Technology Adoption in Healthcare – A Modified TAM Model & Empirical Analysis AI, ML and Automation in Healthcare

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KEYWORDS

Artificial intelligence, Healthcare, Medical Technologies, Opportunities, Challenges, Automation, Machine Learning, Health Applications

ABSTRACT

Purpose - With the advent of the medical in new technology as a concept, becoming a panacea for most challenging issues is inevitable. The new Technologies envisioned as a convergence of Artificial Intelligence (AI), Machine Learning (ML) and Automation have the prospective to revolutionise healthcare practices & processes, making them more systematic and structured, accessible, and interactive. The current research explores the intention to adopt AI, ML and Automation in healthcare & provides an empirical analysis based on a conceptual model.

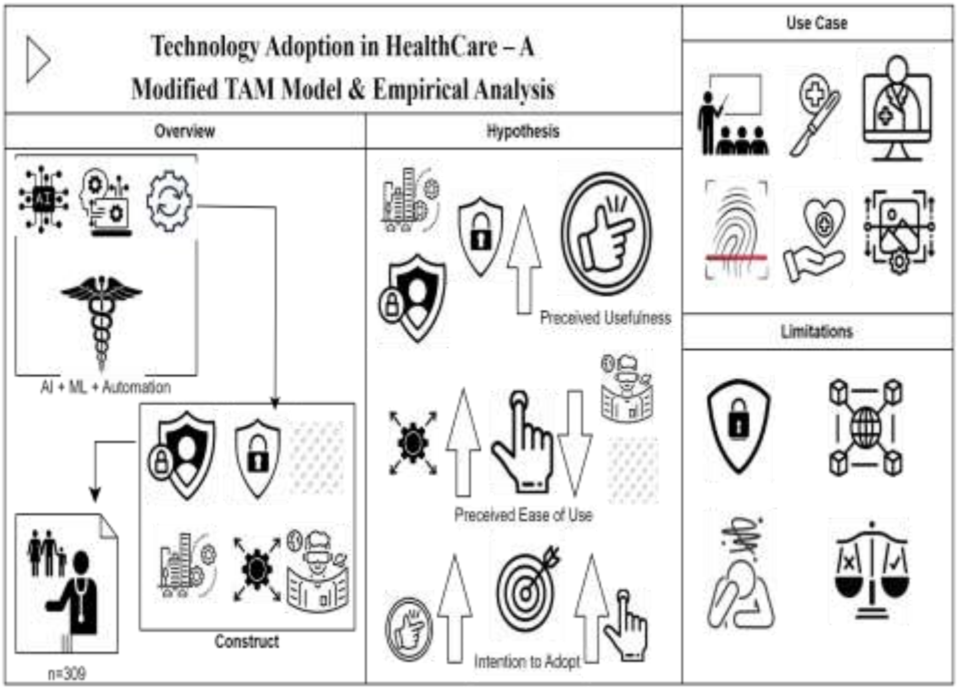
Design/methodology/approach – The action research has drawn on the experience of collaboration and integration of AI, ML and Automation & healthcare. Each term and concept of these new technologies and Healthcare has been built together and understanding the challenges and opportunities is the focus of this analysis. This study was conducted to observe the intention for adoption of AI, ML and Automation in Healthcare. PLS-SEM was used in the study to see the impact and effect of indented or exogenous and dependent Indigenous construct.

Findings—The survey results of 309 respondents show that facilitators, doctors, and healthcare staff are influenced by AI, ML, and Automation and intend to adopt them fully in services. A modified TAM model with major parameters & enablers was added to the study to decide and analyse the users' intention to adopt new technologies in healthcare. We elaborate on how immersive experiences, enable healthcare workers & professionals to provide better patient care across geographical boundaries.

Practical implications – Understanding of challenges and opportunities of new technologies & healthcare handshakes and collaboration which have implications for betterment in future and improvement the healthcare services including medical training and education can also benefit from AI, ML & automation offering healthcare practitioners realistic and dynamic simulations for skill enhancement.

Originality/value – This research will outline the impact of AI, ML and Automation enablers on adoption intention and outline the key implications, use cases and potential challenges to using AI, ML and Automation in the healthcare domain and will investigate how AI, ML and Automation will improve healthcare.

Graphical Abstract



List Of Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
ML	Machine Learning
VR	Virtual Reality
IoT	Internet of Things
PLS – SEM	Partial least squares structural equation modelling

Introduction

The emergence & unfolding of new-age technologies including AI (Artificial intelligence), ML (Machine Learning), and automation, has ushered in a transformative era for various sectors and business verticals, especially in health care. The emerging technologies including virtual reality, IOT, blockchain and immersive digital universe, bring a new revolution in human life and have a social impact. In this research, the new technologies combine AI, ML and Automation. The first is AI, Artificial intelligence. In simple words, we can say, that when a machine works like a human is called an example of AI. AI is science and art, where the machine has the capabilities to learn, think, reason and problem-solving based on scenarios(Simmons & Chappell 1988), (Kozikowski & Sulich 2025). In AI, data is core, based on previous data, machine learning (system) and thinking and working like humans, and this introduced the next technology called ML, Machine Learning. To get the data analysed another technology which adds its footprint is Machine Learning (ML). ML is a technology which heavily relies on data and with the support of data generates predictions and patterns as well (Cohen (2025)), (Boff Medeiros et. Al (2025)). Machine Learning is another major component and pillar of AI, to make AI more stored and robust and to make sure it behaves like humans, machines learn from Data. The ML tech provides the capability to machines to learn from data automatically and identify the patterns, design and the patterns and make the best predictions where less or very little human intervention is required. Not only this, along with the support of AI and automation, VR taking the innovation to new heights. The 3rd in the queue is automation. In simple words, make a process/tool where the reducing task done by machine is called automation. Automation in AI plays a vital role where the system/robots/ tools have been designed and built in such a way that execute the steps which are rule-based, created, and enhanced based on data as part of ML and executed the task-based on given instructions, which not only reduce human errors but also reduce human labour in the task (Beraja & Zorzi (2025)). As these are machines/systems they will work only to the point, that they have been instructed by humans. The need for these technologies not only brings innovation but also brings some challenges and issues as well, in the domain of data security and validity. The emergence of artificial intelligence, a virtual, interconnected, and immersive digital universe, has ushered in a transformative era for various sectors, including healthcare. The current era is all about technology from handheld devices to small pins, technology is at its best now. On one side technology is good for humans and on the other side it brings side effects as well, in this paper, we are building an extending TAM model and doing the empirical analysis to get the intention adoption of AI, ML and automation in healthcare. The integration & collaboration of these technologies or we can call, it a fusion of all these new technologies bring a new and innovative way to improve human life. In this research, we will conduct a thorough investigation, permutation, and combination to put together ML, AI, and Automation in healthcare domains. The fusion of these 3 promises a plethora of advantages.

From the Stone Age to this technological age, medical science has progressed so well that we are in a time where complicated surgeries are performed in minutes and with fewer efforts and risks (Chengoden et al., 2023, Sailer and Homner, 2019). The technology is so vast that it is not an easy task or milestone that anyone or everyone can benefit from. In the current scenario, there are many villages across the world where still doctors are not available, which is one of the biggest problems statements. To overcome this problem, science and technology are used at its best. Clubbing & collaboration of these 4 major niche technologies and health care brings major benefits to human life. Now it is easy for doctors to do operations from miles away just by using some devices and the internet (Innovation, 2021, Choi and Kim, 2017), not only this but the gathering of data /during the operation or surgeries used evolved the new patterns with help of blockchain and processed and help to create a simulated environment for research with the support of Machine Learning and Artificial intelligence.

Health care is now combined with technology and this combination is designated as digital health. The care system is always considered unsustainable, but the latest technology is facilitating it into a sustainable state, and this is possibly a major shift in this industry including the participation, promotion, and establishment of big technology-based companies in health care (Pandi and Nargund, 2018, Ayiter, 2019). Platforms like Big Data consume customer-based information and data and health care itself making and embarking big steps in the market or different industries. This transition is not just a shift in focus, but a seamless journey that bridges the virtual and tangible worlds. The convergence of these technologies and healthcare opens doors to transformative possibilities, addressing critical issues in healthcare and offering innovative solutions. This synergy ushers in an era of digital health that transcends traditional boundaries. Let's delve into how this works and explore the exciting potential of this new frontier.

The unification or meshing of these 3 niche technologies in healthcare promises a plethora of advantages. Telemedicine or e-medicine and remote patient/ telehealth monitoring can become more engaging and effective through immersive experiences, enabling healthcare professionals to provide better care to patients across geographical boundaries. Medical training and education can also benefit from AI, offering healthcare practitioners realistic and dynamic simulations for skill enhancement. Moreover, AI can foster support communities and therapeutic environments that cater to patients with diverse needs, potentially revolutionising mental health care. However, this integration is not without its complexities. Challenges or provocations such as data security, and patient privacy, need to be meticulously addressed to ensure that the metaverse enhances healthcare equitably and without compromise. Furthermore, ethical considerations surrounding consent, identity, and the potential for addiction or misuse must be critically examined (Slater et. al.,2020, Zaidi, 2024, Tsao et al., 2023)

But the question is how these 3 technologies and Healthcare are related to each other or what are the benefits of these in the healthcare domain. Medical New-Age tech is the term used to define the incorporation of new-age technology in the medical domain. Understand that the main purpose of AI along with ML and Automation, is to regulate patient outcomes accurately and efficiently, and this can be done or accomplished with NLP (Natural Language Processing) and MLT (Machine Learning Technology) (Hameed et al., 2023, Shahi et al., 2022). The mingling, fusion and collocation of NLP and MLT, which organize the data and process the data with MLT support. After COVID, the healthcare structure is getting better but country like India where D:P, doctor to patient ratio is 1:854 and in rural India it is 1:1456, which brings the points to find out the factors, barriers opportunities and challenges to adopting AI, ML and Automation in healthcare.

Review Of Literature

Artificial Intelligence in E-health

This new technology, AI is another finest example of today's world. It is a computer system that can execute tasks, activities, and actions based on the beliefs of humans without seeking or consulting advice from humans. In the background, a system is a computer that answers based on the predefined or with several algorithms built based on a large quantity of data. The development in the healthcare industry and the invention of wearable devices bring a new revolution in business. Healthcare, which is always a sensitive industry, is likely to be the first one where AI brought a positive impact, beyond anyone thinking about its usability and positive impact on human lives and as well in other sectors. As per the latest studies published in Neurobiology of Aging, support that AI is so powerful new-age technology that helps to identify the symptoms of Alzheimer’s disease in a patient’s brain before the clinical can. Not only this AI also supported as per a recent paper, the IBM supercomputer, accurately and rightly detected a very rare type of leukaemia in an old lady. University of Tokiyo, Waston also defined that lady's special treatment for recovery. AI also supporting in cardiology and radiology, the clinical decision as well.

Machine Learning in E-health

Machine Learning is another new-age tech which is supporting human lives. In simple words, it is a technology which teaches our machine to perform better and improve through the experience. ML is one of the fast-growing technologies which equally works with data science, computer science and AI. The latest updates in ML bring a new era of improvements in the algorithm and develop the new algorithm for future studies. The adoption of ML is not only in science or technology but also in medicine and healthcare as well. Nowadays every human is suffering from diabetes, low blood pressure and many more such diseases due to unpredictable schedules / unhealthy food habits and no time for exercise. The prediction of disease has mainly these components disease identification, treatment and medicine and machine learning helping doctors and surgeons to build disease identification models, specialist recommendation models for treatment/recovery and the medicine-suggested model this ML supports regular health monitoring, diet, and exercise recommendation models. We are in the era of algorithms and with algo only many industries get influenced. ML is like art, or we can state of art which provides outputs in machine vision, text analytics and voice recognition. ML techniques have been implemented to make these all robust and get accurate results.

Automation in E-health

Automation in AI is a supportive hand. Automation uses AI and ML are the two sides of the same coin and help to automate tasks, workflow improvements and support decision-making. Automation in AI is not an old-school concept now, this is something we are experiencing every day in & day out. Automation in AI helps to detect diseases, helps in analysing lab data, and medical data and supports early diagnosis. Automation helps in RPA (Robotic Process Automation), supporting in discovery of new drugs which use historical data and medical intelligence. We can categorise automation into three areas - software applications, AI-based automation, analysis the medical images, building patterns based on patient data and robotics-based.

This literature review provides an overarching examination of the integration of new-age technology into healthcare, encompassing a thorough exploration of opportunities, challenges, and ethical considerations. Continual advancement in technologies to reshape the healthcare environment & industry, AI, ML and Automation present a novel frontier with profound implications for patient care, medical science education, and research. It elucidates how the combination of new-age tech including AI, ML, VR and AR, and Machine Learning technologies can enhance accurate and right results, patients' real-time updates and medical training, patient engagement, and therapy delivery, transcending geographical constraints and fostering immersive learning experiences. The new-age technologies not only support and make footprints in healthcare but also tourism, entertainment, gaming, real estate and many more.

These Technologies are not only beneficial for human health care about also for animal welfare. This data augmentation, support of digital twins, and avatars, AR, enhanced/learned the system by themselves offers an accurate and quick way of exploring the variation and modulation of animal behaviour as well. To make these technologies possible, there are enablers.

Algorithms: Algos are key in these technologies, algorithms are like step-by-step execution. In simple words, we can say these are mathematical structures that enable artificial intelligence., which learns from data and trained systems. These can be supervised / unsupervised or reinforcement learning. (Petrigna and Musumeci, 2022, Xu et al.,2023).

Sensors: The 4th enabler, with the support of devices like head-mounted or gloves, is the one, that works as sensors. By wearing these devices, a user performs the activity, and the devices have sensors installed that capture the movements, so-called data (Stephenson, 2003, Sun et al.,2022).

Connectivity and Computation: To make AI, ML and Automation work together, connectivity and computations are other key enablers. Lee et al.,2021, Yoo et al.,2023)

Robotics: To make automation possible or the best use of Automation in AI, Robotics is another key enabler. It is one of the enablers who support more and more on the automation side.

Post-COVID-19, the trend has persisted, reflecting a lasting transformation in healthcare towards a more interconnected and patient-centred ecosystem. In short, can these technologies be considered a boon for society, it is still under discussion or research but understanding the collaboration of these technologies makes lots of stuff easy in healthcare. Collaboration of AI, with AR, VR and Automation and to hands join with system/ Machine Learning gives a boost to healthcare. In simple words, we can say it world that relates to the physical or actual world with the support of augmented and virtual reality (VR) even we can say XR and MR, extended and mixed reality, a place which is replicated as the real world and interoperable (Thomason,2021, Tsao et al., 2023), where the machine is intelligent and learn from data and system itself. As per Gartner's report, 25% of the total population logged in or used AI as technology daily or spent hours in the same. The rise has happened during and after COVID-19, as people avoid going out due to fear of the virus and start using AI, ML and to get familiar with this (Yu et al., 2021, Shahi et al. 2024). Many areas or domains get restricted due to COVID, or we can say the physical world becomes limited for humans it includes, education, medical care, fashion, shopping, concerts or social events, exhibitions, etc. moved from real to virtual / from offline to online. People started spending time online more, Netflix, Amazon, etc became quite famous, and rich people who could afford the devices started falling in love with Metaverse. Not only this doctor consultation and health education also moved from real to Smart devices, smartwatches, and smartphones (Wang et al.,2021, Tsao et al., 2023).

Clinical care is another area where the AI has made a huge impact. With the support of AR or Immersive experiences, which create and recreate from any surgery or separation, quick and real-time guidance can be provided and taken from experts. Not only this, AR and Sensors provide real-time data for analysis which helps doctors/scientists to make the right decision and supports planning and future training and education (Koo, 2021, Tsao et al., 2023). The Collaboration of AI with ML & Automation makes it more powerful because with this it is easy to treat individual patients. Beyond AI is working towards building a healthcare AI ecosystem that will be used by new grads, trainees, and experts to improve medical procedures and surgeries (Khosrow-Pour, 2021, Tsao et al., 2023).

Privacy and security concerns look large, as patient data and interactions are transferred into virtual realms. Ensuring data protection, patient confidentiality, and the prevention of cyberattacks become paramount considerations. Furthermore, there are technical hurdles related to interoperability and standardization that necessitate careful deliberation. The ethical including moral, social, and behavioural dimensions or parameters of AI integration in healthcare are equally intricate. The review delves into issues surrounding informed consent, autonomy, and the potential for exacerbating health disparities. It emphasizes and underlines the demand for ethical guidelines and governance frameworks to navigate these complex moral quandaries (Suzuki et al.,2020, Hameed et al., 2023). Not only this but biases in algorithms also directly impact the adoption of AI /ML and automation in healthcare.

Research Gap

If we compare today's world's technology with earlier times or with earlier generations, the accessibility of technology mainly in our context of AI is now easily available and possible, at the place, at time. The AI is only enhanced visualization and supports recognition and deep learning as well & opens doors for more immersive experiences (Park & Kim, 2022, Wong et al. 2024). In & addition, more literature reviews on the course of AI, ML and Automation, in general, and for other applications (Narin, 2021), graphical reviews, animated interactions, and 3D / 4D visualization studies and papers and research in domain of the Metaverse (Singh et al., 2024, Zhao et al., 2022), and mirroring on virtual business/trading or dealing from designing the application and user experience in the AI (Shen et al., 2021, Athar et al. 2023). The literature review and previous studies the research gaps as below:

AI, ML and Automation are New: The collaboration of these 3 new technologies is completely new. The standalone usage and use cases are there but the collaboration is new for humans begin. There are limited studies mainly in the domain of Healthcare and these technologies are less. There is a need for time from the theoretical and conceptual sides to build an extended model with these 3 technology enablers.Moneta (2020), Schlemmer & Backes (2018).

Challenges & Adoption: The users are talking about the standalone use case of AI, ML and Automation and during the literature review, it was found as gap there is a holistic framework missing which uses the perceived usefulness and perceived ease of use and leads to the adoption of Healthcare. The earlier studies talk about individual challenges but there is a direct impact of cooperative challenges and intention adoption.
Empirical Analysis: As AI, ML and Automation are still in the evolving phase, an empirical analysis needs to be performed to understand the adoption of these technologies as a collective in the domain of healthcare.

Every research roam around two major sections. One is a problem, and the other is objective. As this is the integration of two different domains certain issues would inevitably arise such as interoperability which means at any point healthcare workers can transition between the digital or virtual world and the real world, in addition to this is it ethical to capture users' data and confidentiality? These aspects have been widely researched in the past. The second part is the objective. Why this research is important? What is the outcome we expect from this research? Current research addresses the following questions: This article specifically addresses research **questions as follows:**

1. What are the critical drivers & barriers to technology adoption in healthcare?
2. How can a modified TAM be adapted to better explain technology adoption in the sector?
3. What are the challenges and opportunities arising from AI, ML and Automation adoption & implementation in healthcare?

Current research addresses the following objectives:

1. To develop and empirically validate a modified TAM for the healthcare sector that incorporates unique healthcare factors and professional adaptation to technology.
2. Identify and analyze the key factors influencing technology adoption in healthcare.
3. Test the modified TAM through empirical analysis to validate its applicability to healthcare.
4. Provide insights and recommendations to healthcare organizations on optimizing technology adoption.

To conclude, this literature analysis & review presents a complete synthesis of the evolving AI, and ML landscape within the healthcare sector. It underscores the imperative of a balanced approach, where the advantages of this tech integration are harnessed while judiciously addressing the attendant challenges and ethical considerations. By engaging with this nuanced discourse, healthcare practitioners, policymakers, and technologists can collaboratively steer the metaverse's role in revolutionizing healthcare delivery while upholding ethical principles and patient welfare.

Research Methodology

Search Strategy

For the development of the conceptual model, a systematic search was conducted. The search pattern and literature review help to understand the pattern of adoption of AI, ML and Automation by healthcare workers and professionals. The Boolean structure of OR/AND was used in the search of literature. The preference was given to Scopus-indexed articles/literature and considered the recent publication on priority. The systematic search includes academic databases, covering IEEE Xplore, Scopus, Web of Science, and Google Scholar. Keywords such as "AI"," Artificial Intelligence", "ML", "Machine Learning", "Automation" "Healthcare", "Integration", "Opportunities", "Challenges", "Ethical Considerations", "biases" Health Applications" and related terms are used to identify relevant literature. Boolean operators (AND, OR) are applied to refine search queries. The following string was used to locate the articles. The table shows a more detailed view of the systematic search.

Database[1]	**Article's part Searched.**[2]	**Fields Explored**[3]	**Search Conditions**[4]	**Paper Published**[5]
Science Direct	Title, abstract, keywords	All fields	"AI" OR "ML" OR "Automation" "keyword" AND "Healthcare"	2020-2024
Emerald	Title, abstract, keywords	All fields	"AI" OR "ML" OR "Automation" AND HealthCare and Application	
Taylor & Francis	Title, Keywords	All fields	Integration AND Patient Data AND Challenges	
Google Scholar	Keywords	Health Care, AI-ML-Automation, Collaboration	Challenges OR opportunities AND AI OR ML OR Automation AND Healthcare	
Web of Science	Title, Keywords	All fields		
JSTOR	Title, Keywords	All fields		

Table 1 Search protocol for selected literature sources

For the search below point were considered. Figure_1 shows the keywords used in the search.

[1] Refers to the different publishers.

[2] Heading to search in/about paper

[3] Specific words/ keywords to search.

[4] Search conditions.

[5] Duration, in which paper was published.

- Focus on the consolidation of AI, ML and Automation technologies in healthcare.
- Be published in the English language.
- Address opportunities, challenges, and ethical considerations.

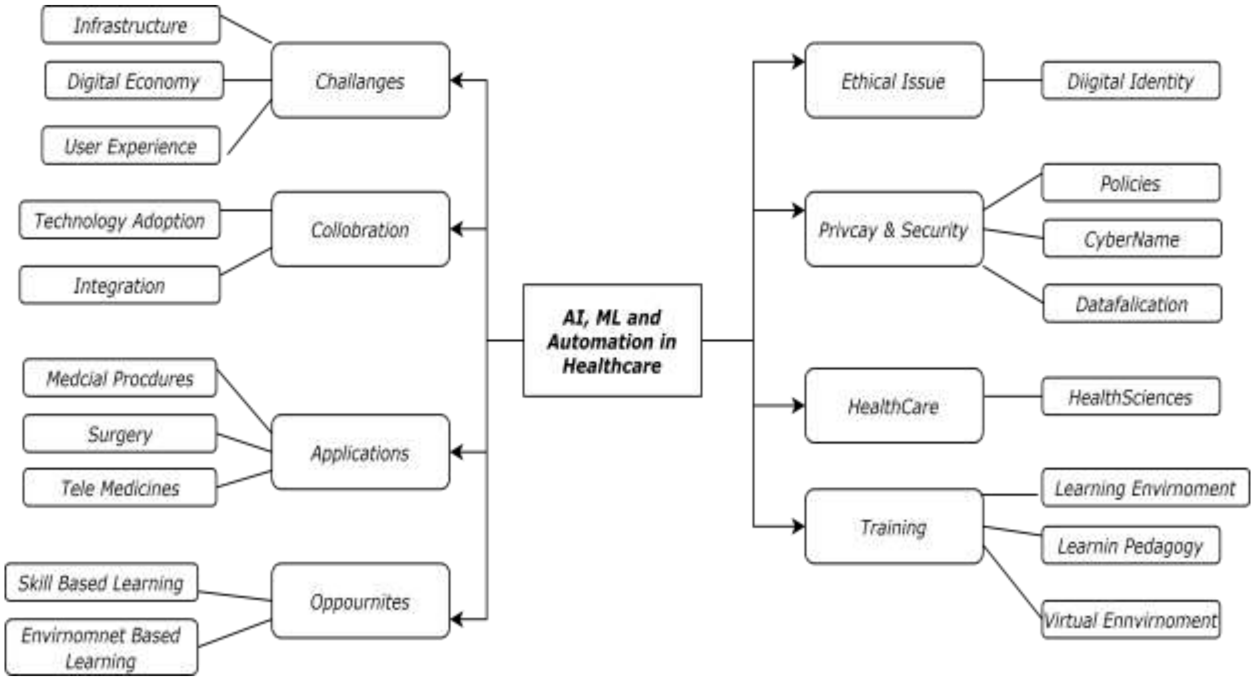


Figure_1 Keywords used in Search.

Subject paper, a set of 366 papers (60% from Web of Science, 10% from IEEE, 10% from Google Scholar, and 20% from Scopus) was initially downloaded for studies. Out of 366, 100 were found good relevant and close to the research paper. Out of 100, 10 papers in considered for final review and cited mainly in the paper. Data extraction involves collecting information on publication details, research methodologies, key findings, and relevant insights. A data synthesis approach is used to categorize and analyze the literature, emphasizing common themes and trends across studies.

Based on the above search and literature review, this section covered AI, ML and Automation and their implication in healthcare. Based on previous literature and studies, challenges, opportunities, and adoption intentions related to technology and supporting and motivating AI, ML, and Automation have been identified and found. As the output, this study is completely inspired by previous published work.

Technology adoption is not easy, and it is specific to application technology Adela (2019). Here the technologies referred to all new technologies including AI, ML and Automation which are always used implemented and adopted by the communities. Technology is the future of business and going forward, it will ease the process and enhance the client experience and user experience as well. The most growing and demanding technology in the current era is AI, ML and Automation (Al-Turjman et al., 2021), in particular. Beck and Frame (2018) state the impact of Artificial intelligence in the current and future via a theoretical framework. The research examined the data uploaded through the software which is built on human intelligence and considered parameters like emotions, thoughts, and memory, not only these but parameters are also trained and optimized based on some memory-driven algorithms which support and guide a system or a machine to build predictions and guide human intellect to take right decisions and now these framework/methods are around us. Researchers like Andrews et al.

(2018) state that there is an integration between AI which supports business operations and focuses on important and specific functions like ML (Machine Learning) Technology. It is a need of an hour for developing countries to adopt AI, and ML in healthcare section Badi et al. (2022). AI and ML together, collaboratively build a bridge between prevention ways and treatment and respective outcomes. AI with Automation and ML help healthcare workers to take recommended treatment or course of action. Is AI, and ML trustworthy? Can we believe in the results or recommendations of AI, another researcher raised this point (Alsalem et al., 2024). Wong et al. (2024) & Ali et al. (2023) picked up 180 pieces of literature, a publication which is mainly on AI, ML integration and collaboration with healthcare and concluded that AI along with ML guided and supported humans in terms of effectiveness, accuracy, and other factors. AI is good in the extraction and image processing process. Singh et al. (2024), in their study, determine the quality impact of AI, and ML in the healthcare domains. Along with a similar line previous studies were conducted to re-examine and recheck how AI, ML and Automation have positive or negative impacts on patient care and the effectiveness of tech-enabled healthcare applications & systems and services & processes Puntoni et al. (2021). Previous researchers Hermes et al. (2020) performed a study to analyse the impact of AI, and ML in the early days of the healthcare system and answered the question of how in the digital world make sure the user data or potential patient/markets are secure in the healthcare sector. Ding et al. (2019) research states that AI services in healthcare mainly on AI-enabled tools, solutions, treatments/recommendations etc. According to the study, AI and ML are used in 2 areas mainly in health records which is 46% and in patient services which is 41%. AI and ML are also used in biomedical research, which follows AI practices and lean principles. With AI and ML, the decision-making power and accuracy have increased which is better than now clinical decisions, and it is possible for AI and ML which study the patient data and enhance the results.

The high-level review shown in the learning & training experience is one of the factors considered as a best use case of AI, ML and Healthcare. The immersive experience in virtual worlds is fun, and the data analysts target precision learning. In the world of AI, the health care workers/doctors/nurses log in as a 3D avatar and get a space where they can collaborate without meeting face to face, can use other content like a digital whiteboard, and do the research and this data, movements, help system to learn more and support human to take a better decision. The collaboration of logged-in users, machine processes, and procedures, data in the virtual world gives confidence to workers to test it safely with the support of their digital twin and find any fault failure, or vulnerability before it is out in the physical or real world or the real environment.

It is not one case, also the AI devices with the support of enablers XR extended reality are used to make the psychological experience of users better and better, and with XR handsets support to alter or modify the treatment of addictions and phobias for the patients. Medical science or health care is the domain, which always preferred the hands-on. When a patient visits a doctor, the doctor not only treats the patient physically but also emotionally Before COVID only 43% of healthcare facilities used Telehealth or telemedicine but this has risen to 95% now. This means this technology also changes the way of working for doctors and facilities and can provide telemedicine/telehealth.

The path of AI, ML and Automation adoption is not easy. Whenever the question of technology adoption comes, researchers picked up TAM (Technology Acceptance Model), Theory of Planned Behaviours (TPB), Unified Theory of Acceptance & Use of Technology (UTAUT), TRA (Theory of reasoned action) along with the parameters of Behaviors, Cognitive, constructive, connectives and follow the product – process concept combination, meta-learning concept and the concept of technological interdependence, mainly used and validated in technology adoption and innovation strategic part. The above model is mainly used in technology adoption around healthcare. But in AI, ML and Automation, these theories are used very limited. Researcher Singh et al., (2023); Zhang et al., (2023), picked up the supports/ enablers for AI, ML or obstacles/barriers of AI, and ML in healthcare (Alsalem et al., 2024; Wu et al., 2020), but the literature about modified TAM still unexplored and missing in the healthcare domain. Policymakers/academics / and healthcare professionals need to understand the modulation and variation of these models and the challenges and opportunities introduced by AI /adoption of AI. It is also important to acknowledge and recognize that what are factors or aspects that can influence or impact and affect the user intention to adopt (Taneja et al., 2024), also the actual adoption and other AI, and related Services in healthcare need to explore exploration (Alsalem et al., 2024; Upadhyay & Gulati, 2023; Visram et al., 2024), as these are key for acceptance & adoption of AI, ML, Automation in healthcare and also build and support and shape the perceptions about and for AI (Ong et al., 2022). Noting wrong to say, that these kinds of studies are here but like in silos and repetitive too (Garavand et al., 2022). The adoption of AI, and ML combination in healthcare also differs from previous technology adoption and factors which influenced the adoption intention. The scope and benefits of AI, and ML, are wide but it is still difficult to understand and determine the factors/ parameters and thoughts among healthcare workers to adopt or not the AI, ML and automation in healthcare (Wu et al., 2020). 12 (Twelve) different Technological theories and models reviewed by researchers Venkatesh et al. (2012). TAM (Technology Adoption Model) is one of the powerful and improved teachers that we are using to form an opinion or judge the adoption of AI, ML and Automation in healthcare. TAM used in AI, and ML in healthcare were explored by many other researchers and there is linkage has been built in technology adoption and innovation (Huang et al., 2024; Kim et al., 2024; Li et al., 2024). Figure_2 shows the conceptual model built in this research.

Drago et al. (2023), traverse and build a bridge of AI, ML, Automation innovation and healthcare, also previous researchers focused on the evolutionary, changing way and role of new-age technologies in healthcare through the different ways of patient data and disease management validation Monaghesh and Hajizadeh (2020). Technology, process, and people are key areas to adoption and these and previous studies reiterate and build a strong relationship of all these 3. TAM framework/model validates the AI, and ML parameters along with the point of view of patients and healthcare workers and other facilitating considerations that strongly push the adoption of AI, ML and Automation in the healthcare domain Huang et al. (2024), Singh et al. (2023).

Changes are not easy to accept especially when it comes to the domain of healthcare. With fast-changing technology AI, ML and Automation play a major role where AI supports the extraction the data via image processing Singh et al. (2024). The different research conducted confirmed that the predictor and the external variable or parameters or factor of TAM play a deciding role in the acceptance and adoption of IT solutions and technologies Kijsanayotin et al. (2009). Other researcher states in previous studies that readiness/fitness/preparation of change positively leads to the adoption and actual usage of technology in healthcare Okazaki et al. (2016). Validation of TAM in respect of AI, ML, and Automation adoption in healthcare concerning Perceived ease of use and ease of usefulness confirmed in previous research Nasseef et al. (2022) The combination of components or enablers of AI, ML and Automation along with TAM factors is studied in this research. The external factors/variables like infrastructure, privacy, security, immersion, ubiquity, and scalability influence the Perceived ease of usefulness and Perceived ease of use, which influence the intention to adopt technology, AI, ML and Automation in our research. When a user/human is introduced to new technology/innovation many internal external factors influence positive or the decision of the user/human about how and when the user will use this technology which depends on Perceived usefulness (This was defined by Fred Davis as "the degree to which a person believes that using a particular system would enhance their job performance".) & Perceived ease-of-use (PEOU) – Davis defined this as "the degree to which a person believes that using a particular system would be free from effort". Along with this decision to adopt the new technology also changes influences or impacts based on the age, gender and Income of the user and previous experience with similar or other technology Uymaz et al. (2023). Infrastructure (INF) is one of the core parameters that exist substantially at all levels which support the AI, and ML implementation in healthcare. AI, ML, and automation are the future of healthcare, continued adoption, and improvement and enhancement are the core for same this technology will improve healthcare services delivery and patient outcomes and further research in healthcare Wong et al. (2024). Ease of use, automation, better immersion, and ubiquity are dominating factors and drivers in AI, ML, and automation adoption Singh et al. (2024). Studies by Li et al. (2024), validate and TAM in healthcare and specific to telemedicine/e-health and confirmed that immersion and ubiquity hurt AI, ML intention to adopt. Kim et al. (2024), a study has been conducted in which states that infrastructure, privacy, and security have a positive impact and significant impact on the intention to adopt AI, ML, and automation in healthcare. The previous research shows there is conflict or disagreement in different findings which state that changes in technology hurt the adoption of AI, ML, and automation Ehrler et al. (2018). This research is required to build the gap and do the valuation of the existing stride. Hence,

H1 The infrastructure enablers are positively related to Perceived usefulness.

H2 The levels of Privacy are positively related to Perceived usefulness.

H3 Security is positively related to Perceived usefulness.

It is also true and found in a study that, due to AI, ML, and automation the way healthcare and medical environment/services work has been changed fundamentally now Albahri et al. (2023). The introduction of AI, ML, and automation drastically improved medical services, disease detection, treatment and prevention and reduced other health issues concerns and risks. The active participation of regulatory bodies and practices and ethics committees also supported the improvement and adoption of AI and ML. A foolproof, 100% secure and trustworthy healthcare system is still a dream. Along with previous studies, this study aims to provide a better and more comprehensive analysis of the Immersion, ubiquity and scalability which mould the direction of intention to adopt AI, ML, and automation in healthcare Vayena et al. (2021)) Vela et al. (2022).

AI is ubiquitous. The meaning of ubiquity in AI and mainly in healthcare plays a vital role. Ubiquitous means, an environment that provides a platform or atmosphere for the user/humans to begin to use the application as similar as used in the physical world. The omnipresent nature /meaning makes AI, and ML more valuable in healthcare Gilbert et al. (2011). The real world or we can say the actual world is present everywhere and ubiquitous to humans (DeCamp & Lindvall, 2023). We are covered and used in this real world 100% and 24*7, 365 days a, either the situation or the phase of life. To make sure AI, ML and automation work, the digital world needs to behave the same as the real world. The surgeries/research and training can be first done in the AI world before going to the real world. AI, ML and Automation combination can be used anywhere, anytime, whenever or wherever a user wants (Agarwal et al., 2023; Chen et al., 2023; Olaoye & Samon, 2024). So, we hypothesize:

H5 The ubiquity is positively related to Perceived usefulness.

Scalability is another major parameter, which influences the Perceived ease of use and intention to adopt AI, and ML in healthcare. Scalability means how much and how wide, we can increase or decrease the performance, or we can enhance or improve the system. AI, ML and automation have a significant impact (Sun et al. 2010). Scalability is key in distributed systems, or these new technologies and it is a fundamental need to scale AI, ML and Automation together. The virtual world is infinite in scale at many levels and in multiple dimensions, which supports to simulation of the real world. Not only this, the scalability in the sense of multiple or concurrent users should be able to log in to the AI domain at the same time Liu et al. (2010). The problem or login of concurrent users in AI and the use of ML at the same time can increase the complexities and influence the perceived ease of use. Thus, we hypothesize:

H6 Scalability is positively related to Perceived usefulness.

Last is immersion or we can say AI is immersive technology. AI is revolutionizing the immersive technology landscape. The ability to see the same content as available in real life and feel and see the same virtually plays a vital role in the intention to adopt AI, ML, and automation, and influences the perceived ease of use and intention to adopt the AI, ML. From VR, AR and simulation which support healthcare workers to learn and improve the system Kouroubali and Katehakis (2019). Digital technologies with the combination of AI, ML and automation offer and support the significance of all healthcare professionals, surgeons, and new medical students in training and further research. With aversiveness, a doctor can do surgery in advance to avoid any loss in real life. To overcome the real-time limitations, medical students/professionals can study patients' diseases with holographic images. The experience of immersion depends on age/ gender as well but as per previous studies, AI as an immersive technology is a great benefit when collated with ML and automation and can develop/ already developed a strong identity in healthcare & is key for future healthcare services. Thus, we hypothesize:

H4 The immersion is positively related to Perceived usefulness.

Perceived ease of use and Perceived ease of usefulness have a positive and significant impact on the intention to adopt technology (AI, ML and Automation), as suggested by previous studies (Taneja et al., 2024). A positive and sustainable intention to adopt AI, and ML in the healthcare domain, resolve problems/issues and doubts related to healthcare support human well-being and make a better healthcare system (Centobelli et al., 2020; Rana et al., 2023; Yadav et al., 2021). Hence,

H7 Perceived ease of Use positively related to the intention to adopt AI, ML, & Automation.

H8. Perceived usefulness is positively related to the intention to adopt AI, ML, & Automation.

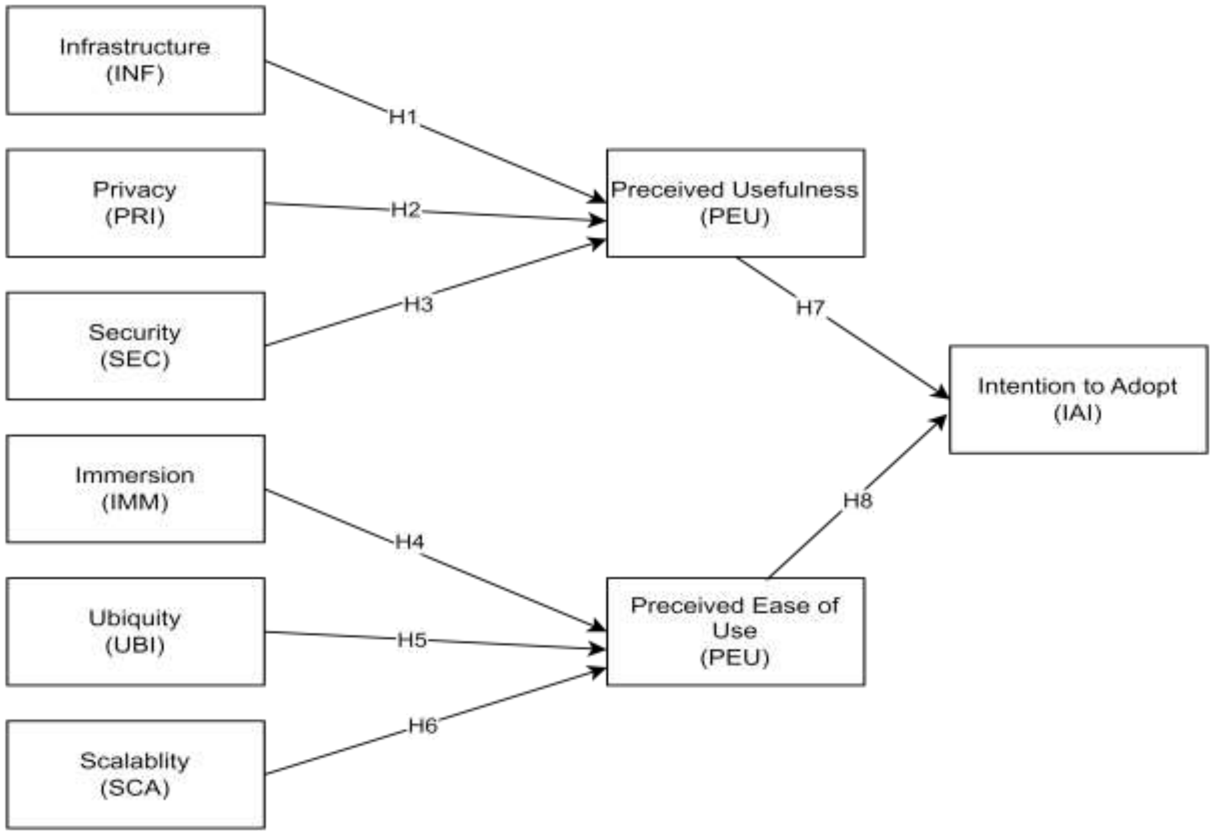


Figure_2 Conceptual Model

Pre-testing of the questionnaire

The scale items in this research were adopted from previous research studies and questioner sent to three industry experts and 3 academicians who are involved in research and using/used AI, and ML in the healthcare domain. The feedback and input have been considered, and changes have been made to questionnaires.

Pilot study

After approval and signoff from experts, the pilot study was conducted. To cover all questions, a Google link is created, and a link is shared with healthcare workers/professionals'/ researchers who are using or using AI, ML-derived tools, and systems. A total of 60 responses were received as part of a pilot study and a reality and validity test was conducted. Cronbach's Alpha was calculated, and the reliability was above the threshold value of 0.7 Nunally (1970), Hair et al. (2013; 2016). (Hair et al., 2011) After the validation and reliability test, the questionnaire is sent for actual data collection.

Data collection

A new Google link is created for questioners after pilot studies, the data collection goes online as well as offline mode. A participant from healthcare has been selected for this study. I tried my best to collect data offline and for online 1-1 meeting has been scheduled. There was no sampling frame available. So non-probability and purposive sampling techniques were used by Schreiber et al. (2006). To get the sample size G Power was used in this study. Based on the number of predictors i.e. 3, we used an effect size of 0.05 and power is 0.95 and calculated the size minimum sample size of 218. A series of preliminary data quality checks were carried out before evaluating and analysing actual data analysis.

Results and Findings

A. *Response Rate Analysis*

The survey was conducted in several ways including online and offline modes. Based on the minimum sample size, the survey was distributed to 400 users and got 320 responses after 1-1 meetings and multiple follow it gave an 80% response rate, which is a good indicator. 11 responses were rejected due to bias issues and received 309 responses. Which is 77.25% rate. Sekaran & Bougie (2010) concluded in the study retained rate of more than 30% is considered good and data analysis can be processed. Table 2 shows the response rate.

Questionnaires[6]	Frequency[7]	Percentage[8]
Distributed	400	100
Returned	320	80.00
Rejected	11	3.43
Retained	309	77.25

Table 2. Response Rate

B. *Demographic analysis*

Demographic Parameters[9]	Category[10]	Response Count[11]	Percentage[12]
Gender	Male	234	75.73
	Female	75	24.27
Age	24 - 35	152	49.19
	36 - 45	135	43.69
	46 and more	22	7.12
Location	Africa	6	1.94
	Asia	199	64.40
	Europe	6	1.94
	North America	18	5.83
	South America	6	1.94
	UK	74	23.95
Organization scale?	Large	188	60.84
	Medium	65	21.04

[6] Survey lifecycle.

[7] Number of responses

[8] %age calculation based on total responses and distributed, returned, rejected, and retained.

[9] Different demographic variables were used to understand the respondent's nature.

[10] Filter parameters based on each variable.

[11] Number of responses against each variable and category

[12] %age based on total number of responses of each variable category vs specific category.

	Micro	14	4.53
	Small	42	13.59
Number of Employees in your Org.	10001 and more	172	55.66
	1001-10000	56	18.12
	1-1000	81	26.21
The term 'AI' means to you.	3d virtual space	2	0.65
	AI is the successor to mobile-based internet with AR & VR.	240	77.67
	It depends on the context	1	0.32
	It is just a name/buzzword	23	7.44
	It is just virtual reality gaming.	43	13.92
AI or ML or Automation experience	No	213	68.93
	Yes	96	31.07
Understanding of the term 'the AI, ML and Automation'?	Detailed up-to-date information.	10	3.24
	Have a good understanding	48	15.53
	Have a little understanding	190	61.49
	Only heard about this	41	13.27
	Never heard of it	20	6.47
Does the company have any designated roles focused on activities within AI, ML and Automation?	No, we don't have such roles	246	79.61
	Yes, we have such roles	63	20.39

Table 3. Demographic Data representation

The demographic response is shown in Table 4. Males and Females both participated in the survey 75.73% of males made a total of 234 and 24.27% of females responded. Major participation from respondents of age between 24-35 which is 49% and the lowest is from above 46 years which is 22 in the count and 7.12% of the total response. From the geographic side, 199, which is 64.40% of Asia and the UK 23.95% responses received. 240 respondents said AI is an Immersive, embodied successor to Mobile internet with AR & VR as per understanding which is 77.67% of total responses. 31.97% responded that they had previous experience in AI or ML solutions at their workplace. 15% of respondents said they have a good understanding of AI, ML and Automation where, and 3.24% responded have a detailed understanding and are always up to date.

Constructs[13]	Items[14]	Std. Estimate[15]	Std. Error[16]
Infrastructure	INF1	0.82	0.05
	INF2	0.94	0.05
	INF3	0.88	0.05
Privacy	PRI1	1.11	0.06
	PRI2	1.03	0.06
	PRI3	1.02	0.06
Security	SEC1	0.94	0.05
	SEC2	0.91	0.05
	SEC3	0.97	0.06
Immersion	IMM1	0.95	0.05
	IMM2	1.01	0.06
	IMM3	0.85	0.05
	IMM4	1.07	0.06
Ubiquity	UBI1	0.73	0.04
	UBI2	0.93	0.05
	UBI3	0.87	0.05
Scalability	SCA1	1.07	0.06
	SCA2	1.11	0.06
	SCA3	1.03	0.06
Perceived Ease of Use	PEU1	0.86	0.05
	PEU2	0.88	0.05
	PEU3	1.07	0.06
	PEU4	0.98	0.06
Perceived Usefulness	PUS1	0.90	0.05
	PUS2	0.89	0.05
	PUS3	1.00	0.06
Intention to adopt AI	IAI1	1.02	0.06
	IAI2	1.08	0.06
	IAI3	1.06	0.06
	IAI4	1.13	0.06

Table 4. Standard Estimate & Std. error Calculation

The mean, minimum, maximum, and standard deviation, were calculated for all independent /endogenous and dependent/exogenous variables. All the calculations for both types

[13] Conceptual model parameters/ constructs

[14] Sub-parameters for each construct

[16] Estimate of the standard deviation of the error term

of variables were calculated on a 5-point Likert scale. Table 5.3 presents the same and the means values and standard deviation were found to be very good, good, and moderate.

Construct	Item[17]	N[18]	Mean[19]	Std. Deviation[20]
Infrastructure (INF)	3	309	4.11	0.87
Privacy (PRI)	3	309	2.21	1.05
Security (SEC)	3	309	4.02	0.94
Immersion (IMM)	4	309	3.91	0.96
Ubiquity (UBI)	3	309	4.18	0.84
Scalability (SCA)	3	309	3.83	1.07
Perceived Ease of Use (PEU)	4	309	3.88	0.94
Perceived Usefulness (PUS)	3	309	4.02	0.92
Intentions to adopt AI (IAI)	4	309	3.8	1.07

Table 5. Standard Calculations

C. *Measurement model*

Table 6 shows the results that are as expected and above the threshold Hair et al. (2011). Table 3 shows the reliability and validity results. Factor loading is the first one in the table, where all the values >0.50, where the highest loading is 0.96, which is considered as good. The factor loading indicates that each question is linked. Mapped or how reliable with a respective construct / a particular contract. The factor loading is considered an indicator of reality. The factor loading/indicator reliability >.40 is considered recommended. In our studies, the factor loading is between 0.50 to 0.96 which stratifies the recommendation Hair et al. (2011). Fornell & Larcker, 1981 recommended an indicatory loading of more than 0.70 for each item (Hair et al., 2014). With this, we concluded that the reality indicator is acceptable.

The composite reality (CR) is the next parameter to evaluate & along with CA (Cronbach Alfa), which helps to understand the internal consistency & reliability check. All constructions hold the CR value >.70 which is acceptable and as per recommendation (Hair et al., 2014). The highest CR is 0.90 and the lowest is 0.77. a value above 0.70 is considered a good strategy. Nunnally (1978), (Hair et al., 2011; Hair et al., 2014) The composite range between 0.40 to 0.75 is considered as good also the CR value range between 0.40 to 0.59 is marked as fair, 0.60 to 0.75 is marked as good and above 0.75 is considered as excellent Cicchetti (1994) along this, the CA Cronbach Alpha which is >.50 for all constructs. The CA ranges between 0.59 to 0.84 which is considered good. Cronbach's alpha values range from 0 to 1 ideally and it can be a negative or low value, which means the respondents answered randomly and had no knowledge about the survey and a higher value indicates greater internal consistency. A value>.70 is acceptable >0.80

[17] Number of questions in each construct

[18] Number of responses

[19] average, is calculated to represent the typical value in a set of numbers.

[20] A measure of how dispersed the data is about the mean.

is accepted as better and a value of 0.90 or above is best considered in studies (Hair et al., 2014), Nunnally and Bernstein (1994), Hair et al. (2010).

The next one is AVE, which represents convergent validity. The purpose of convergent reality is to describe the point of concurrence through different items while measuring a specific concept (Hair, et al., 2011). The AVE value in our studies is above 0.50 which is recommended as per previous research (Hair, et al., 2011). The lowest value is 0.50 and the highest value is 0.72, which is considered good. VIF is the last in the table which is used to test the multicollinearity with any of the 2 constructs highly correlated (Hair et al., 2017). In this student, VIF (variance Inflation Factor) which is less than value 5, means the construct is not highly collinear considered as low colliery (James et al.2013), Zuur et al. (2010), (Hair et al. 2016).

Constructs	**Items**	**Factor Loadings**[21]	**AVE** [22]	**Composite Reliability** [23]	**Cronbach Alpha**[24]	**VIF**[25]
Infrastructure	INF1	0.77	0.58	0.80	0.63	1.3
	INF2	0.77				1.3
	INF3	0.74				1.2
Privacy	PRI1	0.83	0.72	0.89	0.81	1.7
	PRI2	0.89				2
	PRI3	0.83				1.8
Security	SEC1	0.71	0.56	0.79	0.62	1.3
	SEC2	0.82				1.4
	SEC3	0.73				1.1
Immersion	IMM 1	0.84	0.55	0.84	0.74	1.6
	IMM 2	0.71				1.4
	IMM 3	0.72				1.3
	IMM 4	0.74				1.3
Ubiquity	UBI1	0.70	0.59	0.77	0.68	1.3
	UBI2	0.78				1.2
	UBI3	0.96				1.3

[21] The correlation coefficient for the variable and factor

[22] Average variance extracted (AVE), to evaluate the amount of variance a construct captures relative to measurement error.

[23] To measure internal consistency to indicate how well indicators of a construct are associated with each other.

[24] Assessing reliability by comparing the amount of shared variance, or covariance, among the items making up an instrument to the amount of overall variance

[25] Variance inflation factor (VIF) , to measure of multicollinearity among the independent variables in a multiple regression model

Scalability	SCA1	0.84	0.74	0.90	0.83	1.8
	SCA2	0.89				2
	SCA3	0.86				1.9
Perceived Ease of Use	PEU1	0.73	0.52	0.81	0.67	1.4
	PEU2	0.70				1.3
	PEU3	0.77				1.3
	PEU4	0.68				1.2
Perceived Usefulness	PUS1	0.78	0.56	0.77	0.59	1.3
	PUS2	0.80				1.3
	PUS3	0.72				1.1
Intention to adopt AI (IAI)	IAI1	0.83	0.67	0.89	0.84	1.8
	IAI2	0.85				2.2
	IAI3	0.83				2
	IAI4	0.76				1.6

Table 6. Measurement Model Calculations

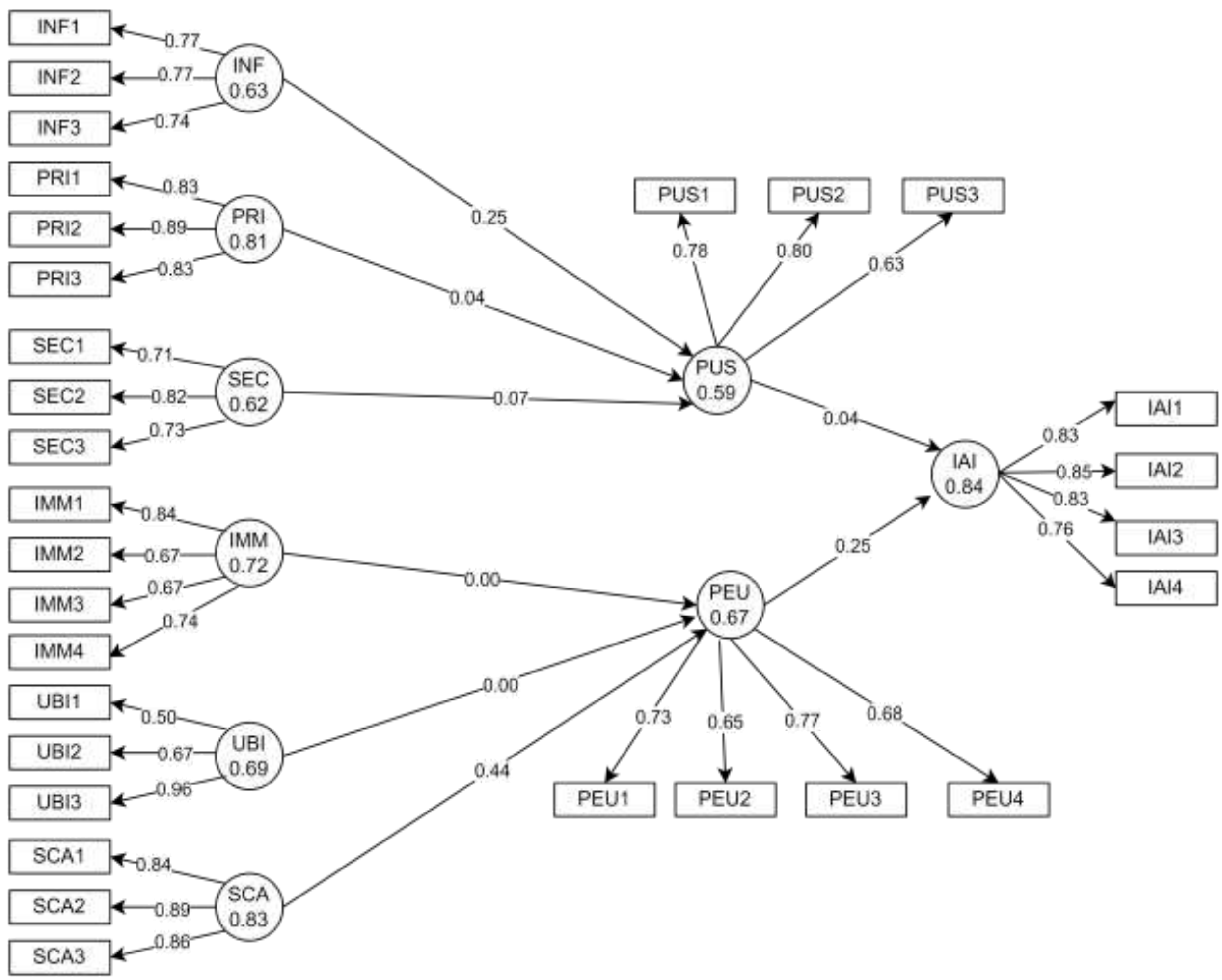


Figure_2 Measurement Model

A discriminant Validity test has been performed to test how the constructs vary from each other (Fornell & Lacker, 1981. This criterion states that “each latent construct's square root of

AVE must be bigger than its squared correlation with every other construct in the model (Fornell & Lacker, 1981)". This test confirms that the constructs are different or unrelated to each other. The value of each construct with itself is higher than others in the same column, which indicates construct are different from each other. The table showed and concluded that the data is reliable and fit for the next level of analysis.

	IAI	IMM	INF	PEU	PRI	PUS	SCA	SEC	UBI
IAI	**0.82**								
IMM	-0.02	**0.73**							
INF	0.47	0.06	**0.76**						
PEU	0.61	0.11	0.46	**0.71**					
PRI	-0.49	-0.01	-0.25	-0.38	**0.85**				
PUS	0.5	0.08	0.57	0.62	-0.35	**0.74**			
SCA	0.27	0.11	0.22	0.56	-0.16	0.41	**0.86**		
SEC	0.43	-0.07	0.42	0.5	-0.33	0.47	0.31	**0.75**	
UBI	0.1	0.02	0.04	0.05	0	0.11	0.07	0.09	**0.73**

Table 7. Discriminant Validity Results

D. *Structural Model*

The next table, Table 8 shows the R Square & R- Square adjusted values, which confirms to test, change in the independent variable, and how much it impacts the dependent variable. The higher side value of R square confirmed or pushed to predict the research objective. Hair et al., (2011) state, that the value of R Square is 0.25 considered small, a value of 0.50 is considered moderate and a value of 0.75 is considered large. In the study, PEU and PUS are 2 dependent variables and change in the independent variable has a 32% variation in PEU and 41% variation and the other side, IAI is dependent and changes in PEU or PUS bring 40% variation in IAT Cohen (1988), Chin (1998b). AI, ML, and automation collaboration are new in the world which brings IA R square to 40%, as AI, ML, and Automation are very new for our respondents.

Constructs	**R-square**[26]	**R-square adjusted**[27]
IAI	0.40	0.39
PEU	0.32	0.31
PUS	0.41	0.4

Table 8. R & R- Square Results

Table 9 represents the results of the structural model. All the fit state a good model fit Byrne (2010). The infrastructure (b ¼−0.43, *p*¼0.00) and Security (b ¼−0.23, *p*¼0.000) have a similar value which states that more good infrastructure and security lead PUS (Perceived usefulness) and lead to Intention to adopt AI, ML, and automation. Whereas IMM (b ¼−0.05, *p*¼0.37) and UBI (b ¼−0.02, *p*¼ 0.82) are insignificant, and reject the hypo testing, which means users/respondent still thinks that immersion experience and Ubiquity are not fully available or working or not developed due to had decline or issues in PEU (Perceived ease of use) in the

[26] The proportion of variance in the dependent variable that can be explained by the independent variable.

[27] A statistical measure that helps determine the goodness of fit for a linear regression model.

healthcare domain. With the support of other constraints Privacy, Scalability have a positive and significant impact on PUS and PEU respectively and the hypothesis is accepted. Last H7 & H8, PUS (b ¼−0.19, *p*¼0.00) and PEU (b ¼−0.49, *p*¼0.00) had a significant positive impact on intention to adopt new technologies, AI, ML and Automation, hence accepting the hypothesis H7 & H8.

Number[28]	**Hypothesis**[29]	**Sample mean**[30]	**Standard deviation**[31]	**T statistics**[32]	**P values**[33]	**Decision**[34]
H1	INF -> PUS	0.43	0.06	7.05	0	Supported
H2	PRI -> PUS	-0.17	0.05	3.37	0	Supported
H3	SEC -> PUS	0.23	0.07	3.47	0	Supported
H4	IMM -> PEU	0.06	0.06	0.9	0.37	Unsupported
H5	UBI -> PEU	0.02	0.07	0.23	0.82	Unsupported
H6	SCA -> PEU	0.55	0.05	11.82	0	Supported
H7	PUS -> IAI	0.19	0.07	2.89	0	Supported
H8	PEU -> IAI	0.49	0.06	8.34	0	Supported

Table 9. Structural Model Results

Discussion & Findings

The first and foremost purpose and objective of this study is to analyse the drivers of AI, ML, and automation adoption in healthcare. From the above tables the data analysis was done and showed a positive impact of Infrastructure, scalability and privacy are dominating factors in the intention of adoption, also it has been supported by previous studies (Rana et al., 2023; Zailani et al., 2014). A better infrastructure, network, standards and robust privacy policies and the scalability of AI, ML in healthcare supported well the studies.

Not only this but to make a robust infrastructure and privacy and security in AI tools, good and educated policymakers and skilled professionals are required / recruitment of skilled professionals for implementation and educating and training to all healthcare professionals for adequate usage. The timely and accurate awareness and readiness to accept change, make a greater impact on the intended adoption of these technologies. The support of external and internal factors like leadership support / top management support is equally important. The right vision of making strategies / making the right & correct decision at the right time aligns and supports the user's decision to adopt AI, ML, and automation. This has been already confirmed and concluded in previous studies of AI, ML, and automation adoption in healthcare (Bernardini

[28] Hypothesis number, structured during the literature review.

[29] Relation between Independent Variable to dependent.

[30] The average of a set of data, or sample, taken from a

[31] Population measure of how dispersed the data is to the mean.

[32] The ratio of the difference in a number's estimated value from its assumed value to its standard

[33] Error the probability under the assumption of no effect or no difference (null hypothesis), of obtaining a result equal to or more extreme than what was observed.

[34] Decision is whether a hypothesis is supported or not.

& Conti, 2021; Kaur et al., 2020). Any new technology adoption or intention to adopt, which makes and brings changes in users' day to day-to-day routines only be implemented with better infrastructure support, a robust privacy policy and a vision to scale it more in future and support of leadership (Sallam, 2023). It is required at the end of users or healthcare workers and professionals to understand the benefits of using the new technologies and this is possible via good training and learning environment. As per SEM bootstrapping results, Immersion and ubiquity emerged as insignificant (Figure). No Immersive experience and no ubiquity are found in previous studies as well. (Bao et al. 2022), Hudson (2019) and Yoo (2018), Choi (2018). The reason of insignificant due to still the availability and reach of AI, ML and Automation in many places across the world, due to poor infrastructure, the low network or bandwidth and the cost of devices to use these technologies. AI, ML, and automation are not so new and still many healthcare professionals have no or very limited experience and very little understanding as well. As the above data state, only 31% of the users have previous experience in AI, ML, and automation and 61% of the respondents have little understanding of this technology (Bakshi & Tandon, 2022; Reddy et al., 2021; Wolff et al., 2021). Making AI, ML, and automation more immersive and ubiquity, needs collaborative work from departments like Infrastructure, the IT department and the science and research department. Organizations need to have dedicated roles and teams for more research, to maintain and enhance AI, ML related environments, and to solve the issue of immersive and ubiquity.

Also, the ubiquity of need is shown as insignificant, which contradicts previous studies (Bao et al. 2022). These insignificant need further evaluation and validation. The prime reason for this insignificance is device cost and low infrastructure availability. And the continued rapid changes in technological advancement. Hence to bring AI, ML, and automation more into use in practice, better infrastructure and low-cost devices need to be brought/made ready. A robust and better infrastructure ensures the intention to adopt AI. ML and Automation in healthcare. All other modified predictors of the TAM model except Immersion and Ubiquity make a significant contribution to this research, thus TAM model broadens the principle of intention to adopt AI, ML and Automation in the healthcare domain (Bakshi & Tandon, 2022; Venkatesh et al., 2012. The results of this study state that there are several benefits the healthcare sector may get from using AI, ML, and automation altogether. A few benefits like a better training environment, early detection of disease, auto-making decision-making, remote surgeries and much more (Deebak, 2021; Sasubilli et al., 2020) and directly improving the performance and productivity of healthcare professionals. Also, it opens more doors for business benefits, quick identification of fraud, workflow enchantment and support (Bernardini & Conti, 2021). As security is also significant, AI may bring more faith in users/ patients to share more data to build better patterns/algorithms which support and facilitate decision-making (Sqalli & Al-Thani, 2019), (Tandon et al., 2023). People benefited as their records are more secure now.

Privacy is also significant in the results thereby explaining the benefit of AI, ML and automation and this finding supports the previous studies (Bao et al., 2022, Zailani et al., 2014). Murray et al. (2019) state the lack of privacy, makes it difficult for users/patients to adopt AI and ML combination and puts a question mark on users' data and information including health diseases (Jameel et al., 2022). broader sections include leakage of personal records, leakage of disease-specific laboratory tests and other details.

The other objective of this study is to understand how the PEU and PUS impact the intention to adopt AI, ML and Automation in healthcare. Both PUS -> IAI and PEU -> IAI have a strong and significant impact of the independent variable (IV) / exogenous variable on the dependent/endogenous variable, thereby accepting both related hypotheses. These findings are very meaningful and support the previous studies as well. (Bao et al., 2022, Bakshi & Tandon, 2022; Rana et al., 2023). Hence AI reduces cost improves performance supports quick decision making and provides a sustainable platform to healthcare organizations. The introduction of robotics surgery, and remote surgeries, reduces error failure or discomfort, and post-surgery pains and helps in quick healing, required for human beings. Thus, this research opens and clears the reasons to adopt or against, Intention not to adopt AI, ML and Automation in the healthcare domain.

After all hypotheses, it is also during the personal survey that the results provided by AI, and ML are biased, it can be historical biases Murray et al., 2019, including old data or data, changed/merged/modified during digitalization which states the results shown by AI, ML-based devices do not reflect the true picture. Another type of bias is patient-related problems Shaban-Nejad et al., 2022, Tsang, 2020 which can be bifurcated into frequent human intervention, errors due to wrong drugs or inaccurate decision trees in day-to-day medical procedures. Maintaining patient data in multiple tools/manuals linked to privacy issues. Several applications used for data raised big concerns and they use AI ML and automation to build the results (Sasubilli et al., 2020). The data (patient data) is collected, processed, stored, and shredded by these applications and platforms, and these platforms/applications have many plus and negative points including but not limited to confidentiality issues, reliability issues, and moral issues. And cyber issues are also ethical issues (Wang et al., 2022). Also, it was discussed and commented on by responding to think about ethics (Jameel et al., 2022). Ethical issues lead to security and privacy being insignificant.

E. *Theoretical implications*

The study mainly opens the doors for the academic industry that wants/is/looking to conduct research in AI, ML and Automation application collaboration in the healthcare sector. This study helps validate the modified TAM model in the domain of healthcare by introducing new variables like interoperability, Immersion, and scalability. Also, this study validates the AI, ML, and automation enablers with the TAM model to reach a holistic approach. Not only this, but this study also builds the theoretical relationship with variables along with factors/parameters that influence or impact the adoption of AI, ML, and automation. From the above variables, immersion and ubiquity are insignificant which leads and need a further investigation and is picked up in further research. There can be/are many reasons which make the immersion and ubiquity significant. This study has an effect and impact on AI, ML collaboration and decision making which leads to the advancement in the healthcare domain. The advancement in AI and ML also supports day-to-day medical procedures, therapeutic procedures, training research and surgeries, which indirectly and directly enhance clinical decision-making and build the strong capabilities of medical organizations. The availability of information and its accessibility and sharing mechanism, which is equally important for AI, ML, and automation-based applications to support and validate data-driven decision-making.

F. *Practical implications*

After the theoretical implication, there are some practical implications as well. First and foremost, this study covered the effects of perceived ease of use and ease of use effects on the intended adoption of AI, ML, and automation in the healthcare domain. Along with this, this study also helps to choose the right and appropriate approach to use AI, ML-based applications, and infrastructure in healthcare. The outcome of this study supports the ability to define and design more AI, ML and automated-based courses and techniques which will help in the digital transformation of the healthcare industry. Alongside TAM fixed variables this research validates the enablers of AI, and ML-like Security, scalability, infrastructure, and ubiquity which played a significant role in the research. These parameters open the doors and vision of leadership/board directors and members of healthcare organizations, who need to understand how fast and quickly technology is changing now and present the opportunities, possibilities, and problems as well. Healthcare management must be ready to adapt the AI and ML adoption plans which help for better results, also healthcare workers need to be trained to handle and operate the AI, ML and automation-based applications and environments. On a similar line healthcare professionals need to understand legal and ethical compliance, so that the interest in adopting AI, and ML based on day-to-day routine work increases without any doubt or fear in mind.

Healthcare researchers, committee members, and the statuary body need to consider and think about strategic digital transformation initiatives from a long-term perspective. The plans need to be created to understand more accurately and better AI, and ML-based analytics to improve customer satisfaction, consumer behaviour, market trends & competition. An ethics-based, trustworthy, and moral AI, ML and automation-based application need to be built, which is not biased. It is the moral and ethical responsibility of our software developers, and mechanical and electrical engineers who design, build, and create AI, ML-based applications, must follow and obey the moral responsibility and follow ethical standards. It looks like it is a misconception that ethical standards applied to AI, ML application but in fact, ethics give accountability to individuals who are involved in designing/ building the application, must build or deploy the application the way they need but follow what best can be achieved which in favour of human begins.

Health Care Training and Education

The 1st and foremost aspect of the AI, ML is in health care training and education. COVID-19 teaches us that education is also possible via virtual way. To train the new doctors, and support staff the immersive experience plays a vital role (Stephenson, 2003). The virtual spaces simulate real-world experiences, situations, and scenarios. Other industries like Banking, and fashion already adopted AI for training and education. The biggest advantage of AI is accessible at any time, anywhere, and has no dependence on location or distance (Kamenev K. 2017). A few examples like surgery application, cardiology, and neurology training where the actual experiments are costlier but with the help of Metaverse it is easy. The combination of visuals and virtual objects makes education more interesting and easier to learn. The visual & virtual object of the human body for surgery is a good case for learning. Not only this, but the literature review also includes that few healthcare facilities use AR and VR to understand eyeballs, nervous systems, and other parts of the body & brain (Nevelsteen, 2017).

Future Health Care Research

The human mind/brain, thoughts, and activities are always tough to understand, and it is not easy to understand the human brain. AI and ML are key here, with the help of devices it is getting easy to understand human health conditions. The online collection of data on human behaviour and personal health information with the support of platforms like ML, big data, and automation helps healthcare workers and researchers to do further studies and it helps to compare the data and results. Sometimes, research in medical studies requires a specific location or environment and metaverse bridges the gap of these obstacles. COVID-19 is an example and still researchers are doing research with the help of the metaverse (Sailer and Hommer,2019).

Day-to-Day Medical Procedures

The prime case of AI and automation is when it supports day-to-day medical procedures. The 1st example we can say is virtual counselling. The first and foremost use case or application of AI in healthcare is Virtual counselling. We can call this telemedical as well, which overcomes the problem or barriers of location / physical presence or geographical. In this doctors & patients log in as an avatar and exchange details. After COVID there is a rise in Telemedicine up to 95%. The second use case is medical check-ups and diagonals. With the help of AR / VR MR and IoT, the diagonals become easy, and more accurate data is captured for treatment. We can call AI and automation an enhancement or simply overcome the initial limitation of human interaction with computers or interconnection and build a solid bridge with and between the physical world and the virtual world.

Medical Surgeries

The integration of AI, ML and automation in medical surgeries has brought about notable advancements. However, it is important to consider several challenges that arise as a result. Reliable and low-latency communication networks are crucial for remote surgeries, as any disruptions can risk the precision of procedures. It is also vital to safeguard patient data privacy, which requires robust cybersecurity measures. Technical glitches pose potential risks, so contingency plans must be in place for prompt issue resolution. Surgeons must undergo comprehensive training and ongoing education for them to adapt to virtual procedures. Regulatory frameworks must address legal and ethical aspects to ensure conformity with healthcare standards (Sun et al. 2022, Thomason,2021). This will help in safeguarding patient safety and maintaining ethical standards. Surgeries and human thoughts are complementary to each other. This means, that when we say the word surgery, humans also get afraid, but with the collaboration of health care and AI, ML, and automation-based applications the surgeries become easy and more accurate, and the results are good. With the support of VR and other tools, surgeons are doing the surgeries by sitting the other locations/places. Also, during surgery, surgeons get accurate and real-time data which supports fast and hassle-free surgery and boosts confidence while preparing and getting ready for the operating room (Slater et. al.,2020).

Limitations and future research

This study helps and supports in many ways healthcare professionals and workers, but it has limitations or drawbacks which may be used in future & further research. AI, the term looks big, but it has many hidden features/benefits/limitations which was not fully covered in academic research that how AI works, in the same manner, ML, is based on data, the more accurate and true data helps but data also manipulated by individuals and there is no control on it. There are limited resources/sources or a shortage of AI and ML and Automation operations which are still inaccessible. In this study, we tried our best to adopt the search techniques, but this research did not consider the draft or unpublished papers. Even in this study, we follow the demographic variable but still, there is a need to go to a more in-depth and specific region, which can be considered for future research. This research provides a conclusion and recommendation for policymakers as well as the industry on the effects and side effects of AI, ML, and automation for practice. The assumption that AI, ML, and automation collaboration help the healthcare industry to expand its footprints is fully supported by previous literature and studies. It is also important to evaluate the challenges like Immersion, ubiquity and infrastructure availability that are core for AI, and ML-based applications in healthcare. Also, it is needed to keep the patient's data secure and confidential throughout the life. The modified TAM model validates the parameters like infrastructure, scalability, and security concerning healthcare, but future research may include more variables which are from the TAM model like actual intention to adopt AI, ML and Automation, including the theory of planned behaviour (TPB) and Theory of reasoned Action (TRA). Further studies also add and validate the construct like baselines, Quality (Service / Information or system) and actual intention of adoption. Future research involving the above parameters/ variables contributes to building and improving the existing framework, policies and practices which enhance the intention to adopt these technologies with social goals.

Data Privacy: The first and foremost is privacy. We humans moving to a digital world and every day we hear about data leakage. Agree, that AI, and ML collaboration is beneficial but there is no rule or regulation about privacy in the same. AI collects huge data and very personal and sensitive data as well, which is not secure in the virtual world and can be leaked and stolen by any unauthorized user and can be used for malfunction or illegal activities (Yoo et al., 2023)

Interoperability: AI is not fully interoperable, which means a user can move from one AI instance to another instance easily and quickly. And it is not that easy to move from one verse to another as there is no bridge or common standards to make the AI, and ML interoperable (Bansal et al.,2022, Wang et al. 2023)

Technology & Infrastructure: Change comes with a cost and these costs are not affordable to everyone. The connection and devices cost more for a normal human and are easily not available in the market or across the world. Also, to run the AI, ML and Automation of the networks which are beyond 5G or 6G (Zaidi, 2024, Yoo, 2023). To make AI possible technology is always a challenge.

Human Feel is Missing: It is well said that when a doctor talks to the patient face to face, half of the worry/tension is over in the patient’s mind. The digital world is progressing but this virtual is taking away the human touch or human feeling. A solution or consultation is provided remotely but sympathy and empathy have more value when it is in person. Few check-ups or treatments which is good in person are not possible in the digital world (Far & Rad, 2022, Khosrow-Pour, 2018)

Ethics & Regulation: Medicine is a profession known for its ethics and regulation, and AI is a challenge in this domain. Losing patient faith or doing illegal activities in the name of technology is not good. There are no regulations or rules if anything goes wrong with patients in the digital world then who is responsible? Currently, AI or ML doesn’t have any regulations or rules or any kind of governance body that can be held responsible, and in medical science, many other parties involved like insurance companies/pharma, and this is a big challenge to bring all these to the same standard and bring legal framework (Khosrow-Pour, 2018).

Conclusion

We have comprehensively examined the potential integration of AI, ML, and automation into the healthcare sector. Our findings reveal a multitude of opportunities, including enhanced patient engagement, telemedicine advancements, and immersive medical training. However, we also highlight significant challenges or issues or problems, such as data security and privacy issues, accessibility issues, and the potential for exacerbating healthcare disparities. Ethical considerations surrounding consent, virtual addiction, and the digital divide are paramount. This review underscores the intricate boundaries of AI, ML and Automation integration in healthcare, offering valuable insights for future research and ethical decision-making in the field Tlili et al., (2022). Data synthesis is performed using thematic analysis, identifying recurring themes, opportunities, challenges, and regulations & ethical dilemmas associated with AI, ML and automation integration in healthcare (Sourin, 2017, Chang et al., 2018).

Virtual worlds are a new era the technology which changes the perspective of humans. Whether it is learning or training or conducting the survey in the metaverse, all become easy now (Chang et al., 2018). The new generation of health care workers/doctors/nurses showed interest in the usage of this digital colour named metaverse. The use of visual and animated 3D/4D images has a positive impact on healthcare learning and day-to-day routines as well (Sailer and Homner, 2019, Ayiter, 2019). What are the components of the new age technologies that are saleable or allow AI and ML to collaborate with ICT resources and completely make it more reliable & expand the origin of healthcare and have a positive impact on the adoption of AI, ML, and automation usage? (Chafiq et al., 2024)

This paper aims to critically analyse the implications of AI, ML, and Automation integration within the healthcare domain. It seeks to provide a comprehensive assessment of the opportunities, challenges, and ethical considerations surrounding the utilization of Metaverse technologies in healthcare settings (Nevelsteen, 2017). By synthesizing existing research, this paper contributes valuable insights for policymakers, healthcare practitioners, and technologists, facilitating a nuanced understanding of the complex interplay between emerging virtual realities and the healthcare landscape (İbili et al., 2024, Koo, 2021).

Each of the tiny changes we make daily, adds up to make a big impact collectively. These new habits are putting us on a path to success with our practice operating model. While we may not see immediate results at the time of making each small change, there is power in collective benefits from small wins – they add up to large gains (Kaddoura and Al Husseiny, 2023, Falchuk et al., 2018). Our hands-on, experiment, and collaboration in technology, and science with Health Care are as a rancher. It is important to understand why working on a ranch felt so rewarding because, after a long day of being on the tractor, we could look back and see the fruits of technology and Science collaboration. So, as we embark on the journey where we want to make sure our Health system is sustained for a long time & we must keep collaborating our efforts with everyone, celebrate our achievements, and pat each other on the back for all that we have accomplished and overcome in these turbulent times. The only way we will win is through the incremental improvements that we make to better ourselves every day.

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Conflicts of interest

The authors certify that there is no conflict of interest with any financial organization regarding the material discussed in the manuscript.

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Definition

S.no	Construct	Definition	Source
1	Infrastructure	Infrastructure that includes hardware and software, programs to use and implement AI, ML, and automation-based applications.	Chatterjee et al. (2021)
2	Privacy	Privacy refers to the user's power and rights to control, access, and their personal information.	Bao et al (2022) Jain et al. (2022)
3	Security	Security refers to how to protect the data from leakage or breach or from cyber-attack.	Dwivedi et al. (2022) Chatterjee et al. (2021)
4	Immersion	It refers to the degree real world and the virtual world look similar and the same.	Bao et al (2022)
5	Ubiquity	It refers to the availability of AI, ML, and automation, anywhere and at any time.	Bao et al (2022)
6	Scalability	Scalability refers to how many users can log in application concurrently and there is no impact on other users/systems.	Bao et al (2022) Jain et al. (2022)
7	Perceived Usefulness	It refers to "the degree the user thinks that the innovation is effortless."	Dwivedi et al (2022) Chatterjee et al. (2021)
8	Perceived Ease of Use	"The degree the user believes that the innovation has significant benefits"	Aburbeian et al (2022) Dwivedi et al (2022)
9	Intention to adopt AI	Intention to adopt technology is defined as "users' preference to accept or decline the technology.	Bao et al. (2022) Jain et al. (2022)

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