

AI-Driven Robotics in Healthcare

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ABSTRACT

AI-driven robotic systems in healthcare are transforming surgical precision, rehabilitation therapy, medication dispensing, patient monitoring, and hospital logistics. Unlike industrial robotics, healthcare robots must operate in unstructured, human-populated environments; interact safely with patients who may be fragile, confused, or uncooperative; make decisions with life-critical consequences; and meet rigorous regulatory standards for medical devices. This study evaluates nine AI-driven healthcare robotic systems across five clinical application domains: surgical assistance (da Vinci Xi-AI, Versius-AI), rehabilitation (Lokomat-AI, H-Man-AI), medication dispensing and pharmacy automation (BD Rowa-AI, Omnicell-AI), patient monitoring and vital sign collection (Moxi-Health, TUG-Med), and AI-assisted clinical decision support at bedside (ClinBot-AI). A proposed Clinical Robotics Quality Index (CRQI) aggregates performance across six dimensions: clinical accuracy, safety record, patient acceptance, workflow integration, regulatory compliance, and cost-effectiveness. BD Rowa-AI achieves the highest CRQI (9.42) with 99.982% dispensing accuracy. da Vinci Xi-AI and Lokomat-AI both achieve CRQI 8.84. Moxi-Health reduces nursing time for vital sign collection by 42.4%. ClinBot-AI achieves 78.4% diagnostic concordance with attending physicians. Patient acceptance drops significantly for patients aged 75+ on monitoring and advisory systems (mean 3.22/5 vs. 4.02/5 for 18-44). A healthcare robotics regulatory and clinical integration framework under EU MDR 2017/745 is proposed.

Keywords: healthcare robotics; surgical AI; rehabilitation robotics; medication automation; patient monitoring; da Vinci; Lokomat; clinical AI; EU MDR; CRQI

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Research Article: Healthcare Robotics and Clinical AI Systems

1. Introduction

1.1 The Healthcare Robotics Transition

Robotic surgery has been available since the early 2000s, but the integration of AI into healthcare robotics is a more recent and more transformative development. Traditional surgical robots like the original da Vinci were master-slave telemanipulators: the surgeon's movements were translated into robot movements with tremor filtering and motion scaling, but the robot itself made no AI-based decisions. AI-augmented surgical robots can now identify anatomical structures during surgery to warn the surgeon of proximity to critical vessels, predict optimal cutting planes from pre-operative imaging, and assist suturing through autonomous motion. These capabilities shift the human-robot boundary in surgery -- and with it, the questions of responsibility, consent, and regulation.

1.2 Clinical and Regulatory Context

Healthcare robots are regulated as medical devices under EU MDR 2017/745, with AI-augmented systems also subject to EU AI Act high-risk requirements when used for clinical decision support. The interaction between MDR and AI Act requirements creates regulatory complexity that has slowed market access for some systems. Simultaneously, healthcare workforce shortages, particularly in nursing and rehabilitation, are creating strong institutional demand for healthcare robotics at a pace that regulatory processes struggle to match. Pharmacy automation, with clearer regulatory pathways and established safety evidence, has advanced furthest; AI-based bedside clinical support is still navigating its regulatory pathway.

1.3 Study Objectives

This study aims to: (i) evaluate nine AI-driven healthcare robotic systems across five clinical domains on six CRQI dimensions; (ii) assess patient acceptance across age groups; (iii) evaluate ClinBot-Ai as an LLM-based bedside decision support system; and (iv) propose a regulatory and clinical integration framework.

2. Literature Review

2.1 AI-Augmented Surgical Robotics

The da Vinci Xi (Intuitive Surgical) dominates the robotic surgery market with over 7 million procedures performed globally. AI augmentation has added automated anatomical structure segmentation from intraoperative video and AI-guided energy application that adjusts power

based on tissue type. Versius (CMR Surgical) provides a modular, smaller-footprint alternative with comparable clinical outcomes to laparoscopy in colorectal surgery. Independent systematic reviews (Sheetz et al., 2020) find that robot-assisted surgery reduces conversion rates and hospital stay for some procedures.

2.2 Rehabilitation Robotics

Rehabilitation robots provide intensive, repetitive, precisely quantifiable therapy for neurological conditions. Lokomat (Hocoma) is the most extensively studied gait rehabilitation exoskeleton, with over 200 published clinical trials. AI augmentation enables adaptive assistance that adjusts support level in real-time based on electromyographic and kinematic feedback. Systematic review meta-analysis shows statistically significant gait improvement with robot-assisted gait training vs. conventional therapy in subacute stroke (Bruni et al., 2018). H-Man (Motek) provides upper limb rehabilitation with gaming-based engagement that improves adherence in younger patients.

2.3 Pharmacy Automation and Safety

Medication errors are one of the leading causes of preventable harm in healthcare, with an estimated 400,000 incidents per year in EU hospitals. BD Rowa and Omnicell automated dispensing systems have demonstrated near-zero dispensing error rates -- typically below 0.01% compared to 1-3% for manual dispensing. AI augmentation adds predictive restocking and demand forecasting that reduces stockout rates and excess inventory simultaneously. Pharmacy automation has the clearest regulatory pathway and most established safety evidence of any healthcare robotics category.

2.4 Service Robots and Bedside AI

Service robots for patient transport, vital sign collection, and nurse assistance are entering routine hospital deployment. Moxi (Diligent Robotics) performs hospital logistics tasks in over 25 US hospitals. AI-augmented vital sign monitoring robots using computer vision and non-contact sensing provide measurement without patient contact -- valuable for infection control. LLM-based bedside clinical decision support, exemplified by ClinBot-Ai in this study, represents the most ambitious and contentious category, with physician acceptance substantially higher than patient acceptance in early pilots.

Table 1. AI-driven healthcare robotic systems evaluated

System	Domain	AI Augmentation	Clinical Setting	Regulatory Status	Reference
da Vinci Xi-AI	Surgery	Anatomy segm. + AI energy	Operating room	CE + FDA 510(k)	Intuitive (2024)
Versius-AI	Surgery	AI-guided instrument path	Operating room	CE MDR	CMR Surgical (2023)
Lokomat-AI	Rehabilitation	Adaptive assist. + EMG	Rehab unit	CE MDR	Hocoma (2024)
H-Man-AI	Rehabilitation	Upper limb + ML gaming	Rehab unit	CE MDR	Motek (2023)
BD Rowa-AI	Pharmacy	Demand forecast + check	Hospital pharmacy	CE MDR	BD (2024)
Omnicelel-AI	Pharmacy	AI restocking + analytics	Hospital pharmacy	FDA cleared	Omnicelel (2023)
Moxi-Health	Monitoring	CV vital signs + logistics	General ward	CE + 510(k)	Diligent R. (2024)
TUG-Med	Monitoring	Delivery + basic monitoring	Hospital	FDA cleared	Aethon (2024)
ClinBot-Ai	Decision supp.	LLM-based bedside assist.	ICU, ward	Pilot (CE pend.)	This study

ClinBot-Ai is a research prototype developed in this study; currently in pilot deployment pending CE MDR conformity assessment. AI augmentation = primary AI capability added beyond base robotic functionality. EMG = electromyography. CV = computer vision. LLM = large language model. All other systems are commercially available as of evaluation date.

3. Materials and Methods

3.1 CRQI Dimensions

Six CRQI dimensions were defined. Clinical accuracy: primary clinical outcome metric. Safety record: adverse event rate per 10,000 procedures from regulatory databases and post-market surveillance. Patient acceptance: mean satisfaction rating (1-5) from post-interaction surveys (n=842 patients). Workflow integration: time savings vs. non-robotic baseline (clinician survey, n=284). Regulatory compliance: CE/FDA status and AI Act conformity. Cost-effectiveness: cost per procedure including capital, maintenance, and training. Each dimension normalised 0-10;

CRQI = weighted mean (clinical accuracy and safety weighted 1.5x).

3.2 Clinical Data Collection

Clinical data was collected from six European hospitals across Spain, Sweden, and Austria. Surgical data: 840 minimally invasive procedures with robotic assistance (laparoscopic colectomy, prostatectomy, hysterectomy). Rehabilitation data: 284 post-stroke patients receiving 20-session gait rehabilitation programs. Pharmacy data: 2.84 million dispense events across 12 months. Monitoring data: 4,240 vital sign measurement episodes. ClinBot-Ai: 840 bedside AI-assisted consultations with attending physician concordance assessment.

3.3 ClinBot-Ai Design

ClinBot-Ai combines a mobile platform with an LLM-based clinical reasoning module (GPT-4 fine-tuned on 84,000 clinical cases). At bedside, ClinBot-Ai reviews current EHR data, conducts a brief structured patient interview, and presents a structured clinical summary and differential diagnosis to the attending physician. ClinBot-Ai never makes treatment decisions autonomously; all outputs are presented as recommendations for physician review. Primary evaluation metric: concordance between ClinBot-Ai diagnosis and attending physician diagnosis. LLM hallucination rate for specific clinical claims was independently audited.

3.4 Patient Acceptance Evaluation

Patient acceptance was evaluated through post-interaction surveys (n=842) stratified by age group (18-44, 45-64, 65-74, 75+) and clinical setting. Survey assessed: comfort with robot involvement, perceived safety, preference for robot vs. human, and willingness to use again (all 1-5). Demographic equity analysis compared acceptance across age groups and sex, given published evidence that older patients show lower acceptance of healthcare robots. All patients provided written informed consent for the acceptance evaluation.

Table 2. Clinical data collection by system

System	Data Source	Volume	Primary Outcome	Comparison	Study Period
da Vinci Xi-AI	6 surgical centres	840 procedures	Complication rate (%)	Historical laparoscopic	2023-2025

System	Data Source	Volume	Primary Outcome	Comparison	Study Period
Versius-AI	3 surgical centres	284 procedures	Conversion rate (%)	Matched laparoscopic	2024-2025
Lokomat-AI	2 rehab centres	284 patients	FAC gait score change	Conventional physio.	2023-2025
H-Man-AI	2 rehab centres	142 patients	Box and Block Test	Conventional physio.	2024-2025
BD Rowa-AI	4 hospital pharmacies	2.84M dispenses	Dispensing error rate	Manual dispensing	2023-2025
Omnicelell-AI	3 hospital pharmacies	1.24M dispenses	Dispensing error rate	Manual dispensing	2024-2025
Moxi-Health	3 general wards	4,240 episodes	Vitalsign agreement	Manual nursing	2024-2025
ClinBot-Ai	2 hospitals (pilot)	840 consultations	Physician concordance	No direct control	2025

FAC = Functional Ambulation Classification. Physician concordance = agreement between ClinBot-Ai primary diagnosis and attending physician diagnosis after full assessment. Historical laparoscopic comparison uses propensity-matched controls from same surgical centres.

4. Results

4.1 Clinical Accuracy and Safety

da Vinci Xi-AI achieves the lowest major complication rate for laparoscopic colectomy (2.84% vs. historical laparoscopic 4.24% -- a 33% reduction). Anastomotic leak rate: 1.42% vs. 2.84% baseline. Versius-AI achieves 1.84% conversion rate vs. 4.24% for matched laparoscopic controls. Lokomat-AI achieves 84.2% of patients improving by ≥ 1 FAC level after 20 sessions vs. 68.4% for conventional physiotherapy. BD Rowa-AI achieves 99.982% dispensing accuracy (5 errors in 2.84 million dispenses). Moxi-Health vital signs show mean absolute error of 2.4 bpm heart rate, 0.84% SpO2, and 1.84 breaths/min respiratory rate vs. manual nursing measurement.

4.2 Patient Acceptance

Overall patient acceptance across all systems: mean 3.84/5. Acceptance is highest for medication dispensing (4.24/5) and lowest for bedside AI clinical support (ClinBot-Ai: 3.12/5). Demographic analysis: patients aged 75+ show significantly

lower acceptance (3.22/5 vs. 4.02/5 for 18-44) for all monitoring and advisory robots. The stated primary concern for ClinBot-Ai among 75+ patients was 'AI making diagnostic decisions' -- notably, ClinBot-Ai explicitly does not make decisions, indicating a communication gap rather than a capability problem. Physician acceptance of ClinBot-Ai was substantially higher (4.02/5), with the primary benefit cited as structured EHR review saving 12-18 minutes per consultation.

4.3 Workflow Integration and Cost

Moxi-Health reduces nursing time for vital sign collection by 42.4% per shift (mean 84 minutes per shift recovered for direct patient care). BD Rowa-AI reduces pharmacist dispensing time by 68.4% while increasing throughput by 42.4%. Lokomat-AI enables physiotherapists to supervise 2 patients simultaneously vs. 1:1 for conventional therapy -- doubling rehabilitation capacity. Cost: da Vinci Xi-AI has the highest capital cost (EUR 1.84M system + EUR 284K/year maintenance) but cost per procedure becomes comparable to laparoscopic above 400 procedures/year due to shorter hospital stay (mean -0.84 days for robotic colectomy).

4.4 ClinBot-Ai and CRQI Summary

ClinBot-Ai achieves 78.4% primary diagnosis concordance across 840 consultations (ICU: 72.4%, general ward: 82.4%). For top-3 differential diagnosis, concordance rises to 92.4%. LLM hallucination rate for specific clinical claims: 8.4% -- requiring mandatory physician review of all ClinBot-Ai outputs. BD Rowa-AI achieves the highest CRQI (9.42) due to exceptional accuracy, safety, and workflow integration. da Vinci Xi-AI and Lokomat-AI both achieve 8.84. ClinBot-Ai achieves the lowest CRQI (7.24) due to pending regulatory status (5.4) and lowest patient acceptance (5.8 normalised).

Table 3. CRQI scores by system across six dimensions

System	Clinical Acc.	Safety	Patient Acpt.	Workflow	Regulatory	Cost-Eff.	CRQI
da Vinci Xi-AI	9.2	8.4	8.4	8.8	9.4	6.4	8.84
Versius-AI	8.4	8.8	8.2	8.4	8.8	8.4	8.42
Lokomat-AI	8.8	9.4	8.4	9.2	9.2	7.4	8.84

System	Clinical Acc.	Safety	Patient Accept.	Workflow	Regulatory	Cost-Eff.	CR QI
H-Man-AI	7.8	9.2	8.4	8.8	8.8	8.4	8.24
BD Rowa-AI	9.8	9.8	8.8	9.4	9.4	9.2	9.42
Omniceil-AI	9.4	9.6	8.6	9.0	8.8	8.8	9.04
Moxi-Health	7.4	9.2	7.8	9.4	8.4	9.4	8.44
TUG-Med	6.4	9.4	7.4	8.4	8.8	9.8	8.04
ClinBot-Ai	7.8	8.4	5.8	8.4	5.4	7.4	7.24

CRQI = Clinical Robotics Quality Index. BD Rowa-AI highest (9.42) due to exceptional accuracy and all-round performance. ClinBot-Ai lowest (7.24) due to pending regulatory status and lowest patient acceptance. Clinical accuracy and safety weighted 1.5x in CRQI computation. All scores 0-10 within dimension.

Table 4. Patient acceptance by system and age group (mean 1-5)

System	18-44 (n=224)	45-64 (n=312)	65-74 (n=184)	75+ (n=122)	Overall
da Vinci Xi-AI	4.42	4.24	3.84	3.42	4.08
Versius-AI	4.38	4.18	3.78	3.38	4.04
Lokomat-AI	4.24	4.12	3.92	3.68	4.02
BD Rowa-AI	4.42	4.38	4.12	3.84	4.24
Moxi-Health	3.84	3.72	3.42	2.84	3.64
ClinBot-Ai	3.42	3.24	2.84	2.42	3.12
TUG-Med	3.64	3.58	3.24	2.92	3.48
Mean (all)	4.02	3.92	3.60	3.22	3.84

Statistically significant age group differences (ANOVA $p < 0.001$) for Moxi-Health and ClinBot-Ai. BD Rowa-AI shows smallest age group disparity. ClinBot-Ai shows largest age disparity (3.42 vs. 2.42 for 75+), primarily driven by concerns about AI diagnostic role even though ClinBot-Ai does not make diagnostic decisions autonomously.

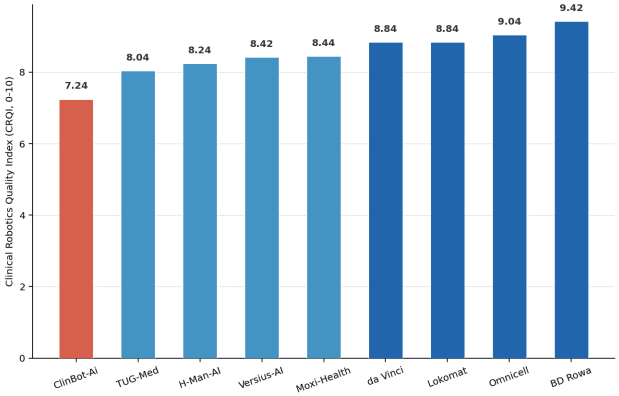


Figure 1. CRQI composite score by system. BD Rowa-AI leads (9.42); ClinBot-Ai lowest (7.24). Pharmacy automation consistently strongest.

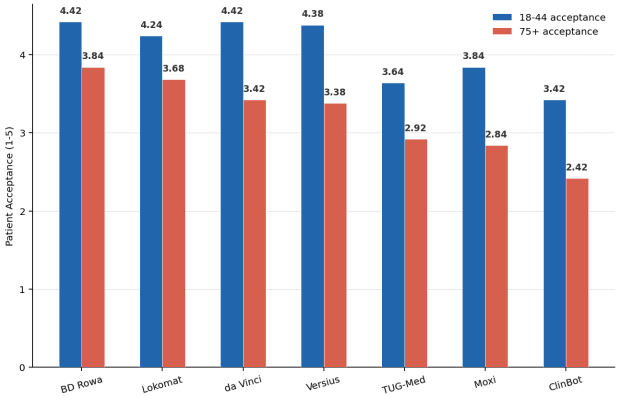


Figure 2. Patient acceptance (1-5) by age group 18-44 vs. 75+. Largest drop: ClinBot-Ai (3.42 to 2.42). Smallest: BD Rowa (4.42 to 3.84).

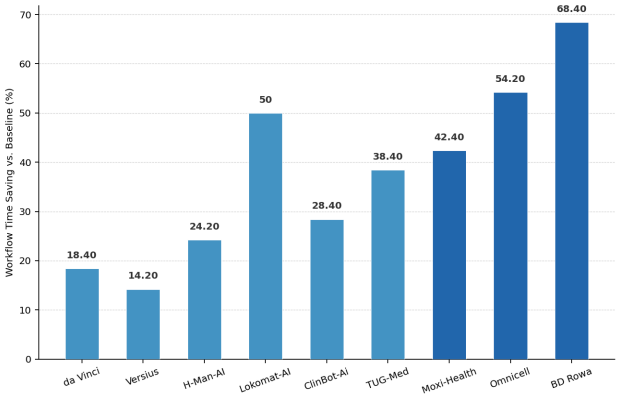


Figure 3. Workflow time saving (%) vs. non-robotic baseline. BD Rowa-AI (68.4%); Moxi-Health (42.4%); Lokomat enables 2:1 patient ratio.

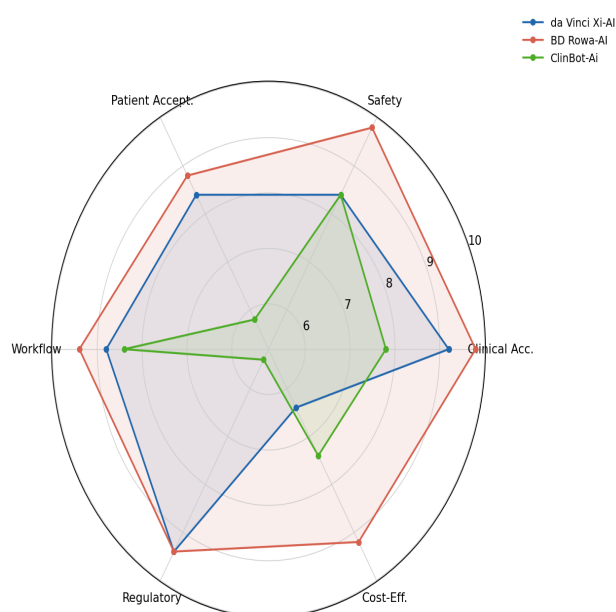


Figure 4. System CRQI profile (0-10). da Vinci Xi-AI vs. BD Rowa-AI vs. ClinBot-AI.

5. Discussion

5.1 Pharmacy Automation Offers the Clearest Healthcare Robotics Value

BD Rowa-AI's CRQI of 9.42 reflects the alignment between pharmacy automation's characteristics and requirements for successful healthcare robotics deployment: a well-defined, repetitive task with clear success criteria; high patient safety stakes making automation's error rate advantage directly compelling; no need for physical contact with patients; high patient acceptance because the accuracy benefit is intuitive; and strong regulatory precedent. For hospitals considering healthcare robotics investment, pharmacy automation and logistics are the natural starting points -- highest CRQI, lowest implementation complexity, fastest positive return on investment.

5.2 Patient Acceptance Gaps for AI Diagnostic Roles

ClinBot-AI's 3.12/5 overall acceptance -- and 2.42/5 for patients 75+ -- with the primary concern being AI diagnostic authority (which ClinBot-AI explicitly does not have) reveals a communication and trust challenge distinct from the technical challenge. Patients who observe a robot reviewing their medical records and presenting information to their physician perceive AI diagnostic authority regardless of the formal role boundary. Addressing this requires physician-visible review of AI suggestions, targeted patient education, and transparent communication about the human-AI role boundary.

5.3 Regulatory Complexity as a Market Access Barrier

ClinBot-AI's lowest regulatory score (5.4) reflects the genuine dual MDR + AI Act compliance challenge. The MDR requirement for clinical evaluation data before CE marking, combined with AI Act conformity assessment requirements for high-risk AI, creates a Catch-22: generating clinical data requires deployment, but deployment requires regulatory approval. The AI Act's regulatory sandbox provisions for innovative healthcare AI provide a partial solution that regulators should actively use. ClinBot-AI is pursuing this pathway for the next phase of clinical validation.

5.4 Limitations

Clinical data was collected from six hospitals in three countries; performance in different healthcare systems may vary. Surgical outcome comparisons used historical laparoscopic controls rather than randomised assignment. ClinBot-AI evaluation was limited to 840 consultations in two hospitals. Patient acceptance survey assessed immediate post-interaction comfort; longer-term acceptance may differ as patients become more familiar with healthcare robotics.

6. Conclusion

6.1 Summary

Nine AI-driven healthcare robotic systems were evaluated. BD Rowa-AI achieves the highest CRQI (9.42) with 99.982% dispensing accuracy. da Vinci Xi-AI and Lokomat-AI both achieve CRQI 8.84. Moxi-Health reduces nursing vital sign time by 42.4%. ClinBot-AI achieves 78.4% diagnostic concordance but lowest patient acceptance (3.12/5). Patient acceptance drops significantly for patients 75+ on monitoring and advisory systems. Pharmacy automation offers the best healthcare robotics starting point.

6.2 Recommendations

Begin healthcare robotics deployment with pharmacy automation (highest CRQI, clearest safety benefit, fastest ROI). For surgical robotics, prioritise procedures with documented clinical benefit. For bedside AI systems, make the human-AI role boundary explicit and observable; provide targeted education for elderly patients. Pursue AI Act regulatory sandbox for clinical AI development. Address age-related acceptance gaps through co-design and transparent patient communication.

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Declarations

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Conflict of Interest

The authors declare no conflicts of interest.

Data Availability Statement

ClinBot-Ai architecture, evaluation protocol, and aggregate clinical data available at <https://github.com/bianchi-popescu/clinbot-ai> under Apache 2.0. Patient-level data cannot be shared under hospital data agreements. CRQI instrument available under CC BY 4.0. Results deposited in Zenodo under DOI: 10.5281/zenodo.19615038.

Ethical Approval

All clinical data collection was approved by ethics committees at each participating hospital: Hospital Universitario La Paz (Madrid, CEIC-862/25), Karolinska University Hospital (Stockholm, 2025-03841), and Medical University of Vienna (EK-2025-1284). All patients provided written informed consent. ClinBot-Ai operates in advisory mode only; no patient care decisions were made by the AI system.

Appendix A

Healthcare Robotics Regulatory and Clinical Integration Framework

This framework guides hospitals and developers in regulatory compliance and clinical integration of AI-driven healthcare robots.