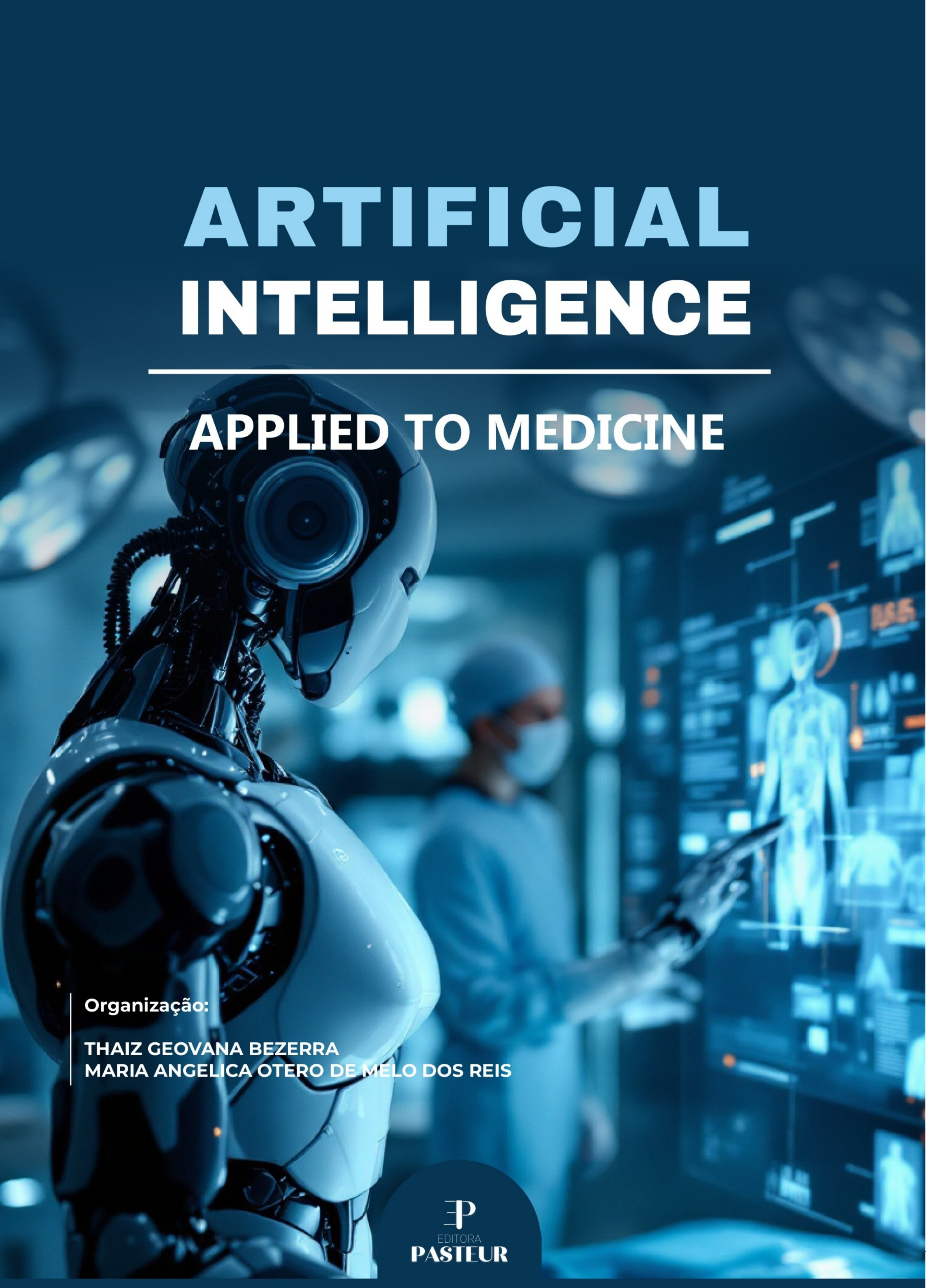

ARTIFICIAL INTELLIGENCE

APPLIED TO MEDICINE

Organização:

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PREFÁCIO

A medicina, ao longo da história, sempre caminhou lado a lado com a evolução científica e tecnológica. Nos últimos anos, contudo, estamos presenciando uma transformação sem precedentes: a integração da inteligência artificial (IA) às práticas médicas. Este avanço representa não apenas uma nova fronteira para a ciência da saúde, mas também uma profunda mudança na forma como médicos, pesquisadores e pacientes interagem com o conhecimento e a tecnologia.

Este livro tem como principal objetivo demonstrar as diversas formas pelas quais a inteligência artificial tem sido aplicada na medicina, abrangendo múltiplas especialidades médicas. Por meio de exemplos práticos, estudos de caso e análises atuais, exploramos como algoritmos inteligentes estão auxiliando na detecção precoce de doenças, na análise de imagens médicas, na personalização de tratamentos, no suporte à decisão clínica e em tantas outras áreas.

Mais do que apenas uma ferramenta tecnológica, a IA emerge como um novo agente dentro do ecossistema da saúde — um parceiro potencial que amplia as capacidades humanas, mas que também traz à tona dilemas éticos, operacionais e sociais. A fronteira entre apoio e competição se torna cada vez mais sutil, nos obrigando a refletir sobre o papel da tecnologia na prática médica contemporânea.

Ao longo desta obra, buscamos não apenas evidenciar os benefícios concretos que a IA pode oferecer — como precisão diagnóstica, agilidade nos processos e maior abrangência de atendimento —, mas também discutir os novos desafios que se impõem: desde a capacitação dos profissionais de saúde até a regulamentação ética e a aceitação por parte dos pacientes.

Estamos vivendo um tempo de reinvenção da medicina. Que esta leitura desperte não só o interesse, mas também a responsabilidade de pensar criticamente sobre o futuro que estamos construindo — um futuro onde ciência, humanidade e tecnologia precisam andar juntas.

Organizadores.

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AI Predictive Models for Infectious and Pandemic Diseases

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INTRODUCTION

Infectious diseases continue to represent one of the greatest challenges to global public health, even in the face of scientific and technological advances over the past decades (WONG et al., 2023). With the emergence of new epidemic threats and the growing problem of antimicrobial resistance, it has become essential to seek innovative solutions for the surveillance, diagnosis, and treatment of these conditions (ALI et al., 2025). In this context, Artificial Intelligence (AI) has been consolidating itself as a transformative tool, capable of offering timely and robust responses to the complexity of these problems (WONG et al., 2023).

AI-based predictive models have been increasingly used to anticipate outbreaks, optimize diagnoses, and boost the development of new drugs (ALI et al., 2025). The COVID-19 pandemic illustrates the potential impact of these technologies, which enabled the monitoring of transmission patterns and supported public health strategies in real time (ONG et al., 2024). Even so, the adoption of AI in clinical practice still faces significant challenges, such as the need for greater reliability, data integration, and proper ethical governance (HASSAN et al., 2024).

In the context of digital transformation in healthcare, the application of Artificial Intelligence (AI) in the management of infectious and endemic diseases has been gaining increasing attention (WONG et al., 2023). Recent literature presents a comprehensive overview of the predictive models used in this context, highlighting their main applications and the factors that influence their adoption in clinical practice, including technical, ethical, and structural barriers (HASSAN et al., 2024). Understanding these elements is essential for the safe, effective, and ethical incorporation of emerging technologies into the healthcare system (ONG et al., 2024).

Overall, the relevance of AI-based predictive models is widely recognized, especially as strategic tools in addressing infectious diseases. Studies highlight their advances, current limitations, and possible future directions (WONG et al., 2023; ALI et al., 2025). By promoting a critical analysis of the topic, scientific research contributes to understanding the transformative potential of these technologies in medical practice, broadening the debate on their responsible and effective integration across different levels of healthcare.

The Use of Artificial Intelligence in Tackling Infectious Diseases

The incorporation of Artificial Intelligence (AI) algorithms has significantly transformed the approach to infectious diseases, especially in the areas of epidemiological surveillance, diagnosis, and prognosis. Models based on deep learning, neural networks, and federated learning have stood out for their ability to process large volumes of heterogeneous data, providing more accurate and timely predictions of infectious outbreaks (ZHAO et al., 2024; ZWIERS et al., 2024).

Recent advances demonstrate how AI can enhance the analysis of complex data. A relevant example is the integration of nanomaterials in biosensors with AI algorithms, which has substantially increased sensitivity and specificity in viral detection. These systems enable real-time analyses, markedly reducing the occurrence of false positives and favoring faster and more effective diagnoses (RAMA-LINGAM et al., 2023).

Federated learning stands out as a promising approach for developing robust models while maintaining data privacy. This technique allows collaborative algorithm training without the need to centralize sensitive information, promoting both security and the integration of data from different sources — an essential aspect in pandemic contexts (ZWIERS et al., 2024).

In addition, AI tools applied to medical imaging have significantly improved early detection of infections. Algorithms based on convolutional neural networks have driven advances in image interpretation, enabling the identification of subtle patterns that might go unnoticed in human assessment. These systems contribute to diagnostic standardization and improved clinical management (CHU et al., 2023).

Despite these advances, the implementation of AI still faces important challenges. Technical issues such as the scarcity of diverse and high-quality data, algorithmic bias, and the complexity of biological systems represent significant barriers (ZHAO et al., 2024). These are compounded by relevant ethical considerations, such as the need to ensure transparency, informed consent, and equity in the use of digital surveillance technologies (ZHAO et al., 2021).

The trend is for AI use in infectious diseases to continue expanding, driven by emerging technologies such as the Internet of Things (IoT), big data, and social media, which generate valuable information for the continuous improvement of models (SOOD; RAWAT; KUMAR, 2022). To maximize the potential of these tools, it is essential to invest in data standardization, information security, and collaboration among healthcare professionals, data scientists, and public policy makers (ZHAO et al., 2021; SOOD; RAWAT; KU-MAR, 2022).

In this context, AI-based systems become strategic elements in modernizing surveillance and tackling infectious diseases, although the full success of their implementation depends on overcoming persistent technical and ethical challenges (ZHAO et al., 2021).

Artificial Intelligence in Pandemic Scenarios and Drug Discovery

The use of AI in addressing infectious diseases and pandemics has gained increasing prominence in the scientific community, especially following the advances observed during the COVID-19 pandemic. Recent evidence suggests that the future of healthcare will depend on the ability to adapt AI to contemporary clinical practice, expanding its application in emergency and high-transmissibility contexts (ANKOLEKAR et al., 2024).

Studies point to significant progress in the use of AI in medical sciences, particularly regarding disease prognosis, clinical outcome prediction, and large-scale data integration (DONG et al., 2021). Technologies such as machine learning (ML) have been used in image classification, analysis of clinical and laboratory data, and prediction of complications. Simultaneously, big data analytics enables the processing of large volumes of clinical, environmental, and population data, optimizing decision-making during health crises (ANKO-LEKAR et al., 2024; DONG et al., 2021).

To be effective in discovering new drugs for the treatment of emerging infectious diseases, AI must go beyond simply identifying promising compounds. It is essential that it can correlate data across different diseases and deeply understand drug mechanisms of action, avoiding antagonistic interactions and reducing development costs (DONG et al., 2021).

However, drug development remains a complex and costly process, requiring multiple stages of validation — especially to distinguish real signals from false positives. This challenge is evidenced by the trend, since 1984, of launching antibiotics based on already known compounds, rather than new molecular structures (BESS et al., 2022).

To mitigate these difficulties, tools such as ComboNet — which predicts drug synergies — and DeepDrug — which evaluates the repositioning of existing drugs — have been developed (BESS et al., 2022). Nevertheless, pharmaceutical development demands the integration of complementary technologies capable of handling the vastness, complexity, and often low reliability of data, in addition to the need to safeguard sensitive information.

Future Perspectives and Ethical, Technical, and Regulatory Considerations

The continuous evolution of the internet, combined with the growing demand for real-time data collection and analysis, shows that we are only at the beginning of a profound transformation in medicine. The advancement in the processing of clinical and epidemiological data is inevitable, and the improvement of AI-based technologies has become a concrete necessity for faster, safer, and more personalized responses to global infectious threats (MCCLYMONT et al., 2024).

However, this progress is accompanied by ethical, technical, and regulatory challenges that must be carefully addressed to ensure safe, fair, and effective implementation (HUDU et al., 2025).

In the ethical realm, concerns include patient data privacy, algorithmic bias, and equitable access to technological innovations. The use of sensitive health information requires rigorous safeguards to protect individuals' confidentiality and autonomy. Additionally, there is a risk that algorithms may perpetuate historical biases present in data, disadvantaging underrepresented populations (SYROWATKA et al., 2021).

From a technical standpoint, the main limitation lies in the reliance on large volumes of high-quality data. The lack of standardization, data fragmentation, and variability across institutions can undermine model effectiveness. Another relevant technical challenge is the low interpretability of many algorithms, which hampers their clinical application and reduces trust among healthcare professionals (HUDU et al., 2025).

In the regulatory field, the absence of clear normative frameworks — especially in low- and middle-income countries — represents a critical barrier. The approval processes for AI technologies are often lengthy and uncertain, hindering large-scale adoption (SADANA et al., 2025).

To overcome these limitations, effective strategies include the use of federated learning and blockchain to protect data privacy; building more inclusive databases to mitigate bias; developing explainable models (XAI); and continuous training of healthcare professionals. Partnerships between governments, universities, and the private sector are also essential to formulate public policies that promote the ethical, safe, and equitable adoption of AI (HUDU et al., 2025).

Thus, by proactively addressing these challenges, it will be possible to consolidate artificial intelligence as a strategic ally in contemporary medicine, fostering a more efficient, fair, and prepared healthcare system to respond to future health emergencies (RABAAN et al., 2023).

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Capítulo 02

Artificial Intelligence in Emergency Medicine: From Automated Triage to Real-Time Support

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INTRODUCTION

Emergency departments (EDs) are highly challenging environments, characterized by overcrowding, limited resources, and a wide range of clinical severity among patients. In this context, triage becomes a fundamental step to establish priorities based on medical urgency, ensuring that the most severe cases receive timely care (TAHERNEJAD et al., 2024).

Traditionally, triage systems use tags or color-coded cards to classify patients according to the severity of their clinical condition. Although these methods are well-established, they have significant limitations, such as limited space to record vital signs, difficulty in locating patients in high-demand settings, and a lack of accuracy in representing the patient's real clinical status (TAHERNEJAD et al., 2024). Moreover, there is considerable reliance on the experience of the healthcare professional conducting the triage, which can introduce subjectivity and inconsistencies (DA'COSTA et al., 2025).

In this scenario, artificial intelligence (AI) emerges as a strategic tool to transform triage processes. The integration of techniques such as machine learning (ML), deep neural networks (DNNs), and natural language processing (NLP) contributes to the standardization, accuracy, and efficiency of triage in EDs (DA'COSTA et al., 2025). AI-based solutions can operate in an automated and integrated manner, from collecting and analyzing clinical data to providing real-time feedback, supporting clinical decision-making through robust algorithms.

Recent studies also highlight the emerging role of AI-assisted virtual triage. This approach involves the use of remote electronic tools in which patients themselves enter their symptoms into automated platforms, which then assess the severity of the cases and guide the type of care needed (NASSER et al., 2025). Virtual triage has proven to be viable and promising, especially in high-demand scenarios such as during the COVID-19 pandemic, reducing individual biases and improving the accuracy of clinical recommendations.

During this critical period, a behavioral AI-based technology — Behavioral Artificial Intelligence Technology (BAIT) — was tested in the Netherlands to support triage decisions in Intensive Care Units (ICUs). The model proved effective by making explicit the implicit criteria adopted by intensivists to determine the eligibility of COVID-19 patients for ICU admission, making the process more transparent and reproducible (DE METZ et al., 2021).

In addition, AI applications have also shown a direct impact on emergency neurological diagnoses. A study conducted in the United States analyzed the use of AI to detect large vessel occlusions (LVO) in patients with acute stroke through imaging exams. The use of algorithms significantly increased the speed and accuracy in identifying these lesions, allowing earlier and more assertive interventions, with the potential to alter clinical outcomes (Forghani & Gupta, 2023).

Given these advancements, this chapter aims to explore the theme *"Artificial Intelligence in Emergency Medicine: From Automated Triage to Real-Time Clinical Support"* in a narrative way, discussing its foundations, practical applications, and ethical implications. The proposed approach seeks to consolidate the most current knowledge on the use of AI in emergency triage, based solely on the scientific evidence available in the studies selected for this review.

Automated Smart Triage

The use of artificial intelligence to support the interpretation of radiological exams has proven particularly valuable in high-demand scenarios, such as intensive care units. In these settings, routine chest X-rays are frequently performed to monitor patients with cardiopulmonary diseases, generating a massive volume of images that require serial analysis—a process demanding a high level of expertise and contributing to professional overload (YUN et al., 2023). To mitigate this issue, Yun et al. (2023) developed a deep learning algorithm based on chest records and image subtraction to automatically identify relevant clinical changes over time. With an area under the curve (AUC) of up to 0.80, the model demonstrated satisfactory ability to differentiate images with and without changes, even in complex clinical contexts such as emergency departments and intensive care units.

Nonetheless, challenges remain. Variability in factors such as patient positioning, level of inspiration, and the presence of medical devices can hinder image standardization and limit algorithm performance (Yun et al., 2023). This technical limitation underscores the importance of incorporating more robust normalization and calibration methods, as well as expanding validation studies across multiple clinical centers.

Another important advancement involves remote triage. AI-based digital tools have been implemented to allow patients themselves to input symptoms and receive an automated assessment of severity, guiding them to the appropriate level of care (NASSER et al., 2025). While results are promising—especially in reducing emergency department overcrowding and improving access—barriers such as low digital literacy among older adults, with 38.2% needing assistance to use these platforms, still hinder full effectiveness (NASSER et al., 2025).

In prehospital and disaster contexts, machine learning algorithms have been applied to expedite victim classification in the field. Technologies embedded in mobile sensors and wearable devices can now analyze vital signs in real time, stratify risk, and prioritize care, increasing agility and reducing stress on health-care providers (ALRAWASHDEH et al., 2024). Additionally, automatic speech recognition systems have been successfully tested to speed up the identification of cardiac arrests in emergency calls, outperforming human operators in detection speed (BIESHEUVEL et al., 2024).

Despite these advances, consolidating automated smart triage still requires addressing structural challenges. Issues such as algorithmic bias, heterogeneity in input data, and a lack of external validation need to be resolved to ensure these technologies truly optimize care without compromising equity (COCCA et al., 2024). The successful integration of these tools into clinical practice demands an interdisciplinary effort focused on standardization, safety, transparency, and acceptance by healthcare professionals.

AI in Dynamic Monitoring and Predictive Alarms

The progress of artificial intelligence in emergency medicine has moved beyond static triage models, gaining ground in more sophisticated applications, such as continuous monitoring of physiological data and the triggering of predictive alarms. These dynamic approaches enable early detection of clinical deterioration, aiding healthcare teams in making critical decisions in real time.

In trauma care, the early detection of hidden hemorrhages is crucial for reducing morbidity and mortality. The APPRAISE–Hemorrhage Risk Index (HRI) algorithm exemplifies AI's potential in this setting. Developed from more than 500 hours of continuous vital sign data from 1,659 patients, the model evaluates heart rate and systolic/diastolic blood pressure to stratify hemorrhage risk into three levels (low, medium, high). The results were consistent, with a significantly higher hemorrhage risk index in the HRI III group (likelihood ratio of 5.75), and the model maintained predictive stability even amidst physiological variations in prehospital environments.

Similarly, Abe et al. (2022) used the XGBoost algorithm to develop a triage model for traumatic intracranial hemorrhage based on simple clinical information collected on-site, such as GCS eye score, scalp wounds, and pupillary abnormalities. Although the initial focus was on triage, the study also evaluated the potential of adapting the model for continuous data monitoring, suggesting that incremental learning could allow updates to predictions as new information becomes available, including evolving clinical signs during transport to the hospital.

The role of smart alarms expands even further in war or disaster contexts. In addition to risk classification, the APPRAISE-HRI also issues minute-by-minute alerts as data are collected, identifying patients in urgent need of intervention. This ability to generate real-time alerts based on changes in vital signs is essential for optimizing decisions about aeromedical evacuation, blood preparation, or activation of emergency surgical teams.

However, not all AI models developed for dynamic support are mature enough. One example is VTriage, applied in hospital settings. This algorithm estimates severity scores based on chief complaint, age, sex, and pain but showed low agreement with nurse-conducted triage (kappa between 0.17 and 0.37) and high rates of overtriage. Its limited interpretation of complex clinical contexts and lack of dynamic physiological data reduced its accuracy and compromised its reliability as a predictive tool.

Another critical point is the need to ensure that algorithms embedded in predictive alarm systems are trained with high-quality, clinically diverse data. Challenges such as algorithmic bias, lack of transparency in alert activation criteria, and possible alert fatigue must be addressed with rigorous methodology and strict ethical governance.

The future trend points toward models based on continuous learning (online learning), which re-evaluate patient risk as new data are recorded—whether through wearable sensors, hospital monitors, or electronic records. These adaptive systems, by integrating dynamic monitoring and smart alarms, may offer proactive and individualized clinical support, transforming the emergency response paradigm.

AI in Real-Time Therapeutic Decision Support

Therapeutic decision support in emergency and urgent care settings demands speed, diagnostic accuracy, and integration of multiple clinical variables. In this context, artificial intelligence (AI) has emerged as a promising tool to assist healthcare professionals, especially during critical moments when time is crucial for patient survival and recovery.

In emergency ophthalmology, the DOTS (DemDx Ophthalmic Triage System) was developed as an AI-based platform to classify eye complaints based on reported symptoms. By assigning urgency levels using color codes, the system aided in the initial triage of adult patients in urgent care, enhancing efficiency and safety. In a recent prospective study, over 90% of participating healthcare professionals found the tool useful and safe, highlighting its impact on reducing misclassification and ensuring appropriate case referral (JINDAL et al., 2023).

In emergency neurology, AI has been used for automated analysis of imaging exams to enable early detection of large vessel occlusions (LVO) in stroke patients. The tool assessed by Forghani & Gupta (2023) showed relevant accuracy in interpreting CT and brain perfusion scans, offering real-time diagnostic support. This approach directly contributes to reducing the "door-to-needle" time, allowing more effective and timely interventions such as thrombolysis or thrombectomy.

Beyond these applied clinical examples, other AI tools have focused on predicting critical clinical outcomes, such as the need for hospital admission, based on initial admission data. In a study by Patel et al. (2018), machine learning algorithms were able to predict admission needs based on parameters like vital signs, chief complaints, and initial lab tests, supporting immediate decisions about referral, support, and resource allocation.

AI capabilities are further expanding with the concept of continuous learning (online learning), where models can update their predictions based on real-time data input. This feature is especially useful in dynamic clinical environments like emergency departments, where patient conditions can evolve rapidly. Abe et al. (2022) noted that XGBoost-based incremental learning systems, when applied to detecting traumatic intracranial hemorrhages, have the potential to refine decisions as clinical monitoring progresses.

Despite these advances, the use of AI in clinical decision support still faces ethical, regulatory, and technical challenges. The so-called "algorithmic black box" — i.e., the opacity of automated decision-making processes—makes traceability difficult and raises concerns about medical accountability. Grant et al. (2020) argue that the lack of transparency in deep learning models can hinder clinical acceptance and advocate for frameworks such as "segmentation and classification networks" to make processes more understandable. Additionally, ongoing debates concern data privacy, legal responsibility, and multicenter algorithm validation.

Ultimately, it is essential to understand that although AI presents itself as a powerful ally in therapeutic decision-making, its safe implementtation depends on rigorous clinical validation processes, efficient integration into workflows, and an ethical balance between medical autonomy and technological delegation.

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Capítulo 03

Application of AI in Pediatrics and Neonatology

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INTRODUCTION

Clear communication between healthcare professionals and patients is essential to ensure safety and quality in medical care, especially in contexts marked by linguistic diversity. In pediatric emergency situations, there is also a need for rapid and accurate estimates of children's weight, which are crucial for the safe administration of medications and clinical management (ISASI et al., 2025). However, conventional methods used for these tasks are often inaccurate, prone to error, and frequently unfeasible in environments that demand quick decision-making. Although tools like Google Translate offer accessible alternatives, their use still entails clinical and legal risks due to the potential for misinterpretation of technical terms. Given these limitations, the search for safer, more effective, and adaptable solutions has become a priority in healthcare services (BRANDENBERGER et al., 2025).

Artificial intelligence (AI) has emerged as an innovative alternative to overcome these challenges. Technologies such as machine learning, deep learning, and artificial neural networks are being incorporated into systems aimed at improving clinical communication, estimating pediatric weight, and supporting diagnosis in complex cases (YING et al., 2024; ISASI et al., 2025; ABUSAMRA et al., 2025). These applications are especially relevant in pediatric and emergency settings, where precision and speed are crucial for clinical outcomes.

Recent advances, such as algorithms for real-time weight estimation or endocrine disorder screening, highlight AI's potential in treatment personalization and safer clinical decision-making (YING et al., 2024; ISASI et al., 2025). These technologies also contribute to reducing complications, hospital costs, and communication barriers — especially in multi-lingual environments — promoting greater efficiency and quality in healthcare delivery (BRANDENBERGER et al., 2025).

Despite the benefits, ethical and operational challenges remain, such as data privacy, algorithmic bias, and the scarcity of representative databases. These aspects reinforce the need for specific regulations, the development of transparent models, and the ethical adoption of these technologies in pediatric settings (ABUSAMRA et al., 2025).

The discussion around the applications of artificial intelligence in pediatrics and neonatalogy is particularly relevant given the increasing demands for diagnostic precision, personalized care, and efficiency in clinical decision-making. This is a rapidly evolving field, with the potential to transform care practices through automated clinical monitoring, disease prediction, neuroimaging analysis, and support for diagnosing critical conditions. In addition to the care benefits, AI can significantly contribute to cost reduction, mitigation of clinical complications, and overcoming structural barriers in healthcare systems, especially in complex pediatric contexts. This chapter is, therefore, essential for understanding recent advances, the challenges to safe and effective implementation of these technologies — such as integration into clinical workflows and the quality of available data — and for reflecting on the future prospects of ethical and equitable AI use in child healthcare (ABUSAMRA et al., 2025).

Advances in Artificial Intelligence for Pediatric Diagnosis and Treatment

The application of AI in pediatrics and neonatology has driven a silent yet impactful revolution in how diseases are diagnosed, treated, and monitored in highly vulnerable populations. Technologies such as supervised machine learning, artificial neural networks, ensemble learning algorithms, and natural language processing have stood out in analyzing large volumes of clinical, laboratory, and imaging data, allowing the recognition of complex patterns that escape human observation and surpass the limitations of traditional methods (KERTH et al., 2024; ABU-ASHOUR; EMIL; POENARU, 2024; KAVAK et al., 2024).

AI-based predictive models have demonstrated high performance in the early detection of conditions such as ventricular dysfunction, appendicitis, appendicular fractures, and acute kidney injury, with areas under the curve (AUC) above 0.9 (ABU-ASHOUR; EMIL; POENARU, 2024; KOKER et al., 2024; ELAHMEDI et al., 2024; HU; RAINA, 2025). These advances contribute directly to treatment personalization through the integration of multiomics data, and explainable algorithms, assisting in the identification of risks such as insulin resistance (TORRES-MARTOS et al., 2024). Moreover, in both chronic and acute settings, AI has improved remote monitoring — such as in children with type 1 diabetes and asthma — and has proven effective in predicting adverse events in pediatric surgery and nephrology.

In pediatric radiology, AI-based tools have shown greater accuracy than specialists in detecting appendicular fractures (AUC 0.97), while algorithms like Random Forest and XGBoost predicted acute kidney injuries up to 48 hours in advance (YOGENDRA et al., 2024; HU; RAINA, 2025). In pediatric cardiology, convolutional (CNN) and recurrent neural networks (RNN) have performed well in detecting systolic ventricular dysfunction and identifying subclinical patterns with prognostic value (ANJEWIERDEN et al., 2024). Explainable AI models have also shown excellent performance in predicting insulin resistance in prepubescent children (TORRES-MARTOS et al., 2024).

Studies on the progression of chronic kidney disease in children using biomarkers (GDF15, EGF, neopterin) achieved 96.77% accuracy, reinforcing AI's role in risk stratification and the definition of individualized management plans (MUSIAL et al., 2025). In pediatric emergencies, AI has demonstrated greater precision than traditional protocols like the Manchester Triage System for triage and care prioritization, as well as high accuracy in diagnosing appendicitis using models such as ANN, Decision Trees, and SVM, although the lack of external validation remains a limitation (KOKER et al., 2024; REY et al., 2024).

Innovations and Challenges of AI in Neonatology

The ability to categorize clinical data has also been enhanced by models like ChatGPT, which have shown greater speed and precision in analyzing imaging reports, although their sensitivity remains lower than that of human evaluation (ABU-ASHOUR; EMIL; POENARU, 2024). However, the broad adoption of AI faces barriers including algorithmic bias, data heterogeneity, lack of external validations, and underrepresentation of low- and middle-income populations in studies (KAVAK et al., 2024).

In neonatology, AI has proven to be a valuable resource when facing critical conditions such as sepsis, prematurity, and hypoxic-ischemic encephalopathy. Predictive models have been used to detect pain in neonates and to forecast clinical outcomes in real time through the integration of clinical and laboratory data (GIORDANO et al., 2024; LEW et al., 2024). However, most of these models are still in the prototype phase, with limited internal validation, which hinders their clinical adoption (SCHOUTEN et al., 2024).

Neonatal ventilatory support has also benefited from AI, particularly in preterm infants, with models capable of predicting the need for mechanical ventilation and enabling safer, more individualized interventions (SALAMI et al., 2025). Nonetheless, challenges such as data standardization, algorithm explainability, and integration into clinical workflows still need to be addressed (REY et al., 2024).

Specific Applications and the Future of AI in Pediatric Care

In pediatric radiology, AI has been used to support radiologists, especially in tasks such as length measurements and detection of bone anomalies. Studies emphasize the need to adapt adult-trained algorithms to pediatric contexts, with operational parameters adjusted for age groups, as demonstrated by improved diagnostic sensitivity for pneumothorax in children under two years old when the operating point was adjusted to 3% (SHIN et al., 2024). *BoneXpert* is a consolidated example of AI in pediatric diagnostics, used to assess bone age and calculate the bone health index, with advantages in data privacy (OFFIAH, 2022).

Still within the musculoskeletal context, studies suggest that AI can be expanded for the diagnosis of dysplasias, evaluation of the axial and appendicular skeleton, early detection of bone diseases, and muscle mass analysis, provided that the models are customized and validated for the pediatric population (OFFIAH, 2022).

In summary, AI has shown great potential to transform pediatric care, with positive impacts on diagnostic accuracy, outcome prediction, and treatment personalization. For these benefits to materialize safely, it is essential to invest in multicenter validations, algorithm transparency, ethical integration into clinical workflows, and attention to disparities in access to technology (ANJEWIERDEN et al., 2024).

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ARTIFICIAL INTELLIGENCE
APPLIED TO MEDICINE

Capítulo 04

Applications of AI in Pediatric Oncology

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INTRODUCTION

Childhood cancer represents one of the leading causes of disease-related mortality among children and adolescents worldwide (ELSAYID et al., 2025). Tumors such as leukemias, neuroblastoma, lymphomas, and central nervous system (CNS) tumors are often aggressive and require a sensitive and personalized therapeutic approach. Despite therapeutic advances and increased survival rates in recent decades, early diagnosis and risk stratification still pose significant challenges in pediatric oncology care (RAMESH et al., 2021). The volume of cases and the variety of cancer types in children further complicate these challenges, making it difficult to establish accurate diagnoses, predict disease behavior, and plan appropriate treatments (ELSAYID et al., 2025).

In this context, artificial intelligence (AI) has emerged as a promising ally in medicine, offering high accuracy (YANG, ZHANG & LI, 2023). In pediatric oncology, AI has been applied from screening and image-based diagnosis to therapy response prediction and disease recurrence monitoring. Tools such as machine learning, deep learning, and artificial neural networks have shown high performance in identifying new biomarkers and predicting which treatments are most effective for each patient. Moreover, these tools contribute to treatment outcome analysis and long-term effect studies, being particularly relevant for monitoring children who have undergone cancer treatment (ELSAYID et al., 2025).

The consolidation of artificial intelligence in medicine has driven a revolution in how health data is interpreted and used. In pediatric oncology, its application is especially promising in addressing the inherent challenges of diagnosing and managing tumors in children, which often present great heterogeneity and demand highly individualized therapeutic approaches (YANG et al., 2023; RAMESH et al., 2021). Techniques such as machine learning and deep learning have been used to integrate clinical, genomic, and imaging data, contributing to more accurate analyses and medical decision support (ELSAYID et al., 2025).

Among the most relevant contributions of AI are improvements in molecular subtyping, prediction of therapeutic response, and medical image segmentation, with promising results in central nervous system tumors and leukemias—often performing comparably to specialists (ELSAYID et al., 2025). However, translating these advances into clinical practice still faces hurdles, such as the lack of robust pediatric databases and limited external validation of models (RAMESH et al., 2021; ELSAYID et al., 2025).

In this scenario, it is relevant to promote a critical analysis of AI application in pediatric oncology — from methodological foundations such as neural networks and random forests to their uses across different types of childhood cancers. This approach covers advances in diagnosis, therapy prediction, and risk stratification, as well as a discussion of major challenges and future perspectives, such as the incorporation of radiogenomics and liquid biopsy. It also highlights the importance of reflecting on AI's transformative potential in pediatric cancer care and the need to effectively integrate data science into clinical practice in an ethical, safe, and patient-centered way (TOZZI et al., 2022).

Overview of Pediatric Cancer and Necessary Advances

Pediatric cancer encompasses a heterogeneous set of neoplasms affecting children, among which leukemias, lymphomas, sarcomas, and central nervous system (CNS) tumors are most prominent. Despite therapeutic advances, cancer remains one of the leading causes of childhood mortality, requiring faster, more accurate, and personalized diagnostic approaches. In this scenario, artificial intelligence (AI) has become a strategic ally, promoting significant advances in precision medicine applied to pediatric oncology (DALDRUP-LINK, 2019; SINGH et al., 2024; WAGNER et al., 2021).

AI Applications in Pediatric Oncology

The use of AI in pediatric oncology has expanded through machine learning algorithms and convolutional neural networks (CNNs), with emphasis on techniques such as radiomics, radiogenomics, and deep learning.

Radiomics allows for the automated extraction of quantitative features from imaging exams, such as shape, texture, and intensity, aiding in the accurate differentiation of tumor types (AK et al., 2022; PACCHIANO et al., 2024). In tumors such as medulloblastoma—the most common pediatric brain tumor—this approach has proven effective in predicting molecular subgroups (WNT, SHH, Group 3, and Group 4), using preoperative imaging and, in some cases, avoiding invasive procedures like biopsy (ISMAIL et al., 2023).

Radiogenomics, in turn, seeks to correlate radiological findings with specific genetic alterations. In pediatric gliomas, for example, this technique has enabled the identification of mutations such as BRAF and H3K27M, even in perilesional areas, highlighting the prognostic value of brain changes adjacent to the main lesion (ISMAIL et al., 2023).

Another significant advancement is the automation of tumor segmentation using algorithms trained to delineate lesion boundaries in imaging exams. The FL-PedBrain platform, based on federated learning, exemplifies this progress. Developed using data from 19 international centers, this technology preserved patient privacy and achieved high performance in tumor classification and segmentation, even with variations in equipment and image quality across centers (LEE et al., 2024).

Artificial Intelligence Applied to Leukemias

In the context of leukemias—which account for about one-third of pediatric cancers—AI has shown increasing applicability. Supervised models such as random forest (RF), support vector machine (SVM), and artificial neural networks have proven effective in predicting subtypes like acute lymphoblastic leukemia (ALL) and acute myeloid leukemia (AML). Studies indicate that RF algorithms reach areas under the curve (AUC) above 0.95 when using simple hematologic variables such as hemoglobin and platelet count, making them promising tools for screening and prognostic stratification (CHENG et al., 2024).

Additionally, CNNs have been employed to differentiate between glioblastomas and CNS lymphomas through imaging, as well as in digital slide analysis, mutation screening, and predicting adverse effects related to cancer therapy. These tools expand the potential for personalized treatment and optimize clinical management, especially in resource-limited settings (KOTSYFAKIS et al., 2022; ISMAIL et al., 2023).

Ethical and Technical Challenges of Clinical AI Implementation

However, clinical implementation of AI still faces ethical, technical, and regulatory barriers. The scarcity of pediatric-specific databases, often fragmented and difficult to integrate, limits model training and validation (TOZZI et al., 2023). Furthermore, algorithms developed with adult data often do not apply adequately to pediatric populations, requiring the development of specific solutions (DALDRUP-LINK, 2019).

From an ethical standpoint, protecting sensitive data privacy is crucial, in accordance with regulations such as the LGPD and GDPR. Algorithmic bias—stemming from the underrepresentation of vulnerable populations—also poses a critical challenge, potentially compromising care equity (KOTSYFAKIS et al., 2022). Added to this is the resistance from some healthcare professionals to adopt "black box" model-based tools, whose lack of explainability reduces trust and clinical applicability (WAGNER et al., 2021).

To overcome these limitations, the development of explainable models (XAI), standardization of ethical and technical validation criteria, and investment in healthcare professional training are recommended. The creation of international collaborative networks can foster the construction of more robust and inclusive databases, essential for consolidating AI in pediatric oncology practice (SINGH et al., 2024).

Thus, by integrating clinical, radiological, and genetic data, artificial intelligence has the potential to revolutionize pediatric oncology, enabling earlier diagnoses, accurate risk stratification, and highly personalized therapies. Its ethical, transparent, and technically validated use represents one of the most promising innovations for improving clinical outcomes in a particularly vulnerable population (YEARLEY et al., 2022).

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Capítulo 05

Artificial Intelligence and Algorithms for Arrhythmia Detection

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INTRODUCTION

Atrial fibrillation is the most common sustained cardiac arrhythmia in clinical practice. It occurs due to disorganized electrical activation of the atria, with the loss of the sinoatrial node's role as the primary pacemaker, resulting in ineffective atrial contractions and an irregular heart rhythm. It is estimated that, in 2019, around 60 million people worldwide were affected by this condition, with projections of continued growth in the coming decades, especially due to population aging and the increased diagnostic capacity currently available. The clinical heterogeneity of AF, which can range from asymptomatic cases to fatal cardiovascular events, makes early diagnosis both a challenge and a crucial element in preventing serious complications such as stroke and heart failure (FRANCISCO et al., 2025).

In this context, the use of artificial intelligence (AI) has driven significant advances in cardiology, particularly in the automated detection of arrhythmias. Deep learning-based algorithms, such as deep neural networks (DNNs), have demonstrated high accuracy in identifying episodes of AF, even in asymptomatic patients or those with brief episodes. The application of these technologies in tests like single-lead electrocardiograms enables not only real-time arrhythmia detection but also the prediction of future episodes based on hidden patterns in sinus rhythm records (QUER & TOPOL, 2024). These tools greatly enhance early and personalized screening capacity for AF.

Additionally, detection systems embedded in wearable devices, such as smartwatches and sensors using photoplethysmography (PPG) technology, have gained prominence due to their ability to continuously and remotely monitor patients across various risk levels. These systems are supported by algorithms validated with high sensitivity and specificity rates, making them clinically and economically viable solutions. A recent meta-analysis showed that technologies based on PPG and single-lead ECG can achieve sensitivity above 95% and specificity over 96%, even in asymptomatic populations (MANETAS-STAVRAKAKIS et al., 2023). Such advancements contribute to effective long-term surveillance, particularly in outpatient settings.

At the same time, the integration of artificial intelligence with Internet of Things (IoT) technologies and mobile platforms has enabled the creation of connected digital environments that allow for continuous and personalized monitoring of cardiac parameters, optimizing the management of patients with AF (UMAR et al., 2022). This approach, combining accessible devices with real-time connectivity and automated data analysis, can reduce the healthcare burden and expand diagnostic access in resource-limited regions. However, it is important to note that data quality, individual variability, and sensor limitations still pose significant technical challenges to the broad implementation of these solutions (MILLER, 2020).

Finally, although wearable devices offer promising capabilities for AF screening, important ethical, regulatory, and equity issues persist, especially in low- and middle-income countries. Most studies have been conducted in high-income countries, and the adoption of these technologies remains limited among older adults, women, and socioeconomically disadvantaged groups (FRANCISCO et al., 2025). The lack of robust validation across all clinical contexts and the absence of standardized protocols for managing AI-generated alerts underscore the need for multicenter studies and specific public policies. Therefore, this chapter aims to analyze the role of artificial intelligence and algorithms embedded in wearable technologies in the early detection and monitoring of atrial fibrillation, focusing on diagnostic accuracy, clinical implications, and the challenges of ethically and safely integrating these tools into medical practice.

Diagnosis of Atrial Fibrillation

Atrial fibrillation AF is one of the most prevalent cardiac arrhythmias worldwide and is associated with serious complications such as stroke, heart failure, and increased cardiovascular mortality. This condition is characterized by disorganized atrial electrical activity resulting in ineffective contractions and an irregular rhythm, often asymptomatic in its early stages, which hinders early detection. Timely diagnosis and risk stratification in AF patients are essential for clinical management, especially in populations with multiple cardiovascular risk factors (FEENY et al., 2020).

In recent years, artificial intelligence AI, and more specifically machine learning (ML), has emerged as a promising tool in cardiac electrophysiology. The application of algorithms to ECG data, cardiac imaging, and electronic health records has demonstrated high accuracy in detecting, classifying, and predicting AF-related events. Supervised learning models and deep neural networks have been able to identify hidden patterns in normal ECGs that suggest the presence of subclinical AF, with performance comparable to that of specialists (FEENY et al., 2020). Beyond detection, these tools have also been explored for phenotypic characterization of the arrhythmia and for predicting therapeutic response to ablation.

Although electrocardiographic analysis is widely used as a screening tool, it presents important limitations related to variability in human interpretation. Studies have shown that physicians' average accuracy in reading ECGs is around 54%, highlighting the need for complementary solutions to optimize clinical practice. In this context, convolutional neural network (CNN)-based algorithms have stood out for providing greater diagnostic precision, being capable of detecting silent AF, asymptomatic ventricular dysfunction, and other electrical disorders based on apparently normal sinus rhythm traces (MUZAMMIL et al., 2024).

Even though traditional AI models demonstrate high performance, a frequent limitation is their low interpretability, which hinders widespread clinical adoption. To overcome this barrier, explainable models such as the NBET (neural back-end tree) have been developed, combining the accuracy of deep networks with transparent decision-making processes. This approach was able to identify AF with an AUC of 0.976, using understandable markers such as absence of P wave and atrioventricular dissociation, thereby strengthening clinical trust in the tool (JO et al., 2021). The ability to explain the diagnostic process is an essential step toward the safe integration of AI into cardiovascular care.

The applications of AI in electrocardiography are not limited to high-complexity centers. Technologies such as ConvLSTM2D networks and neural circuit policy (NCP) architectures have enabled the development of efficient models for use in low-power computing devices, such as microcontrollers and wearable sensors. Recent studies have shown that models like CLTC and CCfC achieved an F1-score above 0.82 and AUROC over 0.96, even under noise and input channel loss (HUANG et al., 2024). This innovation expands access to early AF diagnosis, making it possible to implement intelligent monitoring systems in remote regions and clinical settings with limited infrastructure.

The advancement of these tools is further reinforced by AI's ability to integrate clinical, genomic, and demographic data. Models trained on multicenter datasets have outperformed cardiologists in detecting cardiac dysfunctions and acute myocardial infarctions, in addition to enabling personalized risk estimates and biological age predictions based on ECG (MARTÍNEZ-SELLÉS & MARINA-BREYSSE, 2023). These contributions position artificial intelligence as a key player in the transformation of modern cardiology, especially in the diagnostic and predictive approach to atrial fibrillation.

Advances and Applications of AI in the Field

The use of artificial intelligence in wearable devices has gained prominence in the monitoring and diagnosis of cardiovascular diseases, especially atrial fibrillation. A recent systematic review and meta-analysis identified 102 studies involving AI models developed for use in mobile or wearable devices, with 26 of these specifically focused on AF detection. Deep neural network-based models demonstrated superior performance, with an average sensitivity of 94.8%, specificity of 96.96%, and an area under the curve (AUROC) of 0.981, compared to conventional machine learning algorithms (AUROC of 0.961) (LEE et al., 2022). These findings establish AI as a highly effective tool for AF screening in outpatient settings, using ECG or photoplethysmography (PPG) signals collected in real time by continuous-use devices.

The application of AI in electrocardiography has significantly expanded the ability to detect atrial fibrillation AF, even in challenging clinical scenarios such as patients in sinus rhythm. AI-enhanced ECG algorithms, developed from large institutional databases, have identified paroxysmal AF with AUCs up to 0.90, even in the absence of manifest arrhythmia during the exam. Moreover, predictive models integrated with electronic health records, using both structured and unstructured clinical features, have proven effective in risk stratification and in selecting patients for extended monitoring (HARMON et al., 2023). These approaches have even enabled targeted clinical interventions in prospective studies, showing that individuals with a high probability of AF according to AI algorithms had a fivefold higher diagnostic rate during ambulatory monitoring compared to those classified as low risk.

AI's ability to detect atrial fibrillation AF from sinus rhythm tracings has broadened the diagnostic boundaries of conventional electrocardiography. A retrospective study with over 649,000 ECGs showed that a convolutional neural network model trained to identify ECG signatures of AF during sinus rhythm could detect the arrhythmia with an AUC of 0.87 using just a standard 10-second ECG. When multiple ECGs per patient were analyzed, model performance increased significantly, with an AUC of 0.90, sensitivity of 82.3%, and specificity of 83.4% (ATTIA et al., 2019). These results show that atrial structural changes associated with AF can produce subtle patterns in the ECG, invisible to the human eye but detectable by AI algorithms, enabling early and non-invasive diagnosis even during asymptomatic phases.

The incorporation of AI into electrocardiography has seen remarkable advances, especially in detecting paroxysmal AF from sinus rhythm ECGs. Models like the one developed by Attia et al. have been externally validated by Gruwez et al., showing similar performance across different populations, with AUCs ranging from 0.84 to 0.90 (KALSCHEUR & AKBILGIC, 2023). However, editorials highlight key challenges that must still be addressed before widespread clinical adoption, such as replicating performance in diverse populations, understanding the specific parameters used by the algorithm, and proving that predictive results lead to beneficial interventions. Strategies like federated learning have been proposed as alternatives for training robust models across institutions without direct data sharing, potentially improving model generalizability and safety. These advances pave the way for ECG-based AI models to be incorporated safely and effectively into clinical routines.

Artificial intelligence models applied to electrocardiography (AI-ECG) have evolved beyond the simple detection of atrial fibrillation (AF). They are now also used to predict incident AF, assess AF burden, and stratify risk in patients with embolic stroke of undetermined source (ESUS). A model developed with more than 600,000 sinus rhythm ECGs was able to identify patients with hidden AF with an AUC of 0.90, anticipating diagnosis by several weeks and supporting clinical decisions such as the early initiation of anticoagulation (SEHRAWAT et al., 2023). Furthermore, combining AI-ECG with traditional scores like CHARGE-AF improved predictive capacity for developing AF over up to 10 years. This hybrid approach enables more cost-effective screenings and can guide extended monitoring, especially in patients with ESUS, where clinical studies indicate significant underdiagnosis of paroxysmal AF. These advances illustrate AI's emerging role in the personalization of primary and secondary AF prevention, with direct impact on neurological and cardiovascular outcomes.

Limitations and Challenges of Implementation

Despite the promising advances of artificial intelligence in cardiac electrophysiology, its clinical application still faces significant challenges that limit broad and safe adoption. One of the main obstacles is the phenomenon of overfitting, which occurs when a model is overly tailored to the training data and loses the ability to generalize to new datasets. This limitation can compromise algorithm performance in real-world clinical environments, especially when the input data differ in quality or population characteristics (NAGARAJAN et al., 2021). Furthermore, many machine learning methodologies operate as "black boxes," lacking sufficient transparency about the criteria used in decision-making. This lack of interpretability hinders clinical validation and undermines the trust of healthcare professionals, who may hesitate to use models whose decision-making processes are not clearly understood. Establishing appropriate regulatory standards for non-transparent but highly accurate algorithms remains an urgent challenge to ensure their ethical and safe incorporation into medical practice.

Algorithmic bias is one of the most pressing ethical challenges in implementing AI models for the diagnosis and management of atrial fibrillation (AF). Since these systems learn from large clinical datasets, any existing distortions or inequalities in the data can be replicated or amplified by the algorithm, resulting in discriminatory decisions. Previous studies have shown that algorithms trained on biased datasets may underestimate risk in certain population groups, such as the elderly, ethnic minorities, or individuals with limited access to healthcare services (ISAKSEN et al., 2022). Moreover, the accuracy of models trained on specific populations may not hold in different clinical contexts, a phenomenon known as data shift. Changes in devices, software updates, alterations in data collection protocols, or variations in target population profiles can compromise algorithm reliability and lead to performance degradation. These challenges highlight the need for rigorous external validations, continuous model updates, and strategies like transfer learning, which allow models trained in one context to be adapted for use in different settings.

Although AI-based systems for AF detection show high accuracy under controlled conditions, their use in real-world clinical contexts remains limited by operational and technical challenges. The study by Santala et al. showed that despite the strong performance of AI integrated with mobile health (mHealth) devices, about 20% of ECG recordings included uninterpretable segments due to issues such as improper electrode contact, incorrect sensor placement, or data transmission instabilities (SANTALA et al., 2021). Additionally, the sensitivity for detecting brief AF episodes was considerably lower than for longer episodes, potentially leading to underdiagnosis in patients with intermittent arrhythmias. Frequent ectopic beats were also associated with false positives, requiring medical validation even in the presence of automated alerts. Finally, despite good acceptance of the device by elderly patients, the authors note that healthcare systems are not yet prepared for mass AI-based screening, with gaps in defining care pathways following a positive result and integrating with traditional clinical workflows.

Although AI algorithms have demonstrated superiority in identifying individualized electrophysiological substrates for the ablation of persistent AF, large-scale incorporation still faces significant operational hurdles. The TAILORED-AF study showed that the AI-guided approach, though more effective than conventional pulmonary vein isolation (PVI), resulted in longer procedures, with an average total duration of 178 minutes and double the radiofrequency time compared to the control group (DEISENHOFER et al., 2025). Furthermore, the need to map specific electrogram dispersions increased the technical complexity of the intervention, requiring greater operator expertise and higher reliance on compatible navigation platforms. Despite the algorithm's strong performance (AUC of 0.94), reproducibility across centers and operators still depends on precise system calibration and intracardiac signal quality, limiting its widespread applicability. These factors, combined with the scarcity of advanced equipment and lack of validation in broad, heterogeneous populations, underscore the need for technical improvements and cost-effectiveness studies before this technology can be routinely adopted.

While deep learning algorithms applied to ECGs have shown superior performance in surgical risk stratification—as demonstrated by the PreOpNet model—important limitations remain regarding their generalizability across different healthcare systems. A multicenter study conducted by Ouyang et al. revealed a decline in predictive performance when the algorithm was applied to external cohorts, such as those from Stanford and Columbia institutions, likely due to differences in population composition, procedure definitions, and data collection systems (OUYANG et al., 2024). Moreover, the algorithm was developed and validated retrospectively, requiring prospective validation in real clinical scenarios to confirm its effectiveness. The authors also noted that many patients undergoing low-risk procedures do not undergo preoperative ECGs, limiting the tool's applicability in this group. Finally, although the model is highly efficient and compatible with conventional clinical computers, its integration into care workflows still depends on user-friendly clinical interfaces, professional training, and standardized usage criteria—without which the real impact of AI on reducing postoperative mortality remains uncertain.

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Capítulo 06

Artificial Intelligence and Robotic Surgery

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INTRODUCTION

Technological advancement has played a central role in transforming modern surgery, from the creation of rudimentary instruments to the incorporation of highly sophisticated robotic systems. Robotic surgery, initially developed for military purposes and space missions, has established itself as a viable alternative for high-complexity procedures, especially in contexts with restricted access or emergency situations. Its evolution has been marked by historical milestones, such as the first transcontinental cholecystectomy performed via telesurgery with the aid of a robotic system, highlighting the potential of this technology to enable safe and effective interventions even over great distances (KNUDSEN et al., 2024; MOGLIA et al., 2021).

With the maturation of robotic platforms like the Da Vinci system, there has been a qualitative leap in the performance of minimally invasive surgeries. Features such as three-dimensional visualization, instruments with a wide range of motion, and improved ergonomics for the surgeon have contributed to better clinical outcomes, including shorter surgical times, faster recovery, and lower complication rates (SONE et al., 2023). In parallel, the introduction of digital technologies such as augmented reality anatomical models and software-assisted surgical planning has further enhanced procedural precision (MOGLIA et al., 2021).

In this context, Artificial Intelligence (AI) emerges as a disruptive innovation, bringing new possibilities to surgical practice. Since its conceptualization as a science capable of creating intelligent machines, AI has been applied in multiple areas of medicine, standing out particularly in robotic surgery for its ability to process large volumes of clinical data, images, and surgical videos (HAMILTON, 2024). Machine learning and deep learning tools have been explored for tasks such as anatomical structure recognition, tissue segmentation, automated identification of surgical phases, and prediction of complications, providing real-time decision support (SONE et al., 2023).

Recent studies show that AI can operate at all stages of the surgical process: from preoperative planning based on imaging and clinical variables, to intraoperative support with algorithms capable of suggesting dissection plans and warning of potential risks. Additionally, in the postoperative phase, there is growing interest in using AI to assess surgical performance and predict adverse events based on historical patterns and continuous learning (MORRIS et al., 2024).

Despite promising advances, the implementation of AI in robotic surgery still faces significant challenges, such as data standardization, integration with hospital systems, and ethical issues related to algorithm transparency and accountability for automated decisions

(MOGLIA et al., 2022). Moreover, it is still necessary to validate the real clinical benefits of AI-based solutions in multicenter studies and to establish clear guidelines for their safe and effective use.

Artificial Intelligence and the Enhancement of Surgical Skills

The training of surgeons has always been a gradual, hands-on process, reliant on the supervised repetition of technical gestures in controlled environments. With the growing incorporation of digital technologies into medical education, artificial intelligence has emerged as a transformative tool for teaching, evaluating, and improving surgical skills, both in academic settings and clinical practice (GUERRERO et al., 2023).

AI-integrated virtual reality simulators have stood out as one of the most promising innovations in surgical training. By using machine learning algorithms, these systems can identify movement patterns and analyze the execution of technical tasks with greater accuracy than human observation, offering objective and real-time feedback on learner performance (WINKLER-SCHWARTZ et al., 2019). This approach enables not only quantitative assessment of surgical proficiency but also personalized teaching by adapting challenges to each student's learning curve.

Moreover, AI has been applied in advanced surgical simulation, creating realistic scenarios that replicate anatomical variability, intraoperative complications, and complex clinical decisions. These intelligent simulators train not only technical skills but also competencies such as clinical reasoning, decision-making under pressure, and teamwork (PARK et al., 2022). This is especially relevant in times when access to real surgical cases for training is limited, as seen during the COVID-19 pandemic.

From an evaluation perspective, AI-based tools have been used to develop objective scoring systems for surgical skills. A systematic review by Boal et al. (2024) demonstrated that computational models can accurately measure time, fluidity, applied force, and proper instrument use on robotic platforms, surpassing traditional subjective evaluation methods.

AI's potential goes even further with the application of techniques such as deep reinforcement learning. In autonomous robotic surgery simulations, neural networks have been trained to optimize continuous actions, adjusting in real time to the dynamic characteristics of the surgical environment (SHAHKOO; ABIN, 2023). These models not only assist in training but also contribute to research in highly complex robotic surgery.

Despite these advances, challenges remain. The curation and anonymization of the data used to train algorithms, the representation of diverse population profiles, and the risk of bias in result interpretation are significant ethical and technical concerns (SATAPATHY et al., 2023). Additionally, resistance from parts of the medical community to accept AI as an evaluator or instructor highlights the need for technological inclusion in training curricula and institutional accreditation policies.

Ultimately, AI has shown great value in complementing technical education and democratizing access to high-quality training, especially in regions lacking advanced surgical centers. According to Gupta et al. (2022), AI should not be seen as a substitute for human expertise, but as an extension of the modern surgeon's capabilities—a cognitive tool that enhances technical mastery and procedural safety. Thus, the use of artificial intelligence in surgical education and training not only redefines medical learning methods but also raises the standards of quality and safety in operative practice. With ethical, technical, and pedagogical validation, this technology promises to prepare better-trained surgeons, objectively evaluated and equipped to meet the challenges of contemporary medicine.

Autonomous Robotic Surgery: Emerging Applications

The evolution of robotic surgery represents one of the most significant milestones in 21st-century medical innovation, directly impacting surgical precision, patient safety, and procedural efficiency. From the first teleoperated systems to the integration of artificial intelligence-based technologies, there has been an exponential advance toward surgical autonomy. The fundamental difference between AI applications in diagnostic medicine and in surgery lies in the capacity for physical execution: in surgery, algorithms not only analyze data but make real-time decisions and perform movements with increasing autonomy (GUMBS et al., 2021; IFTIKHAR et al., 2024).

The development of autonomous robotic systems involves three main levels: direct human control (level 1), robotic assistance with active surgeon participation (level 2), and full autonomy (level 3), in which the system is capable of performing complex tasks without direct human intervention (Jamjoom et al., 2022). The Smart Tissue Autonomous Robot (STAR), for instance, was a game-changer by demonstrating its ability to perform intestinal anastomoses with greater precision than experienced surgeons, even in soft and dynamic tissues, which require continuous adjustments in path and force (KHANNA et al., 2025; ZHANG et al., 2024).

The use of deep learning algorithms has also enabled advancements in the automatic recognition of anatomical structures and surgical phases from laparoscopic images (SONE et al., 2023). This allows robots to assist in intraoperative decision-making and, in the future, to perform procedures completely independently. Augmented reality systems integrated with AI have also contributed to the visualization of critical structures by overlaying three-dimensional images onto the operative field, enhancing surgical safety and accuracy (ZHANG et al., 2024).

At the same time, systems such as MySurgeryRisk and POTTER have shown that AI can accurately predict postoperative complications based on electronic medical records and intraoperative variables, allowing for anticipatory action and optimized clinical outcomes (GUMBS et al., 2021). The integration of these tools with multimodal databases—including imaging exams, physiological signals, gene expression, and immunological profiles—has led to the creation of surgical digital twins, which simulate different scenarios and enable extreme personalization of operative strategies (ZHANG et al., 2024).

Despite these promises, technical, ethical, and legal challenges remain significant. Full autonomy requires ultra-precise sensors, real-time adaptability, and robust algorithms capable of handling anatomical variability and emergency contexts (KHANNA et al., 2025; Sone et al., 2023). Limited interoperability between platforms also hampers standardization and large-scale clinical validation (NE et al., 2023).

On the ethical front, the concept of the "moral impact zone" is noteworthy, in which the human surgeon remains accountable for failures even when the decision was made by the robot (Jamjoom et al., 2022). The iRobot Surgeon Survey highlighted this issue, pointing to the urgent need to revise legal frameworks and establish specific regulations for procedures conducted by autonomous systems. Algorithmic bias is also a critical issue, potentially compromising care equity, especially for populations underrepresented in training datasets (ZHANG et al., 2024).

The high cost of AI-based robotic surgery platforms and the need for specialized infrastructure present another barrier, particularly in low- and middle-income regions. This demands public policies that promote equitable access to technology and encourage international collaboration to share knowledge and develop more affordable technologies (IFTIKHAR et al., 2024).

In the educational realm, AI has expanded horizons in surgical training. Adaptive learning-based simulators provide residents with immediate, personalized feedback, accelerating learning curves and standardizing training across institutions (SONE et al., 2023). This is a key strategy for democratizing training in complex surgeries, even in resource-limited settings.

Artificial Intelligence in Surgery: Technological Advances, Ethical Limits, and Future Perspectives

Artificial intelligence has emerged as one of the central pillars of technological transformation in medicine, particularly in the surgical field. Its application goes beyond automation: it aims to enhance decision-making, reduce technical variability, and expand access to high-quality surgical care. The fusion of AI and robotic surgery redefines not only operative technique but the entire ecosystem surrounding the planning, execution, and evaluation of procedures (GUNI et al., 2024; MITHANY et al., 2023).

Currently, AI is present in various stages of surgery. In the preoperative phase, machine learning algorithms analyze imaging exams and predict risks based on clinical data, facilitating personalized patient stratification (GUO et al., 2025; KITAGUCHI et al., 2022). Intraoperatively, computer vision systems identify anatomical structures in real time, guiding incisions and dissections with greater precision. Some systems even offer tactical suggestions during surgery based on previously learned patterns (SIMONE et al., 2022; BODENSTEDT et al., 2020).

Emergency surgery, in particular, stands to benefit greatly from these technologies. The unpredictability of cases, coupled with the need for rapid decisions, makes AI a powerful ally. The ARIES project, for instance, explores how algorithms can support emergency surgeons in prioritizing actions and selecting the best technical approach based on continuous learning from large databases (SIMONE et al., 2022).

However, the full incorporation of AI into surgery still faces significant barriers. From a technical standpoint, the effectiveness of algorithms depends on robust and diverse data. A lack of data from underrepresented populations can lead to biased models, reducing safety and efficacy for certain groups (MITHANY et al., 2023; GUO et al., 2025).

From an ethical and legal perspective, dilemmas arise around machine autonomy and accountability for errors. Who is responsible for a surgical failure when the decision was suggested or made by an algorithm? The absence of clear legal frameworks still hinders appropriate accountability and limits professionals' trust in the technology (BODENSTEDT et al., 2020).

There is also the challenge of professional acceptance. Many surgeons are wary of the growing autonomy of systems, fearing the devaluation of human judgment or professional replacement. In this regard, investing in medical education with a focus on emerging technologies becomes strategic. Familiarity with AI from undergraduate training can boost confidence in the tool and enable more ethical and effective use (GUNI et al., 2024).

Future prospects are promising. The integration of AI, augmented reality, and intraoperative sensors promises increasingly precise and safe interventions. The consolidation of digital twins—virtual models based on real patient data—is also expected to enable procedure simulations before actual execution, anticipating risks and personalizing strategies (KITAGUCHI et al., 2022; GUNI et al., 2024).

Furthermore, advances in deep neural networks and reinforcement learning may empower robots to autonomously adapt their actions in real time, increasing intraoperative autonomy. However, such innovations will only materialize with the strengthening of translational research, multicenter validation, and the updating of global regulatory systems (GUO et al., 2025; MITHANY et al., 2023).

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ARTIFICIAL INTELLIGENCE APPLIED TO MEDICINE

Capítulo 07

Artificial Intelligence and Skin Cancer

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INTRODUCTION

Skin cancer is one of the most prevalent malignant neoplasms globally, with increasing incidence over recent decades and a significant impact on healthcare systems—particularly in countries with high ultraviolet (UV) radiation exposure, such as Australia and the United States. Among its types, non-melanoma skin cancers—basal cell carcinoma (BCC) and squamous cell carcinoma (SCC)—stand out, along with cutaneous melanoma, which, although less frequent, has greater metastatic potential and higher lethality (GOYAL et al., 2020; MILLER et al., 2023). Global survival rates can exceed 99% when diagnosis is made early (GOYAL et al., 2020), underscoring the importance of effective and accessible diagnostic strategies.

Traditionally, the diagnosis of skin cancer relies on clinical visual inspection and dermoscopy, supported by patient history and histopathological confirmation through biopsy. Despite its widespread use, this approach may have limitations in settings with a shortage of specialists, interobserver variability, and difficulty in identifying atypical or early-stage lesions (BRANCACCIO et al., 2024; GOYAL et al., 2020). In this context, Artificial Intelligence (AI) emerges as an innovative tool capable of supporting medical practice through automated analysis of dermatological images, increasing diagnostic accuracy and reducing reliance on subjective evaluations (DAS et al., 2021).

Several AI technologies have been explored in dermatology, notably machine learning (ML), deep learning (DL), and convolutional neural networks (CNNs), which can detect morphological patterns in skin lesion images with performance comparable to—or, in some cases, exceeding—that of specialists (Das et al., 2021; FELMINGHAM et al., 2021). Experimental studies have shown that such algorithms may reduce the need for unnecessary biopsies and optimize the triage of suspicious lesions, particularly in primary care settings (Miller et al., 2023). However, results vary widely when these tools are applied to real-world populations, such as patients with sun-damaged skin or skin tones underrepresented in training datasets (FELMINGHAM et al., 2021; MILLER et al., 2023).

In addition, significant limitations still challenge the safe incorporation of AI into clinical practice, such as the low interpretability of algorithms (so-called “black box” systems), the potential for automation bias, and performance variability across different clinical scenarios (BRANCACCIO et al., 2024; FELMINGHAM et al., 2021). Studies using real-world data have reported sensitivities and specificities lower than those seen in controlled settings—as in the case of the tool analyzed by Miller et al. (2023), which showed only 54.17% accuracy in detecting melanoma in patients seen in primary care.

Given this scenario, it is essential to critically and comprehensively understand the applications of Artificial Intelligence in the field of cutaneous oncology. This chapter aims to discuss the main contributions of AI in the context of skin cancer, covering its use in detecting and triaging suspicious lesions, its potential in melanoma diagnosis, and its role in therapeutic strategies. To this end, it will explore the underlying technologies, the latest evidence from the literature, and the ethical, technical, and clinical challenges that must still be addressed to ensure the safe and effective adoption of these tools in contemporary dermatologic practice.

Application of Artificial Intelligence in the Context of Skin Cancer

Skin cancer is among the most common tumors worldwide, and its prognosis is closely linked to histological type and the stage at diagnosis. Early identification is crucial for improving survival rates, especially in melanoma, whose aggressiveness requires precise and accessible diagnostic strategies (JONES et al., 2022; ZAKHEM, MOTOSKO & HO, 2018). In this context, artificial intelligence (AI) algorithms have been studied as promising tools to assist in screening and early diagnosis, particularly in primary and community care settings, where a shortage of specialists may hinder timely detection (JOBSON, MAR & FRECKELTON, 2022; HAUSER et al., 2022).

Various AI approaches—especially those based on machine learning and deep learning—have been applied to the automated detection of skin lesions. Convolutional neural networks (CNNs), composed of multiple layers, can extract complex visual patterns from dermatological images and generate probabilistic classifications of lesions, achieving performance comparable to that of dermatologists in controlled studies (ZAKHEM, MOTOSKO & HO, 2018; HAUSER et al., 2022). However, the performance of these models can vary depending on the training dataset, and limitations remain when they are applied in real-world clinical settings, particularly in underrepresented populations (JONES et al., 2022).

The emergence of explainable artificial intelligence (XAI) aims to address one of the major limitations of these systems: the opacity of automated decisions. XAI seeks to make the criteria and image regions used by algorithms more understandable to clinicians and patients. Despite its growing adoption, there is still a scarcity of studies demonstrating a positive impact of XAI on diagnostic accuracy or practitioner confidence in dermatology (HAUSER et al., 2022; HAGGENMÜLLER et al., 2024). Data from a multicenter survey show that 42% of patients and 48% of dermatologists reject AI systems whose assessments are not traceable, underscoring the central importance of transparency for clinical acceptance (HAGGENMÜLLER et al., 2024).

Beyond technical advances, ethical and regulatory issues have also come to the forefront with the expansion of AI in dermatology. The growing commercialization of diagnostic software requires strict regulation to ensure patient safety—particularly in light of potential algorithmic biases, the risks of blind automation, and the lack of clinical validation in real-world populations (JOBSON, MAR & FRECKELTON, 2022; BRANCACCIO et al., 2024). The active involvement of dermatologists in the development and oversight of these systems has been recognized as essential to ensuring their safe and effective integration into medical care (ZAKHEM, MOTOSKO & HO, 2018).

Finally, the clinical implementation of AI depends on solid guidelines for standardizing the development, validation, and application of such systems. Initiatives such as the creation of checklists for AI/ML studies and the promotion of prospective studies involving multiple diagnostic classes reflect a push toward greater methodological robustness and practical relevance (JONES et al., 2022; HAGGEN-MÜLLER et al., 2024). While algorithms show promising results, their consolidation as routine diagnostic tools requires not only technical performance but also reliability, explainability, and adaptability to real clinical contexts.

Advances and Applications of AI in the Field

The advancement of artificial intelligence (AI) in medicine—particularly in dermatology—has led to significant transformations in screening and diagnostic strategies for skin cancer. Deep learning models, such as convolutional neural networks (CNNs), have been successfully applied to the analysis of clinical and dermoscopic images, showing diagnostic performance equivalent to, and in some studies even surpassing, that of dermatologists (ESTEVA et al., 2017; CHARALAMBIDES & SINGH, 2020). These networks can extract and interpret complex visual patterns—such as asymmetries, borders, and variations in texture and color—classifying lesions with high accuracy as benign or malignant.

Recent studies reinforce AI’s capability not only in binary classification but also in differentiating among multiple diagnostic categories, including melanoma, basal cell carcinoma, actinic keratoses, and benign pigmented lesions. One example is the 7-class model evaluated by Menzies et al. (2023), which demonstrated performance comparable to specialists and superior to general practitioners, using images captured by mobile devices with attached dermatoscopes. This approach suggests that AI may be viable as a triage tool in low-resource settings and can expand access to diagnosis in primary care.

Beyond technical performance, new implementation models are emerging. Integrating AI into mobile applications and digital platforms has led to the development of automated triage tools and longitudinal monitoring systems. The First Derm app, for example, can suggest differential diagnoses with up to 80% accuracy among its top five options, helping patients identify suspicious lesions and optimizing the demand for specialized care (CHARALAMBIDES & SINGH, 2020). If adequately validated, such tools can serve as complementary diagnostic support in daily clinical practice.

Moreover, emerging strategies aim to integrate multiple data sources—such as clinical information, sequential imaging, and histopathology—to enhance prediction accuracy and enable personalized care (WADA et al., 2020). AI has also become a valuable tool for less experienced physicians, enhancing diagnostic sensitivity and enabling safer decisions, particularly during initial screenings or in high-demand environments (DILDAR et al., 2021). The use of techniques such as GANs to augment datasets and federated learning to preserve privacy illustrates the ongoing evolution of AI from both technical and ethical perspectives (ESTEVA et al., 2017).

Thus, the application of artificial intelligence in oncologic dermatology has proven to be a promising field, offering direct benefits in screening, diagnosis, and clinical follow-up of patients with skin cancer. Strengthening these applications depends on continued validation in real-world clinical settings, inclusion of diverse populations in datasets, and ethical and secure integration of these technologies into existing healthcare systems.

Despite these promising advances, significant challenges remain that hinder the widespread clinical implementation of AI in skin cancer diagnosis and prognosis. Deep learning models, such as CNNs, require substantial computational capacity, complex pre-processing, and high-quality imaging—factors that are not always available in everyday clinical environments (LAI et al., 2023).

Furthermore, many current AI solutions are limited to binary classification of skin lesions (e.g., benign vs. malignant), which does not reflect the diversity of differential diagnoses typically considered by experienced dermatopathologists. This limits the utility of AI in more complex scenarios, where multiclass classification is necessary to support clinical decision-making (WELLS et al., 2021).

Another major obstacle is limited generalizability. Several studies have shown that algorithms trained on specific datasets, such as ISIC, tend to perform poorly when exposed to external images with different clinical features, ethnicities, or acquisition protocols. This reduces model reproducibility and hinders application in primary care settings or regions with fewer technological resources (HEKLER et al., 2019; LAI et al., 2023).

The underrepresentation of individuals with darker skin tones in public datasets is another critical issue, leading to algorithmic bias and lower diagnostic accuracy for these groups. This raises important ethical concerns about equity in care (SANCHEZ et al., 2023). Although data augmentation and federated learning have been proposed as solutions, they are not sufficient substitutes for diverse datasets curated by experts (SANCHEZ et al., 2023; WELLS et al., 2021).

AI-assisted prognostic models, such as the one developed by Xu et al. (2024), show great potential in predicting metastasis and survival in patients with nodular melanoma, outperforming traditional methods. However, these tools are based on retrospective analyses and still lack external validation and prospective multicenter testing. This limits their immediate clinical applicability and points to the need for further standardization, validation, and integration into medical workflows.

Therefore, for AI to be safely and effectively implemented in oncologic dermatology, it is essential to overcome the aforementioned technical, ethical, and regulatory challenges. Investments in computational infrastructure, data diversity, algorithmic transparency, and clinical validation are indispensable not only to ensure efficiency, but also to guarantee equity and trustworthiness in the care of patients with skin cancer.

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Capítulo 08

Artificial Intelligence for Screening of Multiple Optic Nerve Diseases

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INTRODUCTION

Artificial intelligence (AI) is the capability of software to mimic intelligent behavior—in other words, to perform tasks that would normally require human intelligence. Its main goal is to integrate information from various fields, such as image recognition, decision-making, problem-solving, and data learning. In this context, AI encompasses different types of learning—such as machine learning, characterized by a computer's ability to learn outcomes not previously programmed, and deep learning, a more advanced method that allows the computer to improve its algorithm through the use of larger datasets. More recently, generative AI models have emerged, capable of creating new data based on learned patterns, representing a significant advance in the generalization and personalization of solutions (KESKINBORA & GÜVEN, 2020; TING et al., 2019; LI et al., 2021; ABDULLAH et al., 2021; LI et al., 2023; FENG et al., 2024).

Within this framework, the use of AI and its tools has gained great relevance in both social and scientific spheres, as it enables innovation in medicine through the processing of complex data and information. This impact is particularly evident in ophthalmology, where the diagnosis of various diseases—such as diabetic retinopathy, age-related macular degeneration, glaucoma, and retinopathy of prematurity—can be performed in advance and in hard-to-reach areas, with performance comparable to human specialists. Additionally, generative AI is now being applied in the diagnosis of rare diseases, retinal image simulation, multimodal interpretation, and personalized treatment planning, further expanding its potential in ophthalmic care (TING et al., 2019; LI et al., 2021; ABDULLAH et al., 2021; FENG et al., 2024). Among the ocular structures most affected by high-impact diseases is the optic nerve, whose integrity is essential for proper visual signal conduction. The application of artificial intelligence in the screening of optic neuropathies—such as glaucoma—represents an emerging and promising frontier, with the potential to enhance early diagnosis, monitoring, and prognosis of these conditions (FENG et al., 2024).

However, the use of AI also faces significant challenges, especially ethical and operational ones, including algorithmic transparency, data privacy, bias in training datasets, and the difficulty patients may have in understanding the role of such technologies in their healthcare (KESKINBORA & GÜVEN, 2020; ABDULLAH et al., 2021; FENG et al., 2024).

Integrating AI into medicine is essential to overcoming the limitations of traditional methods, such as diagnostic subjectivity and lack of access to specialists in remote regions. AI has the potential to increase diagnostic accuracy, accelerate early detection of conditions like diabetic retinopathy and glaucoma, and personalize treatments—resulting in better clinical outcomes. Recent advances show that AI algorithms can reduce operational costs and complications, such as preventable blindness, while expanding access to care for vulnerable populations. With the advent of generative AI, these benefits are further enhanced by its ability to produce images, reports, and personalized recommendations, as well as to integrate into clinical workflows through continuous learning and real-time feedback (LI et al., 2021; LI et al., 2023; FENG et al., 2024). This chapter is especially relevant within the context of healthcare's digital transformation, highlighting AI's role in revolutionizing medical practice, promoting efficiency and equity, while addressing ethical concerns and the need for regulation to ensure its responsible use.

This chapter will explore the application of artificial intelligence in the detection, diagnosis, and treatment of medical conditions, with an emphasis on its relevance in ophthalmology. First, studies illustrating AI's effectiveness in the early identification of ophthalmic pathologies will be reviewed. Next, practical applications such as automated screening systems and clinical decision support tools will be discussed. Finally, the chapter will address future perspectives, including technological innovations, ethical challenges, and strategies for large-scale implementation. The approach will be based on a narrative literature review, combining scientific evidence, clinical examples, and reflections on the impact of AI in contemporary medicine.

The Importance of the Optic Nerve and the Role of AI in Glaucoma

Artificial intelligence has increasingly established itself as a transformative tool in medical practice, with particularly promising applications in ophthalmology—especially in the diagnosis and monitoring of diseases affecting neural structures such as the optic nerve. Among these conditions, glaucoma stands out as a chronic and progressive optic neuropathy, characterized by the loss of nerve fibers and optic disc cupping. Often asymptomatic in its early stages, glaucoma can lead to irreversible blindness if not detected in time (BALI & BALI, 2021; HOGARTY et al., 2019; HUANG et al., 2023).

The complexity of early glaucoma diagnosis, combined with interobserver variability in interpreting exams such as fundoscopy and optical coherence tomography (OCT), makes this disease a strategic target for AI applications. Machine learning tools and convolutional neural networks (CNNs) are being developed to automatically analyze fundus and OCT images, enabling segmentation of the optic disc and detection of early structural changes.

These systems have shown performance comparable to—or even exceeding—that of human specialists, contributing to automated screening, disease staging, and clinical decision-making support. Furthermore, AI has enabled the development of predictive models capable of estimating glaucoma progression using longitudinal data, as well as classifying the severity of optic neuropathy with greater precision (HUANG et al., 2023; ONG, SELVAM & CHHABLANI, 2021). Clinically validated initiatives such as EyeGrader represent significant advances toward the real-world implementation of intelligent systems in high-demand clinical environments (TAN, SCHEETZ & HE, 2019).

Thus, understanding the applicability of AI in monitoring the optic nerve is essential for optimizing the screening of diseases such as glaucoma, reducing diagnostic variability, and expanding access to specialized care—especially in underserved populations. This section of the chapter will analyze, based on current evidence, the advances, limitations, and future perspectives of artificial intelligence in the evaluation of the optic nerve and management of glaucoma, focusing on diagnostic accuracy, clinical applicability, and its potential impact on global visual health.

Limitations and Challenges of Implementing Artificial Intelligence in Optic Nerve Care

Despite the significant advances of artificial intelligence in ophthalmology, its clinical implementation in the diagnosis and management of optic nerve diseases—such as glaucoma—still faces several challenges. Technical, ethical, regulatory, and clinical acceptance barriers hinder the safe, effective, and equitable incorporation of these technologies into everyday healthcare practice.

Data privacy is one of the foremost ethical concerns. Retinal and optical coherence tomography (OCT) images are considered biometric data and are difficult to anonymize, posing legal and security risks even after metadata removal (SCHEETZ et al., 2021; TSENG et al., 2021). The ability to infer age, sex, or systemic conditions from a single retinal image demonstrates the potential for re-identification and highlights the need for more robust protection mechanisms. Furthermore, failures in data governance can reduce patients' willingness to consent to the use of their images for algorithm training (BETZLER et al., 2023).

Another critical challenge is algorithmic bias. Many systems are trained on data from specific populations and standardized equipment, which limits their generalizability. This is particularly evident in glaucoma detection, as phenotypic characteristics of the optic nerve can vary significantly among different ethnic groups (MARTINEZ-PEREZ et al., 2022; SCHEETZ et al., 2021). The lack of diversity in datasets and the opacity of algorithmic decision criteria hinder the detection and correction of these biases, potentially compromising diagnostic safety for minority populations.

From a technical standpoint, integration with existing clinical infrastructures remains limited. Many hospital information systems use legacy formats or fragmented databases, making interoperability with advanced algorithms difficult (TING et al., 2021). Moreover, there is a gap between performance in research settings and real-world environments, where image quality, equipment, and acquisition protocols can vary significantly (SCHEETZ et al., 2021). This discrepancy undermines the reliability of AI systems in diverse and resource-limited settings.

Clinical acceptance of AI also poses a substantial barrier. Ophthalmologists often express reluctance to adopt systems with opaque decision-making logic—a phenomenon known as the “black-box” problem. Although visualization tools such as heat maps can help illustrate the criteria used by algorithms, legal responsibility for automated decisions remains unclear, making clinicians hesitant to rely on these systems in practice (BETZLER et al., 2023; SCHEETZ et al., 2021).

Finally, regulatory frameworks remain insufficient. Few algorithms have received formal approval from regulatory bodies such as the FDA. Even among approved tools, a major challenge lies in keeping up with constant updates to adaptive systems, which are not easily compatible with traditional static validation models (TSENG et al., 2021; MARTINEZ-PEREZ et al., 2022). This rigidity may delay the adoption of highly promising systems, such as those designed for automated glaucoma screening in primary care settings.

Overcoming these challenges requires a multidimensional approach that includes the development of explainable algorithms, diversification of training datasets, adaptation of legal frameworks, and training of eye care professionals. Only through such comprehensive efforts can artificial intelligence be ethically and effectively integrated into optic nerve disease care, contributing to the prevention of avoidable blindness and the modernization of ophthalmology.

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ARTIFICIAL INTELLIGENCE APPLIED TO MEDICINE

Capítulo 09

Artificial Intelligence in Predicting Preeclampsia Risks

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INTRODUCTION

Preeclampsia (PE) is a serious and multifactorial pregnancy complication characterized by high blood pressure associated with proteinuria or signs of organ dysfunction, potentially affecting the liver, kidneys, central nervous system, and causing fetal growth restriction. Its pathophysiology involves significant placental alterations, such as vascular and inflammatory lesions—including umbilical vasculitis, chronic villitis, and acute atherosis—that directly impact fetal development and maternal health (JUNG et al., 2024). This condition affects between 3% and 5% of pregnancies worldwide, accounting for approximately 46,000 to 76,000 maternal deaths and about 500,000 fetal and neonatal deaths annually (HEDLEY et al., 2023; YANG et al., 2025).

The clinical manifestations of PE can arise suddenly and vary in severity, complicating early diagnosis. The lack of a universally accepted diagnostic criterion, combined with the variability in clinical presentation, remains a challenge in obstetric practice (JUNG et al., 2024). Identifying women at higher risk of developing PE during the first trimester can enable preventive interventions and intensive monitoring, directly reducing maternal and fetal complications (HEDLEY et al., 2023). In this context, predictive methods based solely on clinical findings or placental morphology have proven insufficient.

Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning models, has emerged as a promising alternative to address these diagnostic gaps. These systems can process large volumes of clinical, laboratory, and imaging data, identifying complex, non-linear patterns that are often imperceptible to human analysis (RAMAKRISHNAN et al., 2021). The application of AI in obstetrics has significantly contributed to the early screening of PE by integrating biomarkers, clinical data, epigenetic markers, and reproductive history (HEDLEY et al., 2023). As emphasized by Hennessy et al. (2024), the real impact of AI-based predictive models depends on the quality of clinical data, the representativeness of studied populations, and dynamic integration with real-time care systems.

Models like PIERS-ML, for example, have been successfully used for continuous prediction of maternal risk for severe complications, optimizing clinical monitoring and decision-making, even in resource-limited settings (YANG et al., 2025). Furthermore, AI-powered automated analysis of placental images has shown promising accuracy in identifying histopathological patterns consistent with PE (JUNG et al., 2024).

Use of Artificial Intelligence in First Trimester Ultrasound

Preeclampsia is a multifactorial gestational syndrome characterized by new-onset hypertension and multisystem dysfunction after the 20th week of pregnancy. It is one of the leading causes of maternal and perinatal morbidity and mortality worldwide, particu-larly among pregnant women with obesity, advanced age, or a history of hypertension. Early detection, preferably in the first trimester, is essential for implementing prophylactic interventions such as low-dose aspirin, which can reduce cases of preterm preeclampsia by up to 60% (ANSBACHER-FELDMAN et al., 2022).

In this context, Artificial Intelligence has transformed obstetric screening by enabling the simultaneous analysis of multiple clinical, laboratory, and hemodynamic variables, surpassing the limitations of linear statistical models. Machine learning algorithms, such as Random Forests and deep neural networks, have demonstrated superior performance in sensitivity and specificity by processing complex first-trimester data patterns, such as uterine artery pulsatility index and mean arterial pressure (ANSBACHER-FELDMAN et al., 2022; GIL et al., 2024; SCHOR et al., 2024).

Beyond risk prediction for PE, AI applied to first-trimester ultrasound has significantly expanded diagnostic possibilities in fetal medicine. Convolutional neural network-based models are being applied for anatomical segmentation, detection of imaging planes, and automated measurement of facial and structural markers, with performance comparable to that of experienced specialists (JI et al., 2023; UMANS et al., 2024). Ji et al. (2023), for example, developed an innovative model to measure the fetal facial profile, using semantic segmentation to identify angles and distances between anatomical landmarks—a particularly useful feature for early screening of trisomies and malformations such as cleft lip and palate.

Despite these advances, widespread clinical application still faces significant challenges. Most studies are limited by small samples, lack of multicenter external validation, and underrepresentation of diverse ethnic populations, which can lead to algorithmic bias and reduce accuracy in certain healthcare contexts (UMANS et al., 2024). Additionally, deep neural networks function as “black-box” systems, making it difficult to clinically interpret the factors influencing predictive scores. Ethical and legal issues, such as data privacy under the Brazilian General Data Protection Law (LGPD), also require strict regulation of biomedical data collection, use, and sharing.

To overcome these limitations, strategies such as federated learning—which allows decentralized model training while keeping data at their original centers—and interpretability tools like Shapley values (SHAP), which assign weights to variables in prediction generation, are proposed (ANSBACHER-FELDMAN et al., 2022). Furthermore, the joint formation of multidisciplinary teams composed of obstetricians, clinical engineers, and data scientists is essential to ensure the safety and clinical applicability of AI-based systems.

Future perspectives point to the incorporation of genomic, proteomic, and continuous physiological sensor data (wearables), such as maternal heart rate and blood pressure variability, to recalibrate risk in real time. The creation of “digital twins” of the pregnant patient—virtual representations based on individual data—could revolutionize prenatal care personalization, simulating different therapeutic strategies and optimizing clinical decisions such as the timing of labor induction. However, implementing these advances requires validation through multicenter clinical trials, harmonized protocols, and regulatory certification of software as a high-risk medical device (JI et al., 2023; UMANS et al., 2024). AI applied to first-trimester ultrasound inaugurates a new era for fetal medicine, promoting earlier, more personalized, and more equitable diagnoses. Once technical and ethical barriers are overcome, this technology is poised to become a cornerstone of predictive obstetric medicine.

Predictive Models and Diagnosis of Preeclampsia Supported by Artificial Intelligence

Preeclampsia is a multifactorial, progressive, and potentially fatal obstetric condition. Its pathogenesis involves immunological factors, placental ischemia, and endothelial dysfunction associated with abnormal placentation processes and maternal vascular dysregulation (HACKELOER et al., 2022; LI et al., 2024). PE is estimated to affect 2% to 8% of pregnancies globally, accounting for around 70,000 maternal deaths and 500,000 fetal deaths annually (ZHAO et al., 2024; LI et al., 2024), highlighting the urgent need for more effective diagnostic strategies. In response to the challenge of anticipating diagnosis and efficiently managing PE, predictive models based on artificial intelligence—particularly those developed using machine learning techniques—have gained prominence in clinical practice and translational research (TIRUNEH et al., 2024; LI et al., 2021). These models' ability to integrate clinical, laboratory, genomic, and epigenetic data supports the construction of sensitive, personalized algorithms applicable to diverse populations.

The identification of angiogenic biomarkers, such as the sFlt-1/PlGF ratio, is one of the most notable advances in building risk models. Khalil et al. (2024) developed a model based on circulating cell-free DNA (cfDNA) biomarkers, combining genomic data with maternal clinical features, enabling high-accuracy prediction of PE as early as the first trimester. This multimodal approach represents progress over traditional models based solely on clinical factors.

Population-based studies have significantly contributed to validating these algorithms. Li et al. (2024) used a Chinese cohort of over 14,000 pregnant women and built models using Random Forest (RF) and Extreme Gradient Boosting (XGBoost), achieving areas under the curve (AUC) above 0.90 for early and late PE prediction. Li et al. (2021) demonstrated that using electronic health records, processed by supervised ML algorithms, can anticipate clinical signs of PE and support preventive strategies in intermediate-risk contexts.

Tiruneh et al. (2024), in a systematic review, highlighted that decision-tree-based models—particularly Gradient Boosting and RF—statistically outperform classical logistic regression models in terms of accuracy. Other classifiers, such as Support Vector Machine (SVM) and Naïve Bayes (NBC), also performed well in heterogeneous datasets.

Regarding interoperability between platforms and databases, Zhao et al. (2024) proposed a cross-platform calibration approach that unifies genetic and clinical data in an adaptable system, enabling clinical use of these models across different contexts and institutions. This is a fundamental step in translating AI from research to obstetric care.

Meanwhile, Li et al. (2024) advanced molecular modeling of PE through bioinformatics and weighted gene co-expression network analysis (WGCNA), identifying signatures associated with immune response. Techniques like LASSO were used for variable selection, while ssGSEA characterized immune infiltration, contributing to the development of biologically grounded models.

More recently, Eberhard et al. (2023) proposed a longitudinal predictive model based on machine learning using routine electronic health record data across multiple pregnancy phases. By applying linear regression, Random Forest, XGBoost, and deep neural networks to a cohort of over 120,000 patients, the study achieved AUCs between 0.73 and 0.91, with significant gains compared to current methods. The use of SHAP values enabled local and global model explainability, revealing dynamic and non-linear relationships between predictors throughout pregnancy. These findings reinforce the feasibility of interpretable clinical tools applicable from early pregnancy through delivery.

Despite substantial advances, challenges remain. The lack of external validation limits applicability in heterogeneous populations. Algorithmic bias stemming from homogeneous datasets can compromise accuracy in underrepresented ethnic groups. Additionally, ethical concerns related to the protection of sensitive data and responsibility for automated decisions demand solid and transparent regulations (TIRUNEH et al., 2024).

To address these challenges, the development of multicenter databases, use of explanatory techniques such as SHAP values, and adoption of federated learning are recommended. These strategies help not only to increase model accuracy and equity but also to make them interpretable and clinically applicable (LI et al., 2024). The incorporation of AI-based predictive models represents a new paradigm in the early detection and management of preeclampsia. With proper validation, applied ethics, and multidisciplinary collaboration, these tools can revolutionize obstetric medicine, enabling earlier diagnoses, personalized interventions, and improved outcomes for pregnant women and newborns on a global scale.

Impacts, Advances, and Future Perspectives of Artificial Intelligence in Obstetric Practice and the Management of Preeclampsia

Machine learning, as a subfield of artificial intelligence, has emerged as an innovative tool in transforming methods for predicting and diagnosing complex diseases. Its ability to process large volumes of data and identify relevant clinical patterns makes it essential in the early screening of critical conditions. Moreover, ML-based algorithms have shown significantly superior performance compared to conventional methods, contributing to improved diagnostic accuracy (LI et al., 2024).

In obstetrics, early identification of the risk of preeclampsia—preferably before the 16th week of pregnancy—is a crucial factor in preventing eclampsia, a severe obstetric condition marked by seizures, as well as other adverse maternal-fetal outcomes. The global incidence of PE ranges from 2% to 8%, reaching up to 9.1% in some populations, such as in China, due to cultural, dietary, and lifestyle factors among different ethnic groups (LI et al., 2024).

Although the etiology of PE is not yet fully understood, its diagnosis is based on the presence of hypertension and proteinuria, along with biomarker testing for sFlt-1, PlGF, NT-proBNP, and uric acid. These biomarkers, when analyzed through ML algorithms, have proven promising for enhancing predictive models of the disease. Among them, placental growth factor (PlGF) stands out as one of the most reliable indicators for confirming the diagnosis, being widely recommended by international guidelines (LI et al., 2024; ANSBACHER-FELDMAN et al., 2022).

The use of highly sensitive laboratory platforms, such as SiMoA and Elecsys, in the quantification of these biomarkers has contributed to the development of more robust predictive models. These technologies offer varying sensitivity levels and measurement ranges—features effectively leveraged in AI-based solutions (LI et al., 2024; HACKELÖER et al., 2023).

Recent methodological advances have enabled the application of multiple supervised ML algorithms in PE prediction. A Chinese study evaluated models such as Extra Trees, Voting Classifier, Gaussian Processes, and Stacking Classifier, all of which outperformed traditional methods with more detailed analysis and high accuracy, including for early-onset PE detection (JHEE et al., 2019; LI et al., 2024). The Voting Classifier stood out for its best results, showing high AUC values and detection rates while maintaining a low false-positive rate (TIRUNEH et al., 2024).

Organizations such as the International Society for the Study of Hypertension in Pregnancy and the International Federation of Gynecology and Obstetrics (FIGO) stress the importance of simple, sensitive, and accessible predictive models, particularly in low-resource settings. The adoption of AI-based algorithms is considered essential to expand large-scale screening and improve maternal-fetal outcomes (ANSBACHER-FELDMAN et al., 2022; YANG et al., 2025).

Furthermore, the application of ML algorithms is transforming clinical practice by improving the ability to predict and monitor PE progression. Models that integrate clinical variables and biomarkers non-linearly show superior performance to traditional methods, and the lack of need for normalization to multiples of the median enhances their clinical applicability (ANSBACHER-FELDMAN et al., 2022).

Including variables such as race and ethnic background in algorithms has also been recognized as critical for ensuring greater equity and diagnostic precision. Studies show that excluding these variables reduces model accuracy, especially in non-white populations, highlighting the need for personalized approaches (ANSBACHER-FELDMAN et al., 2022; LI et al., 2024).

Meanwhile, research is exploring new molecular targets. Genes such as CGB5, LEP, LRRC1, PAPPA2, and SLC20A1 have been validated as diagnostic biomarkers and integrated into models such as nomograms and deep neural networks, resulting in high predictive reliability (LI et al., 2024). These advances suggest the feasibility of early, minimally invasive screening with better clinical management.

Another promising milestone is the integration of remote patient monitoring into intelligent systems. This approach enables faster and more personalized interventions, reducing unnecessary hospitalizations and enhancing patient autonomy (HACKELÖER et al., 2023). Combining data from home devices with AI-based predictive models supports more agile and effective obstetric care.

However, challenges remain. The PIERS-ML model, for example, showed a decline in performance with repeated use, indicating the need for dynamic algorithms that incorporate serial data and adapt to clinical evolution (YANG et al., 2025). Current recommendations emphasize interpreting predictions with caution as pregnancy progresses, highlighting the need for continuous refinement of these systems.

Future prospects are promising but depend on multicenter validations, cost-effectiveness analysis, methodological rigor, and ethical compliance. As the latest studies point out, safely and equitably integrating AI into healthcare systems could revolutionize contemporary obstetrics—provided it is accompanied by investment in translational research and specific regulation (HACKELÖER et al., 2023; YANG et al., 2025).

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Capítulo 10

Artificial Intelligence in the Context of Breast Cancer

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INTRODUCTION

Breast cancer is one of the leading causes of death among both premenopausal and postmenopausal women, presenting as a malignant condition with high incidence and clinical complexity. It is often asymptomatic in its early stages and is characterized by high cellular heterogeneity and plasticity, which poses significant challenges for early detection and effective treatment. These features directly impact prognosis, patient survival, and the likelihood of progression to advanced stages of the disease (ZHANG et al., 2022; UWIMANA et al., 2025).

According to the World Health Organization (WHO), breast cancer is the most prevalent type of neoplasm among women worldwide, representing a global public health concern. The International Agency for Research on Cancer (IARC) estimated 2.3 million new cases worldwide in 2020, accounting for approximately 12% of all cancer diagnoses. That same year, breast cancer was responsible for around 685,000 deaths, equating to 6.9% of all cancer-related deaths among women (UWIMANA et al., 2025). Prognostically, breast cancer metastases are responsible for approximately 90% of deaths from this disease, reflecting its high lethality (LA PORTA et al., 2022).

Given this clinical and epidemiological magnitude, the development of increasingly precise diagnostic strategies is crucial, especially those aimed at early detection. However, currently available traditional methods still have significant limitations. Breast ultrasound is highly operator-dependent, hindering standardization and diagnostic reproducibility. Magnetic resonance imaging, though sensitive, is costly and still unable to effectively distinguish tumor subtypes. Mammography, considered the gold standard for screening, presents interpretive challenges and often leads to follow-up exams and additional biopsies (GUO et al., 2023; PANAHIAZAR et al., 2022).

These limitations lead to diagnostic errors, subjectivity in image interpretation, failure to detect subtle lesions, and high false positive and false negative rates, all of which compromise clinical management. In this scenario, Artificial Intelligence (AI) has emerged as a strategic ally in tackling breast cancer, offering innovative solutions with the potential to profoundly transform diagnostic and therapeutic paradigms.

AI is one of the most promising technologies in contemporary medicine, capable of processing large volumes of data with high speed and accuracy, recognizing complex patterns beyond human analytical capacity. Its application in breast cancer spans from screening and early detection to prognosis prediction and selection of individualized therapies. Machine learning-based tools have already demonstrated performance comparable to that of specialists in analyzing mammograms and MRIs and have contributed significantly to risk stratification, especially in aggressive subtypes like triple-negative breast cancer (GUO et al., 2023; LA PORTA et al., 2022; UWIMANA et al., 2025).

Key technologies include machine learning, deep learning, and convolutional neural networks (CNNs), which have been used for analyzing radiological images, histopathological slides, and genomic data. These systems are capable of automatic lesion segmentation, histological subtype classification, and therapeutic response prediction — representing major advances toward personalized medicine (ZHANG et al., 2022; PANAHIAZAR et al., 2022).

Application of Artificial Intelligence in Breast Cancer Histopathology

The integration of artificial intelligence into digital histopathology has led to significant advances in breast oncology, directly impacting diagnostic accuracy, prognostic stratification, and treatment personalization. Machine learning (ML) and deep learning (DL) models have been used to analyze subtle histopathological features, often imperceptible to the human eye, enhancing the detection of cellular and tissue patterns associated with tumor behavior (MCCAFFREY et al., 2024; LIU et al., 2023).

Among the most relevant applications is the automated quantification of tumor-infiltrating lymphocytes (TILs), a prognostic factor in subtypes such as triple-negative and luminal breast cancer. Tools like QuPath have enabled more standardized measurements, overcoming the interobserver variability common in clinical practice. Other parameters, such as mitotic count, tumor-stroma ratio (TSR), and nuclear heterogeneity, are also being analyzed by AI, revealing important associations with proliferative markers like Ki-67 and with clinical outcomes (MCCAFFREY et al., 2024; SOLIMAN et al., 2024).

AI has also contributed to reducing discrepancies among pathologists, particularly in distinguishing between normal tissue, benign lesions, ductal carcinoma in situ (DCIS), and invasive carcinoma. Studies have shown that algorithms trained to assist in lesion classification significantly improved diagnostic accuracy, especially in differentiating DCIS from benign changes—areas traditionally challenging for specialists (SOLIMAN et al., 2024; MALHERBE, 2021).

Innovative solutions like the HASHI algorithm for adaptive analysis of whole-slide images (WSIs) and multiresolution neural networks applied to lymph node metastasis detection have demonstrated robust performance, with increased sensitivity and reduced diagnostic inference time (LIU et al., 2023; PERTUZ et al., 2023). Additionally, digital analyses of biomarkers such as Ki-67 and HER2, assisted by AI, have outperformed conventional visual assessments in terms of reproducibility and prognostic reliability (MCCAFFREY et al., 2024).

In the context of the tumor microenvironment, AI has enabled more accurate assessment of the interaction between tumor cells, the extracellular matrix, and immune infiltration. This capability contributes to the development of more refined predictive models that assess recurrence risk, response to neoadjuvant chemotherapy (NAC), and progression-free survival (MALHERBE, 2021; MCCAFFREY et al., 2024).

In parallel, AI has shown promise in the analysis of digital mammography, tomosynthesis, and risk phenotyping. Saliency maps indicate that algorithms assess broader regions of images compared to radiologists, potentially enhancing the detection of subtle radiologic patterns. Automated quantification of breast density, for instance, enables personalized screening for high-risk women even after negative exams (GASTOUNIOTI et al., 2022; PERTUZ et al., 2023).

Despite these advances, challenges remain, such as the need for external validation of models, data standardization across platforms, algorithm explainability, and addressing biases arising from the underrepresentation of population groups. Nevertheless, AI is already a valuable ally in breast histopathology, with the potential to transform clinical practices, support therapeutic decisions, and expand access to high-quality diagnoses—particularly in settings with limited specialist availability (LIU et al., 2023; MCCAFFREY et al., 2024).

AI in Early Diagnosis and Breast Cancer Screening

Breast cancer remains the leading cause of cancer-related death among women worldwide, with more than 2 million new cases diagnosed annually (VEDANTHAM et al., 2023). The primary tools used in screening and monitoring the disease include digital mammography, breast tomosynthesis, ultrasound, and magnetic resonance imaging (MRI). Although these methods have contributed to reducing mortality, they still present significant limitations in sensitivity, specificity, and dependence on human interpretation—factors that compromise diagnostic effectiveness (BALKENENDE et al., 2022).

To address these limitations, artificial intelligence—particularly through deep learning—has been integrated into breast imaging methods to enhance diagnostic accuracy and reduce subjectivity in image analysis. AI algorithms have proven capable of extracting complex patterns from medical images, assisting radiologists in the early detection of malignant lesions, with the potential to shorten diagnostic times and initiate treatment in earlier stages of the disease (LIU et al., 2023).

Recent studies have shown that AI applied to the analysis of MRI and CT images offers high accuracy in detecting lymph node metastases, even surpassing the performance of specialized radiologists in certain cases. The use of deep neural networks raised accuracy from 77.9% to 87.0% in identifying suspicious lymph nodes, which could reduce unnecessary invasive procedures, such as biopsies, and improve clinical outcomes (BALKENENDE et al., 2022; LIU et al., 2023).

Moreover, AI algorithms have demonstrated performance comparable to that of experienced radiologists in screening tasks, potentially reducing the number of manually reviewed exams by up to 70% without compromising diagnostic sensitivity (RODRIGUEZ-RUIZ et al., 2019; VEDANTHAM et al., 2023). This level of automation represents a major advancement, especially in settings with a shortage of specialized professionals, such as in low- and middle-income countries.

Another promising development is the predictive capacity of AI models. Validated commercial tools have shown the ability to predict breast cancer risk up to six years in advance, outperforming traditional models such as Tyrer-Cuzick (GJESVIK et al., 2024). This type of approach could allow for more personalized, less invasive screening with greater impact on patient survival and quality of life.

Despite these advances, implementing AI in early breast cancer diagnosis still faces significant challenges. Technical barriers, such as the lack of standardized MRI protocols and the need for harmonization among different imaging acquisition systems, limit the generalizability of models (GULLO et al., 2024). Ethical and legal issues also persist, especially concerning data privacy and accountability for clinical decisions based on automated systems.

Artificial Intelligence in Breast Cancer Prognosis

Breast cancer prognosis following initial diagnosis is one of the core pillars of clinical oncology, being essential for defining therapeutic strategies, follow-up plans, and expected outcomes. Traditionally, systems such as TNM (Tumor, Node, Metastasis) and the Nottingham Prognostic Index (NPI) have been widely used to estimate disease progression based on anatomical and histological features, including tumor size, cellular differentiation, and lymph node involvement. However, while useful, these tools have considerable limitations—especially when it comes to individualized outcome prediction. Evidence shows that patients with similar staging may experience vastly different disease trajectories, exposing a gap between predicted and actual outcomes (SHIMIZU & NAKAYAMA, 2019; NASRAZADANI & BRUFSKY, 2019).

In this context, the incorporation of artificial intelligence into prognostic models represents a promising advancement, enabling the integration of genomic, histopathological, radiological, and clinical data to generate more accurate, robust, and personalized predictions. Through machine learning and deep learning techniques, AI offers a new paradigm for risk estimation, surpassing the limitations of traditional methods by handling high-dimensional data and identifying complex patterns beyond human perception (ALSHARIF, 2023).

A landmark innovation in this area is the molecular prognostic score (mPS), developed through the unbiased analysis of all protein-coding human genes. This model generated a 23-gene signature with significant clinical impact, validated across independent cohorts such as The Cancer Genome Atlas (TCGA) and the METABRIC consortium, demonstrating robustness across diverse genetic, histological, and ethnic contexts. The superior prognostic value of mPS compared to traditional systems highlights its applicability in clinical practice, particularly by offering higher accuracy in predicting overall survival (OS) and recurrence-free survival (RFS), and enabling refined stratification for various molecular subtypes, such as luminal breast cancer (SHIMIZU & NAKAYAMA, 2019; NASRAZADANI & BRUFSKY, 2019).

Simultaneously, AI has revolutionized histopathological analysis by automating the identification of patterns in the tumor microenvironment. Models like Digi-sTILs and Digi-TAS use convolutional neural networks to detect, with high precision, features such as tumor-associated lymphocytic infiltration, tertiary lymphoid structures (TLS), and tumor budding (TB). These parameters have significant predictive value—especially in triple-negative tumors—enabling inferences about tumor aggressiveness, metastatic potential, and likelihood of therapeutic response (HOU et al., 2024; GUAN et al., 2023; BATOOL et al., 2024).

Another rapidly growing field is radiomics, which combines AI with medical image analysis to extract quantitative features imperceptible to the human eye. The use of deep learning algorithms to interpret multiparametric magnetic resonance imaging (mpMRI) has proven effective in predicting response to neoadjuvant chemotherapy and detecting recurrence patterns. Recent studies show these models outperform conventional radiological assessments, with areas under the curve (AUC) exceeding 0.85 in patients with triple-negative breast cancer (ZHOU et al., 2023; HUANG et al., 2021).

Additionally, integrating radiomic, genomic, and clinical data—known as a multimodal approach—is advancing a more personalized and comprehensive cancer medicine (Dang et al., 2022).

The disruptive power of AI lies in its ability to merge these multiple layers of information into highly sophisticated clinical decision support systems. Multimodal models, for instance, have been successfully employed to predict response to trastuzumab in HER2-positive cancers by integrating gene expression data, histological images, and clinical parameters, achieving accuracy rates over 90% (UWIMANA et al., 2025). This convergence of heterogeneous data enables the construction of digital twins—virtual patient representations capable of simulating different therapeutic scenarios and optimizing clinical intervention choices based on personalized evidence (ZHANG et al., 2022; ALSHARIF, 2023).

Despite tangible advances, the clinical adoption of AI in breast cancer prognosis still faces important challenges. Standardizing algorithms, achieving multicenter validation, and ensuring interoperability with electronic health record systems are critical steps for model reproducibility and generalizability. Furthermore, significant ethical and legal implications remain, including algorithmic bias, the "black-box" nature of decision systems, and accountability for prognostic errors. As such, strategies like explainable AI (XAI) and strict regulatory frameworks are essential for ensuring safety and building trust in these technologies (UWIMANA et al., 2025; ZHANG et al., 2022; DANG et al., 2022).

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Capítulo 11

Artificial Intelligence in the Control, Diagnosis and Treatment of Diabetes

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INTRODUCTION

Diabetes Mellitus (DM) is a chronic disease with high prevalence and global impact (ODEDRA et al., 2012). It is a condition that significantly compromises patients' quality of life, increases morbidity and mortality rates, and imposes substantial costs on healthcare systems. As its incidence continues to rise — especially in developing countries — the demand for effective diagnostic and treatment strategies is also increasing, requiring progressively greater investments (HOYOS; HOYOS; RUIZ-PÉREZ, 2023).

Type 1 DM has a multifactorial etiology, with predisposing factors such as genetic alterations, dietary patterns, and viral infections — especially enteroviruses (SHAPIRO et al., 2024). Type 2 DM, responsible for approximately 90% of cases, is characterized by a silent progression and a high risk of cardiovascular complications, nephropathy, and ophthalmological disorders, which significantly affect quality of life over time. Diagnosis can be made through fasting blood glucose, random plasma glucose, oral glucose tolerance test (OGTT), and glycated hemoglobin (HbA1c) (JARABA et al., 2024).

Given its high prevalence and associated risks, it is essential to have effective diagnostic screening tools that allow for early identification and timely initiation of treatment, aiming to prevent metabolic decompensation and long-term complications (ODEDRA et al., 2012). However, the costs involved in these processes often make their broad implementation unfeasible. About 87.5% of undiagnosed individuals with DM live in low-income countries, where access to laboratory tests is limited. This highlights the need for complementary tools that can optimize disease detection, expand access, and reduce costs for healthcare systems (JARABA et al., 2024).

In this context, technological advances have become important allies in medical practice. Artificial intelligence (AI), integrated with clinical databases and statistical models, has enabled the development of computerized systems capable of performing complex analyses with high accuracy and low cost. Tools such as support vector machines (SVM), random forest algorithms, and artificial neural networks have been used to build predictive models for DM screening and diagnosis (HOYOS; HOYOS; RUIZ-PÉREZ, 2023). These technologies also hold potential for identifying digital biomarkers, facilitating risk stratification and individualized patient monitoring (JARABA et al., 2024).

The integration of AI into DM diagnosis and treatment processes has shown transformative potential. In addition to supporting the repurposing of previously approved drugs for other conditions, AI helps predict more effective therapeutic combinations, reduce costs and clinical complications, and improve patient care. Approaches such as fuzzy cognitive map–based models, for example, have achieved diagnostic sensitivity of up to 96%, enabling detailed analysis of patterns and risk factors associated with the disease (SHAPIRO et al., 2024).

Despite these advances, significant challenges remain, such as identifying patients with rapid progression to advanced stages and variability in clinical responses to treatment (HOYOS; RUIZ-PÉREZ, 2023). To address these issues, new approaches are being explored, with AI positioned as a tool capable of accelerating diagnosis, discovering disease-modifying therapies, testing personalized interventions, and guiding specific immuno-therapies (SHAPIRO et al., 2024).

This chapter will explore the main technological advances, ongoing challenges, and future perspectives for the integration of AI-based predictive models in the clinical management of Diabetes Mellitus, with an emphasis on improving medical practice and patient outcomes.

Diagnosis of Diabetes Mellitus Through Artificial Intelligence

The early diagnosis of Diabetes Mellitus (DM) represents one of the greatest challenges in contemporary clinical practice, especially in light of the rapidly growing global prevalence. The disease is often asymptomatic and frequently goes undetected until complications arise. In this scenario, effective strategies must go beyond traditional testing. It is precisely in this context that Artificial Intelligence (AI) has gained prominence — not as a replacement for clinical judgment, but as a powerful ally in risk anticipation, enhancing diagnostic processes with greater precision, speed, and above all, accessibility (HOYOS; HOYOS; RUIZ-PÉREZ, 2023; ODEDRA et al., 2011).

AI-based models have been successfully applied at various stages of DM screening and diagnosis. Among the most promising approaches are Fuzzy Cognitive Maps (FCMs), which are used to represent causal relationships between risk factors and facilitate computational clinical reasoning. In a study using clinical data from both diabetic and non-diabetic patients, an FCM-based model — designed to simulate human reasoning — achieved an accuracy of 95%, sensitivity of 96%, and specificity of 94%, even with simple variables such as age, thirst, blurred vision, and presence of infections. This approach proved effective in resource-limited settings and stood out for its clinical interpretability (HOYOS; HOYOS; RUIZ-PÉREZ, 2023).

AI has also been successfully applied in the diagnosis of gestational diabetes mellitus (GDM), as demonstrated in studies that combined clinical data and first-trimester placental ultrasound images to predict disease risk. The tool, evaluated using ROC and DCA curves, showed excellent diagnostic performance, indicating that placental textural features may serve as early markers of GDM. Additionally, factors such as maternal age and body mass index (BMI) were significantly higher in the confirmed GDM group, reinforcing their relevance as predictors (ZHOU et al., 2024).

Another example of a simpler yet equally promising solution is the GDM-AI app, developed using a Support Vector Machine (SVM) algorithm. It uses only two input data — maternal age and fasting blood glucose — and achieved 100% specificity and 88.7% accuracy in external validation. This approach is particularly useful in regions with limited medical infrastructure, as it allows for reliable diagnosis with minimal data. Despite its high performance, the study highlighted key limitations, such as the lack of field usability testing and the absence of integration with health information systems (SHEN et al., 2020).

AI also plays a role in monitoring and preventing diabetes complications. A notable example is the use of wearable sensors and algorithms to track diabetic foot risk through continuous monitoring of temperature and plantar pressure, enabling early interventions before lesion onset. These technologies have shown positive effects on treatment adherence and ulcer prevention, particularly in populations facing barriers to continuous care (SRASS; EAD; ARMSTRONG, 2023).

Thus, Artificial Intelligence is becoming a powerful tool in the diagnosis of Diabetes Mellitus, offering solutions ranging from explainable and accessible models to cutting-edge deep learning technologies. Although challenges remain — such as large-scale external validation and integration with clinical systems — AI is increasingly taking a central role in the screening, diagnosis, and prevention of diabetes, with direct impact on reducing the global burden of the disease.

Diabetic Retinopathy: Detection, Technological Advances, and Application of Artificial Intelligence

Diabetic retinopathy (DR) is one of the most common microvascular complications of type 2 diabetes mellitus (T2DM), responsible for high rates of visual morbidity and functional impairment. Its incidence is directly related to disease duration and glycemic control, making it an early marker of systemic microvascular dysfunction. In this context, Artificial Intelligence (AI) has become a promising tool for the screening and early diagnosis of DR, particularly in populations with limited access to specialized ophthalmologic services (MALERBI et al., 2022; KUKLINSKI et al., 2023).

Among the most relevant technological advances are deep learning–based systems that enable automated analysis of retinal images captured by portable devices. Malerbi et al. (2022) demonstrated the feasibility of using a smartphone-attached camera paired with an AI algorithm, with accuracy validated through optical coherence tomography (OCT), confirming 85.3% of suspected cases of diabetic macular edema (DME). Additionally, Kuklinski et al. (2023) found strong diagnostic agreement between AI-supported teleophthalmology and in-person specialist evaluations, with concordance coefficients (κ) above 0.75, emphasizing the potential of such tools in public health crises and remote areas.

Despite significant advances, key technical challenges persist. One of the main obstacles is the high rate of ungradable images—reaching up to 32.5% in some studies—compromising the effectiveness of automated screening (KUKLINSKI et al., 2023). Furthermore, variability in image quality, training biases in algorithms (often limited to specific population samples), and ethical issues surrounding data privacy and diagnostic responsibility represent major barriers to widespread clinical adoption (MALERBI et al., 2022; MAKROUM et al., 2022).

Future perspectives point to the integration of fundus exams with OCT imaging, enabling more robust structural and functional analyses through deep learning algorithms. The expected spread of low-cost devices, along with the expansion of telemedicine, is likely to strengthen AI's role in population-wide DR screening (HUANG et al., 2024). These systems' ability to stratify the risk of disease progression also opens doors to personalized follow-up and intervention strategies, helping reduce the global burden of preventable diabetes-related blindness (PRESTON et al., 2022).

Diabetes Mellitus Management and Treatment Through Artificial Intelligence

The management of Diabetes Mellitus (DM), especially type 1, has undergone a significant transformation in recent decades, driven by technological advancements and, in particular, the incorporation of Artificial Intelligence (AI) into monitoring and treatment tools. Traditionally, therapy involved manual blood glucose monitoring and insulin administration based on fixed protocols. However, the growing complexity of clinical, laboratory, and behavioral data has demanded more sophisticated methods capable of integrating multiple variables and offering personalized, responsive disease management (RIGLA et al., 2018).

AI applications in diabetes care involve various approaches, including expert systems, machine learning, artificial neural networks, fuzzy logic, decision trees, and support vector machines (RIGLA et al., 2018). Each of these techniques offers a distinct way to analyze data, enabling the prediction of glucose patterns, insulin dose adjustments, and early detection of adverse events such as hypoglycemia and hyperglycemia.

One of the most significant milestones has been the integration of continuous glucose monitoring (CGM) sensors with AI algorithms, allowing not only dynamic glucose tracking but also automatic insulin dose adjustments. This combination has significantly improved glycemic control, reduced the risk of severe hypoglycemia, and enhanced patients' quality of life (VETTORETTI et al., 2020).

In addition, portable devices such as wristbands and smartwatches have been used to correlate glucose levels with behavioral and physiological factors like sleep, stress, and physical activity. These data are processed in real time by intelligent systems that provide immediate recommendations, promoting fast and personalized interventions (AHMED et al., 2022).

The development of decision support systems (DSS) for patients is another notable advancement. These systems, powered by CGM data and AI algorithms, help recommend insulin doses, predict future glucose levels, and continuously adapt therapy parameters in a personalized manner (VETTORETTI et al., 2020). Innovations like artificial pancreases—which integrate CGM sensors with insulin pumps controlled by AI—illustrate the transformative potential for the therapeutic experience of patients with type 1 diabetes (SHAPIRO et al., 2024).

In the realm of therapeutic personalization, machine learning techniques have been employed to adjust medications, predict adverse reactions, and tailor treatment plans based on individual metabolic profiles. Models such as artificial neural networks and multiple regressions enable more accurate insulin dosing calculations based on multiple variables, overcoming the limitations of traditional methods (SHAPIRO et al., 2024).

Despite its promise, the adoption of AI in diabetes management still faces significant challenges, including robust clinical validation, the need to ensure data security and privacy, high technology costs, and limited integration into public health systems (JARABA et al., 2024). Added to this is the complexity of interpreting more advanced models—such as deep neural networks—which hinders acceptance among healthcare professionals and patients.

In summary, the use of Artificial Intelligence in the control and treatment of Diabetes Mellitus represents a disruptive and promising innovation, though it still requires ongoing efforts to ensure scientific validation, appropriate regulation, and equitable access. Future perspectives point to a scenario in which diabetes management becomes increasingly individualized, accurate, and centered on patients' needs.

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Capítulo 12

Artificial Intelligence in the Control, Diagnosis and Treatment of Heart Failure

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INTRODUCTION

Heart failure (HF) is a condition with high prevalence and a significant impact on global health, associated with elevated rates of mortality, morbidity, and costs. It is a complex syndrome whose pathophysiology involves marked hemodynamic alterations—such as reduced cardiac output and systemic congestion—demanding increasingly precise diagnostic and therapeutic approaches (CHEUNGPASITPORN et al., 2024).

In this context, artificial intelligence (AI) has emerged as a promising tool for enhancing care in patients with HF. Through techniques such as machine learning, deep learning, supervised and unsupervised algorithms, reinforcement learning, and neural networks, AI enables the processing of large volumes of clinical, laboratory, and imaging data, facilitating early disease detection, outcome prediction, and treatment personalization (CHEUNGPASITPORN et al., 2024; SINGH et al., 2025).

The integration of AI with blood biomarkers has allowed for greater precision in risk stratification and therapy individualization in HF patients, contributing to more effective clinical decisions and slowing disease progression. Moreover, the concept of interoception—the body's ability to perceive and interpret internal signals such as heart rate and respiration—has proven relevant in the cardiovascular context. Interoceptive alterations can negatively impact prognosis, and AI can assist in understanding and monitoring these physiological mechanisms (SUN et al., 2023; SINGH et al., 2025).

Among the practical applications of AI are imaging processing techniques applied to exams such as echocardiography, cardiac magnetic resonance, and computed tomography, which allow for more accurate structural and functional heart analyses. Additionally, the use of remote monitoring tools, automated analysis of complementary exams, and large-scale language models (LLMs), such as clinical chatbots, has expanded AI's applicability in the outpatient and home management of HF patients (REICH & MEDER, 2023).

Heart failure remains one of the leading causes of morbidity and mortality worldwide, affecting more than 60 million people and placing a substantial burden on healthcare systems (KHAN et al., 2023). Despite recent therapeutic advances, traditional strategies still face limitations, such as late detection and challenges in accurately stratifying patient risk. AI emerges as a strategic ally by integrating clinical, genetic, and imaging data, promoting more personalized and effective care (CHEUNGPASITPORN et al., 2024).

Therefore, this chapter is justified by the need to understand how AI technologies can be integrated into HF management, aiming to enhance diagnostic accuracy, reduce clinical complications, and promote treatment individualization. Given the increasing digitalization of healthcare and the complexity of medical data, it is essential to discuss the opportunities, ethical challenges, and limitations related to the implementation of these technologies in the HF context (REICH & MEDER, 2023; KHAN et al., 2023).

Challenges and Future of AI in Heart Failure

Supervised learning techniques — such as artificial neural networks (ANNs) and support vector machines (SVMs) — have proven effective in analyzing electrocardiograms, while unsupervised approaches have enabled the clustering of patients with similar clinical characteristics, facilitating risk stratification and therapeutic planning (SUN et al., 2023; LI et al., 2022). In the context of myocardial recovery, machine learning algorithms applied to patients with reduced ejection fraction or those supported by left ventricular assist devices (LVADs) have demonstrated the ability to predict clinical outcomes with areas under the curve (AUC) exceeding 0.85 (LANG et al., 2024).

However, despite these advances, the incorporation of AI into clinical practice faces significant challenges. The quality and diversity of the data used to train models are critical to their accuracy and generalizability. Incomplete, biased, or unrepresentative data undermine algorithm performance and can perpetuate disparities — such as those based on race or socioeconomic status (LANG et al., 2024). The low interpretability of models, especially deep neural networks, also hinders their acceptance by healthcare professionals (AMIN et al., 2021).

Moreover, unresolved ethical and regulatory issues remain — among them data privacy protection, legal liability in the event of errors, and the need for methodological standardization. To overcome these limitations, measures have been suggested such as building diverse databases, employing explainable models, training clinical teams, adopting metrics familiar to healthcare providers, and establishing clear data governance guidelines (LANG et al., 2024).

In summary, AI has the potential to revolutionize cardiology, particularly in the management of heart failure. From early detection to continuous monitoring and the discovery of new therapies, the advances observed thus far point to a promising future. Nevertheless, it is essential that these technologies be implemented ethically, safely, rigorously validated, and equitably—ensuring that their benefits are fully realized by all populations (WEYMANN et al., 2023).

Fundamentals and Clinical Applications of AI in Heart Failure

The application of artificial intelligence (AI) in cardiovascular medicine — especially in the management of heart failure (HF) — has gained prominence in recent decades, driven by the growing demand for more effective diagnostic, therapeutic, and monitoring solutions. Given that non-communicable chronic diseases, particularly heart conditions such as HF, rank among the leading causes of morbidity and mortality in Brazil and worldwide, the integration of AI into healthcare systems represents a paradigm shift in clinical practice (FARAH et al., 2021; SOARES et al., 2024).

HF, characterized by the heart's inability to maintain adequate cardiac output without pathologically elevated intracavitary pressures, affects more than 64 million people globally, with prevalence rising due to population aging (MICHELHAUGH & JANUZZI et al., 2022). In this context, AI emerges as a promising tool for early diagnosis, risk stratification, remote monitoring, and clinical decision support. Machine learning models have demonstrated superior performance over traditional methods in identifying asymptomatic left ventricular dysfunction, interpreting echocardiograms, and predicting response to cardiac resynchronization therapy (CRT) (SOUZA FILHO et al., 2020; SUN et al., 2023; NAZAR et al., 2023).

When integrated with AI, clinical decision support systems (CDSSs) have expanded the potential of personalized medicine. The use of algorithms such as XGBoost and LightGBM has proven capable of anticipating critical events—such as cardiac arrest—up to six hours in advance, outperforming previous approaches in accuracy, sensitivity, and specificity (KIM et al., 2023). Furthermore, AI applied to the analysis of electronic medical records (EMRs) and omics data has enabled the discovery of novel biomarkers and more precise stratification of HF subtypes, facilitating targeted therapeutic approaches and individualized prognoses (MICHELHAUGH & JANUZZI et al., 2022).

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Capítulo 13

Artificial Intelligence in the Detection of Cardiovascular Diseases

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INTRODUCTION

Cardiovascular diseases remain the leading cause of mortality worldwide, posing an ongoing challenge for clinical practice and public health systems. Early detection of these conditions is essential to optimize patient prognosis and reduce the social and economic burden of their complications. Traditional methods such as electrocardiography (ECG) and echocardiography, though widely used, have significant limitations, particularly in the early stages of disease. For example, ECG interpretation can be highly subjective, which may lead to delayed diagnoses and suboptimal management.

In this context, Artificial Intelligence (AI) has emerged as a promising tool in cardiology, with significant advancements in the analysis of tests such as ECG, computed tomography (CT), and magnetic resonance imaging (MRI). Using machine learning and deep learning algorithms, AI has shown the ability to identify patterns that are imperceptible to the human eye and to anticipate subtle electrophysiological and structural changes associated with conditions such as atrial fibrillation and left ventricular systolic dysfunction (NAGARAJAN et al., 2021). Furthermore, the integration of data from wearable devices, electronic health records, and complementary tests enables continuous monitoring, supporting personalized medicine and proactive prevention.

Particularly regarding ECG analysis, AI has outperformed human interpretation in diagnostic accuracy, not only optimizing evaluation time but also expanding diagnostic capacity through models trained on large datasets. Deep neural network algorithms have demonstrated the ability to detect silent diseases, such as subclinical atrial fibrillation and left ventricular dysfunction, and even infer parameters such as biological sex, age, and serum potassium levels from ECG data (SIONTIS et al., 2021).

Given this scenario, this chapter aims to examine the current scientific evidence on the use of Artificial Intelligence in the detection and management of arrhythmias, ventricular dysfunction, and early-stage hypertension. It will discuss clinical applications in decision-making, hospitalization prediction, and the definition of personalized therapeutic strategies (CICCARELLI et al., 2023; SIRANART et al., 2024). It will also address the ethical and regulatory dimensions of this technological advancement, considering medical accountability, data protection, and challenges to the full integration of AI into clinical practice.

This analysis will be developed through a narrative literature review grounded in up-to-date and relevant articles, including those by Siontis et al. (2021), Siranart et al. (2024), Ciccarelli et al. (2023), Tolu-Akinnawo et al. (2025), and Nagarajan et al. (2021), which support the discussion on the future of AI in cardiology as a powerful ally in the health–disease continuum.

AI-Based Analysis of Cardiological Tests

The integration of AI into cardiology has enabled remarkable progress, particularly in the automated analysis of electrocardiograms (ECGs), one of the most commonly used tools in clinical practice (NAGARAJAN et al., 2021). Despite its accessibility, manual ECG interpretation still faces significant challenges: studies show that up to one-third of ECG readings may contain clinically relevant errors, mainly due to difficulties in identifying subtle patterns by the naked eye (MUZAMMIL et al., 2024). In this context, AI-ECG emerges as a promising solution, offering more accurate and sensitive diagnoses by processing large volumes of ECG data linked to clinical information.

Among the most widely used methods are deep convolutional neural networks (CNNs), which automatically learn signal patterns within ECGs. Using labeled data, these algorithms run thousands of iterations to identify, with high precision, changes associated with specific cardiovascular diseases. Recent studies have shown that CNN-based models can detect, for instance, signs of hypertrophic cardiomyopathy from a single-lead trace using saliency maps to highlight key ECG segments, such as the ST-T segment (SIONTIS et al., 2023; ATTIA et al., 2021).

Moreover, machine learning (ML) and deep learning (DL) techniques have been widely applied to arrhythmia detection, with particular emphasis on subclinical atrial fibrillation. These algorithms are trained to identify arrhythmogenic foci and slight variations in cardiac cycle intervals, which has enabled significant progress in early screening and risk stratification (NERI et al., 2023). Simultaneously, the proliferation of wearable ECG devices connected to AI systems has made real-time, continuous patient monitoring possible, achieving accuracy rates above 97% in detecting premature atrial and ventricular contractions (NERI et al., 2023).

Despite the benefits, clinical use of AI for ECG analysis still faces challenges. These algorithms often function as “black boxes,” making it difficult to understand the criteria used for clinical decision-making (Attia et al., 2021). In addition, issues such as data standardization, system interoperability, and false positives—such as misclassification of sinus rhythm as atrial fibrillation—must be addressed. Thus, the implementation of these technologies requires robust validation, transparent criteria, and qualified clinical supervision.

In summary, the combination of AI and ECG represents a major step forward in the early detection of cardiovascular diseases, expanding opportunities for screening and personalized interventions. For this innovation to become established in clinical practice, it is necessary to overcome the technical, regulatory, and ethical barriers that still hinder its large-scale adoption.

AI to Improve Diagnostic Accuracy in Cardiovascular Imaging

The integration of AI in cardiovascular imaging methods has significantly enhanced diagnostic accuracy and standardized interpretations, reducing dependence on operator expertise. Tests such as echocardiography, cardiac computed tomography (CT), cardiac magnetic resonance imaging (MRI), and nuclear imaging are essential for anatomical and functional heart assessment, but they traditionally require a high level of specialization for accurate interpretation (TOLU-AKINNAWO et al., 2025).

Recent studies have shown that AI can improve diagnostic accuracy by automatically identifying subtle abnormalities, such as coronary artery stenosis in coronary angiography (CAG) videos. Using 3D convolutional neural networks (3D-CNNs), Yabushita et al. (2021) developed a model capable of detecting ≥75% stenosis in major coronary arteries with excellent predictive performance. The model showed particularly high accuracy for the left anterior descending artery (LAD), which is frequently critical in patients with significant coronary artery disease.

AI has also been applied in CT and MRI image analysis for cardiac structure segmentation (e.g., endocardium and epicardium) and in the automated detection of myocardial fibrosis and infarcted tissue. Tolu-Akinnawo et al. (2025) emphasize that these applications not only accelerate exam interpretation but also contribute to prognostic stratification, offering valuable insights into ventricular remodeling and overall myocardial function.

In nuclear imaging, AI algorithms have demonstrated performance comparable to that of human specialists in SPECT (Single Photon Emission Computed Tomography) analysis, particularly in distinguishing normal from ischemic myocardium. According to Lim, Tison, and Delling (2020), these technologies enable fast, objective analyses, supporting clinical decision-making.

Additionally, Cheikh et al. (2022) demonstrated the use of AI in CT scans for early detection of pulmonary embolism (PE). The model increased diagnostic sensitivity, optimized radiologic workflows, and reduced diagnosis time in cardiovascular emergencies, showcasing AI's potential beyond structural cardiology.

However, despite these advances, significant challenges remain. Broad AI implementation in cardiovascular imaging requires adequate technological infrastructure, multicenter clinical validation, system interoperability, and strong ethical guarantees for data privacy (LIM, TISON & DELLING, 2020). Nevertheless, as automated segmentation and interpretation models continue to evolve, AI is expected to play an increasingly important role in the analysis of large volumes of imaging data, efficiently and safely improving diagnoses and prognoses.

AI in Real-Time Cardiac Biomarker Identification

Cardiac biomarkers are central to the early detection of various cardiovascular conditions, particularly acute myocardial infarction (AMI), which is characterized by myocardial ischemia. The introduction of Artificial Intelligence (AI) in this context has revolutionized biomarker recognition, enabling faster, more accurate diagnoses and potentially saving lives through early intervention—even in asymptomatic patients (MUZAMMIL et al., 2024; CHO et al., 2020).

Among the main methods of capturing these biomarkers is the ECG, especially in its simplified, wearable format. AI, integrated with deep learning algorithms, has been used to interpret signals from portable ECG devices with excellent performance in detecting arrhythmias, AMI, and other cardiac conditions in real time (NERI et al., 2023). ECG is favored for its accessibility, low cost, and usability in low-resource settings.

The use of convolutional neural networks (CNNs) and hybrid models such as CNNs combined with LSTMs (Long Short-Term Memory) has demonstrated high accuracy in recognizing arrhythmic patterns like atrial fibrillation (AF) and premature ventricular contractions (PVCs), with accuracies exceeding 98% in recent studies (NERI et al., 2023; NAGARAJAN et al., 2021). These technologies enable not only detection but also prediction of events using public databases such as MIT-BIH and devices like chest patches or smartwatches equipped with single-lead ECG sensors.

Beyond arrhythmias, AI has also been successfully applied in identifying myocardial ischemia through changes in the ST segment and T wave. Although 12-lead ECG remains the gold standard for infarction diagnosis, wearable single-lead ECG models have already demonstrated comparable accuracy to traditional methods, marking a significant step forward in remote and outpatient diagnosis (CHO et al., 2020; MUZAMMIL et al., 2024).

Studies such as Siontis et al. (2021) emphasize that the main current challenge is making automated ECG interpretation as comprehensive and accurate as that of human experts, with AI trained to detect subtle electrical patterns indicative of early pathology. Meanwhile, AI algorithms are being embedded in everyday wearable devices like wristbands and smartwatches, expanding the reach of real-time continuous monitoring (NERI et al., 2023).

Ultimately, AI has enabled the identification of complex, variable patterns that elude conventional human analysis. The application of deep learning techniques has raised the bar for diagnostic accuracy, making it possible to identify and manage conditions such as AMI, malignant arrhythmias, and heart failure at earlier stages (SIONTIS et al., 2021; NAGARAJAN et al., 2021).

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Capítulo 14

Artificial Intelligence in the Detection of Fetal Malformations

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INTRODUCTION

In recent decades, the influence of the intrauterine environment on lifelong health has been widely discussed. The consolidation of various studies culminated in the formulation of the Barker Hypothesis, which proposes that an unfavorable intrauterine environment—exposed to adverse conditions during fetal development—can predispose individuals to chronic diseases in adulthood, such as cardiovascular diseases, diabetes, and metabolic syndromes (ANDANOTOPO et al., 2025).

Among the most impactful clinical conditions, congenital heart defects stand out, as they affect approximately 1% of newborns and represent the leading cause of death at this stage of life. This highlights the importance of high-quality prenatal care, since early diagnoses can enable timely interventions, guide therapeutic decisions, and significantly reduce neonatal mortality (MA et al., 2024). However, even with advances in imaging exams, traditional methods still present important limitations, such as high interobserver variability and strong dependence on the operator's experience. These factors hinder the early detection of subtle anomalies and the standardization of diagnoses, especially in areas with a shortage of specialists (ANDANOTOPO et al., 2025; CAO et al., 2025).

It is in this scenario that Artificial Intelligence (AI) has established itself as a disruptive tool. Its applications in fetal medicine have enabled the automation of processes, increased diagnostic accuracy, and reduced regional disparities. Specifically, AI has transformed ultrasound exams by allowing automated image capture, precise biometric measurements, and standardized reporting, thus promoting speed and quality in healthcare delivery (MATTHEW et al., 2022). In the field of fetal cardiology, AI-based technologies have contributed to the early identification of congenital heart defects, reducing reliance on the operator's individual skill (MA et al., 2024; BARBER; FREUD, 2024).

Among the technological approaches involved, machine learning systems stand out—especially deep learning and its convolutional neural networks (CNNs)—which have proven highly effective in recognizing complex patterns in images. Additionally, the use of recurrent neural networks (RNNs) and generative adversarial networks (GANs) has further expanded diagnostic possibilities, with the potential to improve image quality and detect alterations imperceptible to the human eye (MA et al., 2024).

The integration of these tools with 4D ultrasound exams enhances real-time behavioral and anatomical assessments, strengthening the correlation between intrauterine conditions and adult diseases, as proposed by the Barker Hypothesis (ANDANOTOPO et al., 2025). Therefore, this chapter aims to present an updated and critical perspective on the application of AI in fetal malformation screening. This approach is justified by the growing complexity of clinical cases, the exponential volume of data generated, and the need for strategies that ensure diagnostic accuracy and personalized care (BARBER; FREUD, 2024; MATTHEW et al., 2022).

Application of Artificial Intelligence in Obstetric Ultrasound

Obstetric ultrasound is one of the main non-invasive tools for assessing fetal development and detecting structural anomalies early. However, its diagnostic accuracy still heavily depends on the operator's skill and the quality of the images obtained—factors that introduce interobserver variability and challenges in exam standardization. In this context, artificial intelligence emerges as a promising ally, offering greater diagnostic precision, standardization of findings, and increased efficiency in automated screening (LIN et al., 2022; SUN et al., 2024).

The advancement of deep learning models, especially convolutional neural networks (CNNs), has significantly expanded the applications of AI in medical image analysis. In obstetrics, these algorithms have been used to detect subtle changes in fetal development, perform biometric measurements with greater precision, and estimate markers associated with fetal growth and well-being (LIN et al., 2022; SUN et al., 2024).

A remarkable example is the PAICS (Prenatal Ultrasound Diagnosis Artificial Intelligence Conduct System), which uses the YOLOv3 algorithm to detect abnormal intracranial patterns in fetal brain reference planes in real time. Studies have shown that its accuracy is comparable to that of experienced specialists, both in concurrent and retrospective modes (LIN et al., 2023). However, limitations are still observed. The model shows lower sensitivity for less prevalent patterns, such as the non-visualization of the cavum septi pellucidi (CSP), revealing that sample distribution affects the algorithm's generalization capacity (LIN et al., 2022).

Another relevant study proposed an AI model to automatically measure intracranial markers in two-dimensional ultrasound images during the first trimester. The measurements—including the anteroposterior diameter of the fourth ventricle and the cisterna magna—showed high concordance with values obtained manually by specialists, reinforcing the potential for diagnostic automation in this stage of pregnancy (SUN et al., 2024). Even so, the results were based on a single equipment model, which limits its broad clinical applicability.

Beyond brain morphology analysis, machine learning models have also been applied to predicting adverse pregnancy outcomes. Wang et al. (2025) developed an algorithm based on placental MRI images and clinical data to predict fetal growth restriction. Despite its good performance, the authors emphasize the need to expand the range of image sequences analyzed, as their study used only T2-weighted scans.

In parallel, deep transfer learning approaches have also shown applicability in orthopedic structural anomalies. Fraiwan et al. (2022) demonstrated, using pelvic X-rays of newborns, the effectiveness of these models in the automated detection of developmental dysplasia of the hip (DDH), reinforcing the versatility of neural networks trained via transfer learning.

Despite promising evidence, there are still relevant barriers to the full clinical implementation of these technologies. Notable challenges include the need for multicenter validation, adaptation to different equipment types, and the expansion of datasets used in model training (FRAIWAN et al., 2022; LIN et al., 2023; WANG et al., 2025). Nevertheless, AI proves to be a valuable resource for hospitals with less expertise in fetal imaging, potentially increasing detection rates of structural anomalies and contributing to earlier and more accurate diagnoses.

AI in Fetal Echocardiography and Congenital Heart Diseases

Congenital heart diseases (CHDs) are the most prevalent structural anomalies in the perinatal period, affecting approximately 8 out of every 1,000 live births and accounting for significant neonatal morbidity and mortality. It is estimated that one-quarter of these cases require surgical intervention within the first year of life, making early and accurate prenatal diagnosis essential (UNGUREANU et al., 2023; SUN et al., 2024). In light of this, cardiac evaluation between 18 and 22 weeks of gestation through obstetric ultrasound is strongly recommended, and artificial intelligence has emerged as a promising tool for optimizing this process (UNGUREANU et al., 2023).

Fetal echocardiography (FE) has evolved from a descriptive tool into a complex diagnostic technique capable of evaluating cardiac morphology, function, and blood flow. However, its accuracy still heavily depends on the operator's experience, fetal positioning, and the quality of the images obtained—factors that limit CHD detection in conventional clinical settings (UNGUREANU et al., 2023). In this scenario, AI has been successfully applied to standardize the acquisition and interpretation of echocardiographic images, contributing to faster and more sensitive diagnoses that are less dependent on the examiner's skill (YANG et al., 2023).

The LIFE protocol, proposed by Ungureanu et al. (2023), exemplifies this application by developing a deep learning architecture for the automated interpretation of first-trimester fetal echocardiograms, aiming to create an intelligent clinical decision-support system. The proposal stands out for integrating medical images with clinical databases, creating algorithms trained to recognize patterns consistent with structural cardiac anomalies. In the second trimester, a meta-analysis by Liastuti and Nursakina (2025) showed that AI models achieved high sensitivity and specificity in the prenatal screening of CHDs, reinforcing their potential as a population-level screening tool.

In addition to echocardiography, new approaches based on fetal electrocardiography are being tested with AI support. De Vries et al. (2023) demonstrated that combining electrocardiographic data with machine learning algorithms can enhance diagnostic accuracy in settings with limited access to advanced ultrasound, allowing screening in lower-complexity environments. Chen et al. (2024) support this strategy by describing a system based on pediatric ECG integrated with clinical concepts to detect CHDs, emphasizing that the fusion of medical expertise and computational intelligence significantly increases diagnostic accuracy.

Despite these advances, Mayer et al. (2024) point out that most AI models focus exclusively on image interpretation, overlooking important contextual clinical variables. Therefore, although AI can automate tasks and optimize specialists' time, the integration of algorithmic analysis with clinical judgment remains essential to ensure individualized and safe medical decisions.

Impacts, Advances, and Future Perspectives: Artificial Intelligence in Obstetric Practice

Artificial intelligence has established itself as one of the most promising innovations today, especially in the field of fetal medicine. It is a branch of computer science focused on developing algorithms capable of simulating human cognitive functions such as reasoning, learning, and decision-making. When applied to technologies like 4D ultrasound, AI significantly enhances diagnostic capabilities, overcoming human limitations through advanced analysis of large volumes of data (MA et al., 2024). Specifically in fetal cardiology, AI has stood out by improving diagnostic accuracy, optimizing clinical workflows, and supporting decision-making in complex scenarios (ANDONOTOPO et al., 2025).

Congenital heart diseases are the most common malformations during the fetal period, with an estimated prevalence of 1 in every 100 births and even higher frequency among neonatal deaths. Early prenatal detection of these conditions is crucial, as it enables timely interventions, birth planning, and family preparation, in addition to significantly improving neurological and surgical outcomes (UNGUREANU et al., 2023). However, fetal echocardiography—although considered the gold standard for this diagnosis—faces significant challenges, especially in the first trimester, such as anatomical limitations, fetal positioning variations, and dependence on the examiner's expertise (UNGUREANU et al., 2023).

AI has shown potential to overcome these limitations. In a recent study, a deep learning model applied to fetal echocardiography was tested on 2,450 exams, achieving an average diagnostic accuracy of 85%, comparable to that of human specialists. In addition to improving image quality and automating the detection of heart defects, AI also demonstrated the ability to identify early pathological patterns, reinforcing its relevance as a supporting tool in anomaly screening (MA et al., 2024). In another application, the integration of epigenetic data and imaging showed that AI algorithms can correlate adverse intrauterine exposures with future risks of organ dysfunction, as predicted by the Barker Hypothesis (ANDONOTOPO et al., 2025).

A notable initiative is the LIFE project, which proposes an intelligent decision-support system for the automated interpretation of fetal echocardiography videos obtained in the first trimester. This system aims to standardize analysis, reduce interobserver variability, and support professionals in lower-resource settings. Despite its promise, the model still presents limitations regarding data generalization and the detection of rare heart defects, as it was trained using images of normal hearts (UNGUREANU et al., 2023).

In parallel, AI is also being increasingly used for the detection of intracranial malformations. The PAICS system, developed for the automated screening of nine brain anomalies, showed a significant increase in sensitivity and diagnostic accuracy when used by sonographers, although it still faces limitations related to sample representativeness in real clinical scenarios (LIN et al., 2023).

Another notable application field is fetal growth restriction (FGR). Radiomic models based on placental magnetic resonance imaging, combined with maternal and fetal clinical data, have achieved high precision rates in the early prediction of FGR, demonstrating the viability of personalized AI-based approaches (WANG et al., 2025).

Despite the advances, the consolidation of AI in obstetric practice still faces major challenges, such as the lack of robust databases, heterogeneity in imaging equipment, and technical limitations for large-scale validation (MA et al., 2024). Nevertheless, the most recent studies point to a rapidly evolving landscape, in which the integration of medical knowledge and artificial intelligence could transform perinatal care, expanding access to quality diagnostics, personalizing clinical approaches, and optimizing resource allocation (UNGUREANU et al., 2023; ANDONOTOPO et al., 2025).

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ARTIFICIAL INTELLIGENCE APPLIED TO MEDICINE

Capítulo 15

Artificial Intelligence in the Diagnosis and Treatment of Alzheimer's Disease

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INTRODUCTION

Alzheimer's Disease (AD) is the leading cause of dementia worldwide, accounting for approximately 60 to 70% of diagnosed cases, making it one of the greatest global health challenges of the 21st century (SHANMUGAVADIVEL et al., 2023). It is a progressive, incurable neurodegenerative condition that significantly impairs cognition, memory, behavior, and functional abilities, directly impacting the individual's quality of life (LI et al., 2022). With the rapid aging of the global population, it is estimated that the number of people affected will exceed 152 million by 2050, which underscores the urgency for early diagnostic strategies and effective interventions (CAVA et al., 2023).

Traditional diagnostic methods for AD—based on neuropsychological testing, neuroimaging, and cerebrospinal fluid biomarker analysis—although relevant, are often expensive, invasive, and of limited accessibility, in addition to showing low sensitivity in the early stages of the disease (CAVA et al., 2023). These limitations often lead to late diagnoses, when neurological damage is already extensive and therapeutic options become limited (Krix et al., 2024). Furthermore, socioeconomic inequalities hinder equitable access to these exams, negatively impacting vulnerable populations and deepening disparities in care (GRANOV et al., 2025).

In this context, Artificial Intelligence (AI) is emerging as an innovative and promising tool capable of overcoming the limitations of conventional methods. AI allows for the analysis of large volumes of clinical, genetic, and imaging data with high accuracy, promoting greater objectivity, speed, and sensitivity in the recognition of early disease patterns (LI et al., 2022; SHANMUGAVADIVEL et al., 2023). Techniques such as machine learning, deep learning, convolutional neural networks (CNNs), and transfer learning have been successfully applied for the early detection of AD, using digital biomarkers, imaging exams, and molecular data (SINGHANIA et al., 2021).

Studies have shown that AI-based models outperform traditional algorithms in terms of diagnostic sensitivity and specificity, with the potential to reduce costs and expand access, especially in more vulnerable contexts (GRANOV et al., 2025; SINGHANIA et al., 2021). This technology also enables personalized monitoring and intervention strategies, aligning with the principles of precision medicine (KRIX et al., 2024).

Artificial Intelligence in Biomarker Analysis for Differential Diagnosis of Alzheimer's Disease

The use of non-invasive biomarkers has proven to be a promising alternative in light of the limitations of traditional diagnostic methods for AD, such as cerebrospinal fluid analysis or conventional imaging exams. In this context, AI has been increasingly adopted as a strategic tool in the analysis of complex biomolecular data, enabling the extraction of subtle patterns and the precise stratification of clinical profiles (GUNES et al., 2022; KRIX et al., 2024).

Supervised learning models have been successfully applied to the analysis of biomarkers in peripheral fluids—such as blood, urine, and saliva—which are more accessible and less costly than traditional exams. Krix et al. (2024) demonstrate that AI-based algorithms applied to blood biomarkers increase the accuracy of early-stage AD detection, in addition to enabling the creation of personalized risk profiles. This approach aligns with the principles of precision medicine, which aims for more effective and individualized interventions.

Furthermore, Gunes et al. (2022) highlight the importance of AI in distinguishing between clinical phenotypes across the AD spectrum, especially when multiple biomarkers are analyzed simultaneously. Such applications allow for more precise classification of individuals with mild cognitive impairment (MCI), established AD, and healthy controls—something that remains a challenge even for traditional neuroimaging methods.

Convolutional neural networks (CNNs) have also been explored for the automated interpretation of brain scans. As demonstrated by Lin, Lin & Lane (2022), these models are capable of identifying structural changes in MRI images associated with the early stages of the disease. These algorithms automatically extract relevant features from large volumes of raw data, eliminating the need for human intervention in preprocessing steps.

Kalkan et al. (2022) expand on this by presenting a model that uses a visual representation of gene expression as input for AI algorithms. This approach converts transcriptomic data from Alzheimer-related genes into images, allowing direct application of CNN techniques for high-precision diagnostic classification. This innovative strategy translates complex genetic variables into formats more compatible with deep learning tools.

Another emerging area involves the use of digital biomarkers derived from language and speech. According to Petti, Baker & Korhonen (2020), natural language processing (NLP) tools combined with machine learning have successfully identified subtle linguistic changes in AD patients—such as reduced syntactic and semantic complexity, frequent pauses, and discourse organization difficulties—which often go unnoticed in standard clinical assessments.

Despite these advances, significant challenges remain for the full clinical implementation of these models. Gunes et al. (2022) and Lin, Lin & Lane (2022) point to the low explainability of many AI approaches, which operate as "black boxes" and hinder acceptance among healthcare professionals. Additionally, the lack of large, standardized clinical datasets compromises model reproducibility and external validation.

Nevertheless, the results achieved so far suggest that the application of AI in biomarker analysis represents an ongoing diagnostic revolution, with the potential to make Alzheimer's Disease diagnosis earlier, more objective, and more accessible.

Artificial Intelligence in Imaging Analysis and Prediction of Alzheimer's Disease Progression

AI-assisted analysis of imaging exams has become one of the most promising approaches for early diagnosis and prediction of AD progression. Neuroimaging techniques such as magnetic resonance imaging (MRI) and positron emission tomography (PET) can detect structural and functional changes in the brain, including beta-amyloid plaques and neurofibrillary tangles. However, these changes often remain invisible to the human eye in the early stages of the disease (LI et al., 2022; MARTIN et al., 2022).

The incorporation of AI algorithms into these imaging methods has greatly increased sensitivity for detecting early changes. Convolutional neural networks (CNNs) and other deep learning models have been employed to interpret brain images with accuracy above 90%, identifying complex patterns even in the absence of evident clinical symptoms (Li et al., 2022). For example, the study by Bi et al. (2021) shows that using Deep Metric Learning (DML) algorithms outperforms traditional CNNs, offering significant improvements in model stability and convergence. DML proved effective in classifying healthy individuals, MCI patients, and those with established Alzheimer's.

Multimodal models are gaining prominence for integrating various data types—such as MRI, PET, and CT scans—with cognitive assessments and clinical information. This integration enables a more comprehensive understanding of AD progression and improves the prediction of MCI conversion to Alzheimer's (EL-SAPPAGH et al., 2021). According to the same study, combining data generates more robust and reliable predictions than unidimensional models.

In the field of supervised learning, classifiers such as Random Forest and Support Vector Machines (SVM) have been successfully applied in hierarchical models. In two-layer structures, the first layer performs triage among healthy individuals, MCI patients, and AD patients, while the second predicts the probability of MCI converting to AD within a period of up to three years (EL-SAPPAGH et al., 2021). To improve model reliability, interpretability techniques like Shapley Additive Explanations (SHAP) have been incorporated, allowing healthcare professionals to understand the criteria underlying each predictive decision.

Beyond diagnostic applications, AI has been used in molecular simulations to deepen our understanding of the disease's pathophysiology. A study by Martin et al. (2022) describes the use of exascale molecular dynamics simulations to investigate protein aggregation mechanisms associated with AD. This approach enables highly detailed analysis of beta-amyloid structure formation and its relationship with structural brain changes in preclinical phases, potentially paving the way for the development of ultra-early biomarkers.

Despite these advances, challenges remain in translating these technologies into clinical practice. The lack of large, diverse, and well-annotated datasets compromises model generalizability (LI et al., 2022). Furthermore, many models still operate as "black boxes," making them difficult for clinicians to interpret. Gunes et al. (2022) warn that although these models perform excellently in controlled research environments, their clinical validation is still limited due to low explainability and the lack of standardization in data collection and analysis protocols.

AI as a Tool for Diagnostic Support and Safety in Alzheimer's Disease Clinical Trials

The advancement of AI has redefined the role of computational analysis in AD care, particularly in three crucial areas: early diagnosis, therapeutic personalization, and clinical trial safety. The application of AI algorithms to large clinical and biomolecular datasets has enabled the detection of patterns invisible to human analysis, increasing diagnostic sensitivity and accelerating response times in critical scenarios (OLATUNJI et al., 2022).

Among the most widely used approaches in AD diagnosis are supervised machine learning algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Adaptive Boosting (AdaBoost), and eXtreme Gradient Boosting (XGBoost). These models have proven effective in handling basic clinical and demographic variables. Olatunji et al. (2022) demonstrate that such models, even with simple input features, can stratify patients and predict risk with solid performance, making them viable for settings with limited resources.

In the field of neuroimaging, AI has also gained significant prominence. Deep learning models, particularly convolutional neural networks (CNNs), are being used to interpret complex images such as MRI and PET scans. According to Aljuhani, Ashraf, and Edison (2024), these techniques have enhanced diagnostic accuracy in dementias by identifying subtle structural and functional patterns quickly and objectively. Unlike conventional analysis, which depends on the subjectivity of the specialist, trained algorithms can integrate multiple variables and provide a probabilistic classification of cognitive status.

Beyond imaging data, blood-based and transcriptomic biomarkers are being explored as non-invasive and accessible diagnostic tools. Krix et al. (2024) describe the use of AI in conjunction with proteomic and molecular profiles to identify early-stage AD indicators, with promising results for clinical integration. Complementing this line of research, Chiricosta et al. (2022) present a model based on blood transcriptome data—trained with microarray datasets—that achieves 89% accuracy in predicting AD, highlighting genes linked to oxidative stress and mitochondrial dysfunction, two central processes in the disease's pathophysiology.

In the context of clinical research, AI has promoted advances in monitoring the safety of clinical trial participants. Natural Language Processing (NLP) techniques allow the automated extraction of adverse events from electronic health records and textual reports, replacing manual and time-consuming processes. Jimenez-Maggiora et al. (2025) show that these tools improve consistency, standardization, and reproducibility in adverse event detection, contributing to participant safety and clinical data reliability.

Despite the progress, some technical and structural challenges still hinder the widespread adoption of these models. According to Jimenez-Maggiora et al. (2025) and Krix et al. (2024), most algorithms have been trained on controlled experimental data, which may limit their applicability in real-world clinical environments, particularly in hospitals with limited infrastructure. Moreover, many models operate as "black boxes," making them difficult to accept among healthcare professionals who demand transparency and interpretability in decision-making processes.

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Capítulo 16

Colorectal Cancer and Artificial Intelligence

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INTRODUCTION

In 2020, colorectal cancer (CRC) ranked third among the most incident neoplasms worldwide, with 1,931,590 cases, accounting for 10% of all cancers. In the same year, it was the second leading cause of cancer-related mortality, with a rate of 12.0 per 100,000 inhabitants, with a higher prevalence among the male population (VISCAINO et al., 2021).

The risk of developing CRC is multifactorial, associated with family history, lifestyle and dietary habits, and especially with the presence of polyps, whether isolated or related to genetic polyposis syndromes (VISCAINO et al., 2021). Modifying behavioral factors and ensuring early detection of precursor lesions, followed by timely treatment, are essential strategies for reducing both the incidence and mortality rates associated with CRC (VISCAINO et al., 2021).

Currently, artificial intelligence (AI) is being integrated into CRC screening and diagnostic methods, particularly through computer-aided detection (CADe) and computer-aided diagnosis (CADx) systems, which enhance the accuracy of identifying and classifying polyps during endoscopic procedures (ARIF, JIANG & BYRNE, 2023; ZACHARAKIS, ALMASOUD, 2022; VISCAINO et al., 2021).

Although colonoscopy is considered the gold standard for CRC screening, with high sensitivity for polyps ≥10 mm, there are still limitations in detecting smaller and/or flat polyps. Factors such as image quality, bowel preparation, and human variables — such as fatigue and the endoscopist's focus — negatively affect the exam's performance (VISCAINO et al., 2021). In this context, AI helps mitigate these limitations by standardizing the procedure and increasing adenoma detection rates, including flat lesions and serrated polyps, which are recognized as malignant precursors in the serrated pathway of colorectal carcinogenesis (VISCAINO et al., 2021; UCHE-ANYA et al., 2022).

The incorporation of advanced algorithms into endoscopy-supporting software, combined with virtual chromoendoscopy techniques and real-time image processing, has improved lesion visualization and characterization, optimizing the diagnostic process (VISCAINO et al., 2021; ZACHARAKIS, ALMASOUD, 2022). In addition, technologies such as AI-assisted robotic surgery offer minimally invasive approaches with greater surgical precision (VISCAINO et al., 2021), while emerging therapeutic strategies like nanoparticle-mediated chemotherapy show promising potential in reducing systemic side effects (MITSALA et al., 2021).

Given the high incidence and mortality associated with colorectal cancer, investing in strategies that promote early detection and effective treatment is essential. In this scenario, the application of artificial intelligence in CRC screening and diagnosis has proven to be a promising tool, capable of improving diagnostic accuracy, optimizing procedures, and personalizing therapeutic approaches. Ongoing advances in this field point to a future in which AI-based technologies will play a decisive role in improving clinical outcomes and reducing the global public health impact of CRC.

Application of AI in the Context of Colorectal Cancer

Artificial intelligence has revolutionized the management of colorectal cancer, especially in the fields of diagnosis, staging, and population screening. In the context of locally advanced CRC, for instance, AI models applied to radiomics and deep learning have shown superior performance compared to conventional radiologist assessments in lymph node staging—a critical step in defining the therapeutic plan. A study by Bedrikovetski et al. (2021) demonstrated that while computed tomography (CT) and magnetic resonance imaging (MRI) have limited performance due to technical and human factors, deep learning-based models achieved an area under the curve (AUROC) of up to 0.917, outperforming both radiomics models (AUROC 0.808) and radiologists (AUROC 0.688). This advancement enhances accuracy in predicting lymph node metastases, facilitating surgical planning and the selection of personalized neoadjuvant therapies.

In the same direction, Feng et al. (2022) developed the RAPIDS (RAdioPathomics Integrated preDiction System), which integrates MRI imaging data with histopathological biopsy data to predict pathological complete response (pCR) to chemoradiotherapy. The model showed high predictive performance (AUROC between 0.812 and 0.872 in multicenter validations), with sensitivity exceeding 90% and strong negative predictive value. This multimodal approach enables individualized clinical decisions, such as active surveillance for complete responders or intensified therapy for refractory patients, bringing AI closer to personalized oncology practice.

In the field of screening and prevention, Areia et al. (2022) conducted a population-based simulation to estimate the impact of AI applied to preventive colonoscopy in the United States. The analysis showed that, with a 60% adherence rate, AI could reduce CRC incidence and mortality by 8.4% and 6.9%, respectively, with a cost saving of $57 per person. With universal adherence, the reduction was even more significant (29.1% and 31.6%), resulting in an estimated population-wide saving of approximately $290 million annually. This effectiveness stems from increased adenoma detection rates (ADR), regardless of polyp size, with an average gain of 1.44 times compared to conventional colonoscopy. Despite its economic and clinical advantages, the study acknowledges limitations in generalizing the results, as it was based on a simulated model without the inclusion of CADx or morphological assessment of adenomas.

Complementing this population-based perspective, Tokutake et al. (2023) proposed an AI model based on simple clinical data, such as blood tests, family history, and lifestyle habits, which outperformed the fecal immunochemical test (FIT) in predicting the presence of colorectal polyps in asymptomatic patients. The model achieved better sensitivity, specificity, and overall accuracy, with Matthews correlation coefficient (MCC) values of 0.37 for men and 0.39 for women, compared to 0.047 and 0.074 from FIT. Additionally, the use of a sigmoid-type KDE data transformation technique improved group separation between polyp-positive and polyp-negative individuals. The main advantage of this model is its applicability in primary care, without the need for invasive tests, offering an accessible alternative for personalized screening.

In practical colonoscopy settings, Roshan and Byrne (2022) emphasize AI's role in standardizing lesion detection and characterization. Computer-aided detection (CADe) and computer-aided diagnosis (CADx) systems have reduced variability among colonoscopists and supported strategies like "diagnose-and-leave" and "resect-and-discard" for diminutive polyps. CADe, for instance, has significantly reduced adenoma miss rates—from 40% to 13.89% in tandem colonoscopy studies. CADx achieved 94% accuracy in differentiating between adenomatous and hyperplastic polyps, with 98% sensitivity and 83% specificity. However, key challenges remain, such as algorithmic bias, false positives caused by debris or bubbles, and data privacy concerns. Despite these limitations, CADe systems have already been approved in Canada, the U.S., Europe, and Japan, while CADx is still pending regulatory approval in North America. Estimated costs range between $2,000 and $4,000 per room monthly, but studies suggest that reduced unnecessary biopsies and CRC prevention could offset this investment.

Advances and Applications of AI in the Field

Artificial intelligence has become a promising ally in the various stages of colorectal cancer management, encompassing everything from population screening to histological diagnosis, therapeutic response prediction, and clinical prognosis. In current practice, colonoscopy remains the gold standard for detecting and removing precursor CRC lesions, but it is susceptible to human perceptual errors that can compromise screening effectiveness. In this context, AI has significantly contributed to improving diagnostic accuracy and reducing missed lesions during examinations.

Among the main AI tools applied to colonoscopy are computer-aided detection (CADe) and computer-aided diagnosis (CADx) systems. CADe assists in the real-time identification of colorectal polyps, improving the adenoma detection rate (ADR), while CADx enables histological characterization of polyps, supporting strategies such as "diagnose-and-leave" or "resect-and-discard," with the potential to reduce unnecessary biopsies and laboratory costs (TAGHIAKBARI et al., 2021; LI et al., 2022). In addition to these functions, AI has also been applied in automated quality assessments of exams, standardizing criteria such as withdrawal time and mucosal coverage, and in risk prediction based on multiple clinical, molecular, and imaging parameters (QIU et al., 2022).

AI's progress is supported by technologies such as Convolutional Neural Networks (CNNs) and deep learning models, which enable automated analysis of large volumes of endoscopic images and clinical data. Models like YOLOv3 and commercial platforms such as GI-Genius and Eagle-Eye have already demonstrated clinical efficacy in randomized studies, with sensitivity above 95% and specificity close to 90% (WALLACE et al., 2022; XU et al., 2023). A meta-analysis by Li et al. (2022), involving over 4,000 patients, showed that CADe increased ADR from 25.2% to 36.6%, particularly for polyps under 5 mm and flat lesions—often overlooked in conventional practice.

In a multicenter clinical trial conducted by Xu et al. (2023), AI-assisted colonoscopy showed a total ADR of 39.9% versus 32.4% with conventional colonoscopy ($p < 0.001$), including significant improvements in detecting advanced adenomas (6.6% vs. 4.9%) and non-pedunculated polyps (27.6% vs. 21.8%). The benefits were observed among both experienced endoscopists and non-specialists, suggesting reduced technical variability across operators. Additionally, models like DEEP2 achieved 88.5% sensitivity for subtle polyps, compared to 31.7% by human endoscopists (LI et al., 2022).

In histological diagnosis, CADx systems have reached up to 94% accuracy and 98% sensitivity, with negative predictive values (NPV) above 95% in endocytoscopy—meeting the criteria proposed by the American Society for Gastrointestinal Endoscopy (ASGE) for biopsy-free discard strategies (TAGHIAKBARI et al., 2021). Furthermore, integrative algorithms analyzing clinical, laboratory, genetic, and radiological data are being developed to predict responses to chemoradiotherapy, drug toxicity, and recurrence risk—paving the way for AI in personalized medicine (QIU et al., 2022).

Despite these advances, there are still significant limitations to AI's full integration into clinical practice. Algorithms rely entirely on the quality of images produced by the colonoscope and cannot detect lesions outside the field of view or in poorly exposed segments (SHUNG & BYRNE, 2020). Factors like bubbles, fecal debris, and mucosal folds can generate false positives. Moreover, AI does not act autonomously—it requires the presence and judgment of the endoscopist, functioning as a simultaneous observer without decision-making capability (TAGHIAKBARI et al., 2021). Legal and ethical issues also arise, as there is still no standardized international regulatory framework for medical AI use, creating legal uncertainty and ambiguity regarding professional liability in case of error (SHUNG & BYRNE, 2020).

To overcome these barriers, strategies such as specific training for healthcare professionals, continuous feedback on AI system performance, and multidisciplinary meetings to review images and adjust conduct based on automated findings have been proposed (SHUNG & BYRNE, 2020). Technology acceptance also depends on interpretability, usability, and end-user trust—factors that require ongoing refinement.

In summary, AI systems have driven remarkable improvements in detecting precursor CRC lesions, especially by reducing adenoma miss rates by approximately 50% in controlled clinical trials (WALLACE et al., 2022). These benefits are most evident in small and flat lesions, which are traditionally difficult to detect, and are accompanied by operational and economic advantages. However, full clinical integration will require multicenter studies with greater population diversity, regulatory standardization, and the development of transparent and auditable technologies.

Limitations and Challenges of Artificial Intelligence Implementation in Colorectal Cancer

The growing integration of artificial intelligence into gastrointestinal oncology has transformed the diagnosis and management of colorectal cancer, especially regarding the detection and characterization of liver, lymph node, and peritoneal metastases. However, despite technological advances, several challenges still limit its full clinical implementation.

Among the main technical obstacles is the variability in image quality used for training models, which compromises the generalizability of algorithms. Studies show that although convolutional neural networks exhibit sensitivity above 85% for detecting liver lesions larger than 10 mm, their accuracy decreases significantly for smaller lesions or those located outside the field of view, as is often the case with peritoneal metastases (ROMPIANESI et al., 2022; WANG & DONG, 2020).

Moreover, the effectiveness of AI models relies heavily on the quality and standardization of images acquired via computed tomography (CT), magnetic resonance imaging (MRI), and intraoperative methods. Systems such as Faster R-CNN have shown promising performance in identifying metastatic lymph nodes with 80% sensitivity, but still face operational limitations, including processing time and the need for calibration based on institutional characteristics (WANG, DENG & BIN, 2021).

Another significant challenge is the dependency on human interaction. Even in AI-assisted environments, diagnostic accuracy depends on the operator's experience in image acquisition and the quality of tissue segmentation performed—especially during laparoscopies and dynamic colonoscopies using fluorescence guidance. AI functions as a secondary observer and is not capable of making autonomous clinical decisions during surgical procedures, which limits its real-time applicability (HARDY et al., 2021).

In the prognostic context, predictive models based on logistic regression or radiomics have achieved areas under the curve (AUC) above 0.85 in forecasting synchronous metastases and 1- to 5-year survival. Even so, these systems still lack multicenter external validation and are mostly tested on institutional or retrospective databases (SUSIČ et al., 2023). This limitation reduces their applicability to more heterogeneous populations and compromises the robustness of their conclusions.

Ethical, legal, and regulatory barriers also pose substantial challenges. The lack of specific guidelines regarding medical responsibility, informed consent for AI use, and the protection of sensitive data creates legal uncertainty for both professionals and patients. The risk of algorithmic bias—particularly when training data do not adequately represent all age groups, ethnicities, or comorbidities—remains unresolved (WANG & DONG, 2020; ROMPIANESI et al., 2022).

Furthermore, the effective implementation of AI requires robust computational infrastructure, integration with hospital systems, and professional training for the critical interpretation of AI-generated outputs. These requirements pose a significant barrier in low- and middle-income countries. Inequitable access to technology and the high cost of specialized software licensing restrict the reach of these innovations to centers of excellence, further exacerbating disparities in oncological care (HARDY et al., 2021).

Therefore, while AI applications in colorectal cancer are promising, their clinical consolidation depends on overcoming technical, operational, ethical, and regulatory hurdles. Conducting randomized, multicenter clinical trials with diverse populations is essential to validate these tools and ensure their safety, equity, and effectiveness. In this regard, AI emerges not only as an instrument of innovation but as a transformative force in oncologic medicine—paving the way toward personalized and precision care, provided it is implemented with responsibility and critical oversight (SUSIČ et al., 2023; WANG & DONG, 2020; ROMPIANESI et al., 2022).

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Capítulo 17

Use of AI in the Context of the Autism Spectrum

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INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurological condition characterized by deficits in social communication, restricted and stereotyped interests, and repetitive behavior patterns (CHADDAD et al., 2021). In many countries, the average age for ASD diagnosis is around four years, since clinical signs are not always evident in the early stages of life (ANAGNOSTOPOULOU et al., 2020). In this context, studies indicate that early diagnosis, combined with immediate intervention, is fundamental to optimizing social development and achieving more favorable long-term outcomes. On the other hand, late diagnoses may require pharmacological therapies and more intensive interventions, with a potentially greater impact on the individual's functioning (SIDDIQUI et al., 2021).

Additionally, the traditional diagnostic approach is often time-consuming and presents limitations in terms of reliability and validity due to the inherent subjectivity involved. This subjectivity is influenced by factors such as professional training, previous experiences, availability of resources, and cultural adaptation of the instruments used (SONG et al., 2019). Considering that one in every 59 children may be diagnosed with ASD, it becomes urgent to improve screening and early diagnosis methods to minimize the negative developmental impacts (SUNDAS et al., 2023).

Given this scenario, artificial intelligence (AI) has emerged as a promising technology in healthcare, especially in the field of neurodevelopment. Several studies have demonstrated the successful application of AI in symptom identification, diagnostic classification, and clinical outcome prediction through the use of structured and unstructured data. Moreover, AI can detect subtle patterns and behaviors that are not easily identified by human observers, contributing to a more accurate and objective assessment (SONG et al., 2019).

Recent evidence suggests that new approaches and devices aimed at the diagnosis and monitoring of ASD may benefit from integration with the Internet of Things (IoT), overcoming the limitations of traditional strategies, such as contact networks, machine learning, and the use of social platforms. For instance, social networks applied to healthcare have proven useful in strengthening communication between patients, families, and professionals, enabling experience sharing and the construction of more well-informed clinical decisions (SUNDAS et al., 2023).

Another significant advancement lies in medical image analysis, which has consolidated as a promising tool for the early detection of ASD. Techniques such as magnetic resonance imaging (MRI) and functional MRI (fMRI) have provided consistent neuroanatomical evidence related to the disorder, expanding diagnostic possibilities and reinforcing AI's role in this process (CHADDAD et al., 2021).

DISCUSSION

ASD has a rising prevalence, currently estimated at 1 in 54 children, which presents significant challenges for early diagnosis and personalized therapeutic interventions. These challenges are especially intensified by the condition's marked clinical heterogeneity, which hinders the identification of uniform patterns and standardized therapeutic strategies (MAENNER et al., 2018).

Traditionally, diagnosis relies on subjective assessments, such as the Autism Diagnostic Observation Schedule (ADOS), which require time, expertise, and specialized infrastructure (LORD, 2020). In light of these limitations, artificial intelligence (AI) emerges as a promising alternative, enabling the analysis of multimodal data—from brain images to facial expressions—making the diagnostic process more objective, faster, and accessible (CHADDAD et al., 2021).

Advances in Diagnosis with Artificial Intelligence

AI has revolutionized the diagnostic approach to ASD through techniques such as machine learning (ML) and deep learning (DL), applied to structural and functional magnetic resonance imaging (MRI and fMRI). Models like deep neural networks (stDNN) and brain morphometry methods such as 3D Transport-Based Morphometry (3D TBM) have shown high accuracy in identifying brain changes associated with ASD and predicting symptom severity (SUPEKAR et al., 2022; KUNDU et al., 2024).

Beyond neuroimaging, techniques like the integration of convolutional neural networks (ResNet152) with Vision Transformers (ViT) allow the detection of micro-expressions and atypical facial patterns with up to 91.33% accuracy in children under five, outperforming traditional tools (MAHMOOD et al., 2025).

Tools like the *SenseToKnow* platform, developed by Duke University, enable diagnosis through automated analysis of social interaction videos, reducing evaluation time from months to minutes with 94% sensitivity (TARIQ et al., 2018). Meanwhile, approaches such as federated learning (FL) have allowed the training of models across multiple institutions without compromising data privacy, delivering significant economic and logistical benefits (FAROOQ et al., 2023).

Applications in Educational Inclusion and Family Support

The interface between AI, psychiatry, and inclusive education represents a promising field. Literature shows that teacher training still lacks integration between theory and practice in inclusion contexts (OLIVEIRA & FERREIRA, 2020; AL BANNA et al., 2020). In this regard, technologies such as AI and the Internet of Things (IoT) have the potential to provide emotional screening, personalized monitoring, and support for behavioral management in school settings (MARIANO et al., 2020).

Furthermore, studies such as that by McFayden et al. (2024) evaluated the use of ChatGPT-4 as an informational tool for caregivers, showing satisfactory results in clarity and comprehensibility, though with limitations regarding practical applicability and reference quality. Similarly, Sundas et al. (2023) highlighted the use of wearable sensors and smart devices for real-time monitoring of autistic behaviors, with promising applications in early detection and personalized interventions.

Limitations and Ethical, Technical, and Regulatory Challenges

Despite advances, several challenges still hinder the widespread adoption of AI in ASD diagnosis. One of the main issues is algorithmic bias: models trained on homogeneous data tend to show lower accuracy in underrepresented populations, perpetuating diagnostic inequalities (MAHAMOOD et al., 2025; SONG et al., 2019).

In addition, collecting and storing large volumes of biomedical data from children raises ethical concerns and requires strict privacy and regulatory protocols, especially in countries lacking robust legal frameworks (CHADDAD et al., 2021; SUNDAS et al., 2023).

From a technical perspective, the low interpretability of DL models and the absence of clear clinical guidelines hinder acceptance by healthcare professionals, who often show resistance to using automated systems in complex decision-making (CHADDAD et al., 2021).

Future Perspectives

The future of AI in ASD lies in the multimodal integration of data, multicenter clinical validation, and equitable access to technologies. Projects such as the *AI-ASD Trial*, involving over 10,000 participants in 15 countries, aim to validate algorithms with high concordance with expert assessments (KUNDU et al., 2024). Simultaneously, initiatives like the *Global Autism Dataset* seek to ensure ethnic and socioeconomic diversity in datasets (DANIELS et al., 2017).

The incorporation of epigenetic data and brain connectivity patterns may enable the definition of ASD subtypes and the prediction of therapy response before implementation (AN-

AGNOSTOPOULOU et al., 2020). Furthermore, technologies based on IoT and smart sensors continue to show promise in providing continuous support for individuals with ASD and their caregivers (SUNDAS et al., 2023).

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