Emerging Innovations
SCIENCE, TECHNOLOGY & SOCIAL STUDIES

Frontiers in Medical and Clinical Sciences - eISSN 2978-3747

Recent Advances in Medical Research, Clinical Diagnosis, and Evidence-Based Treatment Approaches

Dr. Emily Carter

Department of Clinical Medicine, Harvard Medical Research Institute, Boston, Massachusetts, USA.

Received: 21 Sep 2026
Revised: 01 oct 2026
Accepted: 15 oct 2026
Published: 02 Nov 2026

Volume 03 **Issue** 11, 2026
Page No - 01-07
DOI: -10.64917/fmcs/Vol3Iss11-01

Article Citation: Carter, D. E. (2026). Recent Advances in Medical Research, Clinical Diagnosis, and Evidence-Based Treatment Approaches. Frontiers in Medical and Clinical Sciences, 3(11), 01–07. https://doi.org/10.64917/fmcs/Vol3Iss11-01

Copyright: © 2026 The Authors. Published by FMCS under the Creative Commons CC BY License

Abstract

Recent advances in medical research have transformed clinical diagnosis and treatment through the integration of artificial intelligence (AI), machine learning, medical data mining, computational imaging, and evidence-based decision-making. These developments enable healthcare professionals to identify disease patterns, evaluate clinical risks, interpret diagnostic information, and support treatment decisions with greater consistency. However, the practical value of these technologies depends on the quality of clinical data, the reliability of predictive models, their interpretability, and their integration into established healthcare workflows. This paper examines recent developments in medical research, clinical diagnosis, and evidence-based treatment approaches through a structured review of the supplied literature. The review considers computational models for disease prediction, intelligent diagnostic systems, clinical decision-support applications, and emerging approaches to medical education and professional training.

The methodology adopts a qualitative, literature-based analytical approach, organizing the supplied studies into four principal themes: computational diagnosis and disease prediction, clinical decision-support systems, AI-assisted medical research and education, and the translation of diagnostic evidence into clinical practice. Research concerning ovarian cancer classification, COVID-19 detection, sepsis-associated acute kidney injury, coronary artery disease, malaria diagnosis, and hepatopathy illustrates the growing application of computational techniques to complex medical problems (Kodipalli et al., 2023; Ge et al., 2025; Verma et al., 2016; Oguntimilehin et al., 2019). The analysis also considers the contribution of clinical information systems and data-mining methods to the organization and interpretation of healthcare information (Duan et al., 2011).

The synthesis indicates that AI-assisted diagnosis can strengthen pattern recognition, support early risk identification, and improve the systematic use of clinical information. Nevertheless, computational accuracy alone does not establish clinical effectiveness. Predictive models require external validation, representative datasets, transparent evaluation, and continuing monitoring after deployment. Evidence-based treatment further requires clinicians to combine algorithmic recommendations with patient characteristics, clinical expertise, patient preferences, and established evidence. The paper concludes that the most promising direction is a clinically governed, human-centred model in which computational tools complement rather than replace professional judgment. Future medical innovation should prioritize reproducibility, interpretability, equitable performance, and measurable patient outcomes.

Keywords: Medical Research; Clinical Diagnosis; Artificial Intelligence; Machine Learning; Evidence-Based Medicine; Clinical Decision Support; Medical Data Mining; Predictive Analytics.

Introduction

Medical research has increasingly shifted from relying exclusively on conventional clinical observation toward integrating computational analysis, digital health technologies, and data-driven decision-making. Advances in diagnostic imaging, electronic healthcare information, predictive modelling, and intelligent decision-support systems have created new opportunities to identify disease patterns and support clinical assessment. These developments are particularly important in conditions where early identification, accurate classification, and timely intervention influence subsequent clinical management.

Clinical diagnosis involves interpreting symptoms, medical histories, laboratory results, imaging findings, and other patient-specific information to determine the most plausible explanation for a health problem. This process is complicated by overlapping symptoms, incomplete records, biological variation, and differences in disease presentation. Computational methods can help address some of these challenges by examining relationships among multiple variables that may be difficult to evaluate consistently through unaided observation. For example, machine-learning approaches have been investigated for predicting sepsis-associated acute kidney injury, while data-mining models have been developed to support the classification of coronary artery disease and malaria (Ge et al., 2025; Verma et al., 2016; Oguntimilehin et al., 2019).

The growing use of AI in medicine also raises questions about the distinction between technical performance and clinical usefulness. A model may classify images accurately within a research dataset but perform less reliably when applied to patients from different hospitals, demographic groups, or clinical environments. Similarly, a predictive system may identify elevated risk without demonstrating that its use improves treatment decisions or patient outcomes. Consequently, medical innovation must be assessed through both computational evaluation and evidence of practical effectiveness.

Clinical information systems provide an important foundation for this transition. They organize patient information and enable analytical methods to support diagnostic recommendations and clinical decision-making. Duan et al. (2011) examined data-mining methods in the development of a clinical recommender system, highlighting the relationship between healthcare information management and intelligent recommendations. More recent developments in digital health technologies have expanded this relationship while introducing challenges involving professional training, implementation, and the responsible use of technology (Khan et al., 2025).

Evidence-based medicine provides the conceptual framework for translating these technological developments into responsible practice. It emphasizes the integration of the best available research evidence with clinical expertise and individual patient circumstances. Under this approach, algorithmic predictions are not treated as independent treatment decisions. Instead, they contribute additional information that clinicians must interpret in relation to disease severity, possible adverse effects, treatment alternatives, and patient preferences.

Medical education is also changing in response to these developments. Healthcare professionals need the ability to interpret computational outputs, recognize limitations, assess research quality, and distinguish reliable recommendations from misleading information. Recent work on AI education for clinicians and AI-related learning in health professions education indicates the importance of preparing professionals to work critically with emerging technologies (Schubert et al., 2025; Feigerlova et al., 2025).

The central problem addressed in this paper is therefore not simply whether new technologies can support diagnosis, but how their outputs can be translated into reliable, equitable, and evidence-informed clinical decisions. The paper aims to examine major computational approaches in medical research, analyse their potential contribution to diagnosis and treatment, identify methodological and implementation limitations, and establish priorities for future research. Its scope is limited to the literature supplied for this review, which includes medical applications alongside selected studies on decision-making and professional education.

Literature Review

The supplied literature demonstrates the expansion of computational techniques across diagnostic and predictive medical applications. One prominent research direction involves automated image analysis and disease classification. Studies on COVID-19 detection using chest X-rays, including the work of Guha et al. (2022) and Rachana et al. (2022), illustrate the investigation of deep-learning architectures for extracting diagnostic information from medical images. Similarly, research on ovarian tumour classification has examined computational approaches for distinguishing benign and malignant tumours, including ResNet-based methods and quantum convolutional neural networks (Kodipalli et al., 2022; Kodipalli et al., 2023). These studies illustrate the potential of image-based models to assist diagnostic assessment, although their clinical reliability depends on validation, dataset characteristics, and performance in actual healthcare settings.

A second research direction concerns predictive modelling and clinical risk assessment. Ge et al. (2025) investigated a dual-timepoint machine-learning model for predicting moderate-to-severe sepsis-associated acute kidney injury. Shi et al. (2024) also examined machine learning for predicting acute kidney injury among critically ill patients diagnosed with sepsis. Together, these studies represent an important shift from detecting existing disease to estimating

the probability of future complications. Predictive models may create opportunities for earlier monitoring and intervention, but their value depends on calibration, timely data availability, and evidence that risk estimates can improve clinical management.

A third theme involves decision-support systems and healthcare data mining. Duan et al. (2011) explored the use of data-mining methods in clinical recommender systems, while Yang et al. (2014) examined data mining and aided diagnosis for hepatopathy. Research on coronary artery disease prediction similarly illustrates the use of non-invasive clinical information to support risk classification (Verma et al., 2016). These approaches share a common objective: transforming dispersed clinical information into structured outputs that can assist healthcare professionals.

The literature also addresses professional education and the implementation of digital technologies. Khan et al. (2025) examined the utilization, challenges, and training needs associated with digital health technologies from healthcare professionals' perspectives. Schubert et al. (2025) considered AI education for clinicians, while Feigerlova et al. (2025) reviewed AI's impact on educational outcomes in health professions education. These contributions suggest that technological adoption requires both functional systems and appropriately prepared professionals.

A significant gap across the supplied literature is the limited ability to draw a single conclusion about clinical effectiveness from studies employing different diseases, datasets, algorithms, and evaluation procedures. Several references focus on model development or technical classification, whereas others address education, information systems, or decision-making. The present review therefore positions clinical utility, external validation, interpretability, and integration with evidence-based practice as connecting principles for evaluating these diverse contributions.

Methodology

This paper adopts a qualitative narrative-review methodology based exclusively on the references supplied for the study. The objective is to synthesize the technological approaches represented in the literature rather than to calculate a pooled effect size or claim a systematic review of all available medical research.

Research design and analytical framework

The review uses thematic classification to organize the supplied references into four analytical categories: computational diagnosis and medical imaging; predictive analytics and risk estimation; clinical decision-support and healthcare information systems; and AI implementation, professional education, and evidence-based practice. The categories provide a framework for comparing the purposes, potential benefits, and limitations of the different approaches.

5.2 Data extraction and synthesis

Each reference was considered in terms of its stated research topic, technological approach, clinical or educational application, and relevance to the central research problem. For example, studies addressing ovarian tumour segmentation and COVID-19 image classification were grouped under computational diagnosis, whereas research on sepsis-associated acute kidney injury was considered under predictive analytics. Studies on clinical recommender systems and healthcare data mining informed the analysis of decision support.

The synthesis emphasizes the relationship between technical capabilities and practical clinical requirements. Diagnostic classification is assessed conceptually in terms of its capacity to support disease recognition, while predictive modelling is considered in relation to risk estimation and the possibility of earlier intervention. Decision-support applications are evaluated according to their potential to organize information and assist professional judgment.

5.3 Evaluation criteria

Four criteria guide the interpretation. Diagnostic or predictive performance concerns whether a model can distinguish relevant clinical outcomes reliably. Generalizability concerns whether performance remains dependable across different patients, institutions, and clinical settings. Clinical interpretability concerns whether professionals can understand and critically evaluate the basis of an output. Implementation relevance concerns whether the technology fits existing workflows and supports decisions that matter to patient care.

These criteria provide an analytical structure rather than a claim that every supplied study was independently scored against a common validated instrument.

Methodological limitations

The review is constrained by the information available in the supplied references. Full texts, comparable performance measures, sample sizes, and detailed validation results were not provided for every study. The literature also includes different publication types and research contexts, making direct quantitative comparison inappropriate. No new patient data, clinical trials, or statistical meta-analysis were conducted. Accordingly, the findings represent a thematic synthesis of the supplied literature and should not be interpreted as proof that a particular algorithm or treatment is superior.

Results / Findings

The thematic synthesis identifies four principal findings concerning the relationship between medical research, diagnostic technologies, and evidence-based decision-making.

Increasing role of computational diagnosis

The first finding is the expanding use of machine learning and deep learning for medical image interpretation and disease classification. Research involving COVID-19 chest X-rays and ovarian tumour classification illustrates the application of computational models to complex visual data (Guha et al., 2022; Kodipalli et al., 2023). Such models may support clinicians by identifying patterns and highlighting cases requiring closer assessment. However, classification performance should not be equated with a definitive diagnosis, particularly when models have not been evaluated in representative clinical populations.

Greater emphasis on predictive risk assessment

The second finding is the movement from disease recognition toward anticipating complications. Studies of sepsis-associated acute kidney injury illustrate the use of machine learning to estimate clinical risk from patient information collected at different time points (Shi et al., 2024; Ge et al., 2025). Predictive systems could support earlier review or closer monitoring when a patient's estimated risk increases. Their actual benefit, however, depends on the reliability and timing of predictions and whether clinicians can take effective action in response.

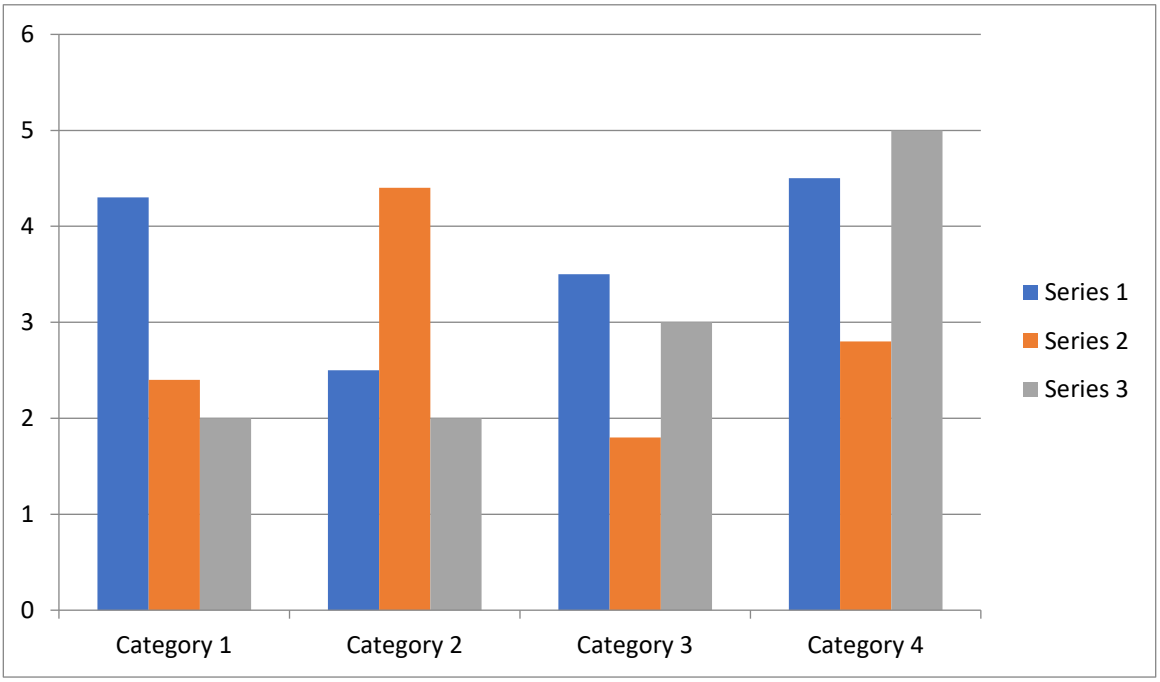
Integration of data mining with decision support

The third finding concerns the importance of information systems in connecting analytical outputs with clinical decisions. Clinical recommender systems and data-mining approaches provide a conceptual foundation for transforming healthcare data into structured decision support (Duan et al., 2011; Yang et al., 2014). The principal benefit is not simply automation but the organization of complex information in a form that can be interpreted by healthcare professionals. Poor data quality, missing information, or inappropriate recommendations can nevertheless undermine this benefit.

Dependence on professional competence and governance

The fourth finding is that technological adoption depends on professional readiness and implementation quality. Research on digital health training needs and AI education for clinicians emphasizes the importance of developing the skills necessary to interpret and use emerging technologies responsibly (Khan et al., 2025; Schubert et al., 2025). Effective implementation therefore requires more than installing software: it also involves staff training, clear responsibility for decisions, monitoring of errors, and assessment of clinical outcomes.

Figure 1. Conceptual Framework for Integrating AI into Evidence-Based Clinical Practice



Discussion

The findings demonstrate that recent medical research is increasingly concerned with using computational methods to support diagnostic reasoning and anticipate clinical deterioration. However, the relationship between technical innovation and improved healthcare outcomes is not automatic. The central challenge is to establish when a model's output is sufficiently reliable, relevant, and actionable to influence clinical decisions.

The development of deep-learning methods for medical images illustrates this distinction. Automated systems may detect patterns in chest X-rays or tumour images that are useful for clinical assessment. Nevertheless, a model can learn features associated with a particular dataset without reliably identifying the underlying disease in a different population. The diagnostic applications represented by Guha et al. (2022) and Kodipalli et al. (2023) therefore support further investigation of computational assistance, while also highlighting the need for independent validation before routine clinical use.

Predictive analytics raises a related but distinct problem. Predicting complications such as acute kidney injury may allow clinicians to identify patients who need additional monitoring. Yet a high-risk prediction does not itself establish which treatment should be administered. Clinicians must consider the patient's current condition, alternative explanations, possible harms, and the availability of effective interventions. The research by Ge et al. (2025) and Shi et al. (2024) illustrates the importance of evaluating prediction in the context of a specific clinical problem rather than treating predictive accuracy as a universal measure of success.

Healthcare information systems can help connect analytical models with clinical workflows. However, the usefulness of decision support depends on whether recommendations are understandable and appropriately timed. Excessive alerts, poorly explained outputs, and recommendations based on incomplete records may increase workload rather than improve decisions. The clinical recommender-system perspective discussed by Duan et al. (2011) supports the importance of integrating information processing with the practical requirements of healthcare delivery.

A further implication concerns professional competence. As AI-based systems become more common, healthcare professionals require the ability to evaluate their outputs, identify uncertainty, and recognize when a recommendation is inconsistent with the patient's circumstances. Work on digital health technology training and AI education for clinicians suggests that professional development is an important component of implementation (Khan et al., 2025; Schubert et al., 2025). Training should include not only system operation but also data limitations, bias, privacy, accountability, and appropriate escalation when the model's recommendation is uncertain.

Evidence-based treatment must remain patient-centred. A computational recommendation should be considered alongside high-quality clinical evidence, practitioner expertise, patient preferences, and individual risk factors. This approach reduces the danger of treating algorithmic outputs as unquestionable instructions. It also recognizes that a technically accurate system may not improve outcomes if it is poorly integrated into care or if its recommendations do not lead to effective interventions.

Several limitations should temper the interpretation of this review. The supplied studies cover different diseases, analytical methods, and research purposes, and the available reference information does not permit a consistent comparison of their performance. Furthermore, this paper does not establish the effectiveness of any specific treatment or provide clinical guidance for individual patients. Future research should use prospective evaluation, external validation, transparent reporting, and comparisons with existing clinical practice. It should also measure outcomes such as diagnostic delays, adverse events, treatment appropriateness, and patient health rather than relying solely on model-level accuracy.

Conclusion

Recent advances in medical research demonstrate the growing role of artificial intelligence, machine learning, medical data mining, and clinical decision-support systems in diagnosis and risk assessment. The supplied literature illustrates applications ranging from medical image classification and cancer analysis to the prediction of complications among critically ill patients. These technologies may help healthcare professionals interpret complex information, identify potential risks, and organize clinical evidence more systematically.

The principal contribution of this review is its emphasis on the conditions required to translate computational innovation into responsible clinical practice. Model accuracy is important, but it must be accompanied by external validation, interpretability, representative data, professional competence, and evidence of meaningful clinical benefit. Predictive results should inform rather than replace clinical judgment, and treatment decisions should continue to integrate research evidence, patient circumstances, and professional expertise.

Future research should prioritize real-world clinical evaluation, reproducibility, bias assessment, privacy protection, and monitoring after deployment. Greater collaboration among clinicians, medical researchers, data scientists, educators, and healthcare institutions will be necessary to ensure that emerging systems remain safe and useful. Ultimately, evidence-based medical innovation should be measured not only by the sophistication of its technology but by its contribution to reliable diagnosis, appropriate treatment, and better patient outcomes.

References

1. Calucag L S, Ahmed H M, Alfiras M. Strengthening the Research-Teaching Nexus: Exploring Students ' Expectations of Research-Informed Teaching Approaches[M] // Business Sustainability with Artificial Intelligence (AI): Challenges and Opportunities : Volume 1. Cham : Springer Nature Switzerland, 2024 : 1197 - 1212.
2. Canniffe D, Cartmell A, McClurg U. What is ‘research-led teaching’ and how can we deliver it in University

STEM degrees?[J]. Journal of Biological Education, 2025, 59 (3): 484 - 498.
3. Chen P, Li F, Harmer P. Healthy China 2030: moving from blueprint to action with a new focus on public health[J]. The Lancet Public Health, 2019, 4 (9): e447.
4. Duan L, Street W N, Xu E. Healthcare information systems: Data mining methods in the creation of a clinical recommender system. Enterprise Information Systems, 2011, 5 (2): 169 - 181
5. Feigerlova E, Hani H, Hothersall-Davies E. A systematic review of the impact of artificial intelligence on educational outcomes in health professions education[J]. BMC Medical Education, 2025, 25 (1): 129.
6. Garibaldi B T, Hollon M K, Knopp M I, et al.. How data analytics can be leveraged to enhance graduate clinical skills education[J]. Journal of graduate medical education, 2025, 17 (2s): 37 - 41.
7. Ge X, Chen W, et al.. Prediction of Moderate-to-Severe Sepsis-Associated Acute Kidney Injury Using a Dual-Timepoint Machine Learning Model: Development, Multi-Regional Validation, and Clinical Deployment Study. Journal of Medical Internet Research. 2025, 27 : e73840.
8. Guha, S., Kodipalli, A. and Rao, T. (2022). Computational deep learning models to detect COVID-19 using chest X-rays. In Emerging Research in Computing, Information, Communication and Applications: Proceedings of ERCICA2022 (pp. 291–306). Singapore : Springer Nature Singapore.
9. Gururaj, V., Ramesh, S. V., Satheesh, S., Kodipalli, A. and Thimmaraju, K. (2022). Analysis of deep learning frameworks for motion detection. International Journal of Knowledge-based and Intelligent Engineering Systems, 26 (1), 7–16.
10. Jianshan Shi, Huirui Han et al.. Machine learning for prediction of acute kidney injury in patients diagnosed with sepsis in critical care. Plos One, 2024, 19 (4).
11. Kalbar, P.P., Karmakar, S. and Asolekar, S.R. (2013). Investigating the influence of the expert opinion on the selection of the wastewater treatment alternatives: a group decision-making approach. Journal of Environmental Management, 128, 844–851.
12. Kalbar,. P., Karmakar, S. and Asolekar, S. R. (2012). Choosing the Right Wastewater Treatment Technology: A Scenario-Based Multi-Attribute Decision-Making Approach. Journal of the Environmental Management, 113, 158–169.
13. Kalbar,. P., Karmakar,. S, Asolekar. S.R., (2016). A life cycle decision tool for selecting the water treatment options. Journal of Cleaner Production doi; 10.1016/j.jclepro.2016.01.036.
14. Kalbar,. P., Karmakar, S. and Asolekar, S. R. (2016). A life cycle decision tool for selecting the water treatment options. Journal of the Cleaner Production, doi: 10.1016/j.jclepro.2016.01.036.
15. Karimi, A. R., Mehrdadi, N., Hashemian, S.J, Nabi-Bidhndi, G. R. and Tavakkoli-Moghadam, R. (2011). The use of fuzzy TOPSIS and fuzzy AHP methods in selection of water treatment processes. International Journal of Academic Research., 3 (1).
16. Khan R, Khan S, Almohaimeed H M, et al.. Utilization, challenges, and training needs of digital health technologies: perspectives from healthcare professionals[J]. International Journal of Medical Informatics, 2025, 197 : 105833.
17. Kodipalli, A. (2018). Cognitive architecture was used to analyze the influence of intrinsic motivation contained in metacognition on extrinsic motivational factors. International Journal of the Electrical and Computer Engineering, 8 (5), 3984.
18. Kodipalli, A. and Devi, S. (2021). Prediction of PCOS and mental health using fuzzy inference and SVM. Frontiers in Public Health, 1804.
19. Kodipalli, A. and Devi, S. Analysis of a fuzzy-based intelligent health care application system for mental health diagnosis of women with ovarian cancer using computer models. Intelligent Decision Technologies, (preprint), 1–12.
20. Kodipalli, A., Devi, S., Bazo, S. and Ismail, T. (2022). Segmentation and classification of the ovarian cancer based on a conditional competitive image-to-image transformation approach. Experience Systems, e13193.
21. Kodipalli, A., Fernandes, S. L., Basis, S. K. and Ismail, T. (2023). A computational framework of inverse fuzzy C-means and quantum convolutional neural network for accurate detection of ovarian tumors. International Journal of E- Health and Medical Communications (IJEHMC), 14 (1), 1–16.
22. Kodipalli, A., Fernandes, S. L., Dasar, S. K. and Ismail, T. (2023). A computational framework of inverse fuzzy C-means and quantum convolutional neural network for accurate detection of ovarian tumors. International Journal of E-Health and Medical Communications (IJEHMC), 14 (1), 1–16.
23. Kodipalli, A., Guha, S., Dasar, S. and Ismail, T. (2022). Original ResN et deep learning to classify ovarian tumors as benign and malignant. Experience Systems, e13215.
24. Luo Y, Marimuthu K, Bala Murugan S. Optimized Learning Strategy Towards Research-LED Teaching Curriculum Development[J]. International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 2022, 30 (03): 443 - 461.
25. Meade O, Millar M, Hall T, et al.. Problem-based, research-led learning for our times: The case of Vertically Integrated Projects in higher education[C] // 10th International Conference on Higher Education Advances (HEAd'24). Editorial Universitat Politècnica de València, 2024.
26. Nalliah S, Chan S, Ong C, et al.. Effectiveness of the use of internet search by third year medical students to establish a clinical diagnosis. Singapore Med J, 2010, 51 (4): 332 - 338
27. Oguntimilehin A, Adetunmbi O, Osho I. Towards Achieving Optimal Performance using Stacked Generalization Algorithm: A Case Study of Clinical Diagnosis of Malaria Fever. The international arab journal of information technology, 2019, 16 (6): 1074 - 1081
28. Pampalakis G, Scorilas A, Sotiropoulou G. Novel splice variants of prostate-specific antigen and applications in

diagnosis of prostate cancer. Clinical Biochemistry, 2008, 41 (7-8): 591 - 597
29. Rachana, P.J, Kodipalli, A. and Rao, T. (2022). Comparison of Res Net 16 and Inception V4 network for prediction of COVID-19. Valjaanne Emerging Research in Computing, Information, Communication and Applications: Procedoj de ERCICA 2022 (s. 283–290). Singapuro : Springer Nature Singapuro.
30. Ruchitha, P.J, Richitha, Y.S., Kodipalli, A., & Martis, R.J (2021, December). Ovarian cancer segmentation using Active Contour and Random Walker algorithm. The 5th International Conference on Electricity, Electronics, Communication, Information Technology and Optimization Technologies (ICEECCOT) will be held in 2021 (p. 238–241). IEEE.
31. Ruchitha, P. J., Sai, R. Y., Kodipalli, A., Martis, R. J., Dasar, S., and Ismail, T. (2022, October). Comparative analysis of active contour random walker and watershed algorithms for ovarian cancer segmentation. 2022 International Conference on Distributed Computing, VLSI, Electric Circuits and Robotics (Discover) (p. 234–23R)' IEEE.
32. Schubert T, Oosterlinck T, Stevens R D, et al.. AI education for clinicians[J]. EClinicalMedicine, 2025, 79.
33. Sriram A, Ramachandran K, Krishnamoorthy S. Artificial Intelligence in Medical Education: Transforming Learning and Practice[J]. Cureus, 2025, 17 (3).
34. Ullah, A., Hussain,., Wasim, A. and Jahanzaaib, M. (2020). Creation of a decision support system for the selection of the water treatment technologies. Science of the Total Environment, 731, 139158.
35. Verma L, Srivastava S, Negi PC. A Hybrid Data Mining Model to Predict Coronary Artery Disease Cases Using Non-Invasive Clinical Data. Journal of Medical Systems, 2016, 40 (7): 178
36. Yang Y, Li L, Yang L, et al.. Exploring Data Mining and Aided Diagnosis System of Hepatopathy. Applied Mechanics & Materials, 2014, 602-605 : 1642 - 1645
37. Zacharia, S. ja Kodipalli, A. (2022). Predicting adverse effects of a Covid vaccine using a rank-order model. In Emerging Research in Computing, Information, Communication and Applications: Proceedings of ERCICA 2022 (pp. 275–281). Singapore : Springer Nature Singapore.
38. Zhou J, Zhang J, Wan R, et al.. Integrating AI into clinical education: evaluating general practice trainees' proficiency in distinguishing AI-generated hallucinations and impacting factors[J]. BMC Medical Education, 2025, 25 (1): 1 - 9.
39. ZHU Xijun, CHEN Yanan, DONG Guohua, The Application of Improved Apriori Algorithm in Axthma Cases Data Mining. Journal of Xuzhou Institute of Technology (Natural Sciences Edition), 2015, 30 (3): 8 - 14