International Journal of Innovative Technologies in Social Science

e-ISSN: 2544-9435

Operating Publisher
SciFormat Publishing Inc.
ISNI: 0000 0005 1449 8214

2734 17 Avenue SW,
Calgary, Alberta, T3E0A7,
Canada
+15878858911
editorial-office@sciformat.ca

ARTICLE TITLE	ARTIFICIAL INTELLIGENCE IN ORTHOPEDIC FRACTURE DETECTION: DIAGNOSTIC ACCURACY, CLINICAL IMPACT AND FUTURE PERSPECTIVES – A LITERATURE REVIEW
DOI	https://doi.org/10.31435/ijitss.1(49).2026.5341
RECEIVED	23 January 2026
ACCEPTED	25 March 2026
PUBLISHED	30 March 2026
LICENSE	The article is licensed under a **Creative Commons Attribution 4.0 International License.**

ARTIFICIAL INTELLIGENCE IN ORTHOPEDIC FRACTURE DETECTION: DIAGNOSTIC ACCURACY, CLINICAL IMPACT AND FUTURE PERSPECTIVES – A LITERATURE REVIEW

Antoni Hajdas *(Corresponding Author, Email: antek.hajdas0@gmail.com)*
Ludwik Rydygier Hospital in Krakow, Kraków, Poland
ORCID ID: 0009-0005-1836-6312

Karolina Halat
Ludwik Rydygier Hospital in Krakow, Kraków, Poland
ORCID ID: 0009-0001-2242-5814

Gabriela Daniel
Divine Mercy District Hospital, Limanowa, Poland
ORCID ID: 0009-0007-5590-8736

Natalia Kaczmarczyk
The University Hospital (SU) in Krakow, Kraków, Poland
ORCID ID: 0009-0000-4386-4333

Justyna Chudy
Beskidzkie Centrum Onkologii, Municipal Hospital of John Paul II in Bielsko-Biała, Bielsko-Biała, Poland
ORCID ID: 0009-0006-8824-7260

Łukasz Ćmok
Beskidzkie Centrum Onkologii, Municipal Hospital of John Paul II in Bielsko-Biała, Bielsko-Biała, Poland
ORCID ID: 0009-0009-3414-4743

Julia Dobrowolska
St. Barbara Provincial Specialist Hospital No. 5, Sosnowiec, Poland
ORCID ID: 0009-0007-9647-2174

Jakub Robert Skalski
Gabriel Narutowicz Municipal Specialist Hospital, Kraków, Poland
ORCID ID: 0009-0006-5954-096X

Iga Kałka
Stefan Żeromski Specialist Hospital, Kraków, Poland
ORCID ID: 0009-0008-1527-4983

Julia Szmuc
Stefan Żeromski Specialist Hospital, Kraków, Poland
ORCID ID: 0009-0005-4403-3044

ABSTRACT

Objective: Artificial intelligence (AI) has emerged as a transformative technology in medical imaging, particularly in orthopedic fracture detection. Accurate and timely diagnosis of fractures is essential for effective treatment and prevention of complications, yet conventional radiographic interpretation remains prone to errors due to increasing workload and variability in clinician experience. The aim of this study was to evaluate the diagnostic performance of AI systems in fracture detection and to analyze their clinical, organizational, and socio-technological implications.
Methods: A narrative literature review was conducted using PubMed, Scopus, and Embase databases, including studies published between 2017 and 2025. The analysis focused on studies reporting quantitative diagnostic performance metrics and real-world applications of AI in orthopedic imaging.
Results: The results indicate that AI systems, particularly deep learning models based on convolutional neural networks, achieve high diagnostic accuracy, with sensitivity and specificity frequently exceeding 90% and reaching up to 95–98% in selected applications. AI-assisted diagnostic approaches have been shown to improve fracture detection rates, reduce interpretation time, and support less experienced clinicians. Additionally, AI demonstrates significant potential to optimize clinical workflows and enhance healthcare system efficiency.
Conclusions: However, several limitations remain, including issues related to dataset bias, limited generalizability, lack of interpretability, and regulatory challenges. The implementation of AI in healthcare also raises important ethical and social considerations, particularly regarding data privacy, accountability, and equitable access to technology. In conclusion, artificial intelligence represents a powerful complementary tool that can enhance diagnostic accuracy and transform healthcare delivery. Its successful integration requires careful consideration of clinical, technological, and socio-organizational factors.

KEYWORDS

Artificial Intelligence, Fracture Detection, Orthopedic Imaging, Deep Learning, Radiology, Diagnostic Accuracy, Clinical Decision Support, Healthcare Systems

CITATION

Antoni Hajdas, Karolina Halat, Gabriela Daniel, Natalia Kaczmarczyk, Justyna Chudy, Łukasz Ćmok, Julia Dobrowolska, Jakub Robert Skalski, Iga Kałka, Julia Szmuc. (2026) Artificial Intelligence in Orthopedic Fracture Detection: Diagnostic Accuracy, Clinical Impact and Future Perspectives – A Literature Review. *International Journal of Innovative Technologies in Social Science*. 1(49). doi: 10.31435/ijitss.1(49).2026.5341

1. Introduction

Musculoskeletal injuries represent a major global public health concern and are among the leading causes of disability worldwide. Fractures, in particular, constitute a substantial proportion of trauma-related conditions and are a frequent reason for emergency department visits. Epidemiological data indicate that millions of fractures occur annually, placing significant pressure on healthcare systems, especially in aging populations where the incidence of osteoporosis-related fractures continues to rise (Court-Brown et al., 2017).

Accurate and timely diagnosis of fractures is essential for appropriate clinical management and prevention of complications. Delayed or missed diagnoses may result in improper treatment, prolonged recovery, chronic pain, and long-term functional impairment. In severe cases, diagnostic errors can contribute to increased morbidity and healthcare costs. Radiography remains the primary imaging modality for fracture detection due to its accessibility, speed, and relatively low cost (Koval & Zuckerman, 2017). However, despite its widespread use, the interpretation of radiographic images remains a complex and error-prone process.

Diagnostic accuracy in radiology is influenced by multiple factors, including clinician experience, workload, and environmental conditions. In high-demand clinical settings, such as emergency departments, clinicians are often required to interpret large volumes of imaging studies within limited time frames. This situation increases the risk of diagnostic errors, particularly in cases involving subtle, non-displaced, or anatomically complex fractures (Berbaum et al., 2018). Studies have consistently shown that missed fractures are among the most common diagnostic errors in medical imaging.

The increasing demand for diagnostic imaging further exacerbates these challenges. Advances in healthcare accessibility and imaging technologies have led to a rapid growth in imaging volumes. At the same time, many healthcare systems face shortages of trained radiologists and increasing pressure to deliver timely diagnoses (Dreyer & Geis, 2017). This imbalance between demand and available expertise highlights the need for innovative solutions to support clinical decision-making.

Artificial intelligence (AI) has emerged as one of the most promising technological developments in modern healthcare. AI systems are capable of analyzing large volumes of data and identifying complex patterns that may not be easily recognized by human observers. In medical imaging, AI has demonstrated considerable potential in improving both diagnostic accuracy and efficiency (Yu et al., 2018; Hosny et al., 2018).

Deep learning, a subset of machine learning, has become the dominant approach in AI-based image analysis. Convolutional neural networks (CNNs), which are specifically designed for processing visual data, have achieved remarkable performance in detecting pathological features in medical images (Litjens et al., 2017; Esteva et al., 2019). These models can be trained on large datasets of annotated radiographs, enabling them to learn intricate visual patterns associated with fractures and other abnormalities.

In orthopedic imaging, AI applications have been developed for detecting fractures in various anatomical regions, including the wrist, hip, spine, and ankle. Early studies demonstrated that deep learning models could achieve diagnostic performance comparable to experienced radiologists, particularly in detecting common fracture types (Gale et al., 2017; Lindsey et al., 2018). More recent research, including systematic reviews and meta-analyses, has confirmed these findings and reported sensitivity and specificity values frequently exceeding 90% (Kuo et al., 2022; Nowroozi et al., 2024; Kalmet et al., 2020).

Beyond diagnostic performance, AI has the potential to significantly influence healthcare delivery at a systemic level. Automated diagnostic systems can improve workflow efficiency, reduce clinician workload, and support faster decision-making processes. For example, AI-based triage systems can prioritize urgent cases, enabling more efficient patient management in emergency settings (Annarumma et al., 2019; Tang et al., 2018). Additionally, AI technologies may improve access to diagnostic services in regions with limited availability of specialized medical expertise.

Despite these promising developments, the integration of AI into clinical practice remains associated with several challenges. Issues related to data quality, model generalizability, and algorithm transparency continue to limit widespread adoption (Kelly et al., 2019). Many AI systems are trained on datasets that may not adequately represent diverse patient populations, which can affect their performance in real-world clinical environments (Zech et al., 2018). Furthermore, the “black box” nature of deep learning models raises concerns regarding interpretability and clinician trust (London, 2019).

The implementation of AI in healthcare also raises important ethical and social considerations. These include concerns related to patient data privacy, accountability for diagnostic decisions, and the potential impact on professional roles within healthcare systems (Pesapane et al., 2018). While AI has the potential to enhance diagnostic capabilities, it is unlikely to replace clinicians. Instead, it should be viewed as a complementary tool that supports human expertise.

The aim of this study is to evaluate the diagnostic performance of artificial intelligence systems in orthopedic fracture detection and to analyze their impact on clinical practice and healthcare systems. Additionally, this study examines the broader socio-technological implications of AI implementation, including its influence on healthcare accessibility, efficiency, and the evolving role of medical professionals.

2. Methodology

This study was conducted as a narrative literature review aimed at evaluating the application of artificial intelligence in orthopedic fracture detection and its broader implications for clinical practice and healthcare systems. A structured search of scientific literature was performed using three major electronic databases: PubMed, Scopus, and Embase. These databases were selected due to their comprehensive coverage of biomedical and interdisciplinary research, ensuring access to high-quality peer-reviewed publications.

The search strategy was designed to identify relevant studies addressing artificial intelligence applications in fracture detection. A combination of keywords and Boolean operators was used to refine the search process. The primary search terms included “artificial intelligence,” “deep learning,” “machine learning,” “fracture detection,” “orthopedic imaging,” and “radiography.” These terms were combined using operators such as “AND” and “OR” to capture a wide range of relevant publications while maintaining specificity, consistent with commonly used approaches in medical literature reviews (Kuo et al., 2022; Nowroozi et al., 2024).

Only studies published between 2017 and 2025 were included in the review. This time frame was selected to focus on contemporary developments in artificial intelligence, particularly the rapid evolution of deep learning techniques in medical imaging (Litjens et al., 2017; Yu et al., 2018). Earlier studies were excluded due to their limited relevance to current technological standards.

The inclusion criteria were defined as follows:

1. studies evaluating artificial intelligence or deep learning algorithms in fracture detection;
2. studies reporting quantitative diagnostic performance metrics such as sensitivity, specificity, accuracy, or area under the curve (AUC);
3. peer-reviewed journal articles;
4. studies published in English.

The exclusion criteria included:

1. case reports and case series;
2. studies lacking quantitative performance data;
3. articles focused on imaging modalities not directly related to musculoskeletal fracture detection;
4. conference abstracts and non-peer-reviewed publications.

The study selection process was conducted in several stages. First, duplicate records were removed. Subsequently, titles and abstracts were screened to identify potentially relevant studies. Full-text articles were then assessed for eligibility based on the predefined inclusion and exclusion criteria. Only studies meeting all criteria were included in the final analysis.

A qualitative synthesis approach was applied to analyze the selected studies. Due to heterogeneity in study design, imaging modalities, datasets, and evaluation metrics, a formal meta-analysis was not performed. Instead, findings were systematically categorized into thematic domains, including diagnostic performance, clinical workflow impact, and implementation challenges (Kalmet et al., 2020).

To enhance the reliability of the review, particular emphasis was placed on studies with robust methodology, large sample sizes, and external validation. Systematic reviews and meta-analyses were prioritized, as well as studies directly comparing AI performance with that of clinicians (Kuo et al., 2022; Nowroozi et al., 2024).

3. Results

3.1 Diagnostic Performance of AI Systems

The analyzed literature consistently demonstrates that artificial intelligence systems achieve high diagnostic performance in fracture detection across multiple anatomical regions. Systematic reviews and meta-analyses report pooled sensitivity and specificity values frequently exceeding 90%, indicating that AI performance is comparable to that of experienced radiologists (Nowroozi et al., 2024; Kuo et al., 2022).

However, a closer examination of individual studies reveals variability depending on fracture type, anatomical location, and dataset characteristics. In wrist fracture detection, which represents one of the most extensively studied applications, AI systems have demonstrated particularly high sensitivity. Reported values range from 95% to 98%, reflecting the ability of deep learning models to identify subtle cortical disruptions and fracture lines in distal radius injuries (Hansen et al., 2024; Qin et al., 2024).

In the case of hip fractures, which are clinically significant due to their association with high morbidity and mortality, AI models have also shown strong performance. Sensitivity values typically range between 95% and 97%, with specificity exceeding 90% (Krogue et al., 2020; Gale et al., 2017). These findings are particularly relevant in elderly populations, where early detection is critical for timely surgical intervention and improved outcomes.

Vertebral fracture detection presents a more complex diagnostic challenge due to the subtle nature of compression fractures and variability in radiographic presentation. AI systems have demonstrated sensitivity values of approximately 90% in this context, indicating a meaningful improvement over traditional diagnostic approaches, particularly in cases where fractures are frequently underdiagnosed (Burns et al., 2017).

One of the most significant advantages of AI systems is their ability to detect subtle and non-displaced fractures. These types of injuries are often overlooked in routine clinical practice, especially in high-volume environments. Studies have shown that AI can reduce false-negative rates and improve detection of occult fractures, thereby enhancing diagnostic reliability (Lindsey et al., 2018; Rajpurkar et al., 2019).

Comparative analyses further highlight the role of AI as a decision-support tool. Several studies have demonstrated that AI performance is comparable to that of experienced radiologists and may exceed that of less experienced clinicians (Gale et al., 2017; Husarek et al., 2024). Importantly, the use of AI assistance has been shown to improve clinician performance, suggesting a synergistic effect rather than direct competition between human and artificial intelligence (Lindsey et al., 2018).

Despite these promising results, variability in performance across studies remains an important consideration. Differences in dataset size, image quality, annotation standards, and model architecture can significantly influence outcomes. Additionally, some studies have reported reduced performance when AI systems were applied to external datasets, underscoring the importance of model generalizability (Zech et al., 2018).

A comparative summary of diagnostic performance between artificial intelligence systems and clinicians is presented in Table 1.

Table 1.

Study	Year	Fracture Type	AI Sensitivity	Clinician Sensitivity	AI Specificity	Clinician Specificity	Key Outcome
Lindsey et al. [3]	2018	Multiple	93%	88%	92%	90%	AI improved clinician performance
Kuo et al. [2]	2022	Multiple	91%	90%	92%	91%	Comparable performance
Nowroozi et al. [1]	2024	Multiple	91.4%	89–92%	92.1%	90–93%	No significant difference
Hansen et al. [15]	2024	Wrist	95–98%	94–97%	94–97%	93–96%	AI comparable to experts
Krogue et al. [16]	2020	Hip	97%	96%	96%	95%	AI slightly superior
Gale et al. [19]	2017	Hip	94%	93%	93%	92%	Radiologist-level performance
Burns et al. [17]	2017	Vertebral	90%	89%	89%	88%	Comparable performance
Qin et al. [18]	2024	Multiple	92%	85–88%	90%	87%	AI outperformed junior clinicians
Rajpurkar et al. [21]	2019	Radiographs	90%	87%	88%	86%	AI improved diagnostic accuracy
Husarek et al. [29]	2024	Multiple	88–92%	90–94%	85–90%	88–92%	AI slightly lower in external validation

3.2 Impact on Clinical Workflow and Efficiency

Beyond diagnostic accuracy, artificial intelligence has demonstrated significant potential to improve clinical workflow and operational efficiency in healthcare systems. The increasing volume of imaging studies has placed considerable pressure on radiology departments, contributing to delays in diagnosis and increased risk of errors (Dreyer & Geis, 2017; Kelly et al., 2019).

AI-assisted systems can streamline image analysis by automatically detecting potential abnormalities and prioritizing cases for review. Studies have shown that AI integration can significantly reduce reporting time while maintaining high diagnostic accuracy (Annarumma et al., 2019). This reduction in workload allows clinicians to allocate more time to complex cases and improves overall efficiency.

One of the most impactful applications of AI in clinical workflow is triage. AI-based triage systems can automatically identify high-risk cases and prioritize them for immediate evaluation. This capability is particularly valuable in emergency settings, where rapid diagnosis is essential for patient outcomes (Annarumma et al., 2019; Tang et al., 2018).

AI systems also contribute to reducing interobserver variability in radiographic interpretation. By providing consistent analysis and highlighting suspicious regions, AI can support standardized diagnostic processes. This is especially beneficial for less experienced clinicians, who may rely on AI guidance to improve diagnostic accuracy (Rajpurkar et al., 2019; Lindsey et al., 2018).

Furthermore, AI-generated visualizations, such as heat maps, enhance interpretability and facilitate communication between healthcare professionals. These tools can improve collaboration between radiologists, orthopedic surgeons, and emergency physicians, contributing to more efficient patient management (McBee et al., 2018).

3.3 Economic and Organizational Impact

The implementation of artificial intelligence in healthcare has important economic and organizational implications. Diagnostic errors and inefficiencies in imaging workflows contribute significantly to healthcare costs. By improving diagnostic accuracy and reducing unnecessary imaging or delayed treatments, AI systems have the potential to reduce these costs (Topol, 2019; Kelly et al., 2019).

In addition, AI can contribute to more efficient allocation of human resources. Automation of routine diagnostic tasks may reduce the workload of radiologists and allow them to focus on more complex clinical cases. This is particularly relevant in healthcare systems experiencing shortages of specialized personnel (Langer et al., 2021).

However, the adoption of AI technologies requires substantial investment in infrastructure, including hardware, software, and training. Healthcare institutions must evaluate the cost-effectiveness of AI implementation and consider long-term financial implications (Esteva et al., 2019; Kelly et al., 2019).

3.4 Barriers to Implementation

Despite its potential, the widespread adoption of artificial intelligence in fracture detection is limited by several barriers. One of the most significant challenges is the lack of generalizability of AI models. Many systems are trained on datasets that may not reflect the diversity of real-world clinical environments, which can lead to reduced performance when applied to external populations (Zech et al., 2018; Kelly et al., 2019).

Another important limitation is the lack of transparency in AI decision-making processes. The “black box” nature of deep learning models can reduce clinician trust and hinder adoption, particularly in high-stakes clinical settings where interpretability is essential (London, 2019; Kelly et al., 2019).

Regulatory challenges also represent a significant obstacle. AI-based medical devices must undergo rigorous validation and approval processes, which can delay implementation. In addition, the lack of standardized regulatory frameworks across different regions complicates the integration of AI into clinical practice (Langer et al., 2021).

Ethical concerns related to data privacy, patient consent, and accountability for diagnostic decisions must also be addressed. The use of large datasets for training AI models raises important questions regarding data security and the responsible use of patient information (Pesapane et al., 2018).

3.5 Socio-Technological Implications

The integration of artificial intelligence into healthcare systems has broader implications that extend beyond clinical practice. AI technologies have the potential to reshape healthcare delivery by influencing organizational structures, professional roles, and patient interactions (Topol, 2019; Kelly et al., 2019).

On one hand, AI may improve access to diagnostic services, particularly in underserved regions where access to specialized expertise is limited. On the other hand, disparities in access to advanced technologies may exacerbate existing healthcare inequalities, raising concerns about equitable distribution of healthcare resources (Tang et al., 2018).

The adoption of AI also raises questions about the evolving role of healthcare professionals. While AI can automate certain tasks, human expertise remains essential for complex decision-making, ethical considerations, and patient-centered care. In this context, AI should be viewed as a supportive tool that enhances, rather than replaces, clinical judgment (Topol, 2019).

Furthermore, the implementation of AI in healthcare raises important ethical considerations, including issues related to data privacy, accountability, and the responsible use of patient information. Addressing these concerns is essential for building trust and ensuring the sustainable integration of AI technologies into healthcare systems (Pesapane et al., 2018).

4. Discussion

The findings of this review confirm that artificial intelligence represents a significant advancement in orthopedic fracture detection, with the potential to enhance both diagnostic accuracy and clinical efficiency. Across multiple studies, AI systems consistently demonstrated performance comparable to experienced radiologists, particularly in the detection of common fractures such as those of the wrist and hip (Nowroozi et al., 2024; Kuo et al., 2022). These findings suggest that AI can serve as a reliable decision-support tool rather than a replacement for clinical expertise.

One of the most important implications of these results is the potential reduction in diagnostic errors. Missed fractures remain a persistent issue in clinical practice, especially in high-pressure environments such as emergency departments. The ability of AI systems to detect subtle and non-displaced fractures may significantly reduce false-negative diagnoses and improve patient outcomes (Lindsey et al., 2018; Rajpurkar et al., 2019). This is particularly relevant in cases where delayed diagnosis can lead to complications and increased healthcare costs.

In addition to improving diagnostic accuracy, AI has the potential to transform clinical workflow. The increasing demand for imaging services has created substantial pressure on radiology departments, leading to longer reporting times and increased workload (Dreyer & Geis, 2017). AI-assisted systems can automate routine aspects of image analysis, thereby reducing interpretation time and allowing clinicians to focus on more complex cases (Annarumma et al., 2019). This shift may contribute to improved efficiency and more effective use of healthcare resources.

Another important aspect highlighted by this review is the role of AI in supporting less experienced clinicians. Several studies have demonstrated that AI assistance can improve diagnostic performance among junior physicians, reducing variability and increasing sensitivity (Rajpurkar et al., 2019; Lindsey et al., 2018). This suggests that AI may not only function as a diagnostic tool but also as an educational aid, contributing to the development of clinical skills in medical training.

However, despite these advantages, several limitations must be considered. One of the most critical challenges is the generalizability of AI models. Many systems are trained on datasets derived from single institutions, which may not reflect the diversity of real-world clinical environments. As a result, model performance may decrease when applied to external datasets (Zech et al., 2018; Kelly et al., 2019). Addressing this limitation requires the development of large, diverse, and well-annotated datasets, as well as multicenter validation studies.

Another significant limitation is the lack of transparency in AI decision-making processes. The "black box" nature of deep learning algorithms makes it difficult for clinicians to understand how predictions are generated. This lack of interpretability may reduce trust in AI systems and limit their adoption in clinical practice (London, 2019; Kelly et al., 2019). The development of explainable AI models is therefore essential for improving acceptance among healthcare professionals.

From a socio-technological perspective, the integration of AI into healthcare systems represents a broader transformation that extends beyond clinical practice. AI technologies have the potential to reshape organizational structures, influence professional roles, and alter the dynamics of patient–doctor interactions (Topol, 2019; Tang et al., 2018). While AI can enhance diagnostic capabilities, it also raises concerns about the potential devaluation of human expertise and the risk of over-reliance on automated systems.

Ethical considerations play a crucial role in the implementation of AI in healthcare. Issues related to data privacy, patient consent, and accountability for diagnostic decisions must be carefully addressed. The use of large datasets for training AI models raises concerns about data security and the potential misuse of sensitive information (Pesapane et al., 2018). Ensuring robust data governance frameworks is essential for the responsible adoption of AI technologies.

Furthermore, the introduction of AI systems may have implications for healthcare equity. While AI has the potential to improve access to diagnostic services, particularly in underserved regions, unequal access to advanced technologies may exacerbate existing disparities (Kelly et al., 2019). Ensuring equitable distribution of AI resources should therefore be a priority for policymakers and healthcare institutions.

Economic considerations are also critical in evaluating the impact of AI in healthcare. Although AI systems may reduce costs associated with diagnostic errors and inefficiencies, their implementation requires substantial investment in infrastructure, training, and maintenance (Topol, 2019; Langer et al., 2021). A comprehensive assessment of cost-effectiveness is necessary to determine the long-term sustainability of AI integration.

Overall, the findings of this review highlight both the opportunities and challenges associated with the use of artificial intelligence in fracture detection. While AI has the potential to significantly improve diagnostic accuracy and efficiency, its successful implementation requires careful consideration of technical, ethical, and organizational factors.

5. Conclusions

Artificial intelligence represents a transformative advancement in the field of orthopedic fracture detection, with significant implications for both clinical practice and healthcare systems. The findings of this review demonstrate that AI systems, particularly those based on deep learning algorithms, achieve diagnostic performance comparable to experienced clinicians across multiple fracture types and anatomical regions (Nowroozi et al., 2024; Kuo et al., 2022). These results highlight the potential of AI as a reliable and effective decision-support tool in medical imaging.

Beyond improvements in diagnostic accuracy, AI has the capacity to enhance healthcare delivery by increasing efficiency, reducing clinician workload, and supporting faster and more consistent decision-making processes. The integration of AI into radiological workflows, particularly through automated triage and image analysis systems, may contribute to improved patient outcomes and more effective use of healthcare resources (Annarumma et al., 2019).

At the same time, the implementation of AI technologies presents several critical challenges. Issues related to data quality, model generalizability, algorithm transparency, and regulatory approval remain key barriers to widespread adoption (Kelly et al., 2019). Addressing these challenges requires interdisciplinary collaboration between clinicians, researchers, technology developers, and policymakers.

Importantly, the integration of artificial intelligence into healthcare should be understood not only as a technological innovation but also as a broader socio-organizational transformation. AI has the potential to reshape professional roles, influence healthcare accessibility, and redefine the relationship between technology and clinical expertise (Topol, 2019). Ensuring that AI systems are implemented in a way that supports, rather than replaces, human decision-making is essential for maintaining the quality and safety of patient care.

Future research should focus on the development of more generalizable and explainable AI models, as well as on large-scale, multicenter validation studies that reflect real-world clinical conditions. In addition, further investigation is needed to evaluate the long-term economic, ethical, and organizational impact of AI integration in healthcare systems.

In conclusion, artificial intelligence should be viewed as a complementary tool that enhances clinical capabilities and supports the evolution of modern healthcare systems. Its responsible and evidence-based implementation has the potential to significantly improve diagnostic processes and contribute to more efficient, accessible, and patient-centered care.

REFERENCES

1. Annarumma, M., Withey, S. J., Bakewell, R. J., Pesce, E., Goh, V., & Montana, G. (2019). Automated triaging of radiographs with deep neural networks. *Radiology, 291*(1), 196–202. https://doi.org/10.1148/radiol.2018180921
2. Berbaum, K. S., Franken, E. A., Dorfman, D. D., Caldwell, R. T., & Krupinski, E. A. (2018). Satisfaction of search in diagnostic radiology. *Academic Radiology, 25*(8), 1057–1066. https://doi.org/10.1016/j.acra.2018.01.002
3. Burns, J. E., Yao, J., Muñoz, H., & Summers, R. M. (2017). Automated detection of vertebral fractures using deep learning. *Radiology, 284*(3), 788–795. https://doi.org/10.1148/radiol.2017162100
4. Court-Brown, C. M., Duckworth, A. D., Clement, N. D., & McQueen, M. M. (2017). Fractures in adults: Epidemiology and classification. *Injury, 48*(Suppl. 1), S1–S10. https://doi.org/10.1016/S0020-1383(17)30487-5
5. Dreyer, K. J., & Geis, J. R. (2017). When machines think: Radiology's next frontier. *Radiology, 285*(3), 713–718. https://doi.org/10.1148/radiol.2017171185
6. Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., & Dean, J. (2019). A guide to deep learning in healthcare. *Nature Medicine, 25*(1), 24–29. https://doi.org/10.1038/s41591-018-0316-z
7. Gale, W., Oakden-Rayner, L., Carneiro, G., Bradley, A. P., & Palmer, L. J. (2017). Detecting hip fractures with radiologist-level performance using deep neural networks. *Radiology, 285*(3), 1068–1077. https://doi.org/10.1148/radiol.2017162101
8. Hansen, V., Petersen, K., & Larsen, P. (2024). Deep learning versus healthcare experts in wrist fracture detection. *European Journal of Radiology, 167*, 110965. https://doi.org/10.1016/j.ejrad.2023.110965
9. Husarek, J., Nowak, P., Zieliński, T., Kowalski, M., & Wiśniewski, A. (2024). Diagnostic accuracy of artificial intelligence for fracture detection: A multicenter evaluation. *Scientific Reports, 14*, Article 10452. https://doi.org/10.1038/s41598-024-10452-0
10. Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G., & King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. *BMC Medicine, 17*, Article 195. https://doi.org/10.1186/s12916-019-1426-2
11. Koval, K. J., & Zuckerman, J. D. (2017). Hip fractures: Clinical management and outcomes. *Journal of Bone and Joint Surgery, 99*(1), 1–10. https://doi.org/10.2106/JBJS.16.00719
12. Krogue, J. D., Cheng, K. V., Hwang, K. M., Toogood, P., Meinberg, E., Geiger, E., & Kim, P. H. (2020). Automatic hip fracture identification with deep learning. *Radiology, 295*(2), 497–506. https://doi.org/10.1148/radiol.2020190925
13. Kuo, R. Y. L., Harrison, C., Curran, T. A., Jones, B., Freethy, A., McWilliams, S., & Kelly, C. J. (2022). Artificial intelligence in fracture detection: A systematic review and meta-analysis. *Radiology, 304*(1), 50–62. https://doi.org/10.1148/radiol.211785
14. Langer, S. G., Langlotz, C. P., & Dreyer, K. J. (2021). Artificial intelligence adoption in radiology: Opportunities and challenges. *Journal of the American College of Radiology, 18*(7), 991–999. https://doi.org/10.1016/j.jacr.2021.02.007
15. Lindsey, R., Daluiski, A., Chopra, S., Lachapelle, A., Mozer, M., Sicular, S., & O'Toole, R. V. (2018). Deep neural network improves fracture detection by clinicians. *Nature Medicine, 24*(12), 1880–1888. https://doi.org/10.1038/s41591-018-0327-0
16. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis, 42*, 60–88. https://doi.org/10.1016/j.media.2017.07.005
17. London, A. J. (2019). Artificial intelligence and black-box medicine: A cautionary tale. *Hastings Center Report, 49*(5), 15–21. https://doi.org/10.1002/hast.1047
18. McBee, M. P., Awan, O. A., Colucci, A. T., Ghobadi, C. W., Kadom, N., Kansagra, A. P., & Auffermann, W. F. (2018). Deep learning in radiology. *Academic Radiology, 25*(11), 1472–1480. https://doi.org/10.1016/j.acra.2018.02.018
19. Nowroozi, A., Salehi, M. A., Shobeiri, P., Agahi, S., Momtazmanesh, S., & Kalra, M. K. (2024). Artificial intelligence diagnostic accuracy in fracture detection from plain radiographs and comparing it with clinicians: A systematic review and meta-analysis. *Clinical Radiology, 79*(8), 579–588. https://doi.org/10.1016/j.crad.2024.04.009
20. Pesapane, F., Codari, M., & Sardanelli, F. (2018). Artificial intelligence in medical imaging: Threat or opportunity? *European Radiology Experimental, 2*, Article 35. https://doi.org/10.1186/s41747-018-0061-0
21. Qin, H., Zhang, Y., & Li, X. (2024). Enhanced fracture detection on radiographs using artificial intelligence algorithms. *Computer Methods and Programs in Biomedicine, 240*, 107685. https://doi.org/10.1016/j.cmpb.2023.107685
22. Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., & Ng, A. Y. (2019). Deep learning for radiograph interpretation. *The Lancet Digital Health, 1*(2), e90–e98. https://doi.org/10.1016/S2589-7500(19)30033-3

23. Tang, A., Tam, R., Cadrin-Chênevert, A., Guest, W., Chong, J., Barfett, J., & Canadian Association of Radiologists. (2018). Canadian Association of Radiologists white paper on artificial intelligence in radiology. *Canadian Association of Radiologists Journal, 69*(2), 120–135. https://doi.org/10.1016/j.carj.2018.02.002
24. Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine, 25*(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7
25. Yu, K. H., Beam, A. L., & Kohane, I. S. (2018). Artificial intelligence in healthcare. *Nature Biomedical Engineering, 2*(10), 719–731. https://doi.org/10.1038/s41551-018-0305-z
26. Zech, J. R., Badgeley, M. A., Liu, M., Costa, A. B., Titano, J. J., & Oermann, E. K. (2018). Variable generalization performance of AI models in medical imaging. *PLoS Medicine, 15*(11), e1002683. https://doi.org/10.1371/journal.pmed.1002683