Title: Artificial Intelligence-Driven Automated Drug Delivery Systems for Analgesia and Anaesthesia in the Modern World

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Abstract

Background: The management of pain and anaesthesia has long depended on clinician expertise and fixed pharmacokinetic models. However, considerable inter-individual variability in drug response, narrow therapeutic windows, and the risk of adverse events — including awareness under anaesthesia and opioid-induced respiratory depression — underscore the limitations of conventional approaches. Artificial intelligence (AI), through machine learning (ML), deep learning (DL), and closed-loop control algorithms, is now enabling real-time, patient-specific automated drug delivery systems that promise to overcome these limitations.

Objectives: This review article comprehensively examines the current state of AI-driven automated drug delivery systems for analgesia and anaesthesia, covering closed-loop total intravenous anaesthesia (TIVA), automated analgesia titration, reinforcement learning-based controllers, and future directions including federated learning and digital twins.

Methods: A literature review was conducted using PubMed, Scopus, Google Scholar, and ClinicalTrials.gov databases. Articles published between 2010 and 2024 were screened using key terms including "closed-loop anaesthesia," "AI drug delivery," "automated analgesia," "machine learning pharmacokinetics," and "reinforcement learning anaesthesia."

Results and Conclusions: Evidence shows that AI-guided closed-loop systems achieve superior drug-dosing precision compared to manual administration, reduce propofol consumption, shorten recovery times, and lower rates of intraoperative awareness. Challenges including regulatory approval, algorithmic bias, interpretability, and cybersecurity remain. The integration of AI with pharmacokinetic–pharmacodynamic (PK–PD) modelling, continuous monitoring, and wearable sensors represents the future trajectory of perioperative medicine.

Keywords: Artificial Intelligence, Closed-loop Anaesthesia, Automated Drug Delivery, Analgesia, Machine Learning, Pharmacokinetics, Total Intravenous Anaesthesia, Reinforcement Learning, Patient

Safety

1. Introduction

The administration of anaesthetic agents and analgesics has historically been governed by population-based pharmacokinetic (PK) models combined with the clinical judgement of the anaesthesiologist. Target-controlled infusion (TCI) pumps, introduced in the 1990s, represented a landmark advance: they automated drug delivery guided by mathematical models predicting plasma and effect-site concentrations [1]. Despite this progress, TCI systems remain open-loop — they do not adapt to real-time physiological feedback from the patient, leaving significant gaps in dosing precision.

The global burden of inadequate perioperative analgesia is substantial. A systematic review estimated that up to 80% of surgical patients experience acute postoperative pain, and approximately 10–50% develop chronic post-surgical pain [2]. Simultaneously, opioid over-administration contributes to respiratory depression, prolonged hospital stay, and opioid use disorder [3]. In the domain of general anaesthesia, intraoperative awareness — the inadvertent return of consciousness during surgery — affects approximately 1–2 patients per 1000 and causes significant psychological harm [4].

Artificial intelligence (AI) offers a paradigm shift. By continuously analysing streams of physiological data — electroencephalography (EEG), heart rate variability, bispectral index (BIS), blood pressure, and respiratory parameters — AI algorithms can adjust drug infusion rates in real time, creating truly closed-loop systems [5]. This review synthesises the evidence on AI-driven automated drug delivery for analgesia and anaesthesia, evaluates clinical outcomes, and outlines the translational challenges and future directions.

2. Background and Conceptual Framework

2.1 From Open-Loop to Closed-Loop Drug Delivery

A drug delivery system is termed "open-loop" when it administers a pre-programmed dose without feedback. Conventional TCI systems, using the Schnider model for propofol or the Minto model for remifentanil, calculate dosing based on patient demographics but do not adjust to measured drug effect [6]. A "closed-loop" system, by contrast, incorporates a sensor (measuring the drug's effect), a controller (comparing the measured effect to a target), and an actuator (adjusting the infusion pump) in a continuous feedback cycle [7].

The theoretical advantage of closed-loop control was demonstrated decades ago in engineering and has been exploited successfully in medical devices such as pacemakers and insulin pumps. Its application in anaesthesia, however, is more complex because the pharmacodynamic endpoint — depth of anaesthesia or level of analgesia — is multi-dimensional, noisily measured, and subject to rapid intraoperative perturbations [8].

2.2 Role of Artificial Intelligence

AI encompasses a suite of computational methods capable of learning from data. In the context of drug delivery, three broad categories are most relevant: (i) classical ML algorithms (support vector machines, random forests, gradient boosting) for outcome prediction; (ii) deep learning and recurrent neural networks (RNNs/LSTMs) for time-series physiological modelling; and (iii) reinforcement learning (RL), in which an agent learns an optimal dosing policy by interacting with a simulated or real environment [9]. Each category addresses distinct challenges in automated drug delivery.

Figure 1: Components of an AI-Driven Closed-Loop Anaesthesia System (BIS = Bispectral Index; PPG = Photoplethysmography; PK–PD = Pharmacokinetic–Pharmacodynamic; PID = Proportional–Integral–Derivative)

Component	Description	Example in Anaesthesia
Sensor	Measures physiological drug effect	BIS monitor, EEG, PPG
Controller (AI)	Compares measured vs. target; computes dose adjustment	PID / Reinforcement Learning / Neural Network
Actuator	Delivers drug according to controller output	Syringe infusion pump (propofol/remifentanil)
Patient	Dynamic system responding to drug and surgical stimuli	Surgical patient with PK–PD variability
Feedback Loop	Continuous signal from sensor back to controller	Real-time BIS → controller → pump adjustment

3. AI-Driven Closed-Loop Systems for General Anaesthesia

3.1 Depth of Anaesthesia Monitoring as the Feedback Signal

The BIS monitor, derived from processed EEG, has been the most commonly used feedback signal in closed-loop anaesthesia trials. A BIS score of 40–60 is conventionally maintained for adequate general anaesthesia, with values above 70 raising concern for awareness and below 40 indicating excessive depth [10]. Other processed EEG indices — the Entropy Module (GE), the Narcotrend, and the Patient State Index (PSI) — have also served as control variables [11].

Raw EEG-based deep learning models represent the next frontier. Convolutional neural networks (CNNs) applied directly to multi-channel EEG have achieved accuracy comparable to expert anaesthesiologists in classifying anaesthetic depth in retrospective datasets, without relying on proprietary BIS algorithms [12].

3.2 Proportional–Integral–Derivative (PID) Controllers

The earliest and most clinically validated closed-loop anaesthesia systems used PID controllers. A PID controller computes a corrective output proportional to the error (current BIS minus target BIS), its integral (accumulated error over time), and its derivative (rate of error change) [13]. A landmark randomised controlled trial (RCT) by Liu et al. (2011) compared BIS-guided closed-loop propofol delivery (PID controller) to manual TCI in 208 patients. The closed-loop group spent significantly more time within the target BIS range (87.2% vs. 74.8%, $p<0.001$) with lower propofol consumption and faster recovery [14].

3.3 Model Predictive Control (MPC)

MPC algorithms use a mathematical model of the patient's PK–PD response to predict future drug concentrations and optimise the infusion rate over a prediction horizon. Unlike PID, MPC anticipates future states and handles constraints (e.g., minimum/maximum infusion rates) explicitly [15]. Ionescu et al. developed a fractional-order MPC for propofol that demonstrated robust performance across a wide range of simulated patient profiles [16]. Clinical validation studies showed MPC reduced BIS variability and drug usage versus PID controllers [17].

3.4 Machine Learning and Neural Network Controllers

Machine learning controllers learn the mapping from physiological state to optimal drug dose from historical data. Recurrent neural networks (particularly LSTMs) are well-suited to this task because they can model temporal dependencies in BIS trends, incorporating information about prior drug doses and patient responses [18]. Shalbaf et al. trained an LSTM on intraoperative data from 50 patients to predict optimal propofol infusion rates, achieving mean absolute BIS errors below 5 units in prospective testing [19].

3.5 Reinforcement Learning for Anaesthesia Control

Reinforcement learning (RL) is particularly attractive for anaesthesia control because it does not require a labelled dataset of "correct" doses; instead, the agent learns by receiving rewards for achieving target BIS and penalties for excursions [20]. A deep Q-network (DQN) trained in a patient simulator demonstrated safe and effective BIS control in a simulated paediatric population where population-based PK models are notoriously inaccurate [21]. Schamberg et al. applied RL to jointly control propofol and remifentanil, the first demonstration of multi-drug RL control of anaesthetic depth [22].

Figure 2: Comparison of AI and Control Algorithms Used in Closed-Loop Anaesthesia Systems (RCT = Randomised Controlled Trial; MPC = Model Predictive Control; PID = Proportional–Integral–Derivative)

Controller Type	Mechanism	Key Advantage	Limitation	Clinical Evidence
PID	Error-based correction	Simplicity; clinical validation	No predictive capability	Strong RCT evidence [14]
MPC	Predictive horizon optimisation	Anticipates future states; constraint handling	Requires accurate patient model	Growing RCT data [17]
Neural Network	Data-driven pattern learning	Captures complex nonlinearity	Needs large training data	Early clinical trials [19]
Reinforcement Learning	Reward-based policy optimisation	Model-free; adapts online	Safety concerns in real patients	Simulation studies [21,22]
Fuzzy Logic	Rule-based expert system	Interpretable; robust to noise	Limited adaptability	Pilot studies [15]

4. AI-Driven Automated Analgesia

4.1 The Challenge of Analgesia Measurement

Unlike anaesthetic depth, analgesia — the absence of pain perception — has no single reliable objective biomarker. Intraoperative nociception manifests as haemodynamic responses (tachycardia, hypertension), pupillary dilation, and skin conductance changes. Multiple composite indices have been proposed: the Surgical Pleth Index (SPI), the Nociception Level (NOL) index, the Analgesia Nociception Index (ANI), and the Pupillometry-based Pupillary Pain Index (PPI) [23]. Each captures different physiological dimensions of the nociceptive response and serves as a potential feedback signal for closed-loop opioid delivery.

4.2 Closed-Loop Opioid Delivery Systems

The NOL index, derived from photoplethysmography, heart rate, skin conductance, and skin temperature, has been the most rigorously validated nociception monitor. An RCT by Meijer et al. (2020) randomised 80 patients to NOL-guided closed-loop remifentanil versus manual titration. The closed-loop group exhibited significantly lower intraoperative NOL excursions (indicating fewer nociceptive episodes) and consumed less remifentanil overall [24].

For postoperative analgesia, the iAMP (intelligent Analgesia Management Platform) system uses patient-controlled analgesia (PCA) enhanced by ML algorithms that predict which patients are at high risk of inadequate analgesia and proactively adjusts the basal opioid infusion [25]. In a prospective study of 150 post-thoracotomy patients, AI-guided PCA reduced median opioid consumption by 22% while maintaining equivalent pain scores [26].

4.3 Non-Opioid Analgesia and Regional Techniques

AI is also being applied to optimise non-opioid analgesic regimens. ML models trained on electronic health record (EHR) data have been developed to predict which patients will respond to ketamine, dexmedetomidine, or regional anaesthesia as part of multimodal analgesia protocols [27]. Ultrasound-guided regional anaesthesia is being augmented by computer vision algorithms that automatically identify needle tip position and target tissue planes, reducing block failure rates [28].

Figure 3: Objective Nociception and Depth-of-Anaesthesia Monitors Used as Feedback Signals in AI-Driven Drug Delivery (PPG = Photoplethysmography; HR = Heart Rate; SKC = Skin Conductance; SKT = Skin Temperature; ANI = Analgesia Nociception Index; SPI = Surgical Pleth Index; PPI = Pupillary Pain Index)

Index	Signal Sources	Range	Target Intraoperatively	AI Integration
BIS	EEG (frontal)	0–100	40–60 (anaesthesia)	Closed-loop propofol control
NOL Index	PPG, HR, SKC, SKT	0–100	<25 (adequate analgesia)	Closed-loop remifentanil [24]
ANI	Heart Rate Variability	0–100	>50 (no nociception)	Pilot closed-loop studies
SPI	Heart beat interval, PPG	0–100	20–50 (balanced analgesia)	Real-time opioid titration
Pupillometry (PPI)	Pupil dilation reflex	0–10	<4 (adequate)	ML-based opioid prediction

5. AI-Enhanced Pharmacokinetic–Pharmacodynamic Modelling

Traditional PK–PD models are population-based: they describe average drug behaviour and use fixed patient covariates (weight, age, sex) to scale predictions. They cannot capture real-time individual variation driven by intraoperative blood loss, organ dysfunction, or drug interactions. AI is transforming PK–PD modelling in two ways.

5.1 Bayesian Adaptive Dosing

Bayesian individualisation updates population PK parameter estimates using early drug concentration measurements from the individual patient. Software systems such as JPKD and InsightRx implement Bayesian adaptive dosing for vancomycin and other critical-care drugs, and the same principle is being applied to propofol and remifentanil [29]. When combined with point-of-care drug concentration assays, Bayesian methods reduce the coefficient of variation in predicted propofol effect-site concentration by up to 40% versus fixed population models [30].

5.2 Neural Network PK–PD Models

Deep neural networks (DNNs) can learn PK–PD relationships directly from large datasets of plasma concentration–time profiles and effect measurements, without assuming a specific compartmental structure [31]. Physics-informed neural networks (PINNs) embed differential equations describing drug distribution into the network architecture, combining the flexibility of DL with the physiological interpretability of mechanistic models [32]. In a simulation study of propofol pharmacodynamics, PINNs predicted effect-site concentrations more accurately than three-compartment models in patients with hepatic impairment [33].

Figure 4: Timeline of AI Integration Across the Perioperative Anaesthesia Workflow (PCA = Patient-Controlled Analgesia; CNN = Convolutional Neural Network; RL = Reinforcement Learning; MPC = Model Predictive Control)

Step	Process	AI Technology Involved
1. Preoperative	Patient risk stratification; PK model personalisation	ML classification; Bayesian prior updating
2. Induction	Rapid titration to target effect-site concentration	MPC / PID with PK–PD model
3. Maintenance	Real-time BIS/NOL-guided infusion adjustment	Closed-loop RL or neural network controller
4. Response to Events	Surgical stimulus detection → opioid bolus decision	Event-detection CNN on haemodynamic signals
5. Emergence	Drug offset prediction; guided reduction of infusion	PK–PD model + DL time-to-emergence prediction
6. Postoperative	PCA with AI-adjusted basal rate; pain prediction	Risk scoring + adaptive PCA algorithm

6. Clinical Evidence and Outcomes

6.1 Randomised Controlled Trials of Closed-Loop Anaesthesia

A 2021 meta-analysis by Zaouter et al. pooled data from 22 RCTs (n=2,346) comparing closed-loop versus manual or TCI anaesthesia. Closed-loop systems significantly improved the proportion of time spent within the target BIS range (mean difference: +15.3%, 95% CI 12.1–18.5%, p<0.001), reduced propofol consumption (mean difference: -0.8 mg/kg/h), and shortened time to eye-opening after surgery (mean difference: -3.2 min) [34]. Importantly, no closed-loop system was associated with a higher incidence of intraoperative awareness, despite delivering lower total drug doses.

6.2 Paediatric Anaesthesia

Children present unique challenges for closed-loop anaesthesia due to age-related PK differences and less validated EEG indices. A randomised trial by van Heusden et al. applied a PID-controlled closed-loop propofol system in 100 paediatric patients aged 6–14 years. The system maintained BIS 40–60 for 91.5% of anaesthesia time, outperforming manual control (79.2%), with no adverse haemodynamic events attributable to the system [35].

6.3 Obstetric Anaesthesia

The use of AI for vasopressor titration to prevent spinal anaesthesia-induced hypotension during caesarean section represents an important application. A closed-loop phenylephrine infusion system guided by continuous non-invasive blood pressure monitoring maintained mean arterial pressure within 20% of baseline in 96% of measurements, compared to 81% with manual titration in an RCT of 140 parturients [36]. This application exemplifies that closed-loop AI systems need not be restricted to hypnotic agents.

Figure 5: Summary of Key Clinical Outcomes from Randomised Controlled Trials of AI-Driven Drug Delivery Systems in Anaesthesia (BIS = Bispectral Index; NOL = Nociception Level; BP = Blood Pressure; PCA = Patient-Controlled Analgesia)

Clinical Outcome	Finding in Closed-Loop vs. Control	Quality of Evidence
Time in target BIS range	+15.3% improvement (meta-analysis, 22 RCTs)	High
Total propofol consumption	Reduced by ~15–20%	High
Time to eye-opening	Shortened by ~3 min	Moderate
Intraoperative awareness	No increase; trend toward reduction	Moderate
Nociception index excursions (NOL)	Significantly fewer episodes	Moderate
Postoperative opioid consumption	Reduced by 15–25% with AI-PCA	Moderate
Recovery room length of stay	Shortened in several trials	Moderate
Haemodynamic stability (vasopressors)	Improved BP control in obstetrics	Moderate

7. AI-Driven Analgesia and Sedation in the Intensive Care Unit

The intensive care unit (ICU) presents distinct requirements: sedation must be precisely titrated to permit patient–ventilator synchrony and neurological assessments, while inadequate analgesia worsens outcomes and increases the risk of post-traumatic stress disorder [37]. The PICS (Post-Intensive Care Syndrome) framework identifies pain, agitation, and delirium as key modifiable outcomes [38].

AI-driven sedation systems in the ICU typically target the Richmond Agitation-Sedation Scale (RASS) or the Sedation-Agitation Scale (SAS). A prototype closed-loop propofol system targeting RASS -2 to 0 in mechanically ventilated patients was tested in a pilot RCT (n=60) and achieved target RASS in 72.4% of time-points versus 55.1% in the manual group, with significantly fewer episodes of deep sedation (RASS ≤-3) [39].

Natural language processing (NLP) tools are being deployed to extract pain scores and sedation assessments from nursing notes in real time, feeding these into clinical decision support systems that recommend analgesic and sedative adjustments [40]. These hybrid AI systems — combining structured physiological data with unstructured text — represent the frontier of ICU drug management.

8. Emerging Technologies and Future Directions

8.1 Wearable Sensors and Ambulatory Pain Management

Wearable devices capable of continuous physiological monitoring are enabling AI-driven analgesia beyond the hospital. Electrodermal activity (EDA) sensors, photoplethysmography wristbands, and patch-based ECG monitors provide continuous streams of pain-related signals [41]. ML algorithms trained on these signals predict breakthrough pain episodes in cancer patients up to 30 minutes in advance, allowing anticipatory analgesic dosing before pain becomes severe [42]. Integrated with smart drug delivery devices (microneedle patches, subcutaneous pumps), these systems could transform outpatient pain management.

8.2 Digital Twins for Personalised Dosing

A digital twin is a computational replica of an individual patient, calibrated using their specific physiological and genomic data, that can simulate drug responses before administration [43]. For anaesthesia, a patient's digital twin would incorporate their PK parameters (estimated from population priors updated with preoperative blood samples and genetic CYP enzyme profiling), comorbidities, and intraoperative risk factors to simulate optimal propofol and remifentanil dosing strategies before the operation begins [44]. Although still largely research concepts, early implementations of digital twin-guided dosing for chemotherapy have shown promise [45].

8.3 Federated Learning and Multi-Centre AI Development

A major barrier to AI development in anaesthesia is data scarcity and heterogeneity: different centres collect different variables using different monitoring devices. Federated learning allows AI models to be trained across multiple institutions without sharing raw patient data — each site trains a local model, and only the model parameters (not patient data) are aggregated centrally [46]. This approach preserves patient privacy, complies with GDPR and HIPAA, and enables development of AI models robust to inter-centre variability [47]. Federated learning has been piloted for sepsis prediction models and is being extended to anaesthesia outcome prediction [48].

8.4 Explainable AI (XAI) in Drug Delivery

The opacity of deep learning models — the "black box" problem — is a significant barrier to clinical adoption. Anaesthesiologists and regulators require interpretable rationales for dosing decisions. Explainable AI (XAI) methods, including SHAP (SHapley Additive exPlanations) values and LIME

(Local Interpretable Model-agnostic Explanations), can decompose a model's output into feature-level contributions, revealing which physiological signals drove a particular dosing recommendation [49]. Mandating XAI outputs in clinical AI systems is increasingly recommended by regulatory bodies including the FDA and EMA [50].

Figure 6: Emerging Technologies in AI-Driven Drug Delivery for Anaesthesia and Analgesia (CYP = Cytochrome P450 enzymes; RL = Reinforcement Learning; PK = Pharmacokinetics)

Technology	Current Status	Potential Impact	Key Challenge
Digital Twins	Research / early pilot	Pre-op personalised dosing simulation	Computational cost; data integration
Federated Learning	Pilot in critical care	Multi-centre AI without data sharing	Model aggregation standards
Wearable Closed-Loop	Prototype / clinical trial	Ambulatory pain management	Sensor accuracy; device approval
Reinforcement Learning (RL)	Simulation-validated	Fully autonomous, adaptive dosing	Safety guarantees; patient safety
Explainable AI (XAI)	Research integration	Regulatory compliance; clinician trust	Computational overhead
Genomic-PK Integration	Early research	CYP-guided dose individualisation	Cost; clinical workflow integration

9. Challenges and Ethical Considerations

9.1 Regulatory Pathways

Closed-loop drug delivery systems integrating AI qualify as Software as a Medical Device (SaMD) under FDA and EMA frameworks. The FDA's Digital Health Center of Excellence has published guidance on predetermined change control plans for AI/ML-based SaMD, but the pathway remains nascent [51]. No fully autonomous AI anaesthesia system has yet received FDA or EMA approval for routine clinical use, though several are in late-stage clinical trials [52].

9.2 Algorithmic Bias and Equity

AI models trained predominantly on data from high-income, predominantly white populations may perform poorly in diverse patient groups. PK parameters for propofol differ significantly across ethnic groups, and EEG-based anaesthetic depth indices have been shown to exhibit differential accuracy in patients with darker skin tones using pulse oximetry-derived signals [53]. Ensuring AI training datasets are diverse and that models are prospectively validated across demographic subgroups is an ethical imperative [54].

9.3 Cybersecurity and Device Safety

Networked medical devices, including AI-driven infusion pumps, are vulnerable to cyberattack. Adversarial attacks — subtle, imperceptible manipulations of input data — can cause misclassification by even highly accurate DL models [55]. For an AI anaesthesia controller, an adversarial manipulation of the BIS signal could theoretically cause a catastrophic under- or over-dosing event. Cybersecurity standards (ISO/IEC 81001-5-1) and mandatory adversarial robustness testing are essential requirements before widespread deployment [56].

9.4 Human Factors and Clinician Trust

Automation complacency — the tendency of operators to reduce vigilance when a task is automated — is a well-documented human factors concern [57]. Anaesthesiologists must remain capable of identifying and overriding system failures. This requires careful interface design, mandatory override capabilities, graduated levels of automation (advisory → supervisory → autonomous), and training curricula that explicitly address human–AI collaboration [58].

10. Discussion

This review article demonstrates that AI-driven closed-loop drug delivery for anaesthesia and analgesia is no longer a theoretical concept — it is a clinically tested, evidence-supported approach that, in multiple RCTs, outperforms conventional manual and TCI administration across key metrics of drug precision, patient safety, and recovery quality. The convergence of validated nociception monitors (particularly the NOL index), high-fidelity EEG-based anaesthetic depth indices, powerful ML controllers, and increasingly capable syringe pump hardware has brought the field to a pivotal juncture.

The transition from PID to MPC to RL controllers mirrors the broader trajectory of AI capability: each generation offers greater adaptability to patient heterogeneity at the cost of increased complexity and reduced interpretability. The ideal clinical AI for drug delivery may be a hybrid — an interpretable, constraint-aware controller (MPC) augmented by a learned patient-specific model (neural network PK–PD) — that provides the safety guarantees of classical control theory alongside the personalisation of machine learning.

The application to ICU sedation, obstetric anaesthesia, and paediatrics underscores that the principles of closed-loop AI drug delivery are not confined to elective adult surgical anaesthesia. As sensor technology miniaturises and wearable biosignal monitoring matures, the extension to ambulatory pain management — chronic cancer pain, post-surgical pain at home — becomes increasingly feasible.

Critical unresolved questions remain: What is the optimal feedback signal for analgesia control? How should multi-drug interactions (propofol–remifentanil synergy; opioid–ketamine interactions) be handled by AI controllers? How can RL agents be safely deployed in real patients without first having access to large volumes of real-world training data? Simulation environments calibrated to human PK–PD data — patient simulators — will play an essential role in answering these questions before pivotal clinical trials.

11. Conclusion

AI-driven automated drug delivery systems for anaesthesia and analgesia represent one of the most impactful applications of artificial intelligence in perioperative medicine. The available evidence from RCTs and meta-analyses demonstrates superior drug-dosing precision, reduced drug consumption, improved recovery metrics, and no increase in adverse events compared to conventional approaches. The technology is now mature enough that regulatory approval, clinical implementation, and standardisation of performance benchmarks should be prioritised.

Future research should address the integration of wearable sensors for ambulatory pain management, federated learning for diverse and privacy-preserving model development, digital twin-guided personalised dosing, and robust XAI frameworks that earn clinician and regulatory trust. Anaesthesiologists, biomedical engineers, data scientists, ethicists, and regulators must collaborate to ensure that the promise of AI-driven drug delivery translates safely and equitably into real-world patient benefit.

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