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Artificial Intelligence in Healthcare sector: Understanding Drivers and Future Prospects

Neelesh Singh

Research Scholar, Chitkara Business School, Chitkara University, Punjab, India

ABSTRACT:

This research tries to study drivers of Artificial Intelligence (AI) with respect to healthcare sector. As a theoretical underpinning, Unified Theory of Acceptance and Use of Technology 2(UTAUT2) was validated. Data was collected from 600 healthcare professionals using AI architecture in their organizations and was analyzed using Structural Equation Modelling (SEM). The results of the study indicated all the drivers has a significant positive impact on behavioural intention except hedonic motivation. This indicates that adoption of AI has more of utilitarian orientation rather than hedonic orientation. Further BI depicted a strong influence on actual usage of AI systems in healthcare segment. Using this information and related facts as a foundation, healthcare organisations can develop effective artificial intelligence enablement practises that consistently lead to the development, design, deployment, and dissemination of appropriate, effective, and sustainable artificial intelligence enabled solutions.

Keywords: Artificial Intelligence, Drivers, Behavioural intention, Actual use

INTRODUCTION

Artificial intelligence (AI) is the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings (Blanchard, 2019). The term refers to process of performing analysis and automation of decision-making using patterns in historical data and other some capabilities, normally thought to be like human intelligence (Mohammadzadeh et al., 2013) such as learning, generalising analysing adapting, self-correction, etc. AI impacts our daily lives in various forms - knowingly and unknowingly. There are hardly any fields, products or services which don't leverage the profound outcome of Artificial Intelligence in some way. Amongst of the most distinctive and well-known computer science subfields today, artificial intelligence, or AI, focuses on the development and designing of intelligent machines (Nadikattu, 2020). It included searches made through search engines powered by Natural Language Programming (Mintz & Brodie, 2020), face detection of group of friends in pictures posted on Facebook (Lau & Staccini, 2019) or medical system detecting anomalies in internal organs using machine learning (Huang et al., 2020). With the advent of new technologies like cloud computing, high performance hardware in portable devices like mobile phones and high-speed internet communication, AI is now realizing its potential to assist humans in almost all aspects (Chen & Deecary, 2020). Some of its phenomenal applications include on-demand transportation, e-commerce,

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bringing people together using social media, crowdsourcing ideas, advanced medical devices, space research and many others. Hardly there are any industries which are not impacted by its usage whether its manufacturing (Fernandes et al., 2020), pharmaceuticals (Kolluri et al., 2022), construction (Na et al., 2022), transportation (Abduljabbar et al., 2019) or Banking (Königstorfer & Thalmann 2019). It's not only solving problems but also influencing the way we think, we work, we learn or even form opinions using recommendation systems. Undoubtedly, it has huge potential to uplift the human's way of life. The market size of AI enabled services is expected to be US$15.7tn by 2030 (PWC, 2020). Primary drivers of AI adoption incorporate economic reasons including increase in productivity, reduction of costs, improving customer satisfaction, reducing errors, reducing time and better prediction (Cockburn & Henderson, 2018). Some of the non-economic reasons why a few organisations also have gone for implementation of AI are Sustainability in agriculture (Fang, 2019; Dharmaraj & Vijayanand 2018) and wellbeing of human's especially elderly patients (Kachouie et al, 2017).

Artificial intelligence (AI) enablement in the functions and sub functions of healthcare operational activities and organisational management is a big worry for healthcare sectors. Today, Indian healthcare is witnessing a major redefining in technology breakthroughs. The adoption of artificial intelligence in Indian healthcare institutions necessitates the use of a multi-skilled workforce that is independent, adaptable, and computer aware (Yu et al., 2018). New service delivery methods must take the place of the conventional way of doing things, and this involves the use of qualified expertise. Healthcare professionals find it challenging to embrace appropriate tactics of artificial intelligence enablement in a country like India where the demand for quality employees is increasing day by day (Venkatesh et al., 2011). The difficulty of enabling artificial intelligence has been made more difficult by the rising high attrition rate on the assimilation of digital technology. The multi-skilled staff retention in Indian healthcare is a major challenge.

The NITI Aayog MEIT Report 2020 predicts that by 2035, the market capital of the economy with artificial intelligence enabled solutions will be INR 957 billion, adding up to the potential creation of 20 million jobs in India. Artificial intelligence-based solutions are a component of digital inclusion in India, which has an impact on the economic growth and industrial development of various sectors in a swift manner. Artificial intelligence applications incorporated in the healthcare space are revolutionising the healthcare industry and are expected to increase the doctor-patient ratio from 4:8:10000 patients in 2017 to 6:9:10000 patients by 2023.

The study attempts to understand the UTAUT 2 as a theoretical model to answer the following research questions:

RQ1: What are the factors which influence behavioural intention to adopt AI in healthcare sector?

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RQ2: What is the impact of behavioural intention on actual use?

THEORETICAL BACKGROUND

2.1 Unified Theory of Acceptance and Use of Technology UTAUT2 (Venkatesh et al., 2012)

Venkatesh et al. (2012) after consolidating eight dominant models proposed UTAUT2 which consists of four core variables mentioned below:

- ❖ Performance expectancy (PE).
- ❖ Effort expectancy (EE)
- ❖ Social influence (SI).
- ❖ Facilitating conditions (FC).
- ❖ Price Value (PV)
- ❖ Habit (HB)
- ❖ Hedonic Motivation (HM)
- ❖ Four moderating variables-gender, age, experience and voluntariness of use.

Reviewed fourteen technology acceptance theories and models and propounded that UTAUT has a higher explanatory power and seemed to be an improved theory that could certainly provide a better tool to assess the probability of success of various Technology acceptance and adoption studies.

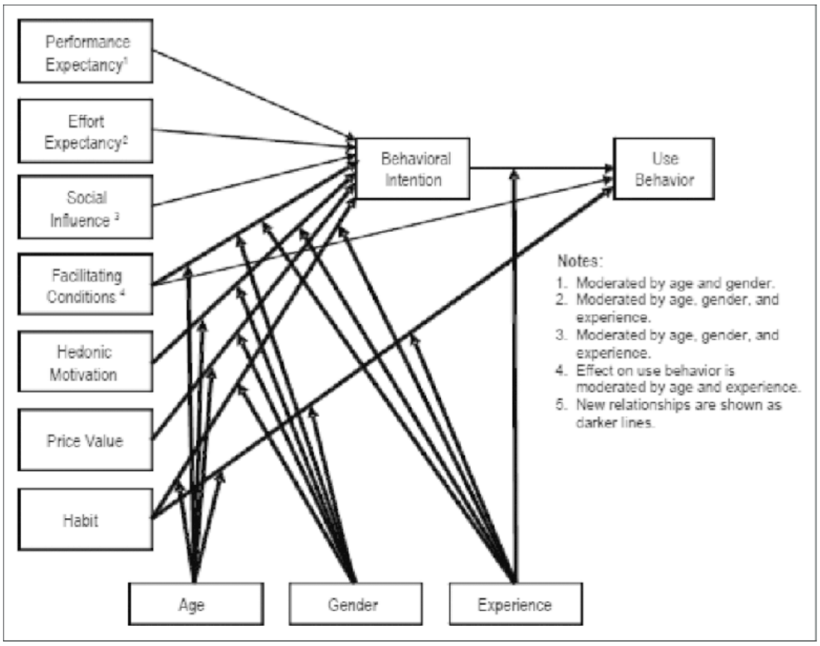

Figure 2: Unified Theory of Acceptance and Use of Technology UTAUT2

Table 1: Construct Definitions

S.no	Construct	Definition	Source
1	Performance Expectancy (PE)	It refers the extent of the participant's belief that his job performance will be enhanced by using the Artificial intelligence.	Venkatesh *et al.*,(2003)
2	Effort Expectancy (EE)	It refers to perception of the user about how easy it is to use Artificial intelligence.	Venkatesh, *et al.*,(2003)
3	Facilitating Conditions (FC)	It is defined as perceived physical and mental capabilities to use the technology possessed by the participants and the degree to which technical support is available as and when required.	Venkatesh *et al.* (2003)
4	Social Influence (SI)	It refers the degree to which the user believes that his significant others support his use of the Artificial Intelligence.	Venkatesh *et al.*(2012)
5	Habit	It is the learnt tendency of the people to perform behaviors involuntarily or sub-consciously.	Venkatesh et al. (2012)
6	Hedonic Motivation (HM)	The pleasure component associated with usage of technology	Venkatesh *et al.* (2012)
7	Price value (PV)	It is consumer's cost benefit analysis between the perceived benefits of the applications and monetary cost of using these. .	Venkatesh *et al.* (2012)

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Venkatesh et al. (2012) encouraged scholars to investigate the application of the new model to various challenges in various situations to validate it in different cultures and technologies. Refer to Tandon (2021), work that even though UTAUT has been validated in a variety of situations, there are still several chances for researchers to investigate and enhance the discipline.

2.2 Hypotheses development

UTAUT2 has been used across various sections namely e-learning (Tandon et al., 2022), online shopping (Tandon,2021; Kiisanayotin *et al.*, 2009). However, adoption with respect to Artificial Intelligence is still needs to be validated in developing countries context.

According to a study conducted in the community health centres in Thailland by Kiisanayotin *et al.*, (2009), acceptance of IT solutions by healthcare professionals is influenced by PE, EE and SI along with individual voluntariness. Previous reported research by Chang *et al.* (2016) validated facilitating conditions as a significant construct but on the other hand in the study of Kijsanayotin*et al.* (2009), facilitating conditions indicated a weak impact on telemedicine adoption. According to Mengesha *e al.*, (2019), the external environment in which artificial intelligence is implemented provides stimulus for its use. Presence of facilitating conditions, the compatibility of the system with medical practice as well as physicians preferred work style are the most significant constructs in context of this problem. Thus, the same telemedicine system when transferred from a developed nation to a developing one, will face different issues in the uptake of the system. Kohnke *et al.*, (2014) studied the reasons behind not utilizing the telemedicine equipment by clinicians and patients. Based on UTAUT, they validated drivers of behavioral intention to use AI equipment by patients and health professionals. By surveying 126 participants using AI equipment, authors concluded that behavioural intention of patients and clinicians differs in use of AI equipment.

According to Jinka (2015), most of the medical resources are available in urban areas. Further, low accessibility of healthcare in rural and remote population has been noted. It is essential to understand the perception of doctors about implementation of telemedicine in India in order to improve accessibility of healthcare services. Jinka found out that readiness and positive mind-set of doctors towards telemedicine are the determinants of behavioral intentions. The readiness in turn can be derived from Knowledge (Jinka, 2015) and Personal Innovativeness of Doctors (Bakshi & Tandon, 2019). According to Serrano and Karahanna (2016), the information exchange between the patient and doctor differs in quality depending on the skills required in information giving in case of the patient and the skills required in information seeking in case of the doctor. Another important aspect to the adoption of AI in healthcare is the communication process. The communication competence of both the patient and the doctor are important though the skills that they require for a successful communication process are different. Okazaki et al., (2017) also highlighted the perceived value of the outcome to be an important factor in uptake of tele-consultations. Hoque and

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Ahmad (2023) has proposed that perceived usefulness and ease of use are important influencers as suggested by TAM which has been considered as the most influential model in technology adoption followed by the UTAUT model (Garavand *et al*.,2016). Collectively, the literature suggests that the Ease of use, perceived usefulness, facilitating conditions, social context and outcome, attitudes as well as behavior of users are the factors that are effective in comprehending the acceptance and adoption of technological interventions in healthcare. Paying particular attention to these factors may increase the rate and ease of the adoption of ICT in healthcare. Hence, based on the above literature, the following hypotheses have been proposed:

H1: PE leads to BI to use AI in healthcare.

H2: EE leads to BI to use AI in healthcare.

H3: FC leads to BI to use AI in healthcare.

H4: SI leads to BI to use AI in healthcare.

H5: HM leads to BI to use AI in healthcare.

H6: HA leads to BI to use AI in healthcare.

H7: PV leads to BI to use AI in healthcare.

H8: BI leads to Actual use to use AI in healthcare.

RESEARCH METHODOLOGY

3.1 Participants

This research was carried out on the healthcare professional working on AI tools in thoer respective organizations. The participants were contacted all over India.

3.2 Sampling Strategy

We considered mixed-method sampling technique so as to increase the response rate. To arrive at a representative sample, we preferred non-probability random sampling techniques like purposive and convenience sampling. Non-probability sampling technique was preferred due to non-availability of adequate sampling frame. Bentler & Chou (1987) suggested a 5:1 ratio of a sample size to the number of free variables, Schreiber et al. (2006) has examined with subject to item ratios of 10:1 or less, which is a rule-of-thumb for the determination of a sample size. Due to the limited time available and accessibility to a larger population, a non-probability technique is further advised. Therefore, we took a sample size of 600.

3.3 Instrumentation

The scale items were adapted from Venkatesh et al., (2012). These items were further modified to fit AI usage in healthcare context. PE comprised of four scale items indication

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that AI technology enhances performance. Similarly, EE and FC had three items respectively measuring ease to adopt any technology and adequate infrastructure to support adoption of any technology. HM had scale items related to fun, excitement where as PV had items signifying value for money. The dependent variables like BI and AU also had three items each specifying intention to adopt AI and actual use.

3.4 Data collection procedures and pilot study

To obtain accurate answers and reduce the possibility of personal bias, a preliminary survey was conducted and a pilot group of 27 AI professionals was referred. This group was selected according to the convenience sampling method. Pilot groups responded positively to the questions and suggested changes in the drafting and relevance of the questions. Their recommendations were included in items based on interactions with academicians. After receiving input from academics and administrators, several questions were amended, added and others deleted, as the survey was considered too long. This exercise helped with response sensitivity. After pre-testing, a google form was created and mailed to AI professionals in healthcare sector. Both field and online surveys were conducted in this study. We tried our best to reassure respondents that they would maintain the anonymity of their responses to control social desirability bias and motivated them to respond as sincerely as possible (Podsakoff et al., 2003; Du Leeuw, 2008). After evaluating all the responses received, 385 responses were retained for further analysis.

Preliminary data quality checks were carried out in order to check the quality of data. Non-response bias was addressed by tabulating the differences between early and late respondents. No significant differences were found between two groups indicating absence of non-response bias. Due to the substantial correlation across constructs and the fact that a web-based survey was utilised for collecting the data, common method bias may have arisen. All constructs were put through a principal component factor analysis with varimax rotation to mitigate common method bias. The findings of the unrotated factor analysis showed that 38% of the variation had been accounted for by a single factor. As a result, no particular factor was discernible (Podsakoff et al., 2003), proving that the common method bias in the data set is acceptable.

RESULTS AND FINDINGS

4.1 Descriptive Analysis

Mean and Std. deviation explicates the distribution and indication of how far the variables of a group are spread above and below the mean. Table 2 presents the mean, and std. deviation of identified constructs. Mean and standard deviation of subconstructs for driver values indicated that effort expectancy (M=5.71, SD=0.87) had highest mean value followed by performance expectancy (M=5.52, SD=0.1.01) which had a slightly lower mean. In case of Behaviour Intention, the values are 5.59 (Mean) and 1.09 (Standard Deviation)

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Table 2: Descriptive Statistics

Variable	Minimum	Maximum	Mean	Std. Deviation
Performance Expectancy	2.00	7.00	5.52	1.01
Effort Expectancy	3.00	7.00	5.71	0.87
Facilitating Conditions	2.00	7.00	5.52	1.06
Social Influence	2.00	7.00	5.27	1.11
Hedonic Motivation	2.00	7.00	5.37	1.26
Habit	1.00	7.00	5.25	1.38
Price Value	1.00	7.00	5.07	1.44
Behavior Intention	2.00	7.00	5.40	0.97
Actual Implementation	1.00	7.00	5.59	1.09

4.2 Measurement Model

Confirmatory factor analysis was performed to ensure fit between observed data and a theoretically grounded model that signifies hypothesized causal relationships between latent and observed indicator variables. The results of CFA are indicated in Table 3 specify that standardized loadings of all the items of the constructs are significant and above the threshold values specified by Kline (2005). Further, AVE and Composite Reliability values are also above the threshold values of 0.5 and 0.7 respectively indicating construct and convergent reliability. Table 4 further proves discriminant validity as square root of AVE are more than the inter-item constructs.

Table 3: Measurement Model

		Std. Estimate	S.E.	C.R.	AVE	Composite reliability
Performance Expectancy	PE1	0.814				
	PE2	0.894	0.036	27.379		
	PE3	0.876	0.038	26.494		
	PE4	0.887	0.034	27.059	0.754	0.924
Hedonic Motivation	HM1	0.722				
	HM2	0.892	0.045	22.236		
	HM3	0.824	0.05	20.439		
	HA1	0.863				
	HA2	0.9	0.042	26.299		
	HA3	0.931	0.034	34.021	0.673	0.891
Social Influence	SI1	0.933				
	SI2	0.519	0.038	13.893		
	SI3	0.856	0.027	31.314	0.624	0.825
Effort Expectancy	EE1	0.61			0.546	0.779

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	EE2	0.886	0.104	15.87		
	EE3	0.693	0.08	13.7		
Price Value	PV1	0.713				
	PV2	0.889	0.048	26.411		
	PV3	0.834	0.059	19.933	0.665	0.855
Facilitating Conditions	FC1	0.629				
	FC2	0.767	0.093	17.277		
	FC3	0.662	0.092	15.426	0.574	0.729
Behavioural intention	BI1	0.826				
	BI2	0.817	0.032	26.606		
	BI3	0.73	0.042	22.792	0.628	0.834
Actual Use	AU1	0.756				
	AU2	0.749	0.048	18.779		
	AU1	0.933	0.046	23.376	0.668	0.856

Table 4: Discriminant Validity

	HB	PE	EE	FC	SI	HA	HM	PV	BI	AU
HB	**0.751**									
PE	0.671	**0.888**								
EE	0.012	0.280	**0.839**							
FC	0.175	0.398	0.831	**0.889**						
SI	0.515	0.408	0.167	0.524	**0.890**					
HA	0.396	0.524	0.493	0.771	0.665	**0.898**				
HM	0.499	0.594	0.429	0.719	0.722	0.879	**0.841**			
PV	0.192	0.394	0.533	0.856	0.546	0.749	0.685	**0.815**		
BI	0.645	0.568	0.271	0.371	0.564	0.777	0.521	0.353	**0.792**	
AU	0.487	0.521	0.274	0.350	0.585	0.510	0.607	0.234	0.485	**0.817**
Items in bold represent square root of AVE										

4.3 Path analysis

Table 5 indicates path analysis. All the fit indices showed an appropriate fit. These results suggest that the hypothesized model is a logical representation of the structure underlying the observed data. Of all the drivers, facilitating conditions emerged as the strongest predictor of behavioural intention to use AI (β= .43, p=0.001). this was followed by PE (β= .29, p=0.001) and EE (β= .22 p=0.001). However, Hedonic motivation (β= .0.02, p=0.33) emerged insignificant indicating that managers consider utilitarian values more important as compared to hedonic factors.

Table 5: Structural Model

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			Estimate	S.E.	C.R.	p-value
Behavioural Intention	<---	Performance Expectancy	0.29	0.02	12.59	0.001
Behavioural Intention	<---	Effort Expectancy	0.22	0.03	7.79	0.001
Behavioural Intention	<---	Facilitating Conditions	0.43	0.03	15.11	0.001
Behavioural Intention	<---	Social Influence	0.11	0.03	4.98	0.04
Behavioural Intention	<---	Hedonic Motivation	0.02	0.02	3.97	0.33
Behavioural Intention	<---	Habit	0.13	0.02	6.40	0.03
Behavioural Intention	<---	Price Value	0.12	0.01	10.61	0.02
Actual Implementation	<---	Behavioural Intention	0.77	0.03	22.77	0.001
CMIN/DF=4.359, GFI=0.938, NFI=0.485, IFI=0.959, TLI=0.946, CFI=0.959, RMSEA=0.068						

5 DISCUSSIONS AND CONCLUSIONS

The study findings create an understanding about the intricate relationships among the drivers i.e PE, EE, SI, FC, HM, PV, HB and BEH for the use of AI by healthcare practitioners in India. This collaborates with the previous research by Schmitz *et al.*,(2022) that found noteworthy, straight, and positive effects of PE, and EE on the behavioural intention to use AI with respect to healthcare. Another study by Shiferaw et al., (2021) is also in sync with the findings of this study where that healthcare professional's acceptance of AI is not only significantly predicted by EE, but also by PE, self-efficacy and FC. Further, the findings of this study also support the study by Yamin and Alyoubi(2020) where PE, EE, SC, and FC in predicting usage of wireless sensor network applications for healthcare delivery during Covid-19 pandemic. Additionally, behavioural intention has a significant positive effect on actual implementation, indicating that people are more likely to carry out a behaviour when they have an increased desire to do so as validated in previous studies (Tandon et al., 2021). These findings, taken together, offer perceptions into the variables impacting behavioural intention and subsequent execution, which can be helpful for developing interventions and strategies meant to encourage certain behaviours in the context of the adoption of AI in healthcare sector.

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The results of the present investigation have improved understanding of the factors that affect healthcare professionals' adoption of AI, especially in the setting of a developing country like India. They have also added to the body of knowledge already available on the subject. The research's output, a model, provides a thorough understanding of the many aspects influencing and forecasting the behaviours desire to employ AI in healthcare.

The study attempts to empirically examine relationship of behaviour intention and actual usage. The study further validates the connection between behavioural intention and actual usage indicating positive behavioural intention leads to

5.1 Practical implications

Healthcare providers in India and other developing nations would be better able to predict AI adoption if they understood the variables highlighted in the developed research model. This increased usage of AI could complement physical access to healthcare and ease the strain on the current infrastructure.

Healthcare organisations in India should inform healthcare personnel about the benefits of utilizing AI technology. Along with giving access to expert advice from remote locations, it may tackle the problems of quick response, ending the cycle of spread of infection, and cost effectiveness.

Other factors that influence adoption include performance expectations, price value, enabling circumstances, social influence, and effort expectations. Given the nature of the profession, the less substantial correlation of hedonic motivation suggests that hedonic variables are less prominent in healthcare settings.

Undoubtedly, effective adoption and implementation of AI systems depend on technical acceptability. The substantial correlation between price and value emphasises how crucial it is to take implementation costs into account when considering adoption of AI in healthcare. The adoption of digital health technologies will rise further if everyone on the team uses them, which may be assisted by fostering positive social impact. AI systems are incredibly accurate at analysing complicated medical data, including pictures, scans, and medical records. This makes it possible for speedier and more precise diagnoses, which allows for prompt interventions and treatment programmes that are unique to each patient's needs. Predictive models powered by AI may examine patient data to find patterns and trends that could spell the beginning of illnesses or problems. By enabling early identification and management, this may be able to stop the course of the disease and improve patient outcomes. In conclusion, using artificial intelligence to healthcare has enormous potential for better patient care, furthering medical research, and streamlining administrative processes. To maximise the benefits of AI technologies, it's crucial to approach their adoption carefully, addressing ethical concerns and making sure that they are easily incorporated into the current healthcare infrastructure.

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6 LIMITATIONS AND FUTURE SCOPE OF THE STUDY

This study has certain limitations that offer a chance for more research to expand on the current body of information and conduct new studies in relevant fields. The study is limited to healthcare sector, therefore the results may not be generalized for other sectors like retail, IT, automotives etc. Since this research is based upon cross-sectional design, future studies may conduct such a type of study based on longitudinal data or experiments which may better explain causal relationships. Future studies may also study biases associated with the adoption of AI in healthcare. Also, variables like satisfaction, legal support and top management initiatives may also be validated along with the predictors of UTAUT2. Strategies for effective adoption may be informed by more research into healthcare professionals' and patients' experiences, attitudes, and hurdles to embracing AI technology. Research might concentrate on comparing AI models and algorithms to industry-recognized best practises in healthcare to ensure their correctness and dependability in actual clinical settings. Strategies for effective adoption may be informed by research into healthcare professionals' and patients' experiences, attitudes, and hurdles to embracing AI technology. Despite the fact that the study's limitations may have affected the breadth and robustness of its conclusions, fixing these issues and investigating the recommended future paths might open the door for more thorough, instructive, and significant research in the area of AI in healthcare.

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