

Deep Dive



AI in action in clinical research: Applications, limitations, and the emerging regulatory framework

Authors: Fanny Muet^{1,4} and Güliz Vanli Jaccard^{2,3,4}

Affiliations: ¹Regulatory Affairs Specialist; ²Regulatory Affairs Watch Project Lead and Editor; ³Swiss Clinical Trial Organisation (SCTO) National Regulatory Affairs Platform Coordinator at the Clinical Trial Unit of the Clinical Research Centre (CTU-CRC), Faculty of Biology and Medicine (FBM), Lausanne University Hospital (CHUV), and University of Lausanne (UNIL); and ⁴Member of the SCTO Regulatory Affairs Platform

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Artificial intelligence (**AI**) is influencing clinical research in many interconnected ways. It has the potential to address long-standing challenges throughout the research process by improving efficiency, supporting decision-making, and enabling new research methodologies. At the same time, clinical research generates the data and evidence needed to develop, validate, and evaluate AI-enabled technologies before they can be used in clinical practice. AI is also reshaping the regulatory landscape, both as a technology requiring appropriate regulatory oversight and as a tool that regulatory authorities may use in their own activities. This Deep Dive article focuses primarily on how AI may help address challenges facing clinical research by illustrating how it can be applied throughout the clinical research ecosystem. The article then looks beyond clinical research to explore the evolving role of AI in the broader regulatory landscape. A dedicated **Regulatory Spotlight** section provides a concise overview of the European Union's Artificial Intelligence Act and its implications for AI-enabled medical devices.

Challenges facing clinical research

As clinical research becomes increasingly complex, costly, and data-intensive, improving the research process itself has become an important area of investigation. The recurring patterns that emerge from such investigations reveal that many challenges in clinical research are systemic rather than study-specific.

Within clinical research, clinical trials remain one of the most resource-intensive and operationally challenging settings. Large analyses of clinical trials consistently identify participant recruitment, protocol complexity, prolonged study timelines, feasibility constraints, high costs, and premature trial discontinuation as persistent barriers that undermine both trial efficiency and scientific yield. For example, a machine learning analysis of over 16,000 trials found that protocol complexity has risen substantially over the past decade, correlating with longer trial duration.¹ A separate, systematic review of 347 randomised trials across the UK, Switzerland, Germany, and Canada found that 31.1% of the trials were discontinued, predominately due to poor recruitment.² A similar pattern was found in surgical trials: in a study of more than 2,500 randomised surgical trials, fewer than one in five were finished on time, and almost 20% were stopped early due to an insufficient number of participants.³

These challenges highlight opportunities for improving how clinical research is designed, conducted, and managed. And because these challenges are not isolated to individual studies but reoccur across trials, settings, and countries, addressing them at the level of the research process itself has become an important objective in its own right.

One resource that can be used to address these challenges is artificial intelligence (**AI**). Because AI tools can be used across many studies, they may help solve these problems more broadly and thus reduce the need to find a different fix for each trial. Researchers are starting to conduct studies that look at how much efficiency AI can bring to clinical trials, for example in the

areas of recruitment and retention, and that examine whether AI can reduce costs and increase patient satisfaction.⁴ The following sections illustrate how AI is increasingly being explored across four different domains of the clinical research ecosystem in order to address some of the challenges facing clinical research.

Using AI to address challenges across the clinical research ecosystem: Examples from four domains

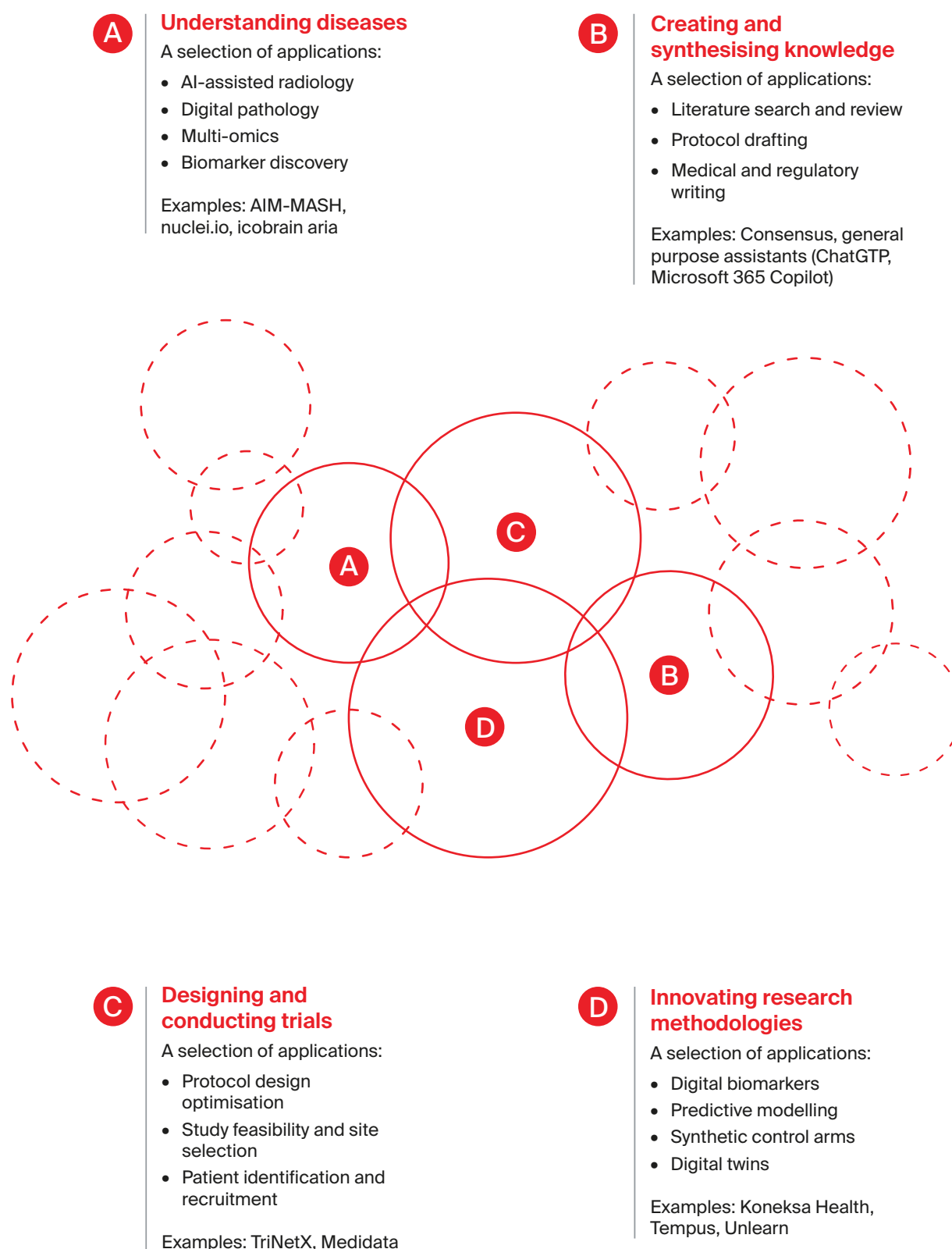
AI applications range from understanding disease biology and supporting trial operations to analysing complex data outputs and facilitating regulatory activities. This section explores applications in the following four domains: understanding diseases, creating and synthesising knowledge, designing and conducting trials, and innovating research methodologies. **Figure 1** provides examples of how AI is being used within these four domains, although the maturity, real-world adaptability, and adoption of the specific applications may vary.^A Furthermore, the domains are interconnected rather than sequential, and advances in one domain may support progress in another. And while some applications are already well established (e.g. AI-assisted radiology and digital pathology), others are still being evaluated for their methodological and/or regulatory feasibility (e.g. digital twins and synthetic control arms).

Domain A: Understanding diseases

Among all AI applications currently being used in health care and clinical research, some of the most mature ones are AI-assisted radiology and digital pathology applications. Once radiological images and pathology slides are digitised, AI algorithms can be used to detect and quantify features such as cell types, tissue structures, or disease markers at a scale and consistency that would be difficult to achieve with visual human assessment. This reduces both the time required for review and the inter-observer variability between different specialists. Using AI in this field can support disease characterisation, patient stratification, and biomarker discovery.^{5,6}

^A The tools named in the figure are used for illustrative purposes only and do not imply any endorsement, recommendation, or assessment of their performance or regulatory status by either the authors or the Swiss Clinical Trial Organisation (**SCTO**).

Figure 1: Examples of how AI is being applied within selected domains of the clinical research ecosystem



Besides processing images, AI can also combine multi-omics data such as genomics, transcriptomics, and proteomics with imaging-based data. This has shown promise in areas such as precision cancer diagnosis and prognosis.^{7,8}

AI-enabled research methodologies are beginning to enter formal regulatory evaluation. One example of regulatory maturity within the domain of understanding diseases is the AI-based measurement of metabolic dysfunction-associated steatohepatitis (**AIM-MASH**) tool. This AI-powered pathology methodology is used for scoring liver biopsies in metabolic dysfunction-associated steatohepatitis (**MASH**) clinical trials.⁹ In 2025, the European Medicines Agency (**EMA**) issued a qualification opinion^{B,C} for its defined context of use that supported its application in future MASH drug development.¹⁰

Domain B: Creating and synthesising knowledge

This domain focuses on how AI supports the creation, synthesis, and communication of knowledge across the clinical research ecosystem. The AI tools in this domain are generally built on large language models (**LLMs**) that are trained on large amounts of text in order to generate and process natural language. These tools can review scientific literature, clinical guidelines, and regulatory documents in order to produce a summary or to answer or draft scientific and regulatory documents.¹¹ These AI-supported capabilities have the potential to improve efficiency and consistency while reducing administrative burden, thus allowing researchers to focus more on scientific interpretation and decision-making. However, independent evaluations of LLMs' real-world performance remain limited to date.¹² As with all AI applications in clinical research, human oversight remains essential, and outputs require critical reading and verification, particularly in regulated research environments.

Unlike AI software intended to directly benefit individual patients or support treatment decisions, these AI-supported knowledge synthesis tools are not usually

considered medical device software under the EU's Medical Device Regulation (**MDR**) as long as they do not claim a medical purpose (MDR, Article 2(1); MDCG 2019-11 Rev1). Therefore, they generally fall outside of the MDR and are not subject to its clinical evaluation or conformity assessment requirements. However, regardless of their MDR status and depending on how they are used, AI-supported tools may be subject to requirements under the EU's Artificial Intelligence Act (**AI Act**) (e.g. transparency requirements concerning certain AI-generated content) and to data protection legislation such as the EU's General Data Protection Regulation (**GDPR**) and Switzerland's Data Protection Act (**FADP**) (e.g. if an AI-supported tool is used to process documents containing identifiable patient information).

Domain C: Designing and conducting trials

Clinical trial operations remain one of the most challenging aspects of clinical research and, consequently, one of the most promising domains for AI applications. Researchers are increasingly exploring how AI could support different aspects of trial planning and conduct, including protocol optimisation, study feasibility, site selection, participant recruitment, and the identification of data anomalies or unusual patterns that require further investigation while a trial is being conducted.^{13,14}

Patient recruitment constitutes one of the most critical bottlenecks in clinical trials. AI can significantly support this phase by automating the screening of electronic health records and matching patients to complex eligibility criteria potentially more rapidly than manual processes. AI models can also be used to optimise site selection by analysing historical site performance, patient availability, and geographic factors. Together, these approaches may improve recruitment rates, reduce screening failures, and enhance overall trial efficiency.

While several commercial solutions have emerged in this domain, routine implementation remains limited

^B EMA qualification is a voluntary procedure in which the Committee for Medicinal Products for Human Use (**CHMP**) issues an opinion on whether a method is acceptable for a specific use in medicine development that is tied to a defined context of use. A qualification opinion concerns the method rather than a medicinal product, and it is not a marketing authorisation.

^C The tool is now called AIM-MASH AI Assist; the EMA opinion retains the earlier AIM-NASH name because the qualification was filed before the revised MASH nomenclature was accepted.

and heterogeneous across organisations and research settings. Trial design and conduct therefore represents an area of active innovation rather than established clinical research practice.¹⁵

Regulators are taking an active interest in understanding how AI could improve clinical trial operations. For example, in April 2026 the US Food and Drug Administration (**FDA**) issued a request for information on the proposed AI-Enabled Optimization of Early-Phase Clinical Trials pilot programme, seeking input on how AI-enabled technologies could improve the efficiency, speed, and quality of decision-making in early-phase trials.¹⁶

Domain D: Innovating research methodologies

Generating robust clinical evidence on the safety and efficacy of interventions is the ultimate goal of clinical trials. AI is being increasingly explored to support how evidence is generated, analysed, and interpreted. Current developments in this domain include digital biomarkers (i.e. objectively quantifiable indicators of biological processes or responses to treatments or to interventions, measured using digital technologies), predictive modelling, synthetic control arms, and digital twins, among others.¹⁷

The increasing adoption of digital health technologies (**DHTs**) and decentralised clinical trials (**DCTs**) has driven wider use of wearable devices that continuously monitor patients outside the clinic and track signals such as heart rate, movement, or sleep instead of relying on occasional site visits. AI-based algorithms then convert this continuously collected data into digital biomarkers that are clinically meaningful, standardised measurements that can complement or substitute endpoints.¹⁸

AI is also being used for predictive modelling, which looks at clinical and real-world data together to predict how a disease might progress, how a patient might respond to treatment, or other outcomes of a trial. A more recently developed methodology is the synthetic control arm, in which researchers use existing external data to build a comparison group instead of enrolling a separate group of patients to receive a placebo or standard of care. Another application is a digital twin, where a virtual version of a specific patient is created to simulate how they might have progressed without

treatment. In practice, this could mean fewer patients need to be enrolled, thus reducing the exposure to a placebo or to a less effective comparator and making trials more feasible, particularly for rare diseases where the eligible population is small. These methods are still at different stages of scientific and regulatory maturity, but they point to how AI could gradually change the way clinical evidence is generated.¹⁹

Some research methodologies have already entered formal regulatory evaluation. One example is Prognostic Covariate Adjustment (**PROCVA**), a methodology developed by Unlearn that received an EMA qualification opinion in 2022 for use in phase 2 and phase 3 trials with continuous outcomes. By incorporating AI-derived prognostic predictions based on patients' baseline characteristics into the statistical analysis of randomised clinical trials, it has been shown to improve the precision of treatment effect estimates.²⁰

It is important to keep in mind that these four domains should not be viewed as independent applications or sequential stages of clinical research. Advances in one domain generate new data, knowledge, and evidence that strengthen the other domains. Improved disease understanding informs better trial design; more efficient trials generate higher-quality evidence; and newly generated evidence contributes to refining scientific knowledge while supporting the development and validation of future AI applications. In this way, AI is progressively becoming embedded within a continuous learning ecosystem, where advances in both clinical research and AI reinforce one another.

AI beyond clinical research

AI can be applied across a range of areas related to clinical research and drug development. One of the most active application fields is pharmacovigilance, where AI is being explored to support case processing, literature screening, signal detection, safety surveillance, and benefit-risk assessment. In its recent report [Artificial Intelligence in Pharmacovigilance](#), the Council for International Organizations of Medical Sciences (**CIOMS**) Working Group XIV concludes that AI has considerable potential to improve pharmacovigilance activities by increasing efficiency and consistency.

At the same time, it emphasises that AI should augment rather than replace human expertise and that its implementation requires appropriate validation, transparency, governance, and human oversight.²¹

Regulatory authorities are also beginning to adopt AI in selected activities. The European Medicines Agency (EMA) and the Heads of Medicines Agencies (HMA) jointly adopted one of the most structured approaches in their [Data and AI in Medicines Regulation](#) workplan, which covers activities from 2026 to 2028. By providing guidance, opportunities for collaboration and experimentation, and access to AI-enabled tools, the workplan promotes the responsible use of AI across the European medicines regulatory network. The EMA has also introduced [Scientific Explorer](#), an AI-assisted search tool that helps assessors quickly retrieve relevant scientific advice, assessment reports, and previous regulatory information but leaves scientific judgement to the assessor. In the United States, the FDA has also started integrating AI into its internal workflows through [Elsa](#), a generative AI assistant designed to support activities such as scientific review and document analysis.

Future perspectives

Artificial intelligence holds significant potential to support researchers throughout the clinical trial life cycle: from study design and patient recruitment to data analysis and operational monitoring. By enabling more efficient use of data, improving patient matching, and supporting real-time decision-making, AI may contribute to addressing some of the long-standing inefficiencies that have historically limited trial performance. In fact, AI is already being applied throughout many stages of clinical research, and its use is expected to continue expanding. At the same time, how AI is implemented – i.e. how it is validated, governed and integrated into existing workflows – is receiving increasing attention.

AI's integration into clinical research cannot be considered purely as a technological enhancement. The use of AI introduces new operational, ethical, and compliance challenges. In addition to the regulatory and technical considerations, the deployment of AI systems can also be resource-intensive, requiring

specialised expertise for development and validation as well as significant effort and cost to ensure verification, regulatory compliance, and ongoing performance monitoring. The successful implementation of AI tools requires robust data governance, data protection, data security, transparency, and continuous oversight, which may fundamentally reshape how clinical trials are designed, conducted, and evaluated.

Another emerging consideration is the environmental impact of AI, which is becoming an increasingly important dimension of its future governance. The development, training, and deployment of increasingly complex AI models require substantial computational resources and energy consumption. In the context of growing efforts to reduce the environmental footprint of health care and research activities, future policies may increasingly consider the sustainability of AI systems alongside their performance and safety. This could lead to the emergence of new expectations regarding resource efficiency, model optimisation, and the responsible use of AI technologies.

Conclusion

Several use cases of AI applications in clinical research already exist, with many more on the horizon. However, understanding where AI can deliver the greatest value also requires identifying the major operational challenges that continue to limit the efficiency, quality, and success of clinical trials. Moreover, AI should not be viewed as a replacement for research and clinical expertise but rather as a complementary tool that can enhance human capabilities. Its long-term value will depend on achieving a careful balance between innovation, regulatory compliance, ethical responsibility, and the resources these systems consume. Maintaining this balance will ensure that advances in AI translate into meaningful improvements in trial efficiency, scientific validity, and patient outcomes.

Regulatory Spotlight

AI regulation is developing differently across jurisdictions. The European Union has introduced the Artificial Intelligence Act (AI Act) as a broad, horizontal, and risk-based framework. Switzerland has not opted for a comparable horizontal law, and the Federal Council confirmed in February 2025 that AI will continue to be regulated through existing sectoral legislation and targeted amendments where needed. In March 2025, Switzerland signed the Council of Europe Framework Convention on Artificial Intelligence and Human Rights, Democracy and the Rule of Law, the first legally binding international treaty in this field. Switzerland intends to implement the Convention through amendments to existing law, sector-specific measures where needed, and non-binding measures such as standards, industry solutions, and voluntary commitments.²² Draft legislation implementing the Convention in Swiss law is expected by the end of 2026. The EU has also signed the Convention, which it implements through its AI Act.

A closer look at the AI Act

The EU's AI Act currently provides the most developed horizontal legal framework for AI and has important implications for AI-enabled medical devices and other healthcare applications. It is the first legal framework adopted at the EU level to regulate the development, marketing, and use of artificial intelligence systems. Initially proposed by the European Commission in April 2021, it was formally adopted in 2024, with phased implementation running to 2028 depending on the specific provisions.

This regulation reflects an effort to balance technological innovation with the protection of fundamental rights, safety, and public health. Unlike sector-specific regulations, the AI Act follows a cross-sectoral approach that applies

broadly across the fields where AI systems are developed or deployed. Certain activities are nonetheless excluded: the regulation does not apply to any research, testing, or development activity related to AI systems or AI models prior to them being placed on the market or put into service. It also does not apply to systems developed and put into service for the sole purpose of scientific research. The regulation's wording is not always clear, which has made it difficult to apply in practice and has led to calls for clearer definitions and guidance.²³

A risk-based approach

The AI Act classifies artificial intelligence systems according to their risk and potential level of harm. It distinguishes the following four main categories:

- **Unacceptable-risk systems** (e.g. systems involving certain types of behavioural manipulation or social scoring) are prohibited.
- **High-risk systems** (e.g. AI systems used in recruitment processes or credit scoring as well as AI systems that are medical devices) are subject to strict requirements both before and after being placed on the market.
- **Limited-risk systems** (e.g. chatbots) must comply with specific transparency obligations.
- **Minimal-risk systems** (i.e. most AI applications that do not fall into the categories above, such as spam filtering or basic recommendation systems) may generally be used freely with few obligations under the AI Act.

This tiered approach makes it possible to tailor regulatory requirements to the potential impact of each system on individuals and society.

Requirements for high-risk systems

AI systems used in clinical research may fall into the high-risk category depending on their intended purpose and applicable regulatory classification, particularly when they are incorporated into regulated medical devices (e.g. certain AI-based diagnostic imaging or pathology software). Such high-risk systems will be subject to a set of harmonised requirements at the EU level. When AI systems used in critical contexts (such as health care and clinical trials in particular) are considered high-risk, they require the following in particular:

- the implementation of a risk management system covering an AI system's entire life cycle
- robust data governance and quality standards for training, validation, and testing datasets
- the preparation of comprehensive technical documentation demonstrating regulatory compliance
- transparency obligations and, to some extent, requirements related to explainability
- post-market monitoring measures, including performance tracking and incident management.

The goal of these requirements is to ensure that high-risk AI systems achieve a high level of safety, reliability, and robustness while remaining controllable by human users.

Scope and applicability

The AI Act applies not only to entities established within the EU but also to organisations located outside the EU whose AI systems are sold on the European market or used within it. Therefore, the regulation has significant influence beyond the EU's borders and encourages international actors to align their practices with its requirements in order to ensure access to the European market.

The interplay between AI regulation and medical device legislation

The interplay between the EU's AI Act and its [Medical Device Regulation \(MDR\)](#) is particularly significant, as many AI-based systems used in health care fall under multiple regulatory regimes. Frameworks such as the AI Act introduce risk-based requirements for AI systems, particularly for those in high-stakes areas like health care. For AI-based medical devices, these requirements are in addition to obligations in existing legislation, thus further increasing regulatory and operational complexity in clinical research. At the EU level, when software incorporating AI is intended for medical purposes – such as the diagnosis, prevention, monitoring, prediction, or treatment of a disease – it may be classified as medical device software (**MDSW**) under the MDR. It is important to emphasise that the use of AI alone is not a determining factor for medical device classification. The assessment is based solely on the intended purpose of the software. As a result, the same algorithm may be considered a medical device in a clinical context but not when used for general wellness or non-medical applications.

How the MDR and AI Act interact

When an AI system is classified as a medical device, it becomes subject to two regulatory regimes simultaneously:

- the EU's MDR, which governs the safety, clinical performance, and classification of medical devices
- the EU's AI Act, which sets specific requirements for high-risk AI systems.

This results in a layered regulatory structure rather than the replacement of one framework by another. The AI Act does not supersede the MDR; instead, it complements it by introducing additional requirements that are specific to AI.

Implications for compliance and regulatory convergence

A key point is that medical devices incorporating artificial intelligence may be classified as high-risk systems under the EU's AI Act, depending on their intended purpose and whether they require third-party conformity assessment under the MDR or the In Vitro Diagnostic Medical Devices Regulation (IVDR) (see AI Act, Article 6(1) and Annex I). This implies that such systems must comply not only with applicable requirements of the MDR or IVDR (including CE conformity marking, conformity assessment, and clinical evidence) but also with the additional obligations applicable to high-risk AI systems described above. This dual regulatory oversight reflects a broader shift towards a convergence of frameworks governing digital health technologies. While the MDR establishes a product-centred approach focused on the medical device itself, the AI Act introduces a complementary perspective centred on the behaviour of algorithmic systems and their dynamic life cycles.

This overlapping structure raises important challenges for manufacturers, particularly in relation to the following issues:

- the consistency of compliance requirements across frameworks
- the cumulative regulatory burden
- the integration of quality management systems
- the life cycle management of software and updates to AI models.

In this context, an analysis of the implications of the AI Act for medical devices cannot be viewed in isolation from the existing regulatory framework. Rather, it requires an integrated approach that takes into account both traditional safety and clinical performance requirements as well as the new obligations specific to AI systems.

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