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PAPER

Applied Informatics in the Sphere of Medical Informatics Innovation: A Review Article

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ABSTRACT

This systematic review critically examines the pivotal role of applied informatics in advancing medical innovation, with a particular focus on the integration of artificial intelligence (AI) and machine learning (ML) technologies. By bringing together recent research, the study demonstrates how these computer tools can transform healthcare, particularly by enhancing the accuracy of illness diagnosis using advanced medical imaging and enabling real-time patient monitoring. New trends in the field indicate that deep learning (DL), the Internet of Things (IoT), and intelligent computer systems are being increasingly utilized, all contributing to enhanced patient care and the development of more effective healthcare systems based on data. The review also examines foundational enablers for sustainable innovation, including the standardization of medical data formats, interoperability across health information systems, and the implementation of robust cybersecurity protocols to safeguard patient privacy and ensure data integrity. While the integration of AI and ML is primarily perceived as beneficial within the healthcare domain, the review identifies several persistent challenges. These include issues of clinician trust in algorithmic decision-making, the need for ethically sound implementation practices, and the development of evolving regulatory frameworks to accommodate rapid technological change. Additionally, the application of ML and data mining in predicting outcomes and aiding clinical decisions shows enormous potential, which could transform how we approach preventive and personalized medicine.

KEYWORDS

applied informatics, medical informatics, medical informatics innovation, artificial intelligence (AI) for medical, machine learning for medical

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1 INTRODUCTION

1.1 Background on applied informatics in medical innovation

Recent advancements in the domain of medical informatics, particularly through the integration of machine learning (ML), artificial intelligence (AI), and big data, have substantially transformed the delivery of healthcare and enhanced patient outcomes. ML has significantly improved disease diagnosis, facilitated personalized medicine, and augmented operational efficiency, demonstrating accuracy comparable to that of human experts in areas such as cancer detection [1].

1.2 Current trends

Applied informatics trends in medical innovation demonstrate the use of advanced computer methods, particularly AI and ML, to enhance healthcare. These include using deep learning (DL) algorithms in medical imaging to find diseases early and make treatments more effective. The Internet of Things (IoT) offers real-time health monitoring and disease modeling, enabling more accurate clinical diagnoses through big data analytics. Computational intelligence (CI) is emerging as a trend that combines various AI methodologies to refine patient care [2–4]. This approach allows innovative information technologies to transform healthcare by increasing accessibility, reducing costs, personalizing treatment plans, and creating more efficient data-driven healthcare systems that prioritize patient outcomes and ethical standards [5–6].

Medical imaging for early disease detection. Technological advancements within the medical field, including MRI, X-ray, ultrasound, and CT scans, are pivotal in the early detection of diseases [9]. Early diagnosis is crucial for facilitating timely interventions before the progression of the disease, thereby enhancing patient outcomes and lowering healthcare costs [9]. Recent developments in AI and ML have significantly improved the efficacy of medical imaging, enabling more accurate and efficient analyses of images [10].

Artificial intelligence-powered medical imaging methods are capable of precisely identifying anomalies, segmenting pictures, and categorizing illnesses [10]. AI medical imaging helps detect tumors, heart conditions, and various types of cancer in their early stages, surpassing traditional diagnostic techniques in this aspect [10]. Utilizing DL models like convolutional neural networks (CNNs), which enhance the accuracy of disease identification, AI medical imaging is becoming a crucial tool in modern healthcare [11].

Real-time health and disease monitoring. To provide continuous health tracking and real-time health and illness monitoring, modern technology such as wearable sensors, IoT, and AI is quickly becoming an essential healthcare approach. These technologies facilitate early disease identification through real-time patient data analysis, enabling individualized healthcare interventions and improved patient well-being outcomes [12]. By utilizing predictive analysis and ML algorithms, health irregularities can be addressed by identifying them before they worsen [13]. Additionally, the growing use of mobile health tracking applications has transformed remote patient monitoring, greatly enhancing the quality of care for individuals with chronic conditions, such as diabetes and heart disease [14]. Despite its potential, data privacy, security, and interoperability issues remain significant barriers to the widespread adoption of real-time health monitoring systems.

Emerging trend: Computational intelligence. The unique discipline of computational intelligence, resulting from the merging of artificial intelligence, neural networks, fuzzy logic, and evolutionary computing, is a system that can learn and adapt on its own. Healthcare, cybersecurity, and banking are just a few examples of industries that can benefit from CI methodologies' ability to optimize decision-making, automate more processes, and deal with uncertainty [15]. More and more people are using and improving DL reinforcement learning, which makes pattern recognition and problem solving in unpredictable contexts more practical [16]. Developing hybrid systems incorporating various CI techniques has also improved accuracy and effectiveness in data-driven applications [17]. Research into computational complexity, ethical considerations, and the interpretability of AI models is ongoing, although CI is expanding rapidly.

1.3 The objectives and scope of the study

This systematic review seeks to examine the role of applied informatics within the field of medical informatics, with a particular emphasis on innovation and the integration of modern technologies. The objective of this study is to provide a comprehensive analysis of the impact of technological advancements have on patient outcomes, system efficacy, and healthcare decision-making processes. This review will consider technological perceptions within the medical informatics community, essential requirements for innovation in medical informatics, and the role of machine learning and data mining in optimizing healthcare systems.

By systematically reviewing relevant studies, this study contributes to and elucidates the current state of medical informatics while providing valuable insights for healthcare professionals, researchers, and policymakers.

1.4 Significance and future implications

The integration of informatics solutions, particularly AI and ML, into healthcare systems is increasingly recognized as essential for enhancing patient care and operational efficiency. Current literature highlights AI's potential to improve diagnostic accuracy, streamline treatment processes, and facilitate personalized medicine while also addressing challenges related to unstructured data and ethical concerns such as data privacy and algorithmic bias. Future research should focus on overcoming these barriers, exploring innovative applications, and developing comprehensive policies to ensure equitable access and effective implementation of informatics solutions in healthcare [7–8].

2 METHOD

2.1 Category of research

This study provides a comprehensive review focusing on applied informatics within the field of medical informatics and emphasizing innovation. The aim of this review is to identify trends, obstacles, and advancements in understanding modern technology, as well as the requirements for innovations and the integration of machine learning and data mining into medical informatics. This synthesis of existing literature achieves these objectives.

2.2 Research questions

The systematic review addresses the following research questions: The first question is, how do individuals in the field of medical computing respond to novel technologies? The second question is, what are the most significant advancements required for innovation in medical computing? Finally, the third question is, how do ML and data mining methodologies contribute to the enhancement of medical informatics?

2.3 PICO framework

The PICO framework is an essential instrument in health research, particularly in developing research questions or systematic reviews. It aids researchers in delineating problems with greater clarity and efficiency, particularly in clinical research and healthcare.

The PICO framework is an acronym that includes the following details: P (Patient/Problem/Population): Healthcare professionals, IT specialists, and patients. I (Intervention): Using informatics technologies, machine learning, and data mining. C (Comparison): Traditional or alternative methods to medical informatics. O (Outcome): Improved medical informatics innovation, decision-making, and system efficiency.

2.4 Search strategy

The search strategy will target high-quality academic and industry literature. The Iuliu Hațieganu University of Medicine and Pharmacy in Cluj-Napoca (UMF Cluj) database was primarily utilized as a key resource in this systematic review due to its well-established journal in Applied Medical Informatics. Other databases, such as IEEE Xplore and MU databases, were also used to gather a range of relevant studies. This study uses a combination of search parameters as detailed in Table 1.

Table 1. Domains of the research study and the search parameters

Domains	Search Parameters
• Perception of Modern Technology in Medical Informatics	(“Medical informatics” OR “Health IT” OR “Applied informatics”) AND (“Technology perception” OR “User acceptance” OR “Adoption of digital health”)
• Requirements for Driving Innovation in Medical Informatics	(“Medical informatics innovation” OR “Healthcare innovation” OR “Technology healthcare”) AND (“Challenges” OR “Technical barriers” OR “Policy requirements”) AND (“Digital transformation” OR “Health IT implementation”)
• Application of Machine Learning and Data Mining in Medical Informatics	(“Machine learning” OR “Data mining”) AND (“Predictive analytics” OR “AI-driven healthcare”) AND (“Medical big data” OR “Healthcare analytics” OR “Medical informatics”) AND “Applications”

2.5 Inclusion and exclusion criteria

Inclusion and exclusion criteria represent explicitly defined guidelines utilized to ascertain the suitability of particular works for incorporation into the research sample of the study. The objective is to obtain a relevant sample that aligns with the research question while minimizing variability in the data. The criteria for inclusion and exclusion are delineated in Table 2.

Table 2. The criteria for inclusion and exclusion

Domains	Details
Inclusion Criteria:	• The articles are published in peer-reviewed journals or conference proceedings. • The studies were published between 2020 and 2025. • There is a wealth of literature discussing perceptions of modern technology, innovation requirements, or machine learning in medical informatics. • Publications are available in both English and French.
Exclusion Criteria:	• Articles focused solely on non-healthcare domains. • Studies lacking empirical data or theoretical relevance to medical informatics. • Non-English and French publications and literature without credible sources.

2.6 Selection and screening process for research work

The selection and screening procedure employs a multi-stage methodology to guarantee the inclusion of pertinent and high-quality studies. Firstly, researchers implement an automated screening method using database search algorithms to eliminate duplicate entries and clearly irrelevant studies based on established exclusion criteria.

Two independent reviewers conduct title and abstract screening to exclude papers that do not conform to the research scope. Studies that advance to this phase undergo a comprehensive examination of the complete text, where eligibility is assessed based on relevance to the research topics, methodological rigor, and contribution to the field of medical informatics. Researchers utilize a dual-reviewer procedure to enhance reliability, ensuring that two independent reviewers evaluate each study. Any difficulties or conflicts are addressed through discussion or by consulting a third reviewer. This methodology aids in selecting the most relevant studies for the subsequent quality assessment phase.

In the data extraction phase, researchers manage the content through a standardized data extraction form designed to collect pertinent information. This information encompasses the following elements: author(s), publication year, publication types, study objectives, methodologies, sample size, key findings regarding technology perception, innovation requirements, machine learning algorithms, and the outcomes and limitations of the research.

2.7 Quality assessment

Researchers utilized the relevance and rigor matrix (RRM) as the primary quality assessment tool to ensure the inclusion of high-quality, methodologically sound studies. The RRM assesses each study based on five fundamental dimensions:

the first dimension is relevance to medical informatics; the second dimension is innovation and machine learning components; the third dimension is methodological rigor; the fourth dimension is data and empirical evidence; and the final dimension is impact and contribution. Table 3 provides a summary and definitions of RRM assessments.

Table 3. A summary and definitions of RRM assessments

Dimensions	Details
Relevance to Medical Informatics	This criterion evaluates the degree to which a study enhances the discipline of medical informatics. Studies that directly confront challenges, advancements, or applications within medical informatics are awarded higher scores, whereas those with indirect or peripheral relevance are assigned lower ratings.
Innovation and Machine Learning Components	Given the focus on applied informatics, this criterion evaluates the study's incorporation of innovative methodologies, emerging technologies, and machine learning techniques. Higher scores are assigned to research that explores novel frameworks, models, or algorithms with practical implications for medical informatics.
Methodological Rigor	This criterion evaluates the design, validity, and reliability of the study's findings. Well-structured research, featuring clearly defined methodologies, robust experimental designs, and reliable statistical analyses, is awarded higher scores. Conversely, studies characterized by poorly defined methodologies or deficient validation techniques are assigned lower ratings.
Data and Empirical Evidence	This criterion measures the quality, completeness, and reliability of the data presented in the study. Research that utilizes large, well-documented datasets with strong empirical support receives higher scores, while studies lacking empirical data or relying on anecdotal evidence are rated lower.
Impact and Contribution	The final criterion evaluates the overall significance of the study in advancing knowledge and practice in medical informatics. Studies that introduce groundbreaking concepts, influence policy or practice, or contribute substantially to academic discourse receive higher scores, while studies with minimal impact receive lower scores.

Each criterion is assessed on a five-point scale, resulting in a maximum total score of 25. Research studies were divided into three groups based on their RRM score: studies scoring below 13 were left out because they didn't have strong methods or weren't directly related to medical informatics; studies with scores between 13 and 18 were set aside for more discussion among reviewers; and studies scoring above 18 were included in the final results of the systematic review because they showed strong methods, clear relevance, and significant contributions to the field.

3 RESULTS

3.1 Inclusion and exclusion of works

This systematic review encompasses 81 research studies that correspond with the search strategies across the three databases. After a meticulous manual screening process adhering to predefined inclusion and exclusion criteria, 48 studies were chosen for subsequent quality evaluation, whereas 33 research studies were discarded. The rationale for the rejected research can be further examined in Figure 1.

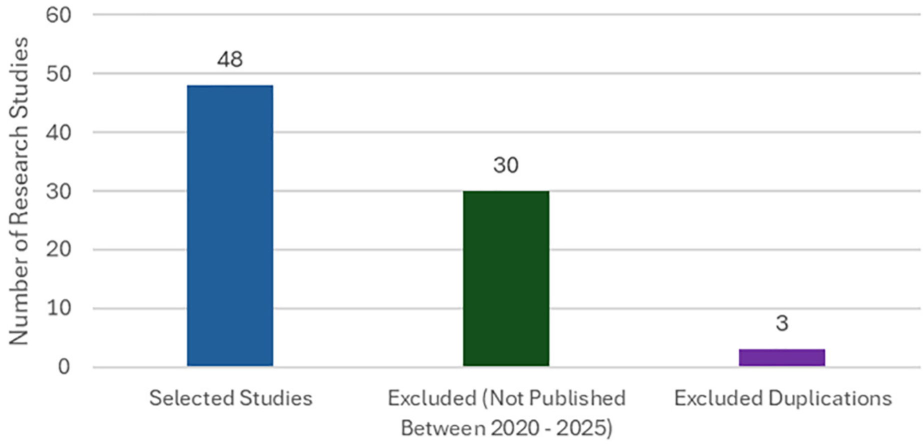

Fig. 1. Selection and exclusion of studies in the screening process

Out of the 33 studies, the initial 30 were excluded for not meeting the publication criteria from 2020 to 2025. The remaining three excluded studies were identified as duplicates from different databases. Consequently, the quality assessment process involved the remaining 48 studies, utilizing the relevance and rigor matrix.

3.2 Quality Assessment

Relevance and rigor matrix. The quality of the 48 studies selected for further review was evaluated using the RRM, which assesses methodological rigor and relevance to the research objectives, assigning a score between 0 and 5 for each topic. The assessment yielded three outcomes: studies scoring below 13 were excluded, those between 13 and 18 were flagged for further discussion, and those above 18 were included. Table 4 summarizes the RRM scores for all selected studies, detailing the distribution of included and excluded studies and studies for further discussion.

Table 4. Quality assessment of 48 studies using relevance and rigor matrix

Study ID	Relevance	Innovation & ML	Methodological Rigor	Data & Evidence	Impact & Contribution	Total Score	Decision
[18]	5	3	3	2	3	16	Discussion
[19]	5	5	4	4	4	22	Included
[20]	5	4	4	4	4	21	Included
[21]	5	5	4	4	4	22	Included
[22]	2	1	2	1	2	8	Excluded
[23]	4	4	3	3	3	17	Discussion
[24]	5	4	3	3	3	18	Discussion
[25]	3	4	3	3	3	16	Discussion
[26]	5	2	2	1	2	12	Excluded
[27]	3	3	4	4	4	18	Discussion
[28]	5	1	4	4	4	18	Discussion

(Continued)

Table 4. Quality assessment of 48 studies using relevance and rigor matrix *(Continued)*

Study ID	Relevance	Innovation & ML	Methodological Rigor	Data & Evidence	Impact & Contribution	Total Score	Decision
[29]	4	3	2	2	2	13	Discussion
[30]	4	2	2	1	2	11	Excluded
[31]	5	3	4	4	4	20	Included
[32]	5	2	3	2	3	15	Discussion
[33]	5	3	2	2	2	14	Discussion
[34]	5	5	3	3	3	19	Included
[35]	5	3	3	2	3	16	Discussion
[36]	4	5	5	3	5	22	Included
[37]	5	4	3	3	3	18	Discussion
[38]	5	5	4	4	4	22	Included
[39]	5	5	4	4	4	22	Included
[40]	5	2	2	2	2	13	Discussion
[41]	5	1	3	4	3	16	Discussion
[42]	3	2	4	4	4	17	Discussion
[43]	4	5	4	3	4	20	Included
[44]	5	1	4	4	4	18	Discussion
[45]	1	3	4	4	4	16	Discussion
[46]	4	4	3	3	3	17	Discussion
[47]	5	4	3	3	3	18	Discussion
[48]	5	2	2	1	2	12	Excluded
[49]	5	3	4	4	4	20	Included
[50]	5	1	4	4	4	18	Discussion
[51]	5	3	2	2	2	14	Discussion
[52]	5	2	2	1	2	12	Excluded
[53]	4	3	4	4	4	19	Included
[54]	5	2	3	2	3	15	Discussion
[55]	5	3	2	2	2	14	Discussion
[56]	5	5	3	3	3	19	Included
[57]	5	3	3	2	3	16	Discussion
[58]	5	5	5	3	5	23	Included
[59]	4	4	3	3	3	17	Discussion
[60]	5	5	4	4	4	22	Included
[61]	5	5	4	4	4	22	Included
[62]	5	2	2	2	2	13	Discussion
[63]	5	1	3	4	3	16	Discussion
[64]	5	2	4	4	4	19	Included
[65]	3	5	4	3	4	19	Included

As shown in Table 1, there is a range of scores, with 17 studies meeting the inclusion criteria, 26 requiring further discussion, and five studies being excluded. This structured assessment ensures that only methodologically sound and relevant studies contribute to the final review.

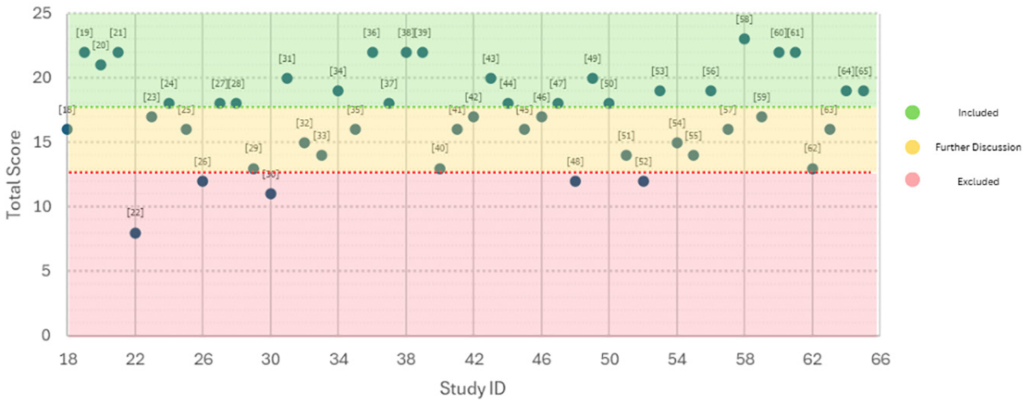

Fig. 2. Quality assessment of 48 studies using a relevance and rigor matrix

Studies are categorized into three groups based on their scores: Included (green), further discussion (yellow), and excluded (red/pink). The horizontal lines indicate the thresholds for each category; studies scoring above 18 are included, studies scoring between 13 and 18 are flagged for further discussion, and studies scoring below 13 are excluded (see Figure 2).

Final determination for discussion – Selected studies. Following the RRM assessment, researchers identified twenty-six studies for discussion due to their borderline scores. These studies underwent an additional qualitative evaluation based on their contributions to the research objectives, methodological robustness, and potential impact. Table 5 presents the final decisions for each study initially identified for discussion. We derived this final decision from further scrutiny, ensuring researchers preserved only the most pertinent and rigorous studies for the review.

Table 5. Final determination for discussion – Selected studies

Study ID	Title	Previous Total Score	Final Decision
[18]	A Comprehensive Review of Privacy and Security Techniques in Electronic Health Records (EHRs)	16	Included
[23]	An Innovation Pathway for Well-Being, Aging and Health: A Croatian Case Study	17	Excluded
[24]	Application of Machine Learning in Predicting Diabetes: A Detailed Evaluation Using Support Vector Machine Classifier	18	Included
[25]	Approaches and tools for teaching biomedical data science during the COVID-19 pandemic: A systematic literature review	16	Excluded
[27]	Clinical Decision Support Systems in Ophthalmology: A Systematic Search and a Narrative Review	18	Included
[28]	Contactless Palmprint Recognition System: A Survey	18	Included
[29]	Creating Medical Datasets using Robot Process Automation	13	Excluded

(Continued)

Table 5. Final determination for discussion – Selected studies *(Continued)*

Study ID	Title	Previous Total Score	Final Decision
[32]	Digital Technology Supporting Children's Speech Therapy	15	Excluded
[33]	Digital transformation in healthcare organizations: The role of innovation labs	14	Excluded
[35]	Digital transformation: How has telemedicine impacted UAE's healthcare sector during the Covid-19 pandemic?	16	Excluded
[37]	Enhancing Cybersecurity Education for the Healthcare Sector: Fostering Interdisciplinary ManagiDiTH Approach	18	Included
[40]	Information Technology Driven Innovations in Healthcare: Mapping the Research Trends by Co-Word Analysis	13	Excluded
[41]	Integrating Big Data, ML, and DL for Predictive Analytics in Healthcare: A Comprehensive Analysis and Hybrid Framework Proposal	16	Included
[42]	International Recommendations on Education in Biomedical and Health Informatics – An Overview	17	Included
[44]	Machine Learning Applied to the Field of Genomics	18	Included
[45]	Machine Learning Methods in Health Economics and Outcomes Research-The PALISADE Checklist: A Good Practices Report of an ISPOR Task Force	16	Excluded
[46]	Machine Learning Models for the Diagnosis of Parkinson using Audio Signals	17	Included
[47]	Natural Language Processing Techniques and FAIR Principles for Assisting Drug Prescription	18	Included
[50]	Optimizing the Specifications of a Fall Detection System	18	Included
[51]	Patients' Perceptions of Integrating AI into Healthcare: Systems Thinking Approach	14	Excluded
[54]	Secure Integration of IoT-Enabled Sensors and Technologies: Engineering Applications for Humanitarian Impact	15	Excluded
[55]	Self-Assessment of Computer Literacy Competence Among Medical Undergraduates	14	Excluded
[57]	Technical part of evaluation solution for cooperative vehicles within C-ROADS CZ project	16	Included
[59]	The Impact of Digitization of Intensive Care Services on Patient Safety in the Pius Brânzeu Emergency County Hospital in Timisoara	17	Included
[62]	Tuition of Project Management for Digital Health for Engineers.pdf	13	Excluded
[63]	Usability Evaluation of a Digital Teleradiology Case Study Using the.pdf	16	Excluded

After further qualitative evaluation, 13 studies were selected for inclusion in the final review. The selection process prioritized studies that closely aligned with medical informatics, demonstrated methodological rigor, incorporated innovation and machine learning, and provided empirical evidence with significant contributions. This refined selection ensures that the systematic review maintains high quality and relevance, leaving the final number of studies to include at 30.

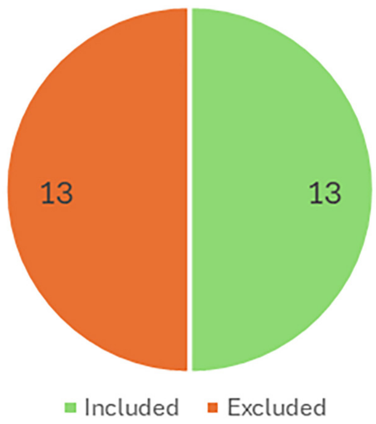

Fig. 3. Final determination for discussion - Selected studies

Figure 3 displays the final inclusion/exclusion decision for the 26 studies selected for further discussion after the initial quality assessment. Notably, an equal number of studies (13) were chosen as included and excluded in the final analysis, indicating a balanced outcome after the secondary review process.

3.3 Results and synthesis of findings

This section provides information and insights from the 30 selected studies, highlighting key trends, challenges, and emerging innovations in medical informatics. The results are organized around the research questions guiding this systematic review.

Perception of modern technology in medical informatics. The perception of contemporary technology in medical informatics is predominantly favorable, with several studies emphasizing its capacity to enhance efficiency, accuracy, and patient outcomes. Among the selected research, numerous studies can be classified into distinct categories as follows:

Studies discussing barriers to adoption include clinician trust, interoperability, and ethical concerns [18, 27, 41]. While AI-driven tools offer significant advancements, healthcare professionals remain cautious about their reliability and the lack of transparency in decision-making. In addition, studies suggest that acceptance varies depending on factors such as user experience, regulatory clarity, and institutional support [50, 59].

Finally, regulatory frameworks play a crucial role in shaping the integration of AI in healthcare, emphasizing the need for robust ethical guidelines to mitigate bias and ensure fair decision-making [37].

Critical requirements for innovation in medical informatics. For innovation to thrive in medical informatics, several foundational challenges must be addressed. One of the key concerns is the issue of data standardization and interoperability [42, 46]. Many healthcare institutions operate on fragmented systems, making seamless data sharing difficult. Without unified standards, most advanced AI models face limitations in real-world applications. However, as hybrid AI approaches combined with ML, traditional rule-based systems have shown promise in bridging gaps for predictive accuracy and reliability. Additionally, cybersecurity remains a pressing issue; with the increasing reliance on cloud-based medical records, stronger encryption methods and decentralized security models have been proposed to safeguard sensitive patient information [37, 41].

Application of machine learning and data mining. Data mining and ML are playing an increasingly significant role in transforming medical informatics [53, 60, 64]. A substantial focus has been placed on disease prediction and diagnostics, where advanced models such as support vector machines, CNNs, and natural language processing are utilized to enhance early detection and decision-making. For example, research highlights the successful application of ML in diabetes prediction, demonstrating improved accuracy over traditional diagnostic methods [24]. Decision support systems have also gained traction, as AI-driven recommendations assist clinicians in patient management by analyzing vast datasets for optimized treatment plans [27, 50]. Moreover, automation is reshaping hospital workflows, with robotic process automation and AI models streamlining administrative processes, reducing workload, and allowing medical professionals to focus more on patient care [28, 47].

4 DISCUSSION

This systematic review's findings underscore the evolving dynamics of medical informatics, emphasizing the crucial role of digital technologies, particularly AI, ML, and DL. Healthcare professionals typically view these technologies in medical informatics positively, recognizing their potential to enhance efficiency, decision-making, and patient outcomes. Challenges persist, particularly concerning interoperability, ethical considerations, and trust in AI-driven decision support systems. Numerous studies indicate the necessity for transparent AI models and standardized regulatory frameworks to facilitate adoption and reduce bias. Although some healthcare professionals support digital transformation, issues related to data security, algorithmic transparency, and the adaptability of legacy systems continue to be prevalent.

The review also underscores the fundamental requirements for driving innovation in medical informatics. Key barriers include fragmented data systems, regulatory constraints, and limited collaboration. Studies indicate that successful innovation requires a synergy between technological advancements and well-defined policies that support seamless integration and standardization. Furthermore, cybersecurity remains a pivotal concern, as increased reliance on digital health solutions amplifies the risks associated with data breaches and privacy violations. The adoption of blockchain, federated learning, and advanced encryption techniques has been proposed as a solution to enhance security and trust. These findings suggest that the future of medical informatics depends on balancing technological advancements with ethical and operational considerations to ensure widespread adoption and effectiveness.

The implementation of AI, ML, and DL within the domain of medical informatics has notably transformed healthcare analytics, decision support systems, and predictive modeling. This review identifies a burgeoning trend toward utilizing AI-driven models for disease prediction, automated diagnostics, and personalized treatment planning. Numerous studies illustrate the efficacy of machine learning in enhancing diagnostic accuracy for various conditions, including diabetes and neurological disorders. Furthermore, AI-powered automation has demonstrated significant potential in optimizing administrative workflows, alleviating clinician workload, and improving hospital efficiency. However, issues such as data bias, understanding how machine learning models work, and the need for large, high-quality datasets must be carefully tackled to utilize AI in medical informatics fully.

5 LIMITATIONS AND FUTURE DIRECTIONS

Despite the comprehensive approach taken in this systematic review, several limitations must be acknowledged. A key limitation is the reliance on a specific set of databases, including the UMF Cluj database, IEEE Xplore, and MU databases. While these sources are reputable, excluding other major databases may have limited the scope of studies reviewed.

Another limitation is the inherent challenge of synthesizing findings across diverse methodologies and study designs. Considering the interdisciplinary nature of medical informatics, variations in research focus, sample sizes, and technological applications may lead to inconsistencies in reported outcomes. The quality assessment using the Relevance and Rigor Matrix provided a structured evaluation; however, subjective elements in the scoring process could have influenced the final selection of studies. Additionally, while efforts were made to include both English and French publications, language barriers may have excluded valuable research published in other languages.

Finally, the dynamic nature of technological advancements poses a limitation regarding the review's longevity. Given the rapid evolution of AI, machine learning, and data mining in healthcare, new developments may emerge that challenge or expand upon the findings presented in this study. Future research should incorporate real-time updates and longitudinal analyses to capture ongoing advancements and their implications for medical informatics. Despite these limitations, this review provides a solid foundation for understanding the current landscape and guiding future innovation in the field.

6 CONCLUSION

This systematic review provides a comprehensive analysis of the perception of modern technology in medical informatics, the critical requirements for driving innovation, and the application of machine learning and data mining techniques. The findings indicate that while these technologies offer significant advancements, challenges related to data security, interoperability, and ethical concerns continue to hinder full-scale adoption. Addressing these challenges requires collaborative efforts among healthcare professionals, policymakers, and technology developers to establish standardized frameworks and transparent AI models that enhance trust and usability.

Innovation in medical informatics relies on overcoming key barriers such as fragmented healthcare systems, regulatory constraints, and cybersecurity threats. The review emphasizes the significance of integrating hybrid AI approaches, enhancing encryption techniques, and fostering interdisciplinary collaboration to drive sustainable advancements in the field. Furthermore, ensuring that healthcare professionals receive adequate training and resources to adapt to emerging technologies is crucial, as it is vital for successfully implementing digital health solutions.

The application of ML and data mining has shown significant potential in enhancing disease prediction, clinical decision support, and hospital workflows. However, challenges such as data quality, algorithmic bias, and interpretability need to be addressed to optimize AI-driven healthcare solutions. Future research should focus on creating AI models that are easy to understand, improving ways to share data, and conducting studies to assess how these technologies affect medical informatics over time. Ultimately, the ongoing progress of medical informatics will depend on finding a balance between new technology and essential ethical, legal, and practical issues to ensure healthcare innovation is fair and sustainable.

7 ACKNOWLEDGMENT

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