Kurdish Studies
December 2022
Volume: 10, No: 2, pp 682-690
ISSN: 2051-4883 (Print) | ISSN 2051-4891 (Online)
www.KurdishStudies.net

DOI: 10.53555/ks.v10i2.3719

Generative AI-Driven Frameworks for Streamlining Patient Education and Treatment Logistics in Complex Healthcare Ecosystems

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Abstract
Healthcare ecosystems are increasingly compounded with a plethora of patients presenting with an array of diseases and relying on interdisciplinary treatment approaches. Patient scenarios frequently encompass complex comorbidities, and the provision of care must comply with intricate interplays between diagnostic test results and clinical decisions. Patients' understanding of clinical procedures and treatment logistics is key for successful therapeutic procurement and favorable therapeutic outcomes. As a result, specialized patient education resources have been developed, providing personalized materials to guide patients through diagnostic and therapeutic procedures. Such resources usually include: (i) short training sessions with healthcare professionals; (ii) reading materials describing the medical background; and/or (iii) short educational videos illustrating the treatment process. Nonetheless, patient education materials are commonly oblivious to the underlying medical terminology and complex treatment algorithms, precluding patients from making well-informed choices regarding their therapeutic options. These challenges are propelled by the intricate prescription decisions, which necessitate a comprehensive knowledge of the disease specifics and the therapeutic property of drugs. To this end, MissingLink enables a personalized patient journey within the healthcare facility, aimed at educating patients in heterogeneous healthcare ecosystems with a program consisting of interdisciplinary treatment decisions. MissingLink can help streamline patient therapeutics by dispatching personalized educational materials tailored to the patient's disease and treatment armamentarium. Inline missing terms, acronyms, drugs, proteins, or complex pathologies are automatically deciphered using explainable artificial intelligence (XAI) components, fostering better patient comprehension. In view of facilitating the comprehensive deciphering of complex educational videos, an Explainable Video Summarization framework is proposed for the concise generation of clinical tests and the underlying decision-making process carried out by clinicians.

Keywords: Generative AI, Patient Education, Treatment Logistics, Healthcare Ecosystems, AI-Driven Frameworks, Personalized Healthcare, Medical Decision Support, Clinical Workflow Optimization, Patient Engagement, AI in Healthcare.

1. Introduction

Recent advances in artificial intelligence (AI), especially in the field of deep learning, have led to an explosion of interest in AI and its applications to various industries not traditionally associated with computer science. One notable field poised to be reshaped by AI is healthcare. The wide range of potential tech involved with the implementation of AI into medical practice, particularly in the areas of image generation and predictive diagnostics, left some of the most striking opportunities.

There are numerous recent federal initiatives and financial support to standardize medical record-keeping and encourage institutional management standards. Prominent software companies working in AI have allocated vast resources for healthcare projects, which combined with the industry's reputation for space providing important future advances to the field. There is an increasingly prominent field of AI-generated art and research that has begun illuminating the potential of creative AI in relatively complex, subjective tasks. Also, with machine-generated description improving each year, quickly heading towards the point where an image (or even audio) can be accurately described to a point indistinguishable to an average listener, it is natural the quality of medical visual data will soon begin to surpass the capacity for human analysis. Not only are these large, high-dimensional datasets highly suited to analysis through various deep learning techniques, but utilizing AI to augment image analysis could soon prove the only practical way for human healthcare providers to process the vast quantity of visual medical data generated each year.

Fig 1: Generative AI in Healthcare Industry

1.1. Background and Context

Patient comprehension and treatment adherence can be improved through education about their condition and the associated treatment management process. However, treatment logistics within complex health care ecosystems can challenge providers, patients and caregivers, and optimal educational formats may vary across stakeholders. An approach is proposed for AI-driven generation of educational courses—enrolled "action-able knowledge"—that semantically tailor educational material to various stakeholders in a health care ecosystem. This framework can operationalize a wide variety of course personalizations, through ideating activities that extend course content and the customization of these actions across participant roles. These capabilities are demonstrated through a proof-of-concept eLearning-based implementation of an ideating course for atrial fibrillation patients.

Treatment can be conceptualized as the accomplishment of a number of activities. Study investigated how a course could be structured to semantically prepare participants to better accomplish those actions. Through an ideating approach grounded in the cognitive theories of planned behavior, goal setting, self efficacy, and barrier management, a set of activities were developed to address various sub-sets of simple actions that can make patients more engaged and compliant with therapy. These ideating activities encompass goal setting, barrier detection and mitigation, and the routine reporting of symptoms and progress. On the basis of a patient's feedback about these actions, concrete courses of actions were prepared in a semantically reasoned manner.

Equ 1: Patient Data Integration

Where:

- P_i = Patient profile for patient i
- D_i = Demographic data of patient i
- M_i = Medical history of patient i
- E_i = Environmental and lifestyle factors for patient i
- S_i = Symptoms or clinical data (e.g., vital signs) for patient i
- f = Function to integrate and process diverse data sources

$$P_i = f(D_i, M_i, E_i, S_i)$$

2. Theoretical Framework

In previous work, an ideating approach grounded in behavioral theories that motivate and engage patients in education about their medical condition and treatment is proposed as a means of fostering adherence to a treatment plan. The design of personalized pedagogical solutions is of significant complexity that requires automating support for developing, implementing, and maintaining such educational activities. The current work aims at constructing courses personalized across four axes of the patient: the medical condition and treatment, the comprehension level, the learning style, and, novel to this work, the level of understanding of specific course content. The eLearning ontology represents medical and educational concepts and their relationship. It operationalizes an ontology-driven design for the personalization of educational materials for a patient. The four above axes are instantiated as medical condition and treatment, estimated patient knowledge, Felder-Silverman learning style, level of understanding of specific course topics. A method of reasoning about the eLearning ontology is detailed that given a blueprint course and the values of the patient axes outputs a personalized course comprising a sequence of learning objects demonstrated with practical use cases.

The use cases demonstrate the opportunity for reusing some course content for different patients with different medical conditions. The course is then personalized toward the patient with respect to the content of the slides. This, in turn, supports customized presentation modalities regarding both the course material, as well as automatically generated Q&A text. The framework analyzes the patient goals and begins to generate some pedagogically relevant queries to be included in the Q&A sections at particular moments of delivering the slides. The entire approach is general, i.e., it is applicable to any medical condition being represented in the ontology, and it is not limited to the provided use cases. The framework combines an ontological representation of medical and educational knowledge with procedural reasoning. It is methodologically distinct from existing approaches; while the widespread ones are logic-based and therefore use rules, the proposed approach operates on precompiled plans represented within the ontology. The procedural knowledge is used to control the sequencing of courses natively, with no need for the introduction of additional concepts, such as sequence markers or coherence relations between the courses.

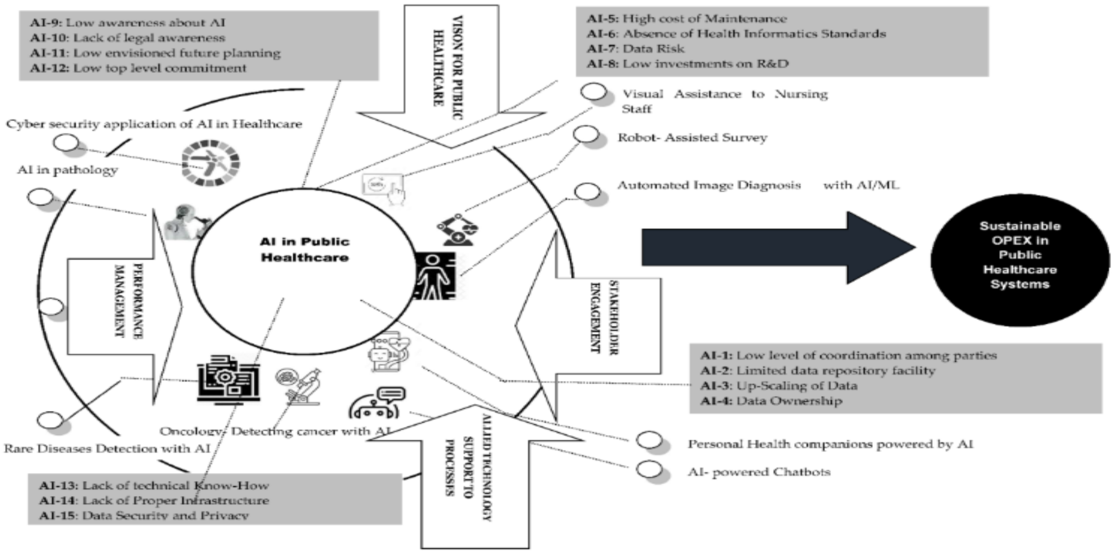

Fig 2: Modeling Conceptual Framework

2.1. Generative AI in Healthcare

The rise of generative AI has enabled the development of advanced generative models that can perform human-like text completion harnessing the power of deep neural networks trained on vast corpora of text data. Due to the advancements in Natural Language Processing, the latest iterations of generative models demonstrate impressive performance in medicine-related tasks. With the development of generative models, new applications in human-technology interaction and conversational agents have been explored. Efforts towards developing personalized health conversations powered with generative models, particularly for patients and to enhance existing conversational agents used in health settings, are observed. Healthcare and health management are important matters to the world's inhabitants, as health conditions can affect individuals both physically and emotionally. Understanding the complexity and importance of one's health issues can support medical professionals in taking better care of patients, providing psychological help, and designing treatments. However, medical information can be hard to understand due to the bulk of contents, complex and professional terms, and individual differences in cognition. Generative models are established for medical applications allowing dialogue with doctors by answering patients' medical queries and providing explanations and evidence in real time. In addition, the proposed methods combine both templated and text ranking models facilitating generating responses from various perspectives effectively. It is of significance to improve the ability to understand at times heavy medical jargon for lay people, enhancing knowledge transfer from medical professionals to patients. Difference in attitudes between doctors and patients towards the rationality of the same medical conditions can also affect the quality of medical conversation. A novel method is suggested making use of feminine definitions to tokenize and lemmatize the contextual bits of the text, and subsequently find and compute cos similarities using those definitions.

3. Literature Review

As increasingly complex conditions in patients with multiple comorbidities characterize contemporary healthcare ecosystems, the challenge of patient education and engagement grows exponentially across the care continuum. A standardized and optimized approach to digital channels, workflows, and back-office solutions for healthcare practitioners is unavailable and therefore not individualized in most healthcare systems. The key to effective health management is the efficient coordination of different service providers that interact with a patient – primary care providers, specialty care practices, pharmacies, laboratories, inpatient care, etc. Healthcare practitioners typically spend an inadequate amount of time coordinating patient activities, outside of therapeutic interventions. This results in incomplete communication loops, fragmented information exchange, and in inadequately informed patient engagement practices. The proposed system configuration consists of two novel semi-automated AI systems that; (i) process data for patient clustering across sophisticated and basic automated methods, and (ii) automatically generate educational and organizational materials regarding designated health issues, according to the patient clusters and medical literature. Machine learning classifiers in combination with unsupervised learning methods are trained on vast amounts of digitized doctor-patient communication data to provide tier-one patient clustering across a range of content complexity and patient technological intractability. The clustering results are fed into an open pipeline for evaluation and the unsupervised clustering algorithms of the lower tiers are re-adjusted according to the manual feedback. At the higher patient clustering levels, for appropriate health conditions, educational materials are automatically generated concerning patient background, disease etiology, possible symptoms, and treatments. In parallel with this, logistic and foundational materials are produced regarding organization, necessary third-party encounters, terminology explanation, and insurance issues. All materials are output in different formats that can be digitally shared with patients: simple text messages, videos and infographics, and also practitioner-facing detailed text summaries and back-end links to procurement actions to ease the burden of organizing mentioned activities for the healthcare practitioners.

Equ 2: Patient Education Generation

Where:

- E_i = Educational content for patient i
- h = AI model that generates content
- P_i = Patient profile
- T_i = Treatment plan for patient i

$$E_i = h(P_i, T_i)$$

3.1. Current State of Patient Education and Treatment Logistics

Many complex life-long healthcare conditions, such as cancer disease, require continuous outpatient care, follow-up treatment, and patient education on their condition. Despite its importance, patient education about the medical condition and its treatment can often fall between the cracks. This problem gets exacerbated in larger and complex healthcare systems, where patients receive their treatment fractionated among many departments over a span of time.

There are clear reasons for this: Hospitals are not primarily set-up for patient education. Similarly to other institutions, patient education is mostly information-centric and the patient needs to inquire information for it to be provided. Furthermore, the time of healthcare practitioners (HCPs) is very limited in this aspect. In the very complex and busy clinical context found in hospitals, doctors and nurses need to focus on their primary attention - namely, directly addressing the condition and its treatment. Many patients, particularly in more complex cases like multiple comorbidities, progressive cancer cases, etc, show a short attention span to new medical information, or may develop anxiety about their understanding limitations. In these cases, HCPs may as well underestimate the patient's interest or literacy levels and refrain from further explanations. And, as described by the patients, the communication tends to be very authoritarist with the HCPs just shouting orders, sometimes in an indignant or patronizing way, reinforcing the patients' belief that the HCPs are interested exclusively in talking to each other, disregarding the patient's presence altogether. Due to all these reasons taken together, the business as usual in this context of providing patient education results in very poor educational experience for patients.

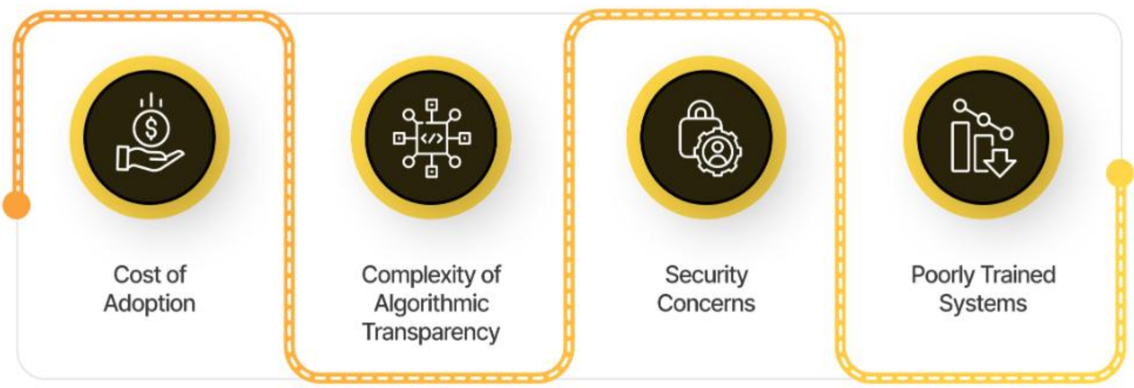

Fig 3: AI in Logistics

4. Methodology

Introduction Improved health literacy, education, personal health records, and digital health interventions are recognized as important tools to ensure accountable, transparent, and patient-centric service provision by alleviating the omnipresent cognitive overload. Ideally, to help understand a complex health ecosystem condition and tackle a health threat effectively, patients need to be provided with a comprehensive, up-to-date, machine-processable description of both their condition and the therapeutic plan. However, the patient may simply be unable to process extensive and learning-demanding information regarding their health condition, the treatment, the therapy venues, the treatment schedules, and the potential adverse events. People are empirically known to miss, forget, lose focus, conflict, or simply not appreciate the information, even when profoundly interested in it. As a very optimistic evaluation, about 70% of the health information passed is either forgotten or comprehended erroneously. In a real-world situation, the figures involved could grow even worse due to the impact of stress, distress, or traumatic experiences on cognitive abilities.

4.1. Data Collection and Analysis

Data-Driven Design of AI-Driven Patient Experience Generative System User is requested to submit a long paper or short paper using the ACM Two-Column format that will be presented at the IEEE ICBC conference in Vancouver. In this paper, the conventional Figure/Table format is inadequate, as some text and result content for the proposed study can be provided in running text form only.

5. Case Studies

Healthcare is quickly shifting towards becoming more collaborative, interdisciplinary, and patient-centric. The future of healthcare and strategies that would contribute to streamlining patient education and treatment logistics within the increasingly complex healthcare are investigated. A framework for the two-way communication and collaboration between the patients and healthcare providers is developed. Patient-selected healthcare providers from multiple organizations can share the same electronic health records (EHRs) on the platform. The EHRs are converted into a patient educational plan that includes patient-specific disease information, education materials and videos, nutritional and life-style suggestions, and codes to facilitate the logistics. The patient educational plan is shared with the caregivers (unpaid and paid, including the healthcare providers). The platform additionally uses technology to manage the privacy, transparency, and ownership of the data, and to collect the anonymous patient satisfaction feedback on the healthcare providers.

Patients are oriented to participate in their treatment decisions, yet they often face difficulties in expressing their medical concerns. Mental models are employed to untangle the complex thinking processes of the patients by mapping their lay terms and knowledge fragmentations within treatment networks. Generative systems are developed to harness these maps as procedural guidelines for automating the production of questions to stimulate participatory behavior in the patients. A pilot study is conducted within the context of breast cancer surgery, where interviews and treatment networks are obtained from 10 patients regarding the side effect concerns of two surgical options. A qualitative analysis uncovers the fragmented concerns and emotions of the patients that are aggregated into treatment networks. Upon mapping the lay terms to this network, the final mental model of each patient is obtained. The Generative-Stimulant Design consists of Graph and transformers for the automatic generation of questions that connect with these cognitive maps. A comparison study with healthcare personnel and multi-aspect evaluation metrics in terms of accuracy, diversity, informativeness, and naturalness are provided. The ambulance dispatch policy has a significant impact on the patient's experience in emergency situations, especially for non-urgent (low acuity) incidents. The ER category associated with non-urgent dispatches have sparked public controversy as they use ambulances as a private taxi service. Japan experienced a surge in emergency calls during the pandemic. National emergencies and similar thereby exacerbated the discussion of dispatch policies. Estimations show that one out of every five cases is coded as ER2 with non-urgent dispatches. Due to this coding mismatch, non-urgent dispatches have increased tenfold, stressing capacity management. In this work, ER categories and dispatch calls are enriched with patient experience data, which is formulated under 17 topics for non-urgent events. Both qualitative analysis and optimization study are conducted to scrutinize possible repercussions of dispatch policies in detail on patients (either public or individual level), as well as to potential improvements in consideration of patient experience.

5.1. Applications of Generative AI in Healthcare

The role generative artificial intelligence (AI) could play in democratizing advanced AI-driven frameworks for streamlining patient education and treatment logistics in the complex healthcare ecosystems is investigated. Currently, most AI-based developments in healthcare communication and marketing are created by tech developers and are too expensive and inaccessible for solo practitioner shops and small businesses. The rise of AI advances for creators makes both its aptitudes and the required know-how more democratic. Alongside the appearance of open AI-powered platforms that house efficient machine learning models and simplify machine learning training and utilization, there has been an increase in the availability of AI tools. Nonetheless, health practitioners and small businesses must acquire the kind of know-how, training, and resources required to work with them. Enablement in AI toolkits could support practitioners in democratizing patient health knowledge and education in healthcare Chile. Eligible betters in this RFP must use or be supported by an AI-contributed toolkit to automate processes or information content for widened warning and benefit in patient care. By the application of such emergent AI contributions, efforts could assist practitioners in democratizing intricate information and skillfulness in the extensive network of healthcare providers in Southern California. Receiving that apprehension of the complicated physician's jargon is a recurrent obstacle in managing care and tracking medical recommendations, especially in minority and lowproductive areas, there are calls for technologized perks in patient-directed health education resources and encompassing screening and preventive treatments.

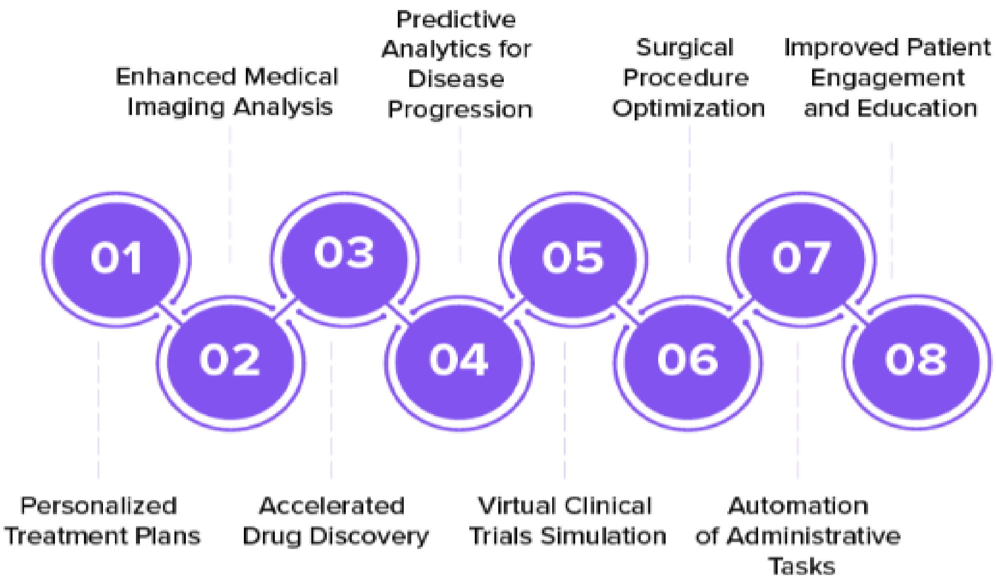

Fig 5: Applications of Generative AI in Healthcare

6. Discussion and Implications

AI technologies and generative models have become a popular choice by leading healthcare organizations in order to leverage patient data and their specific circumstances to generate detailed information. Nevertheless, patient data processing and the information exchanged in these contexts may require a higher level of assurance in terms of privacy and data disclosure verification than in other contexts.

An AI-driven methodology is proposed that streamlines the P2C information flow logistics in complex ecosystems while providing transparency on the information exchanged between patients and caregivers. A security layer is developed, enabling both patients and caregivers to securely analyze the information exchanged using AI models. The methodology can be adapted to any environment and healthcare service, independently of the information source and AI model utilized for data processing and decision-making.

Wariness concerning medical care is often identified as a rationale for seeking a variety of therapeutic options, as well as for not seeking care in general. To learn about a person's attitudes, beliefs, and perceptions surrounding their medical care, a newly developed and validated Medical Mistrust Index (MMI) could be used. Furthermore, the relationship between gender and MMI was explored, which revealed that MMI was significantly different based on gender. Implications for the study of mistrust in health care were discussed based on the results. It is found that the size of the differences is a function of the sample used, and with the most generalizable results favoring a seven-factor structure for MMI. However, the newly developed three-factor structure could be used most effectively with demographic variables, such as age and self-designation as either depressed or currently taking a prescription medication, which were related to MMI, suggesting avenues for potential further research.

Equ 3: System-Wide Healthcare Optimization

Where:

- H = Overall healthcare system performance
- N = Number of patients in the system
- O_i = Outcome of treatment for patient i
- R_i = Resource utilization by patient i
- T = Number of tasks or resources in the system
- C_t = Cost or resource requirement for task t
- x_t = Allocation of task t to the system

$$H = \sum_{i=1}^{N} (O_i \cdot R_i) - \sum_{t=1}^{T} (C_t \cdot x_t)$$

7. Conclusion

1. Hospitals face a growing challenge to streamline and coordinate large volumes of information for a populace that often has limited access to or understanding of emerging technologies and patient management practices. Systems for streamlining patient education and managing treatment logistics should standardize linguistic interpretations and treatment plans across diverse providers. For maximum benefit, treatment information must be made user-friendly and be evenly accessible to patients and practitioners across platforms.

2. To address these needs, an AI-driven framework is proposed. The framework focuses on the creation of generative content models of treatment plans from the medical lexicon, as well as fine-tuning a patient-friendly translation engine using generative content that can learn the hospital's multiline and multimodal educational content. RPA systems are then programmed to pick and hand off the generated content and almost automatically populate and distribute it in IT admin systems. The solution is then modeled as an optimization and validated in a case study, resulting in substantial efficiency gains and increased patient attendance, underpinning the potential of generative AI frameworks to optimize complex healthcare ecosystems.

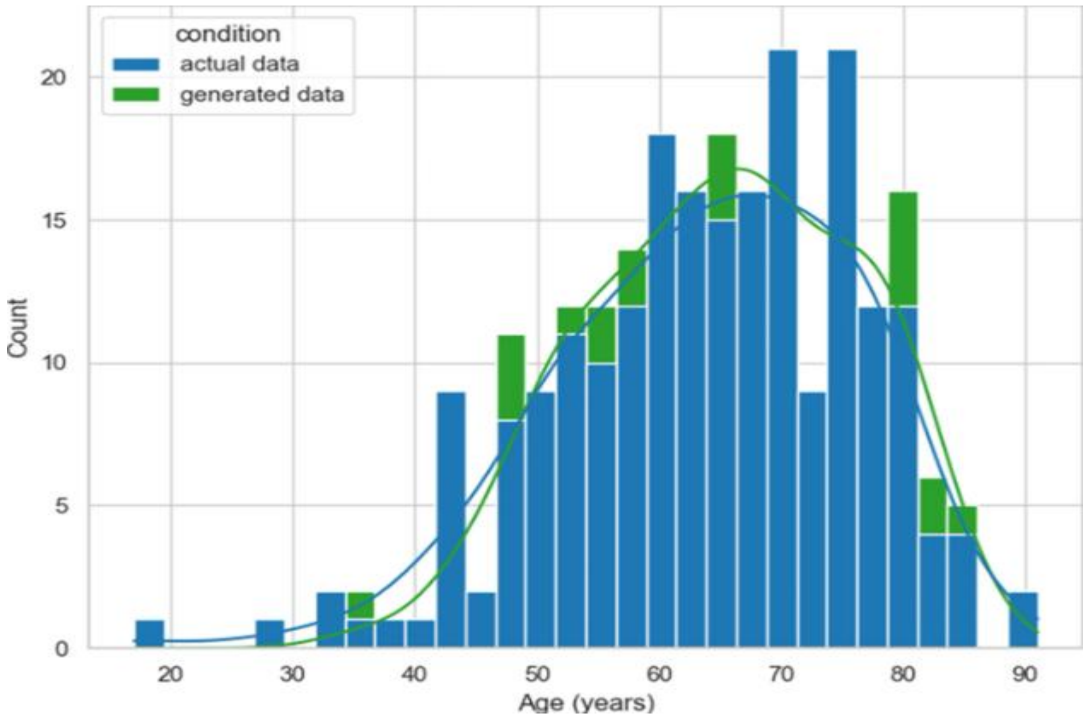

Fig : Utilizing an artificial intelligence framework

7.1. Summary of Findings

As AI-driven tools for mediating health-related information and data grow more ubiquitous, new and innovative frameworks are required to ensure that they can be accessed effectively. Ongoing works reckons the promise posed by a suite of AI-driven tools including the interface tool, comprehensive tool, interpretive tool, and interactive tool, advocating for procurement and research beyond clinical settings. Enough of these tools, an AI-driven semantic framework is proposed for helping patients find detailed, simple-to-understand assays at the point-of-care or near health facilities. The development of this framework is motivated by healthcare systems in which patients may be embraced by bewildering processes and systems. Towards endorsing concrete, unbiased, patient-oriented guidelines and micro- and macro-needling any procedure or clinical record, natural language publications and queries initiated by patients are evaluated semantically so that commensurate clarified sentences become viewable or hearable in an interface app or via telephone, potentially with translation.

Users imperfectly grasp healthcare systems both because they are inherently complex and because educational disaccord and prejudicial biases are present. Autologous healthcare delivery dialogs thought to be driven by machine learning are transcribed and evaluated to place constraints on AI interactions. New healthcare delivery dialogs primarily driven by machine learning are transcribed and evaluated using both a rare ML quality score and a semantic form score, which is relaxed if the dialog contains a proper query. Varied evaluative and corrective activities take place within a healthcare delivery dialog, much of which is kin-minded. Too little of the dialog occurring during healthcare delivery in general is understood by the layman end of dialogues because healthcare systems are complex. A demographic divide disproportionately favors the well-educated providence of the care. Another aspect of the divide is that many patients are biased and mistakenly believe that they are averse to understanding healthcare comprehensively. Court-based procedures can potentially reduce appropriate biasing and confused querying of complexities through the development of tools that help patients better understand inferred lists and potentially become more self-advocating.

7.2. Recommendations for Future Research

Health AI and digital health technologies are expanding in hospital settings and evolving to aid new potential health management roles. Considering individuals' increasingly integrated exposure to these technologies, it is vital to prepare future healthcare managers to interact effectively with these evolving tools. However, the professional literature lacks concrete insights relating to this timely necessity. As an initial exploration, patients' well-being was targeted through patient health record (PHR) context. The objectives were to design professional-learning activities based on an advanced AI-driven application for health managers, and to qualitatively evaluate their value for the emerging needs of health management students. It is an exploratory, adoptive educational research where a healthcare management academic course embedded with professional-learning activities was developed and conducted. The activities included a series of AI-driven data analysis tasks on a hospital database, conducted individually or in groups.

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