necessary technology and digital literacy, creating a gap in the ability to utilize AI-driven healthcare services effectively among different population segments.
Perceived Loss of Human Touch (PLHT)	The concern that AI integration in healthcare may lead to a decrease in direct human interaction and empathy in the patient-care provider relationship.
Cost Concerns (CC)	Financial impediments related to the use of AI in healthcare, including the affordability of AI-based services and the lack of insurance coverage for such technologies.

The items IHO1 through IHO4 focus on the patient's belief in the potential of AI to enhance medical outcomes, personalize treatment plans, and increase confidence in medical care. These questions aim to gauge optimism towards AI's role in advancing healthcare quality, reflecting the direct impact on patient health and well-being. Moving to Convenience and Accessibility (CNA), the items CNA1 to CNA4 explore the perceived ease of accessing healthcare services through AI, emphasizing the reduction of barriers like geographical limitations and time constraints. The Empowerment Through Personalization (ETP) items, from ETP1 to ETP4, examine how AI-driven personalized care can make patients feel more in control and engaged in their healthcare journey. For Technological Sophistication (TS), items TS1 to TS4 assess the importance of advanced AI technology in instilling trust and confidence in healthcare services among consumers.

Table 4. Questionnaire Items for drivers

Variable (Driver)	**Likert-Scale Questionnaire Items**
Improved Health Outcomes (IHO)	IHO1: I believe AI-driven medical insights could significantly improve my health outcomes.
	IHO2: AI technologies in healthcare will lead to more accurate and personalized treatment plans for me.
	IHO3: The use of AI in healthcare increases my confidence in the effectiveness of medical treatments.
	IHO4: I am optimistic that AI in healthcare will contribute to better overall health management for me.

Convenience and Accessibility (CNA)	CNA1: AI-enabled healthcare services make it easier for me to access medical care.
	CNA2: The availability of AI in healthcare reduces the challenges I face in getting medical attention.
	CNA3: AI technologies make healthcare services more accessible to me, especially in remote areas.
	CNA4: I find that AI in healthcare significantly reduces the time and effort needed to receive medical services.
Empowerment Through Personalization (ETP)	ETP1: AI in healthcare empowers me by providing care that is tailored to my personal health needs.
	ETP2: I feel more in control of my health when using AI-driven personalized healthcare services.
	ETP3: Personalized healthcare through AI enhances my understanding of my health conditions.
	ETP4: AI-driven personalization in healthcare makes me feel more engaged in my treatment process.
Technological Sophistication (TS)	TS1: Advanced AI technology in healthcare is essential for providing high-quality medical services.
	TS2: The sophistication of AI technology in healthcare increases my trust in the treatment I receive.
	TS3: I am more likely to use healthcare services that employ cutting-edge AI technology.
	TS4: The advanced features of AI in healthcare make me more confident about the future of medical care.
Market Competition (MC)	MC1: A competitive market in AI-driven healthcare services leads to better quality care.
	MC2: I prefer to use healthcare services from providers who are leaders in AI technology.
	MC3: The presence of competition among AI healthcare providers influences my choice of service.
	MC4: Market competition in AI-driven healthcare encourages innovation and improvement in services.
Government Endorsement (GE)	GE1: Governmental support of AI in healthcare increases my trust in these technologies.
	GE2: I am more likely to use AI-driven healthcare services that are endorsed by the government.
	GE3: Government promotion of AI in healthcare reassures me of its safety and effectiveness.
	GE4: Official recognition and endorsement of AI in healthcare by government bodies make me more comfortable using these services.
Social Influence (SI)	SI1: My decision to use AI-driven healthcare services is influenced by the opinions of my family and friends.
	SI2: I am more inclined to trust AI in healthcare if it is widely accepted by my social circle.
	SI3: Recommendations from peers play a significant role in my choice of AI-driven healthcare services.
	SI4: Social trends and peer acceptance significantly impact my views on AI in healthcare.
Brand Reputation (BR)	BR1: I trust AI healthcare services more if they are provided by a well-known and reputable brand.

	BR2: The brand reputation of AI technology providers influences my healthcare choices.
	BR3: I prefer AI healthcare services that are associated with established and trusted brands.
	BR4: Brand name and reputation play a key role in my confidence in AI healthcare services.
Media Coverage (MCV)	MCV1: Positive media coverage of AI in healthcare impacts my willingness to adopt these services.
	MCV2: I am more aware of the benefits of AI in healthcare due to its coverage in the media.
	MCV3: Media reports on AI-driven healthcare influence my opinions about its reliability and effectiveness.
	MCV4: Extensive media coverage of AI in healthcare shapes my perceptions and acceptance of these technologies.

In Market Competition (MC), items MC1 to MC4 investigate how competitive dynamics in the AI healthcare market influence consumer choices, looking at aspects like innovation and service quality. Government Endorsement (GE), through items GE1 to GE4, examines the impact of governmental support on consumer trust and comfort with AI in healthcare. Social Influence (SI) items, SI1 to SI4, aim to understand the extent to which social networks and peer recommendations affect the adoption of AI-driven healthcare services. Brand Reputation (BR) items, from BR1 to BR4, look at how the reputation of AI technology providers shapes consumer preferences and trust. Lastly, Media Coverage (MCV) items, MCV1 to MCV4, explore the role of media in shaping perceptions and acceptance of AI in healthcare, highlighting the influence of public discourse on consumer decisions.

The Likert-scale items developed to evaluate the barriers to AI adoption in healthcare from the perspective of consumers are formulated to examine the deeper apprehensions and concerns that may hinder their acceptance and usage. These barriers include Concerns About Data Privacy (CADP), Understanding and Trust in AI Systems (UTAI), Digital Divide (DD), Perceived Loss of Human Touch (PLHT), and Cost Concerns (CC).

For Concerns About Data Privacy (CADP), items CADP1 to CADP4 go into the fears and uncertainties related to the security and confidentiality of health data within AI systems. These questions are for understanding the extent to which privacy concerns might deter consumers from embracing AI in healthcare. The items for Understanding and Trust in AI Systems (UTAI), from UTAI1 to UTAI4, explore the skepticism and doubts regarding the efficacy and reliability of AI in healthcare. This set aims to capture the trust deficit and lack of comprehension that could be significant obstacles in the adoption of AI-driven health services. Items DD1 to DD4 address the issues of unequal access to technology and digital literacy, which can create disparities in the utilization of AI in healthcare. These items help in assessing how technological inequities might prevent certain consumer segments from benefiting from AI advancements in healthcare.

Table 5. Questionnaire Items for barriers

Variable (Barrier)	Likert-Scale Questionnaire Items
Concerns About Data Privacy (CADP)	CADP1: I am concerned about the security of my health data in AI healthcare systems.
	CADP2: The risk of my personal health information being misused in AI systems worries me.
	CADP3: I hesitate to use AI in healthcare due to uncertainties about data privacy.
	CADP4: Protecting my personal health information is a significant factor in my reluctance to adopt AI in healthcare.
Understanding and Trust in AI Systems (UTAI)	UTAI1: I am skeptical about the effectiveness of AI in managing health issues.
	UTAI2: My lack of understanding of how AI works in healthcare affects my trust in it.
	UTAI3: I doubt that AI systems can understand and address my health needs as well as human healthcare providers.
	UTAI4: I am not confident in the accuracy and reliability of AI-driven healthcare decisions.
Digital Divide (DD)	DD1: My limited access to technology is a barrier to using AI-driven healthcare services.
	DD2: I feel disadvantaged in adopting AI in healthcare due to my lack of digital literacy.
	DD3: The digital divide makes it challenging for me to benefit from AI in healthcare.
	DD4: Inadequate access to reliable internet and digital devices hinders my use of AI healthcare services.
Perceived Loss of Human Touch (PLHT)	PLHT1: I am concerned that AI-driven healthcare will reduce the human interaction in my care.
	PLHT2: The lack of personal touch in AI healthcare services makes me uncomfortable.
	PLHT3: I value face-to-face interactions with healthcare providers, which I believe AI cannot replace.
	PLHT4: The impersonal nature of AI in healthcare detracts from the care experience for me.
Cost Concerns (CC)	CC1: The potential high cost of AI-based healthcare services is a deterrent for me.
	CC2: I am worried about the affordability of AI-driven healthcare services.
	CC3: Financial considerations play a major role in my decision to adopt AI in healthcare.
	CC4: The lack of insurance coverage for AI healthcare services is a significant concern for me.

The Perceived Loss of Human Touch (PLHT) items, PLHT1 to PLHT4, concentrate on the concern that AI in healthcare might lead to impersonal and less empathetic medical experiences. They address the value consumers place on human interaction in their healthcare journey and their apprehensions about its potential diminishment with AI integration. Cost Concerns (CC), through items CC1 to CC4, investigate the financial implications of AI-based healthcare services. These questions aim to discern how perceived or real cost barriers could impact consumer decisions to adopt AI in healthcare.

Table 6. Machine learning implementation

Description	Value
Session id	123
Target	Adoption
Target type	Multiclass
Target mapping	1: 0, 2: 1, 3: 2
Original data shape	(376, 15)
Transformed data shape	(376, 15)
Transformed train set shape	(263, 15)
Transformed test set shape	(113, 15)
Numeric features	14
Preprocess	True
Imputation type	simple
Numeric imputation	mean
Categorical imputation	mode
Fold Generator	StratifiedKFold
Fold Number	10
CPU Jobs	-1
Use GPU	False
Log Experiment	False
Experiment Name	clf-default-name
USI	4ae7

Results

Table 6 presents the correlation coefficients and Cramér's V correlations for each of the 14 variables with respect to the target variable *Adoption*. The most striking result is observed with the variable Digital Divide (DD), which exhibits a notably high negative correlation coefficient (-0.932) and a substantial Cramér's V correlation (0.885). This indicates a strong inverse relationship between the digital divide and the willingness to adopt GenAI in healthcare, suggesting that as the digital divide increases, the likelihood of adopting these technologies decreases significantly.

Conversely, Understanding and Trust in AI Systems (UTAI) shows a very low negative correlation (-0.100) and an almost negligible Cramér's V correlation (0.046), indicating a minimal influence of this variable on the adoption decision. Technological Sophistication (TS) and Convenience and Accessibility (CNA) exhibit negligible correlations with the Adoption variable, suggesting these factors may not significantly influence the adoption decision in the current context.

Market Competition (MC) and Perceived Loss of Human Touch (PLHT) have almost no correlation with the Adoption variable, indicating these factors are not substantial determinants in the decision-making process of healthcare consumers regarding GenAI adoption. Interestingly, Government Endorsement (GE) and Empowerment Through Personalization (ETP) also show very low negative correlations, implying a limited influence on adoption. Social Influence (SI) demonstrates a modest positive correlation (0.094) with a slightly higher Cramér's V correlation (0.062), suggesting some level of influence on the adoption decision. Cost Concerns (CC) and Concerns About Data Privacy (CADP)'show minimal to low negative correlations, indicating these concerns have a limited but notable impact on adoption decisions.

Brand Reputation (BR), Improved Health Outcomes (IHO), and Media Coverage (MCV) exhibit negligible correlations with the Adoption variable, suggesting these factors do not play a significant role in the decision-making process for adopting GenAI-based healthcare services. The correlation analysis in table 6 reveals that among the 14 factors examined, the digital divide appears to be the most significant barrier to the adoption of GenAI in healthcare, while other factors such as understanding and trust in AI, market competition, and brand reputation have minimal influence.

Table 6. **Correlation Coefficients and Cramér's V Correlations with the Variable 'Adoption'**

#	Variable	Correlation Coefficient	Cramér's V Correlation
1	Digital Divide (DD)	-0.932	0.885
2	Understanding and Trust in AI Systems (UTAI)	-0.100	0.046
3	Technological Sophistication (TS)	-0.000	0.060
4	Convenience and Accessibility (CNA)	0.062	0.047
5	Market Competition (MC)	-0.016	0.000
6	Perceived Loss of Human Touch (PLHT)	-0.015	0.056
7	Government Endorsement (GE)	0.044	0.000
8	Empowerment Through Personalization (ETP)	-0.079	0.043

9	Social Influence (SI)	0.094	0.062
10	Cost Concerns (CC)	0.005	0.070
11	Concerns About Data Privacy (CADP)	-0.118	0.060
12	Brand Reputation (BR)	-0.014	0.000
13	Improved Health Outcomes (IHO)	0.002	0.038
14	Media Coverage (MCV)	-0.008	0.000

Table 7. the performance metrics for various machine learning models, including accuracy, AUC, recall, precision, F1 score, Kappa, Matthews Correlation Coefficient (MCC), and the time taken in seconds (TT) for each model's execution.

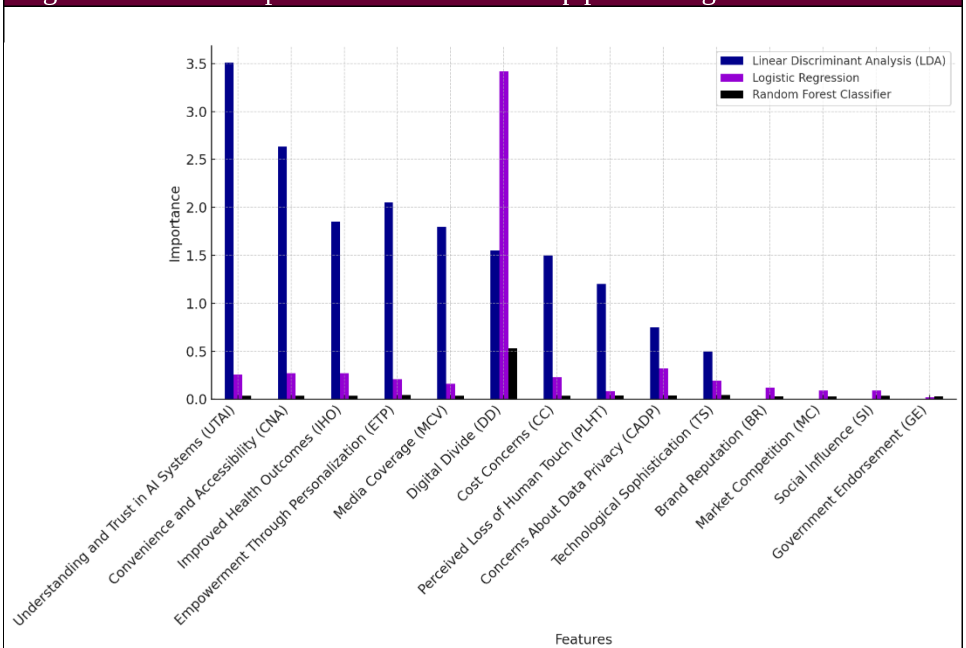
Model	Description	Accuracy	AUC	Recall	Precision	F1	Kappa	MCC	TT (Sec)
lda	Linear Discriminant Analysis	0.9509	0.9968	0.9509	0.9540	0.9505	0.9262	0.9281	0.0380
xgboost	Extreme Gradient Boosting	0.9359	0.9877	0.9359	0.9399	0.9345	0.9038	0.9069	0.1980
lr	Logistic Regression	0.9279	0.9936	0.9279	0.9349	0.9278	0.8919	0.8954	0.7260
rf	Random Forest Classifier	0.9278	0.9812	0.9278	0.9338	0.9260	0.8916	0.8960	0.3890
catboost	CatBoost Classifier	0.9242	0.9901	0.9242	0.9317	0.9221	0.8864	0.8916	9.6280
gbc	Gradient Boosting Classifier	0.9205	0.9850	0.9205	0.9266	0.9191	0.8807	0.8849	0.5000
knn	K Neighbors Classifier	0.9165	0.9899	0.9165	0.9210	0.9152	0.8746	0.8780	0.0540
lightgbm	Light Gradient Boosting Machine	0.9165	0.9877	0.9165	0.9234	0.9154	0.8747	0.8789	0.3100
nb	Naive Bayes	0.9128	0.9875	0.9128	0.9173	0.9121	0.8692	0.8720	0.0380
qda	Quadratic Discriminant Analysis	0.9050	0.9846	0.9050	0.9152	0.9032	0.8571	0.8628	0.0390
et	Extra Trees Classifier	0.8976	0.9780	0.8976	0.9051	0.8962	0.8464	0.8508	0.3090
dt	Decision Tree Classifier	0.8751	0.9060	0.8751	0.8805	0.8744	0.8124	0.8157	0.0360
ridge	Ridge Classifier	0.7222	0.0000	0.7222	0.7434	0.6525	0.5832	0.6378	0.0560
ada	Ada Boost Classifier	0.7148	0.9664	0.7148	0.8093	0.6953	0.5708	0.6212	0.1410
svm	SVM - Linear Kernel	0.6199	0.0000	0.6199	0.5559	0.5349	0.4316	0.4965	0.0430
dummy	Dummy Classifier	0.3154	0.5000	0.3154	0.0996	0.1514	0.0000	0.0000	0.0520

This study used a set of performance metrics, including Accuracy, Area Under the Curve (AUC), Recall, Precision, F1 Score, Kappa, Matthews Correlation Coefficient (MCC), and Time Taken (TT) in seconds.

As shown in table 7, Linear Discriminant Analysis (LDA) emerges as the top performer with the highest accuracy (0.9509), AUC (0.9968), and a very high F1 score (0.9505). Its performance is further supported by a strong Kappa score of 0.9262 and an MCC of 0.9281, all achieved in a low execution time of 0.038 seconds. This suggests that LDA not only provides highly accurate and reliable predictions but also does so with remarkable efficiency. In contrast, the Extreme Gradient Boosting (XGBoost) model, while exhibiting a slightly lower accuracy of 0.9359 and AUC of 0.9877, still maintains strong performance metrics across the board. However, its execution time of 0.198 seconds is notably higher than LDA, indicating a trade-off between performance and computational efficiency.

Simpler models like the Dummy Classifier demonstrate markedly lower performance across all metrics, with an accuracy of only 0.3154, an AUC of 0.5000, and negligible Kappa and MCC scores. Notably, models like the Ada Boost Classifier and SVM - Linear Kernel show significantly lower performance compared to the leading models, with accuracies of 0.7148 and 0.6199 respectively.

Figure 1. Feature importance from selected top performing models.



As shown in figure 1, Understanding and Trust in AI Systems emerges as the most influential factor with an importance score of 3.51, suggesting a paramount role in shaping attitudes towards GenAI adoption in healthcare. Convenience and Accessibility, with a score of 2.63, and Improved Health Outcomes, scoring 1.85, also stand out as significant determinants. Empowerment Through Personalization and Media Coverage are identified as moderately influential, with scores of 2.05 and 1.8 respectively. The Digital Divide, although not the most significant, still holds considerable weight with a score of 1.55, followed closely by Cost Concerns at 1.5. Perceived Loss of Human Touch and Concerns About Data Privacy appear less influential in the LDA model, with scores of 1.2 and 0.75, respectively. Technological Sophistication, with the lowest score of 0.5, suggests a relatively minor role in this model.

The Logistic Regression model offers a slightly different perspective on feature importance. Here, the Digital Divide is the most significant feature with a score of 3.42, highlighting its crucial impact on adoption decisions. Interestingly, Concerns About Data Privacy, which had a lower score in the LDA model, shows increased importance in Logistic Regression with a score of 0.32. Convenience and Accessibility, Improved Health Outcomes, and Understanding and Trust in AI Systems are also key factors, albeit with lower scores ranging from 0.26 to 0.27. Cost Concerns, Empowerment Through Personalization, and Technological Sophistication follow suit with moderate importance. Media Coverage, Brand Reputation, Market Competition, Social Influence, Perceived Loss of Human Touch, and Government Endorsement are observed to have the least impact on the adoption decision, with scores all below 0.2.

In the Random Forest Classifier model, the Digital Divide stands out as the most influential factor with a high score of 0.531, substantially higher than other features. This is followed by a cluster of features with relatively lower but similar importance scores: Technological Sophistication, Empowerment Through Personalization, Perceived Loss of Human Touch, Concerns About Data Privacy, Cost Concerns, Social Influence, Media Coverage, Improved Health Outcomes, and Convenience and Accessibility, all ranging between 0.028 to 0.044. Understanding and Trust in AI Systems, Government Endorsement, Brand Reputation, and Market Competition appear as less influential in this model, with each scoring below 0.05.

Table 8. Results from Probabilistic regression model

Dependent Variable: Adoption
Method: Probabilistic regression
Sample: 1 376

Included observations: 376

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Digital Divide (DD)	-0.123504	0.002308	-53.50354	0.0000
Brand Reputation (BR)	0.004771	0.050868	0.093782	0.9253
Concerns About Data Privacy (CADP)	-0.048360	0.010048	-4.813041	0.0000
Convenience and Accessibility (CNA)	0.153614	0.048633	3.158613	0.0017
Cost Concerns (CC)	-0.104641	0.049571	-2.110934	0.0355
Empowerment Through Personalization (ETP)	0.141612	0.049398	2.866783	0.0044
Government Endorsement (GE)	0.008518	0.048194	0.176740	0.8598
Improved Health Outcomes (IHO)	0.143914	0.048640	2.958765	0.0033
Market Competition (MC)	-0.041080	0.049055	-0.837437	0.4029
Media Coverage (MCV)	-0.091594	0.049448	-1.852316	0.0648
Perceived Loss of Human Touch (PLHT)	-0.108656	0.051614	-2.105155	0.0360
Social Influence (SI)	0.016967	0.048336	0.351031	0.7258
Technological Sophistication (TS)	0.045296	0.049645	0.912409	0.3622
Understanding and Trust in AI Systems (UTAI)	-0.176644	0.049462	-3.571325	0.0004
Constant	6.099952	0.117191	52.05125	0.0000

R-squared	0.892565	Mean dependent var	2.005319
Adjusted R-squared	0.888399	S.D. dependent var	0.816479
S.E. of regression	0.272760	Akaike info criterion	0.278624
Sum squared resid	26.85760	Schwarz criterion	0.435390
Log likelihood	-37.38131	Hannan-Quinn criter.	0.340854
F-statistic	214.2266	Durbin-Watson stat	2.047603
Prob(F-statistic)	0.000000		

In probabilistic regression analysis results in table 8, the model demonstrates a high degree of explanatory power with an R-squared value of 0.892565, implying that approximately 89.26% of the variability in the willingness to adopt is accounted for by the independent variables. The adjusted R-squared of 0.888399 further strengthens the model's credibility, adjusting for the number of predictors. A low standard error of regression (0.272760) and a highly significant F-statistic (214.2266) indicates the model's robustness in accurately predicting the willingness to adopt.

The coefficients of the variables reveal divergent impacts on the willingness to adopt. The Digital Divide (DD), with a coefficient of -0.123504 and a highly significant t-statistic of -53.50354, suggests a strong negative correlation; as the digital divide widens, willingness to adopt diminishes significantly. Conversely, Convenience and Accessibility (CNA) positively influences willingness to adopt, indicated by its coefficient of 0.153614 and a significant t-statistic of 3.158613. This suggests enhancing convenience and accessibility could significantly boost adoption willingness. Notably, Understanding and Trust in AI Systems (UTAI) has the most pronounced negative effect, with a coefficient of -0.176644 and a significant t-statistic of -3.571325, highlighting the paramount importance of trust in technology for increasing willingness to adopt. In contrast, variables like Brand Reputation (BR) and Government Endorsement (GE) have minimal impact, as evidenced by their low coefficients and non-significant t-statistics, suggesting these factors might be less influential in affecting willingness to adopt.

Table 9. Significant and Insignificant Factors Influencing Health Consumers' Perspectives on AI in Healthcare

Category	Factor	Description
Significant Drivers	Improved Health Outcomes (IHO)	Reflects the potential for better health outcomes through AI-driven medical insights.
	Convenience and Accessibility (CNA)	Denotes the ease of accessing healthcare services facilitated by AI, particularly in remote areas.
	Empowerment Through Personalization (ETP)	Represents the personalized care and empowerment of patients through AI.
Significant Barriers	Concerns About Data Privacy (CADP)	Indicates apprehensions about the security and privacy of health data in AI systems.
	Understanding and Trust in AI Systems (UTAI)	Denotes the lack of understanding and trust in AI's capability to manage health issues.
	Digital Divide (DD)	Reflects disparities in technology access and digital literacy.
	Perceived Loss of Human Touch (PLHT)	Indicates concerns over the reduction of human interaction in AI-driven healthcare.
	Cost Concerns (CC)	Represents financial barriers associated with accessing AI-based healthcare services.
Insignificant Drivers	Technological Sophistication (TS)	Denotes the advanced nature of AI technology, which is less of a direct driver for patients.
	Market Competition (MC)	Indicates the influence of competitive dynamics among service providers.
	Government Endorsement (GE)	Reflects the role of governmental support or promotion of AI in healthcare.
	Social Influence (SI)	Denotes the impact of social and peer influences on patient decisions.
	Brand Reputation (BR)	Indicates the influence of brand names in technology or healthcare.
	Media Coverage (MCV)	Represents the role of media exposure in influencing patient decisions.

Other variables also demonstrate varying degrees of impact. Empowerment Through Personalization (ETP) and Improved Health Outcomes (IHO) exhibit positive coefficients (0.141612 and 0.143914, respectively) with significant t-statistics, indicating these factors positively correlate with willingness to adopt. On the other hand, Concerns About Data Privacy (CADP) and Cost Concerns (CC), with coefficients of -0.048360 and -0.104641 respectively, negatively impact willingness to adopt. These negative coefficients and significant t-statistics suggest that increasing concerns about data privacy and cost are deterrents to the willingness to adopt.

Conclusion

The findings of this study shows that the adoption of generative AI in healthcare services is significantly driven by factors that resonate with health consumers' needs and expectations.

Generative AI can analyze vast amounts of medical data, including patient records, research studies, and real-world data, to identify patterns and insights that might be missed by human practitioners. This capability can lead to more accurate diagnoses, personalized treatment plans, and even the discovery of new therapeutic approaches. For health consumers, the potential for better health outcomes is a strong motivator, as it directly impacts their health and wellbeing. This technology can also help in predicting health risks and preventing diseases, thereby improving the overall quality of life.

AI can make healthcare services more accessible and convenient, especially for people in remote or underserved areas. Through AI-driven platforms, patients can access medical consultations, diagnostic services, and health monitoring remotely. This reduces the need for physical travel, which can be costly and time-consuming, especially for those living far from medical facilities or those with mobility issues. AI can also help in managing appointments, follow-ups, and medication adherence, making the healthcare journey smoother and more user-friendly. For many, the convenience offered by AI-enabled healthcare services can be a deciding factor in seeking timely medical attention.

Generative AI has the capability to tailor healthcare to individual patients in a way that was not possible before. By analyzing a person's genetic makeup, lifestyle, and environmental factors, AI can provide personalized healthcare recommendations and treatment plans. This personalization empowers patients, making them active participants in their health management. It leads to a sense of control and understanding of their health conditions, fostering better engagement with treatment protocols. Moreover, personalized healthcare often translates to more effective treatments with fewer side effects, as they are specifically designed for the individual's unique physiology and health needs.

These drivers—Improved Health Outcomes, Convenience and Accessibility, and Empowerment Through Personalization—address fundamental desires of health consumers for better, easier, and more personalized healthcare experiences. They highlight the transformative potential of generative AI in making healthcare more effective, accessible, and patient-centered.

Health data is extremely sensitive and personal. Consumers often express apprehension about how their data is used, stored, and protected in AI systems. The fear that their health information might be exposed to unauthorized entities or used for purposes other than their care (like targeted advertising or insurance premium adjustments) can be a major barrier. Ensuring robust data security measures and transparent data usage policies are critical to address these concerns.

Many consumers lack a thorough understanding of how AI works in the context of healthcare. This lack of understanding can lead to mistrust in AI's capabilities and skepticism about its effectiveness and safety. Without trust, consumers may be reluctant to use AI-driven healthcare services. Education and transparent communication about the capabilities, limitations, and regulatory oversight of these systems are essential to building trust.

Not all consumers have equal access to the technology needed for AI-based healthcare services. Disparities in access to digital devices, reliable internet connectivity, and digital literacy can prevent segments of the population from benefiting from AI in healthcare. This digital divide can exacerbate existing health inequities. Addressing these disparities is crucial for the equitable implementation of AI-driven healthcare.

Many consumers value the human element in healthcare—the empathy, understanding, and personal interaction with healthcare providers. There is a concern that AI-driven healthcare might reduce these human interactions, leading to a more impersonal and less compassionate healthcare experience. Balancing AI's efficiency with the maintenance of human elements in care delivery is key to overcoming this barrier.

The perceived or actual cost of accessing AI-based healthcare services can be a significant barrier. Consumers may worry about the affordability of these services, especially if they are not covered by insurance or if they are perceived as premium offerings. Ensuring that AI-driven healthcare solutions are cost-effective and accessible to a broad range of consumers is essential for widespread adoption.

While the advanced nature of AI technology is a key factor in its capabilities, for most health consumers, the intricacies of the technology are not a primary concern. They are generally more interested in the outcomes and benefits of the technology (such as improved health outcomes or convenience) rather than the sophistication of the technology itself. As long as the technology meets their needs in a user-friendly manner, the underlying complexity is often of secondary importance.

The competitive dynamics among service providers might influence the development and pricing of AI healthcare services, but for the average consumer, these market forces are often not a direct consideration in their decision to adopt these services. Patients are typically more focused on the accessibility, quality, and cost of the services rather than the competitive landscape of the providers.

While government endorsement can lend credibility to AI in healthcare and influence regulatory and funding, it may not be a primary driver for individual health consumers. Patients are more likely to be influenced by factors that have a direct and tangible impact on their personal health experience, such as the efficacy and safety of the technology. The reputation of the brand behind a technology or healthcare service can influence consumer perceptions and trust. However, in healthcare decisions, clinical efficacy, safety, and personal health needs typically take precedence over brand reputation. Patients might recognize and appreciate well-known brands, but this factor alone is unlikely to be a decisive driver in choosing AI-based healthcare services.

Media exposure can raise awareness about AI in healthcare and influence public opinion, but it's not a primary factor in individual healthcare decisions. Health consumers are more likely to base their decisions on personal health needs, recommendations from healthcare providers, and direct benefits they perceive from the service.

Health care has several attributes that make the successful deployment of new technologies even more difficult than in other industries; these have challenged prior efforts to implement AI and electronic health records. However, genAI has unique properties that may shorten the usual lag between implementation and productivity and/or quality gains in health care. Moreover, the health care ecosystem has evolved to make it more receptive to genAI, and many health care organizations are poised to implement the complementary innovations in culture, leadership, workforce, and workflow often needed for digital innovations to flourish.

The research used a sample of 376 healthcare consumers, a sizeable yet potentially non-representative segment of the wider population. The diversity inherent within the healthcare consumer demographic is characterized by varied socio-economic backgrounds, health conditions, and other demographic factors. Consequently, the conclusions drawn might not encapsulate the entire spectrum of experiences and viewpoints present in the broader population.

The use of machine learning multiclass classification methods, correlation analysis, and a probabilistic ordered regression model provides a numerical predictive understanding. However, these methods may not fully capture the dynamic attitudes, beliefs, and personal experiences of individuals regarding GenAI in healthcare.

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