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Medical Specialists' Perception About Adoption of Artificial Intelligence in the Healthcare Sector

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Abstract

Artificial Intelligence (AI) has numerous potential applications in the healthcare sector. These applications vary from its use in quicker disease diagnosis to its assistance for efficiently dealing with pandemic situations. Many countries have successfully laid out their strategy for the effective implementation of AI. However, several developing countries are still working on their plan to increase the penetration of AI in various fields, including healthcare, to harness AI's potential benefits. The research objective is to understand the perception of Medical Specialists about using AI by identifying significant factors that impact their adoption of AI to perform medical tasks. Several medical specialists were surveyed based on five factors taken from 2 popular technology adoption models- UTAUT2 and TAM2. The data analysis on the collected responses (N=111) was done using PLS-SEM. Based on the analysis results, two factors, namely- Facilitating Conditions and Performance Expectancy, are found to positively impact medical specialists' behavioral intention to adopt AI in their professional life. Decision-makers of developing countries can take appropriate measures based on identified two significant factors to boost AI healttocations' adoption in their country to solve existing healthcare problems and improve the quality of healthcare services.

Keywords

Artificial Intelligence (AI); Technology adoption; UTAUT2; TAM2; Healthcare; Doctors; Medical Specialists; PLS-SEM

Imprint

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1. Introduction

Artificial Intelligence is a combination of various technologies that help in developing human-like intelligent machines. It enables designing systems with human capabilities, such as the ability to sense, understand and act accordingly. AI has continuously evolved over decades and is now booming due to factors like digitalization, the evolution of new technologies like neural networks, deep learning, machine learning, easy access to high computing power, and many more. Applications of AI such as facial recognition, virtual personal assistants, automated cars, chat bots, and many more are successfully integrated into our daily lives. AI has disrupted many industries from manufacturing to retail due to enormous benefits it provides, such as improved work efficiency, reduction in costs, increased accuracy, and higher performance. AI has also found its way to a very critical sector of healthcare and medicine [1].

The two most important things that are must for accurate decision making related to patients' treatment are knowledge and experience. As AI is built on the same principles, it can be of great assistance for treating patients. It can quickly gather data from various sources such as medical books and healthcare research studies and acquire experience by processing patients' historical data and treatment [2]. AI in medicine and healthcare has applications in various areas, including medical diagnosis, robotics, human biology, medical statistics, and many more. The AI algorithms are designed to perform functions such as therapy selection, stratifying risk, diagnosis generation, limiting errors, and increasing productivity. Due to its potential for various applications in healthcare, the growth of the global AI health market is estimated at a CAGR of 40% and is estimated to reach $6.6 billion by 2021 [3]. Effective implementation of AI requires the development of policy and regulations, infrastructure development, HR development, thorough research and development, and it is observed that several countries such as the USA, South Korea, China have successfully laid out their strategy for it, but other countries like India are still struggling on that front [4]. It is asserted that the economic growth of developing countries like India can be increased to a great extent by utilizing the potential of AI in sectors such as manufacturing, healthcare, smart cities, education, smart mobility, energy, and agriculture. Effective implementation of any budding technology requires rigorous research, but it is found that India has only 386 Ph.D. educated researches out of 22,000 total researchers of the world, which implies that there is a lack of required resources for the implementation of AI in developing countries and tremendous effort is required from various entities such as government, the industry as well as academia to facilitate its emergence.

In [5] for solving contemporary problems such as mal-distribution of doctors and lower quality of healthcare. However, the use of AI will solve such existing healthcare problems and help generate more annual savings by its use in AI-assisted nurses, Administrative workflow, and Virtual nurses. Many studies have referred to AI as assisted intelligence; it can be used as a tool in healthcare to assist healthcare practitioners but cannot replace it [6]. This indicates that the potential of AI applications in healthcare can be utilized only if medical practitioners incorporate its use in their professional life. Therefore, it is imperative to encourage healthcare professionals to adopt AI healthcare applications, but in order to do so, it is required to first understand their perception about the use of AI in achieving their work outcomes [7].

Despite AI's great potential in solving healthcare problems of developing countries by increasing productivity, saving costs in the long run, improving health care facilities in a holistic way, its penetration in such countries' healthcare is observed to be very slow [8]. Therefore, the objective of this paper is to understand the factors impacting the acceptance of AI by medical specialists for performing healthcare tasks. To serve the above purpose, we have considered the five pertinent constructs from 2 well-known models of technology adoption- UTAUT2 and TAM2. The four factors, namely- effort expectancy, facilitating conditions, performance expectancy, and price value, are chosen from UTAUT2, and the last factor, called results demonstrability, is chosen from the TAM2 model. Considering 4 out of 5 constructs from UTAUT2 is done because research shows that UTAUT2 is more explanatory than its previous version- UTAUT, as it is capable of explaining the variance of about 56% to 74% in behavioral intention and variance of about 40 to 52% in the use of technology. The responses to a questionnaire based on the mentioned five factors and the behavioral intention construct are analyzed to produce the required findings [9]. These findings will clearly indicate factors that significantly impact the adoption of AI in healthcare by Medical Practitioners and will be helpful for decision-makers of countries looking forward to harnessing potential benefits of AI in their healthcare sector by increasing its adoption proportion.

2. Literature Review

As per the literature, AI's applications in healthcare and medicine are very promising. According to the Harvard Business Review, AI has ten promising healthcare applications, including virtual nursing assistance, fraud detection, robot-assisted surgery, dosage error reduction, connected machines, administrative workflow, clinical trial participation, preliminary diagnosis, cybersecurity, and automated image diagnosis. These applications of AI can save lots of money in healthcare annually. It is estimated that by 2026, healthcare AI applications in the USA would create up to $150 billion in annual savings. AI in medicine is implemented as two principal branches- virtual and physical [10]. Virtual branch uses deep learning techniques of AI to manage health information management systems to help predict disease diagnosis, while physical one includes using robots for patient care and in surgeries. The data-driven application of AI can be used for computer-aided diagnosis of various diseases such as oesophageal cancer and help in therapy selection support. AI has also helped in the development of targeted nanorobots, which enables efficient delivering drugs into bodies. Some existing systems that use AI are IBM's 'Watson' for diagnosis and treatment of cancer, Jvion' s 'clinical success machine' for identifying patients who are most at risk, and patients who are more likely to respond to the therapy [11].

Applications of AI in medicine are not limited to only specific departments; it has potential in almost all medical branches. For example, in Paediatrics, AI-based algorithms are used to detect persistent asthma in children with great accuracy during early childhood, which otherwise is very difficult to detect due to common viral symptoms such as coughing and breathing issues in young children [11]. Similarly, AI applications in the field of Dermatology include early diagnosis of skin diseases such as Psoriasis, Skin Cancer, and Onychomycosis based on readily available clinical images used to train AI systems. It is also found that AI applications can assist dental surgeons in performing healthcare activities more efficiently related to various fields of Dentistry such as Forensic Odontology, Dental, and Maxillofacial Radiology, Orthodontics, Oral and Maxillofacial Surgery, and many others. AI in surgery can be used to improve patient treatment with the assistance of AI systems which is trained using a large database containing electronic medical records (EMR), vital signs, and operative videos to enhance clinical decision making in all the three phases- pre, intra and post-operative phases [12].

Various papers present AI-enabled system's capability to improve the healthcare facilities provided to the needy. AI-based chatbots are helpful in spreading health awareness, providing easy access to healthcare services, answering basic healthcare queries, and encouraging small lifestyle changes for better health. AI systems can be developed to help patients manage their chronic conditions and timely persuade them to consistently abide by their health management routine. Customized e-learning platforms can be developed using AI that provides a set of relevant learning materials to patients as per their symptoms, enabling them to understand their condition in a better way and improve self-care accordingly [13]. With the increase in the importance of mental health, research studies are carried out to find out how AI can be applied for improved mental healthcare. Mental healthcare professionals traditionally use direct interaction with patients to diagnose mental illness, which usually requires a lot of time, but it is observed that diagnosis time can be reduced if AI applications are used to pre-screen patients based on their psycho-bio-social details. A research study shows that emotion AI can be used to detect depression by using easily available social media data such as twitter's tweets. AI-based platforms are also helpful for suicide care, that is, the use of machine learning to determine suicide risk factors for identifying at-risk individuals with reduced efforts and providing required emotional support to prevent suicides [14].

AI can also be useful in better dealing with pandemic situations. According to the research, techniques of AI can be used in CT image analysis for automating the detection of corona-infected persons, thereby reducing the time and effort required by health practitioners. Various AI tools can be used along with smart city networks for collaborative and transparent data sharing between pandemic-affected regions to avoid misinformation and also facilitate collective working on a vaccine for the disease. Different AI tools can be used to understand people's health-seeking behavior and emotions during a pandemic by tracking twitter or using entomology or infoveillance, which will help the government understand the concerns of people and educate them accordingly reduce panic among them. During an epidemic, simulation models, along with the use of AI, can be very useful to track the spread of disease and predict its rate of spread providing scientific proof to the government to undertake measures like social distancing, quarantines, etc. [15]. The use of AI in pandemic situations can enable real-time predictions for the potential sites of infection, the number of possible infected people in a region, and then accordingly will be helpful in arranging the number of beds, medical equipment, and healthcare staff needed to provide effective treatment to affected people. Studies also show that AI can be used along with IoT to help in faster infection detection during pandemics by using data acquired from smartphones sensors like microphones, cameras, temperature sensors, etc.

The use of AI in healthcare has tremendous benefits, but there are also many challenges to be addressed for its fruitful execution. Big healthcare data is required for an effective AI implementation that helps to improve disease diagnosis outcomes, gain valuable insights for diagnosis, and even predict outbreaks of pandemics, but there arises various security and privacy concerns when dealing with big data. Other concerns include transparency of AI algorithms in performing their jobs without any biases, accountability issues in the case of incorrect diagnosis, patients' safety concerns in case of glitches or down-time of the AI systems, huge finance required for the setup and maintenance, lack of a concrete framework for data standardization and its integration, need for a proper framework, policies, and strategies for the use of AI in healthcare. There is also a prevailing notion that the implementation of AI can lead to job loss of health professionals, but it has been found to be untrue due to various limitations of AI.

From the above literature, it is quite evident that though there are tremendous benefits of AI implementation in various branches of medicine, there are also some challenges associated with its implementation. Governments of developing countries like India prioritize undertaking measures such as allocation of funds, training the workforce, and building the digital infrastructure for dealing with associated challenges, and enabling effective AI execution to harness its tremendous possible benefits (Marda, 2018). Effective implementation of AI applications, followed by their acceptance for use by medical professionals, will lead to increased AI penetration in the medical field. Hence, it is imperative to determine doctors' opinions about the use of AI healthcare applications in performing their professional tasks.

Various models called Technology Adoption Models are designed to determine significant factors that influence its potential users' adoption and use of technology. One such widely used model is the Unified Theory of Acceptance and Use of Technology (UTAUT) model, postulated from its eight preceding models of technology adoption- TRA, TAM, MM, TPB, TAM2, DOI, SCT, and model of personal computer use. The four constructs, namely effort expectancy, performance expectancy, social influence, and facilitating conditions to determine acceptance of technology in the UTAUT model, are proven to explain 70% of the variance in behavioral intention to adopt technology, which is much higher than its preceding technology adoption models. However, UTAUT was designed for determining employee reception of technology and use a setting on a wide organizational level. Hence, to make the model capable of determining technology acceptance at a more specific individual level, three additional constructs – hedonic motivation, habit, and price value were added in the extended UTAUT (UTAUT2) model. As UTAUT2 is more explanatory and customer-centric, it is being used by many researchers for individual acceptance of the technology. Another popular model calledTAM2 was developed based on prior model TAM to include two processes: social influence and cognitive instrumental processes. TAM2 was found to be more effective than TAM, as it explained about 60% of technology acceptance compared to the lower explanatory power of about 40% - 50% of the TAM model.

3. RESEARCH METHOD

3.1. Research Design

Doctors' acceptance of AI in healthcare is studied based on five potential constructs taken from 2 technology adoption models- UTAUT2 and TAM2 described in Table 1. These five constructs form our research model's independent variables, whereas the dependent variable is behavioral intention. Behavioral Intention (BIn) is the probability that a person will perform some specified future behavior as per his/her point of view. Thus, we have considered our five independent variables to determine factors influencing medical doctors' behavioral intention to adopt AI to perform medical tasks. Figure 1 presents the research model used for this study and analysis.

3.2. Instrument Development

The research method used is a positivists approach. Positivism is a view that believes in the analysis of quantifiable observations with statistical tools and encourages the use of prevailing theories to design hypotheses to be tested. Thus, the development of the questionnaire was done based on five constructs specified in Table 1 and BIn to measure responses and perceptions of the doctors towards the use of AI in healthcare. The questionnaire was developed in English and used a seven-point Likert scale to record responses. The questionnaire consisted of 2 main segments- the first segment captured the demographic details of the survey respondents, and the second segment included questions based on EEx, FCs, PEx, PrV, RsD, and BIn. On average, four questions per construct were included for more accurate measurements and analysis. Table 2 presents the outcome of questionnaire develop-

TABLE 1

The constructs considered for this study and their definitions

Constructs	Definition of construct
Performance expectancy (PEx)	The degree of belief of a person about a system's utility to his or her advantage towards enhancing the job performance.
Effort expectancy (EEx)	The extent of effort ease that the system can bring about with its use.
Facilitating conditions (FCs)	The degree to which an individual believes that the required support structures are made available from both organization and technology standpoints.
Price value (PrV)	Buyers' cognition about the equilibrium between the expected gains of the applications and the cost component incurred in using them.
Results Demonstrability (RsD)	The tangibility of the results of using the innovation.

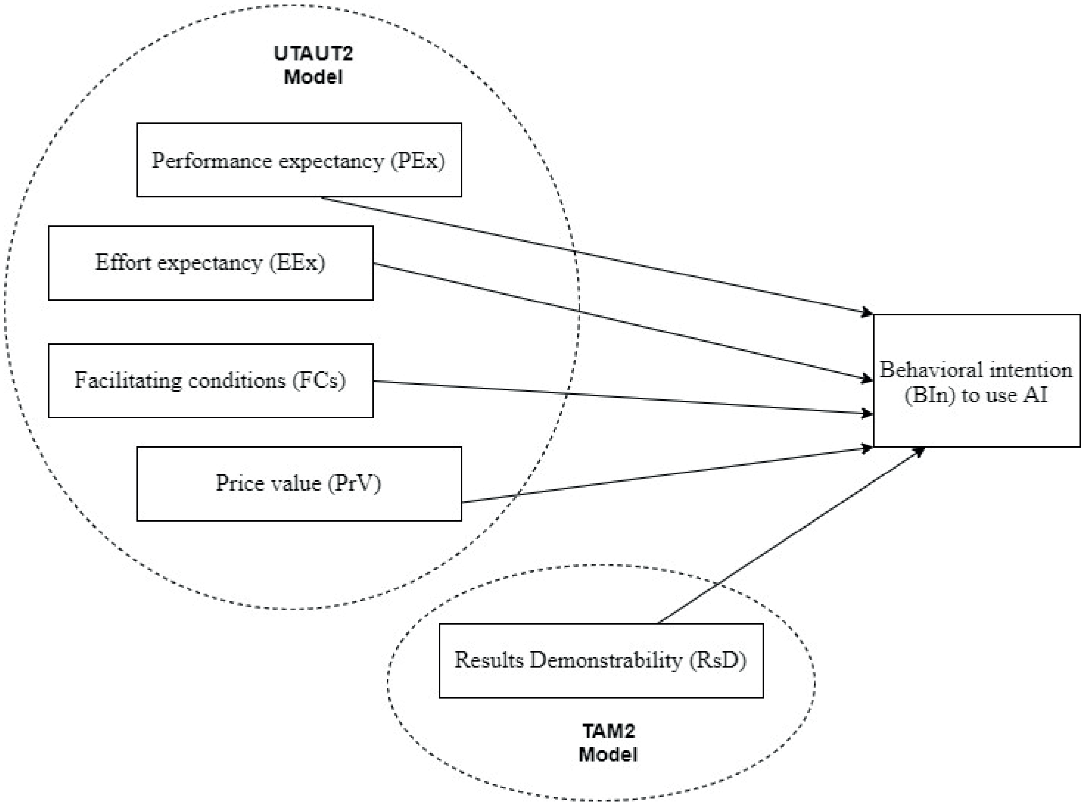

FIGURE 1: Research Model

TABLE 2
Questionnaire Items

Construct	Items
Effort Expectancy (EEx)	EEx1: I believe my interaction with healthcare AI applications would be clear and understandable.
	EEx2: I believe learning to operate healthcare AI applications would be easy for me.
	EEx3: I believe I would find healthcare AI applications easy to use.
	EEx4: I believe It would be easy for me to become skillful at using AI applications in the medical field.
Facilitating Conditions (FCs)	FCs1: I believe I have the resources necessary to use and access AI applications for performing my professional tasks
	FCs2: I believe I know the necessary to use AI applications to complete my professional tasks effectively.
	FCs3: I believe the required support and training teams are available to help me with my difficulties in using healthcare AI applications.
	FCs4: I think healthcare AI applications are compatible with other technologies I use.
Performance Expectancy (PEx)	PEx1: I believe AI is useful to perform my tasks in the medical profession.
	PEx2: I believe assistance from AI would enable me to perform my tasks in the medical profession more quickly and timely.
	PEx3: I believe the use of AI applications would increase the productivity of my professional work.
	PEx4: I believe the use of AI applications would improve my professional work performance.
Price Value (PrV)	PrV1: I believe healthcare AI applications are reasonably priced.
	PrV2: I believe healthcare AI applications are of good value for money.
	PrV3: I think it is cost-effective to use healthcare AI applications for my decision-making.
Results Demonstrability (RsD)	RsD1: I believe I have no difficulty telling my peers about the results of using AI applications to carry out my professional tasks.
	RsD2: I believe I could communicate to my peers the consequences of using healthcare AI applications.
	RsD3: I believe the results of using healthcare AI applications are apparent to me.
Behavioral Intention (BIn)	BIn1: I intend to continue using healthcare AI applications in the future.
	BIn2: I will always try to use AI applications to perform my daily professional tasks.
	BIn3: I plan to continue to use healthcare AI applications frequently.

ment, clearly specifying questionnaire items included for each required construct.

3.3 Data Collection and Sampling

The survey questionnaire containing questionnaire items depicted in Table 2 was circulated online to collect responses in India. The chosen target population consisted of both- doctors who were pursuing masters for specialization in their medical area of interest and medical specialists who had already completed their advanced education and training in a particular medical field. The focused choice for the audience was made as specialization in a specific medical area enhances healthcare practitioners' advanced knowledge in a chosen field. Thus, it increases the probability of using advanced technologies such as AI applications to achieve their desired work outcome. The participation was voluntary, and there wasn't any financial incentive or any other reward offered for participation. The target population was requested to fill in the questionnaire by briefly informing them about the research objective.

3.4 Respondent's profile

The total number of samples collected was 150, out of which 111 samples were selected for this research study based on completeness and genuineness. This comprised of both- doctors pursuing masters in the medical field and medical specialists holding a specialized degree. Results revealed that about 54.04% of the respondents were males, 40.54% were females, and the rest were others or preferred not to say. About 36.94% of all respondents were 25 years or below of age, 42.34% belonged to the age group of 26 to 40 years, 15.32% were 41 to 55 years of age, and 5.41% belonged to 56 years and above of age. In terms of qualifications, about 36.94% of all respondents were MD doctors, about 8.11% were MS doctors, about 5.41% were DNB doctors, 9.01% were MDS doctors, and about 40.54% were doctors pursuing MD/ MS/ DNB/ MDS specialization.

4. Data Analysis and Results

PLS-SEM can be used to estimate causal relationships among variables even when the sample data set is small. Hence, PLS-SEM was used for data analysis of collected 111 samples. It was done using the Smart-PLS tool in 2 phases – first, assessing the measurement model for checking its reliability and validity using various criteria described in section Measurement Model and then, hypothesis testing through structural model delineated in section Hypothesis Testing.

Measurement Model

The Research Measurement model was evaluated for assuring its reliability and validity. The construct reliability can be validated by observing Composite reliability (CR) and Cronbach's alpha (CA) values. CA, as well as CR, should be greater than 0.70 to ensure internal consistency. Table 3 shows none of the CR and CA values lower than 0.732, implying that the model had good internal consistency. Our model also assured indicator reliability from Table 4, which shows that correlation values between all constructs and its indicators were greater than 0.7.

TABLE 3

Model Measurement using AVE, CR, and CA values

Construct	AVE	CR	CA
BIn	0.792	0.919	0.868
EEx	0.704	0.905	0.860
FCs	0.653	0.883	0.823
PEx	0.648	0.880	0.818
PrV	0.648	0.846	0.732
RsD	0.726	0.888	0.812

TABLE 4

Loadings and cross-loadings

	BIn	EEx	FCs	PEx	PrV	RsD
BIn1	0.8642	0.6173	0.7235	0.6153	0.6311	0.7297
BIn2	0.8829	0.6750	0.7307	0.6934	0.7102	0.6770
BIn3	0.9212	0.6885	0.7943	0.7205	0.6622	0.7206
EEx1	0.6669	0.8065	0.6928	0.6232	0.6055	0.6034
EEx2	0.5709	0.8652	0.6011	0.6878	0.5859	0.5314
EEx3	0.6069	0.8300	0.6568	0.6991	0.5934	0.5535
EEx4	0.6361	0.8536	0.6874	0.6566	0.5591	0.6060
FCs1	0.6824	0.6312	0.8318	0.5772	0.7408	0.7209
FCs2	0.6413	0.5557	0.7814	0.5451	0.6183	0.6765
FCs3	0.6255	0.6278	0.7745	0.5518	0.6275	0.6619
FCs4	0.7645	0.7263	0.8429	0.7071	0.6109	0.6564
PEx1	0.6539	0.6018	0.6523	0.8015	0.5480	0.5668
PEx2	0.5001	0.5545	0.5255	0.7118	0.4964	0.5580
PEx3	0.5965	0.6561	0.5603	0.8660	0.5013	0.5432
PEx4	0.6780	0.7301	0.6349	0.8328	0.6284	0.5945
PrV1	0.4533	0.4257	0.5629	0.3308	0.7496	0.5685
PrV2	0.6472	0.6488	0.7044	0.6551	0.8355	0.6925
PrV3	0.6743	0.5831	0.6549	0.5967	0.8266	0.6278
RsD1	0.6817	0.5388	0.7158	0.5239	0.6965	0.8713
RsD2	0.6404	0.5152	0.6963	0.5433	0.6988	0.8562
RsD3	0.7095	0.6918	0.7274	0.7182	0.6152	0.8288

The convergent validity of the model is examined by observing Average variance extracted (AVE) values of constructs, which need to be greater than 0.5. Table 3 depicts AVE values of constructs, which are all greater than or equal to 0.648. Hence convergent validity criterion was also satisfied for the considered measurement model.

The discriminant validity was examined by two criteria- cross-loadings and Fornell- Larcker. For the first criterion of cross-loadings, it is required that an indicator's loading values should be greater than its cross-loading values with the other constructs. The loading and cross-loadings values shown in Table 4 satisfy this required criterion. The second criterion Fornell-Lacker for discriminant validity is a more stringent one, which requires that the values of shared variance between a construct and its indicators be greater than its shared variance values with other constructs. For this condition to be met, constructs' all correlation values with other constructs should be less than the square root of its AVEs. This criterion was met as shown in Table 5 with non-diagonal elements (correlation with other constructs) lesser than diagonal elements (square root of AVEs).

TABLE 5

Discriminant validity by Fornell-Larcker Criterion

	BIn	EEx	FCs	PEx	PrV	RsD
BIn	0.890					
EEx	0.743	0.839				
FCs	0.843	0.79	0.808			
PEx	0.761	0.794	0.741	0.805		
PrV	0.750	0.700	0.798	0.679	0.805	
RsD	0.797	0.687	0.766	0.702	0.785	0.852

Note: All diagonal components in bold are the square root of AVE values, and non-diagonal components are correlations between constructs

Hypothesis Testing

Hypotheses mentioned in Table 6 were tested for the research's structural model by executing the bootstrapping procedure on SmartPLS. The results are shown in Table 7, keeping in mind the criterion that a relationship between constructs is significant only if the t-value >= 1.96. As per the results, the relationship between EEx and doctor's BIn to adopt AI is not significant. Similarly, the relationships between PrV and BIn, RsD, and BIn were observed to be not supported. However, results showed that the relationship between FCs and doctor's BIn to adopt AI is significant (β = 0.398, p-value < 0.008). Also, it was observed that the relationship between PEx and doctor's BIn to adopt AI is also significant (β = 0.227, p-value < 0.022).

TABLE 6

The hypothesis to be tested

Hypothesis	Description
H1: EEx → BIn	Effort expectancy positively impacts medical specialist's behavioral intention to use AI.
H2: FCs → BIn	Facilitating conditions positively impact medical specialist's behavioral intention to use AI.
H3: PEx → BIn	Performance expectancy positively impacts medical specialist's behavioral intention to use AI.
H4: PrV → BIn	Price value positively impacts medical specialist's behavioral intention to use AI.
H5: RsD → BIn	Results Demonstrability positively impacts medical specialist's behavioral intention to use AI.

TABLE 7

Results of Hypothesis testing

Hypothesis	β value	T value	P-value	Decision	f^2
H1: EEx→ BIn	0.051	0.373	0.709	Unsupported	0.003
H2: FCs→ BIn	0.398	2.651	0.008	Supported	0.132
H3: PEx→ BIn	0.227	2.283	0.022	Supported	0.071
H4: PrV→ BIn	0.080	0.753	0.451	Unsupported	0.008
H5: RsD→ BIn	0.206	1.639	0.101	Unsupported	0.047

The R^2 for the structural model was found to be 0.77, which is acceptable and suggests that five constructs considered in our research model explain about 77% of the variance in medical specialists' behavioral intention to adopt AI. Q^2 was observed to be 0.583 (greater than 0) for medical specialists' BIn to adopt AI. This Q^2 value acts as evidence that our structural model has large predictive relevance. Table 7 also shows effect sizes (f^2) for all hypotheses considered. It was observed that effect sizes for constructs H2, H3, and H5 are small, whereas the other two constructs do not have any notable effect on doctor's BIn to accept AI.

Discussion

This research study was conducted to identify factors that influence AI adoption by medical specialists. The research model is unique as it is comprised of relevant constructs from 2 popular technology adoption models- UTAUT2 and TAM2. Thus, this research explores a distinctive way to understand the perception of medical specialists based on relevant factors selected from 2 different models rather than adhering to the traditional approach of using one particular technology adoption model only for analysis.

The study was able to identify two significant factors that influence medical specialists' behavioral intention to adopt AI healthcare applications. Both FCs and PEx have been identified as significant factors, with FCs serving as a stronger predictor than PEx. This suggests that even if healthcare professionals consider AI healthcare applications to be useful in performing their medical tasks, they won't adopt those applications unless they feel there is adequate availability of required resources such as training courses and support teams to facilitate and smoothen their AI adoption process.

The research study also results in other notable findings, such as the identification of a few factors that don't have a significant impact on BIn. As per these findings, the factors- EEx, PrV, and RsD-do not significantly impact medical specialists' BIn to adopt AI healthcare applications. This indicates that if AI healthcare applications are perceived to be of great use in performing medical tasks by healthcare practitioners, then the high price associated with its use won't stop them from investing in it. Similarly, medical practitioners would be willing to put any required amount of effort into adopting AI applications if they find such applications to be helpful in increasing their work productivity and there is the availability of necessary resources to use them. Similarly, results demonstrability won't change their intention to adopt AI healthcare applications.

Such a study for the identification of significant factors can be helpful for decision-makers of developing countries in taking appropriate measures to harness the potential benefits of AI healthcare applications. According to this study, to encourage the use of AI by medical specialists, decision-makers need to focus on facilitating conditions and performance expectancy. Few measures that they can take based on identified significant factors are spreading awareness about AI's potential benefits in healthcare among medical professionals, demonstrating using few scenarios how incorporating AI healthcare applications in daily lives can increase their work performance and productivity, setting up educational courses at minimal prices for healthcare professionals to train them in using AI applications, establishing easily accessible support teams to help doctors with challenges in accessing AI applications. Such actions by decision-makers can tremendously boost the AI adoption rate in the healthcare sector of their country and thus, improve the quality of their healthcare services.

Though this study used samples from India for analysis, its applications are not limited only to India. This study can also provide assistance to other developing countries which face similar issues like that of India. Designing the solution in India to tackle a problem implies developing a solution for a similar problem for more than 40% of the world. Therefore, other developing countries which are struggling to increase the proportion of AI adoption in their healthcare sectors can use the research findings of this study to meet their objective.

Conclusion and Future Directions

The use of Artificial Intelligence (AI) in healthcare has numerous potential benefits. Few of these benefits include a reduction in costs, increased accuracy and performance, and improved work efficiency. To harness such benefits, Decision-makers are required to take appropriate measures to encourage AI adoption by medical professionals. The 2 identified significant factors by this study that influences behavioral intention of AI adoption by medical professionals - Facilitating Conditions, and Performance Expectancy can be focused on by decision-makers to plan required actions.

This study included an analysis of medical specialists' behavioral intention to adopt AI at a particular time. However, it is observed that behavioral intention to adopt any technology may change over time. Thus, Future research studies can incorporate a longitudinal approach to determine the behavioral intention of medical practitioners to adopt AI healthcare applications for procuring more generalized results. The study considered a lesser number of constructs as candidates for significant factors that influence behavioral intention. This was done to avoid a lengthy questionnaire that may lead to a loss of interest and attention of respondents in the middle of the survey. However, future researchers can concentrate on considering other relevant constructs from various available technology adoption models, or they can continue with the same set of constructs with the addition of a few more variables. This will help in identifying a greater number of significant factors that impact the behavioral intention of medical specialists to adopt AI applications in healthcare.

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There is no conflict of interest among the authors

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