SIAARTI
PRO VITA CONTRA DOLOREM SEMPER

UNIVERSITÀ DI PARMA

Applicazione in sala operatoria, dalla gestione dei flussi di lavoro alla clinica
Risultati di un'applicazione concreta

Trieste, 17 ottobre 2025

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CONGRESSO NAZIONALE
SICUT 2025

PARMAI
PERIOPERATIVE MEDICINE

Conflict of interest

None

Why innovation matters...?

Outcomes

Complexity

Efficiency

Excellence

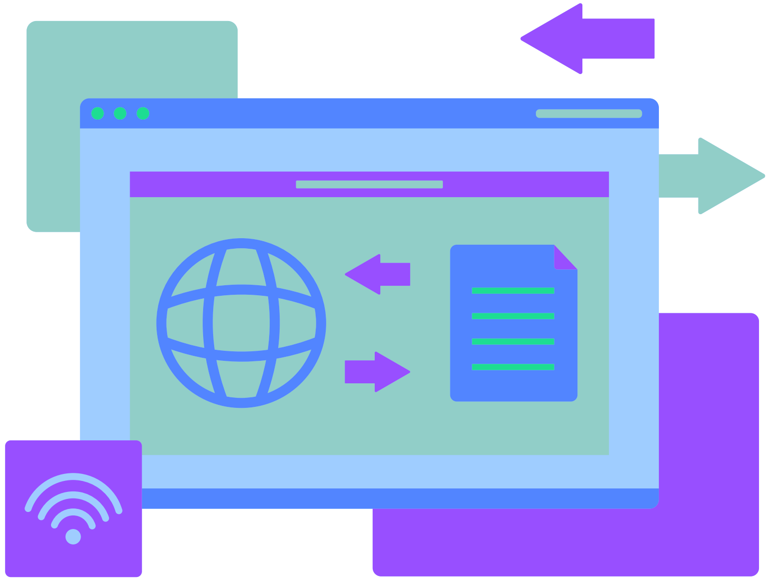
Sustainability

….to improve our patients' outcomes, to improve efficiency, to manage complex situations…

Digitalization in healthcare

However, the mere digitalization of records is not enough. The next step is **digital transformation**, where data is actively used to improve patient care. This involves:

- **AI-driven analytics**
- **Predictive models**
- **Decision-support systems**
- **Clinical or management**



....that leverage big data to **optimize outcomes**

Key AI technologies in healthcare

Predictive AI

Forecasts patient outcomes and disease risks

Generative AI

Creates new content, including medical documentation and chatbot-based patient interactions

Explainable AI

Enhances trust by making AI-driven decisions transparent and interpretable for clinicians

Machine Learning

Machine Learning (ML) is a subset of AI that enables systems to learn from data without explicit programming. It powers many of the AI-driven innovations in medicine. It is classified into **three types**.

Deep Learning (DL)

Deep Learning (DL), a subfield of ML, employs artificial neural networks to process complex medical data, including images and time-series physiological signals

Supervised Learning

Algorithms learn from labeled datasets, making accurate predictions (e.g., mortality risk stratification models in perioperative care).

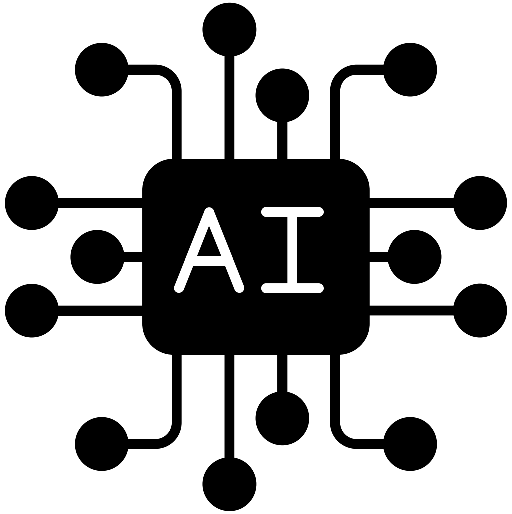
Unsupervised Learning

The system identifies patterns in data without pre-existing labels (e.g., clustering ICU patients based on response to treatment).

Reinforcement Learning

AI learns optimal actions through trial and error (e.g., adaptive ventilator control for critical patients)

How AI is applied in medicine



Clinical Decision Support Systems (CDSS)

AI helps doctors by analyzing patient history, laboratory results, and imaging data to suggest and management OR/ICUiagnoses

Predictive Analytics in ICU & Surgery

AI predicts complications like sepsis, intraoperative hypotension, or post-surgical infections, allowing for early intervention

Automation in Anesthesia

AI-driven systems monitor depth of anesthesia, adjusting drug dosages to maintain optimal sedation while minimizing side effects

Natural Language Processing (NLP)

AI-powered chatbots assist patients by summarizing medical notes, explaining conditions in plain language, and supporting clinical workflows

Understanding Artificial Intelligence

Artificial intelligence (AI) is a broad field that encompasses technologies capable of performing tasks that traditionally required human intelligence. It includes reasoning, learning, decision-making, and perception.

AI is not meant to replace doctors but to augment their abilities

In medicine, AI is used for clinical decision support, medical imaging analysis and patient monitoring. AI systems range from simple rule-based algorithms to complex deep learning models that autonomously improve with experience

Le nuove tecnologie in OR

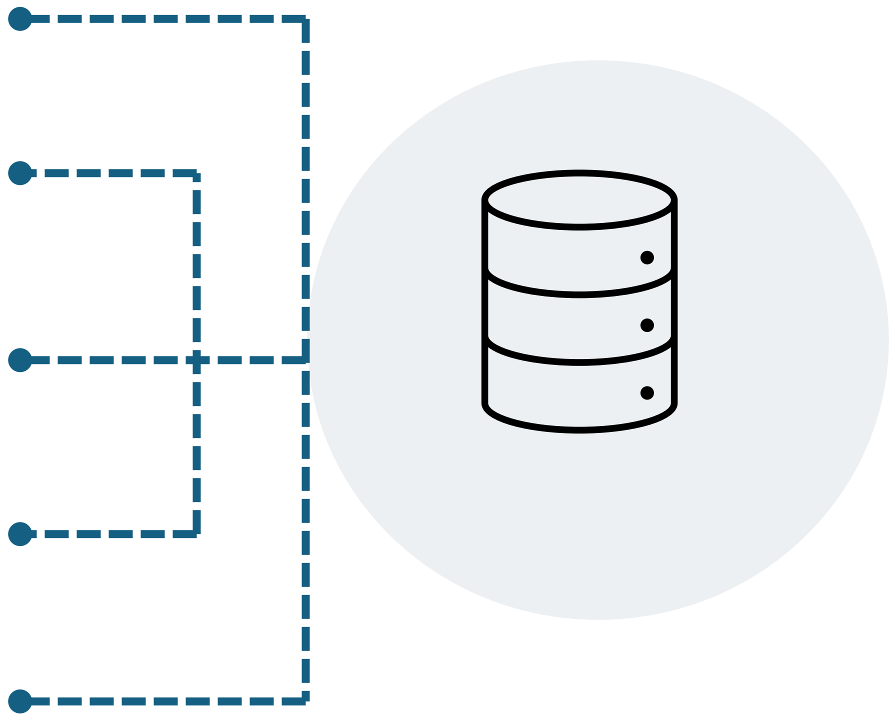
Intelligenza artificiale predittiva e generativa 1

Wearable device 2

Telemedicina 3

Metaverso 4

Robotica 5



Le nuove tecnologie in OR e Io(m)T

1. Intelligenza artificiale predittiva e generativa
2. Wearable device
3. Telemedicina
4. Metaverso
5. Robotica

Artificial Intelligence & NT

PARMAI
PERIOPERATIVE MEDICINE

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INTELLIGENZA ARTIFICIALE

La sala operatoria è un sistema straordinariamente **COMPLESSO**

I pazienti e le loro condizioni

Strumentazione sofisticata

Alto volume di infomazioni da processare

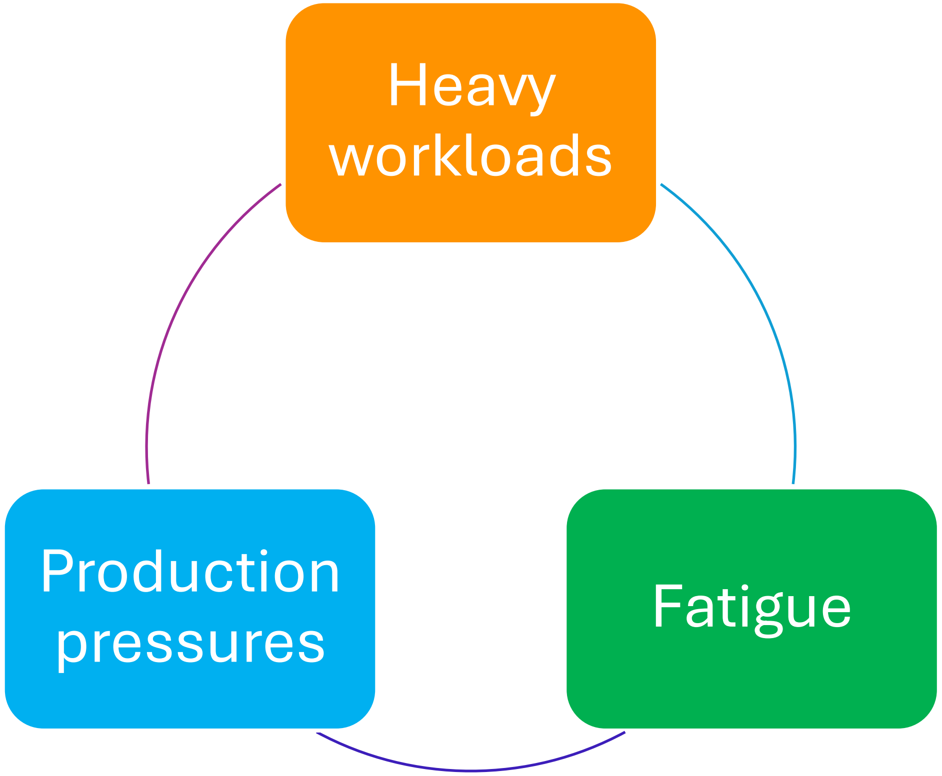
La natura della comunicazione e la coordinazione del team

Vincent et al. *Annals of Surgery*. 2024

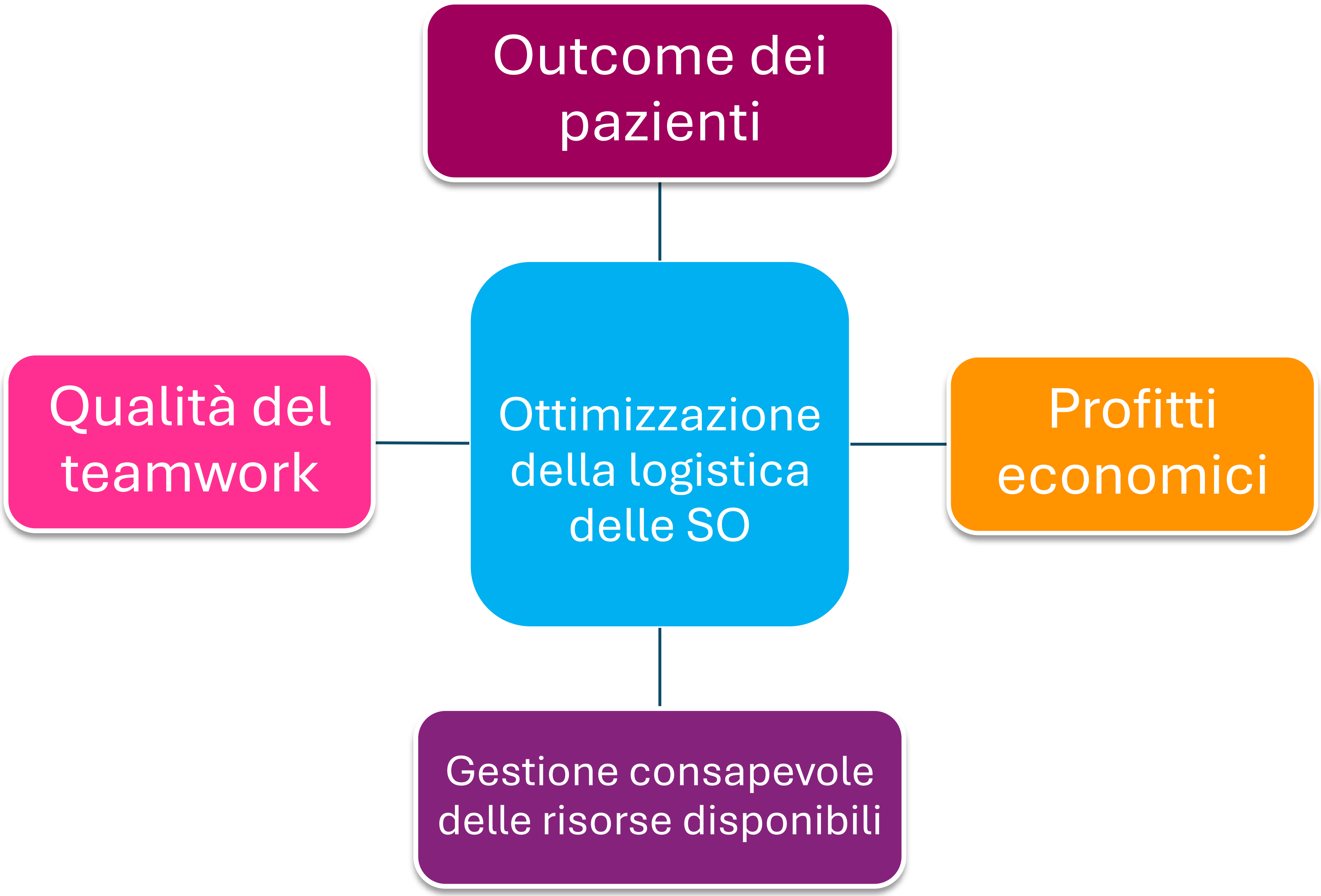
La sala operatoria è considerate un ambiente VULNERABILE

COMPLESSITÁ

+



Vincent et al. *Annals of Surgery*. 2024


Outcome dei pazienti
Qualità del teamwork
Ottimizzazione della logistica delle SO
Profitti economici
Gestione consapevole delle risorse disponibili

L'intelligenza artificiale sta trasformando la chirurgia moderna

L’innovazione è guidata principalmente da aziende private

Open Access Original Article

Transforming Surgery With Artificial Intelligence: An Early Analysis of Private Industry Trends

Yash B. Shah [1, 2], Akshay S. Krishnan [1], Zachary N. Goldberg [2], Varun Jayanti [1], Erika D. Harness [1], David B. Nash [2]

1. Sidney Kimmel Medical College, Thomas Jefferson University, Philadelphia, USA 2. College of Population Health, Thomas Jefferson University, Philadelphia, USA

Coinvolgimento dei chirurghi essenziale per:

- Allineare tecnologia e cura del paziente
- Ridurre disuguaglianze
- Rafforzare la regolamentazione e la sicurezza

Tipologie di prodotto principali

- Analisi immagini intraoperatorie
- Imaging diagnostico
- Robotica chirurgica autonoma

Chirurgia Data-Driven: Priorità di Ricerca per la Chirurgia Mini-Invasiva

Original Study

ANNALS OF SURGERY OPEN

OPEN

Consensus for Operating Room Multimodal Data Management: Identifying Research Priorities for Data-Driven Surgery

Alain Garcia Vazquez, MD,* Juan Verde, MD,* Ariosto Hernandez Lara, MD,* Didier Mutter, MD,†
Lee Swanstrom, MD*; 5G-OR Research Committee, 5G-OR Consensus Panel

Identificare le aree di ricerca prioritarie per migliorare la gestione dei dati in sala operatoria (OR) nella chirurgia minimamente invasiva.

Le sale operatorie moderne sono ambienti ricchi di dati
Uso intelligente in tempo reale dei dati
Strategie per una gestione integrata e standardizzata

- Digitalizzazione delle attività in sala operatoria
- Miglioramento dello streaming dati e tecnologie avanzate
- Protocolli uniformi per dati multimodali
- Integrazione dell’AI per efficienza e sicurezza

Quali sono gli elementi che influenzano il turnover in sala operatoria?

- Approccio anestesiologico
- Comunicazione efficace
- Staff
- **<u>Pianificazione (come?...IA?)</u>**
- Standardizzazione

What affects operating room turnover time? A systematic review and mapping of the evidence

Lani MacMillan[a], Grace M. Madura, BA[a], Melana Elliot[a], Daniel M. Frendl, MD[b], Irving A. Jorge, MD, MBA[a], Zhi Ven Fong, MD, DrPh[a,c], Christopher Hasse, PhD[b,d], David A. Etzioni, MD, MSHS[a,c,*]

Surgery 181 (2025) 109263

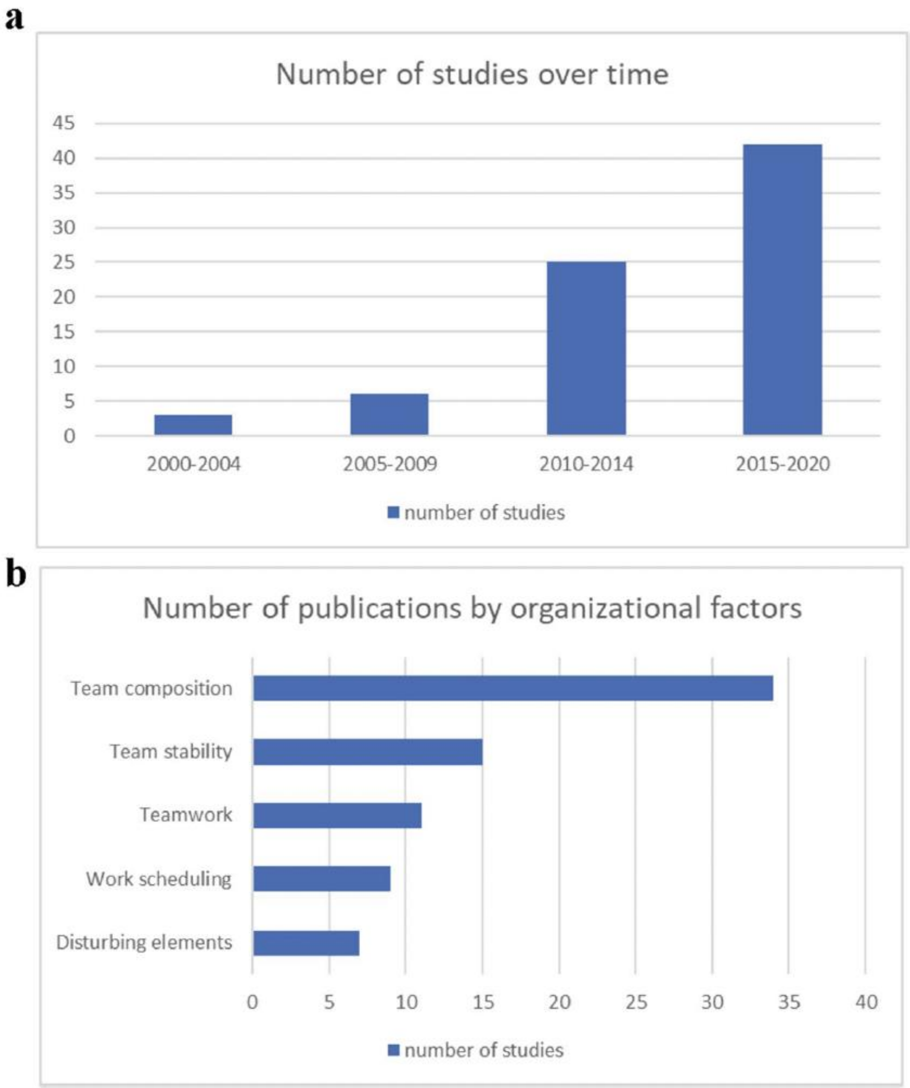
Pasquer *et al. Patient Safety in Surgery* (2024) 18:5
https://doi.org/10.1186/s13037-023-00388-3

Patient Safety in Surgery

REVIEW Open Access

Operating room organization and surgical performance: a systematic review

Arnaud Pasquer[1,2,5*], Simon Ducarroz[1], Jean Christophe Lifante[1,3,5,6], Sarah Skinner[1,3], Gilles Poncet[2,4,5] and Antoine Duclos[1,3,5]



Nonostante la quantità limitata di studi e la loro eterogeneità, i **fattori organizzativi** sembrano svolgere un ruolo significativo negli esiti chirurgici.

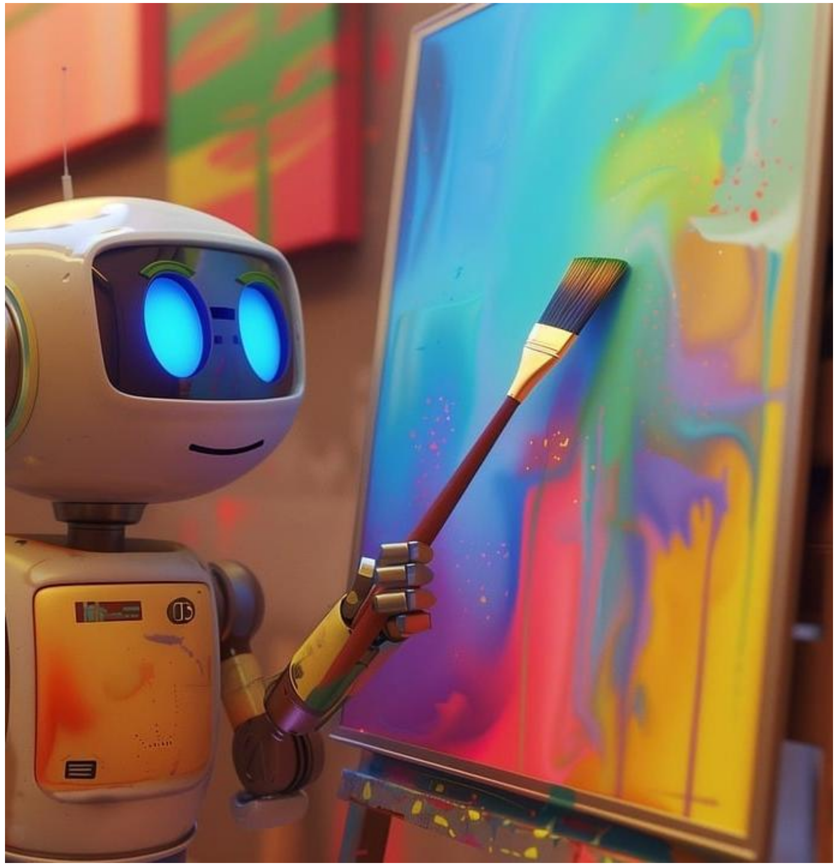
Pasquer et al. *Patient Safety*. 2024

Blocco operatorio....

- Attività chirurgica: elezione o urgenza/emergenza

- Sale operatorie
- Recovery room/PACU (monitoraggio o sala di «lavoro»)

- Dimissione: reparto/ICU



…e come il ML può impattare l'attività di sala operatoria?

- Rilevamento e riduzione delle cancellazioni dei casi chirurgici
- Ottimizzazione dell’allocazione di risorse
- Previsione della durata degli interventi
- Aumentare l’efficienza
- Semplificare il coordinamento del flusso di lavoro riducendo le inefficienze operative

Cureus
Part of SPRINGER NATURE

The Role of Machine Learning in Management of Operating Room: A Systematic Review

Alaa Merghani Abdelrazig Merghani [1], Abdullah Khaled Ahmed Esmail [2, 3], Ahmed Mohamed Elamin Mubarak Osman [4], Nihal Ahmed Abdelfrag Mohamed [5], Safwa Mustafa Mohamed Ali Shentour [1], Shaima Merghani Abdelrazig Merghani [6]

1. General Medicine, National Ribat University, Khartoum, SDN 2. Surgery, Dubai Academic Health Corporation, Dubai, ARE 3. Clinical Sciences, Sulaiman Alrajhi University, Albukairiah, SAU 4. General Medicine, Jouf University Medical Services Center, Sakaka, SAU 5. Obstetrics and Gynecology, Armed Forces Hospital, Ministry of Defense Health Services, Wadi AlDawsir, SAU 6. Emergency Medicine, National Ribat University, Khartoum, SDN

Journal of Medical Systems (2020) 44: 20
https://doi.org/10.1007/s10916-019-1512-1

2019

SYSTEMS-LEVEL QUALITY IMPROVEMENT

Check for updates

Artificial Intelligence: A New Tool in Operating Room Management. Role of Machine Learning Models in Operating Room Optimization

Valentina Bellini[1] · Marco Guzzon[2] · Barbara Bigliardi[2] · Monica Mordonini[2] · Serena Filippelli[2] · Elena Bignami[1]

Received: 5 July 2019 / Accepted: 26 November 2019 / Published online: 10 December 2019

2023

Journal of Medical Systems (2024) 48:19
https://doi.org/10.1007/s10916-024-02038-2

REVIEW

Check for updates

Artificial Intelligence in Operating Room Management

Valentina Bellini[1] · Michele Russo[1] · Tania Domenichetti[1] · Matteo Panizzi[1] · Simone Allai[1] · Elena Giovanna Bignami[1]

Received: 29 November 2023 / Accepted: 5 February 2024

INTELLIGENZA ARTIFICIALE

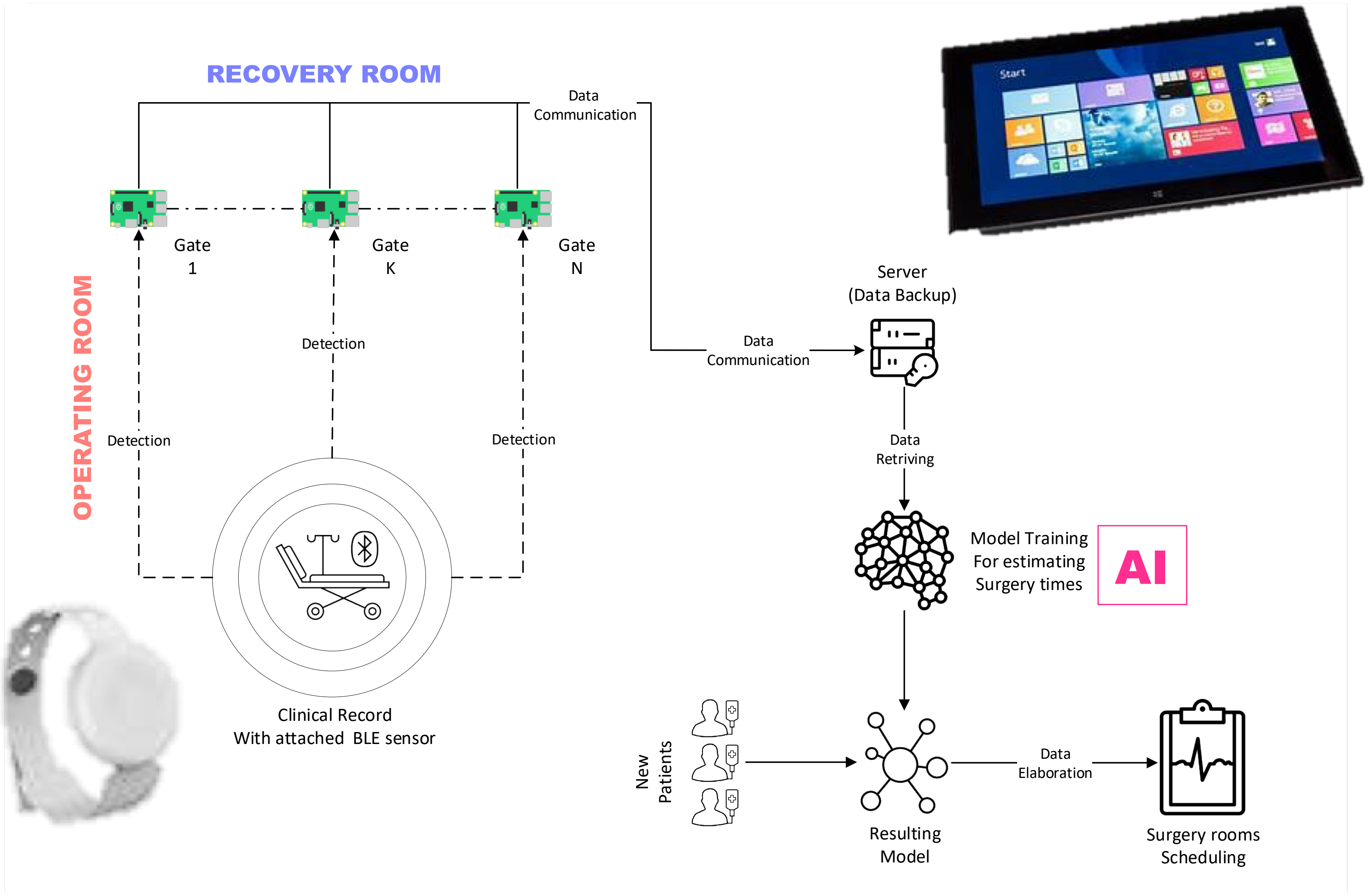
I risultati mostrano come l'AI può essere impiegata con successo per tre differenti scopi:

- Predizione durata chirurgica
- PACU LOS
- Rischio cancellazione interventi

Bellini, Bignami et al. *Journal of Medical Systems*. 2024

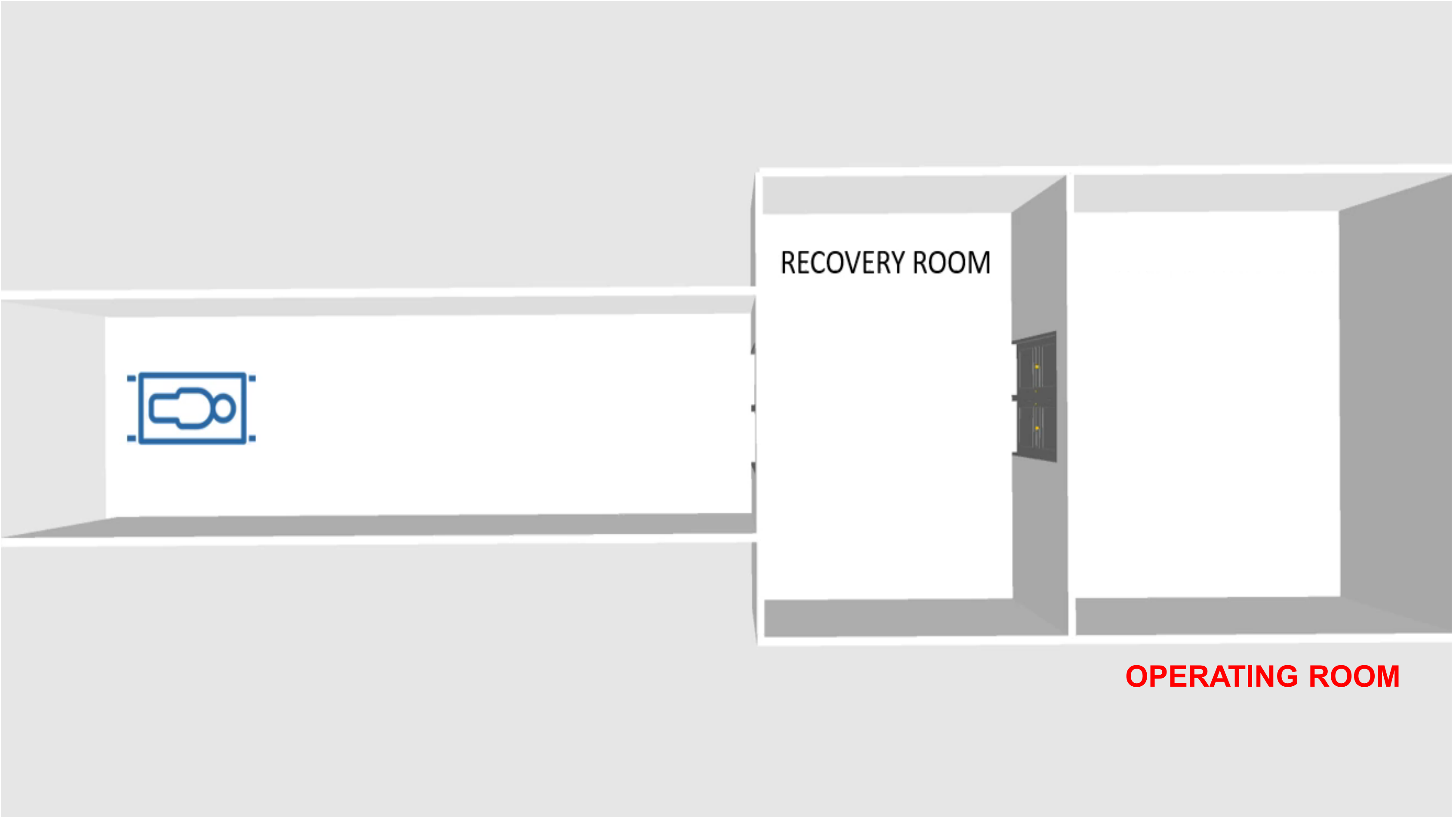
Studio BLOC-OP

(bluetooh tracking indoor system)

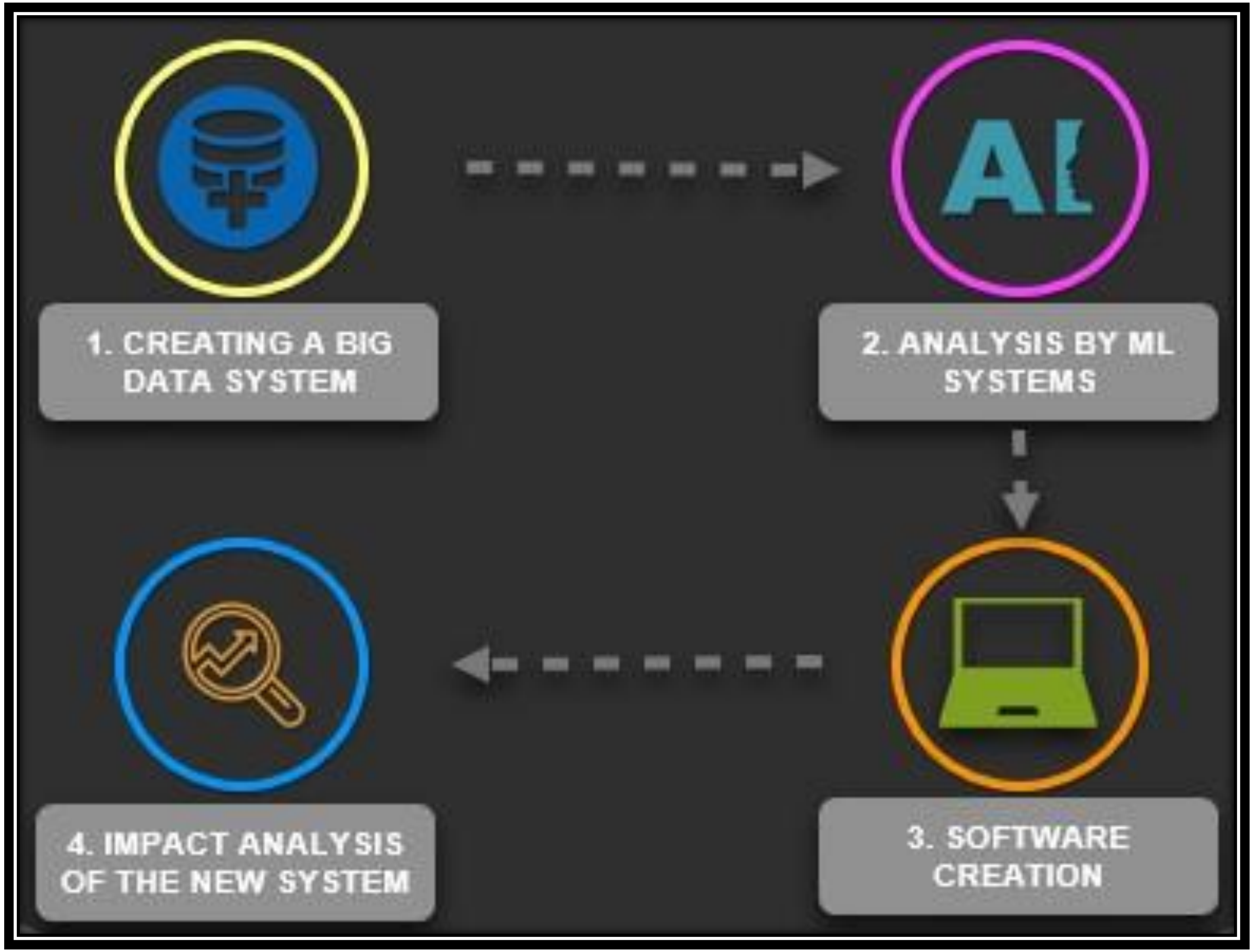


JMIR 2023 Jul 5:12:e45477

I punti in cui viene registrato il passaggio del paziente:
ENTRATA in RR e OR, USCITA dalla OR, poi USCITA dalla RR
dopo l’intervento chirurgico e monitoraggio



BLOC-OP STUDY: scheduling and monitoring ®



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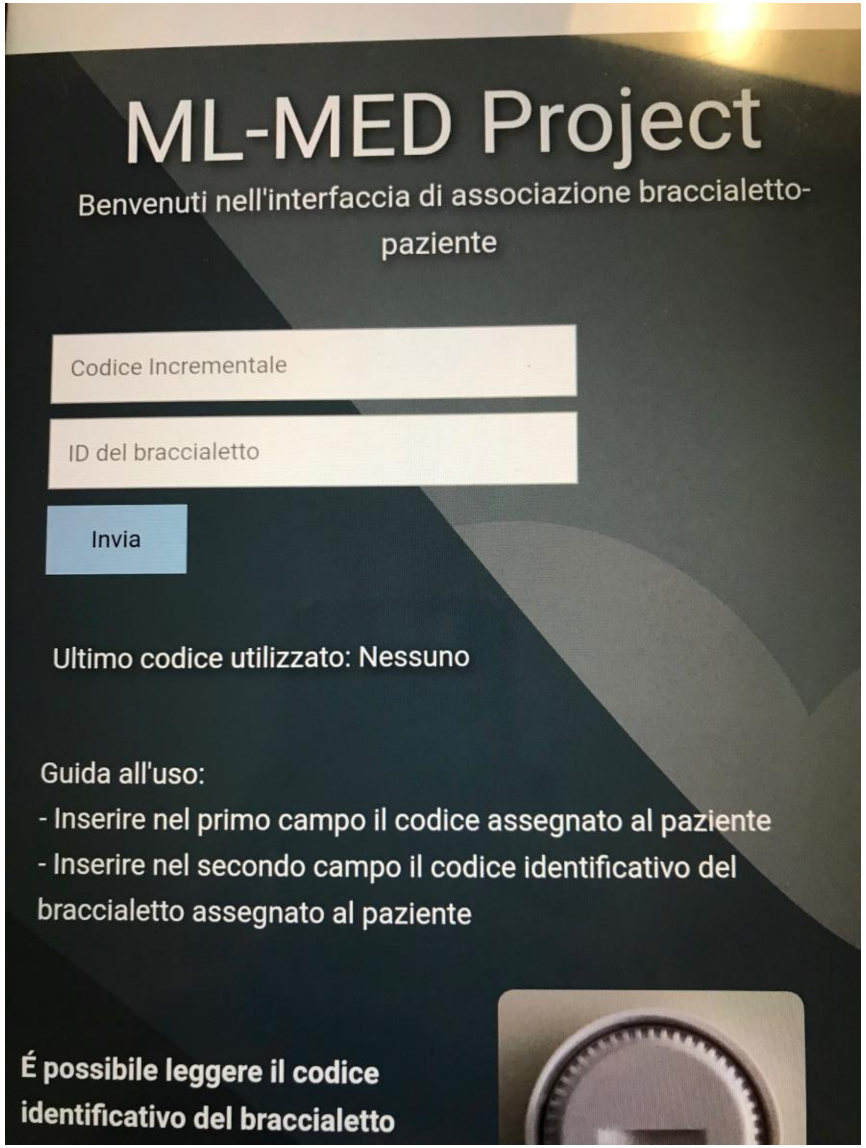
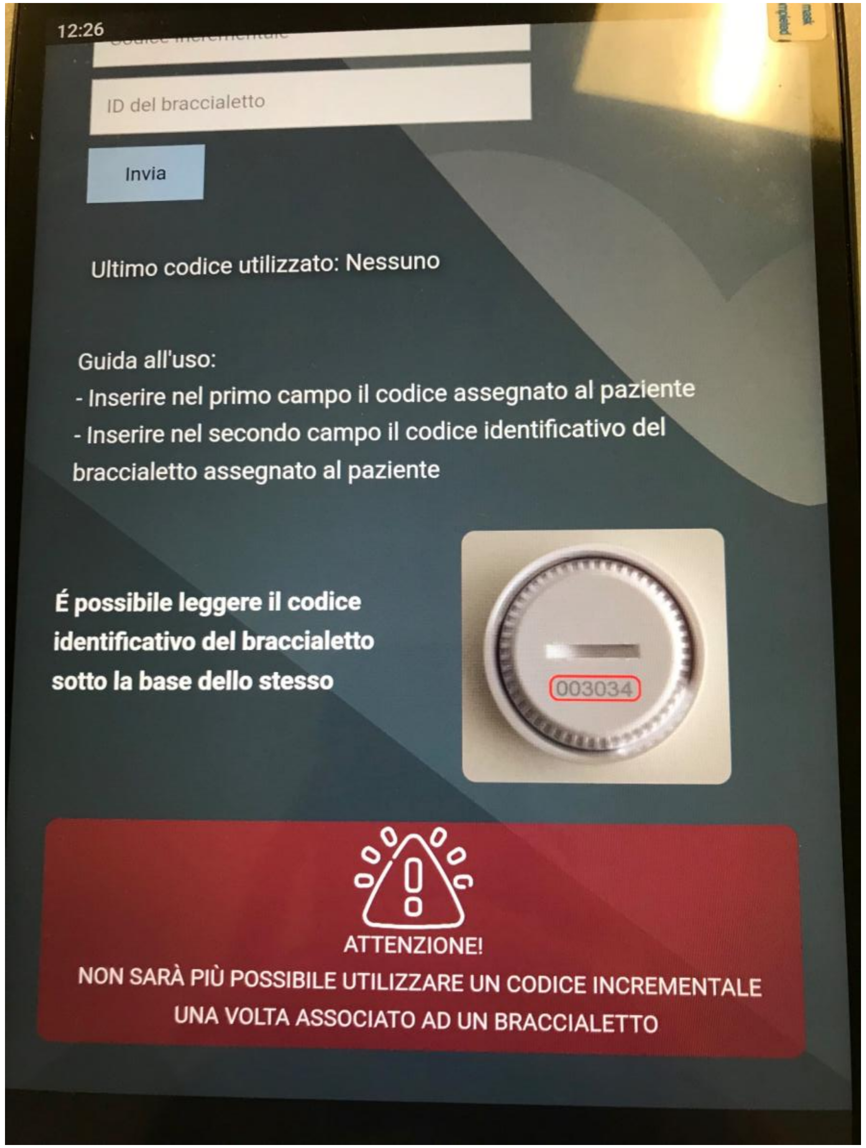
PERIOPERATIVE MEDICINE

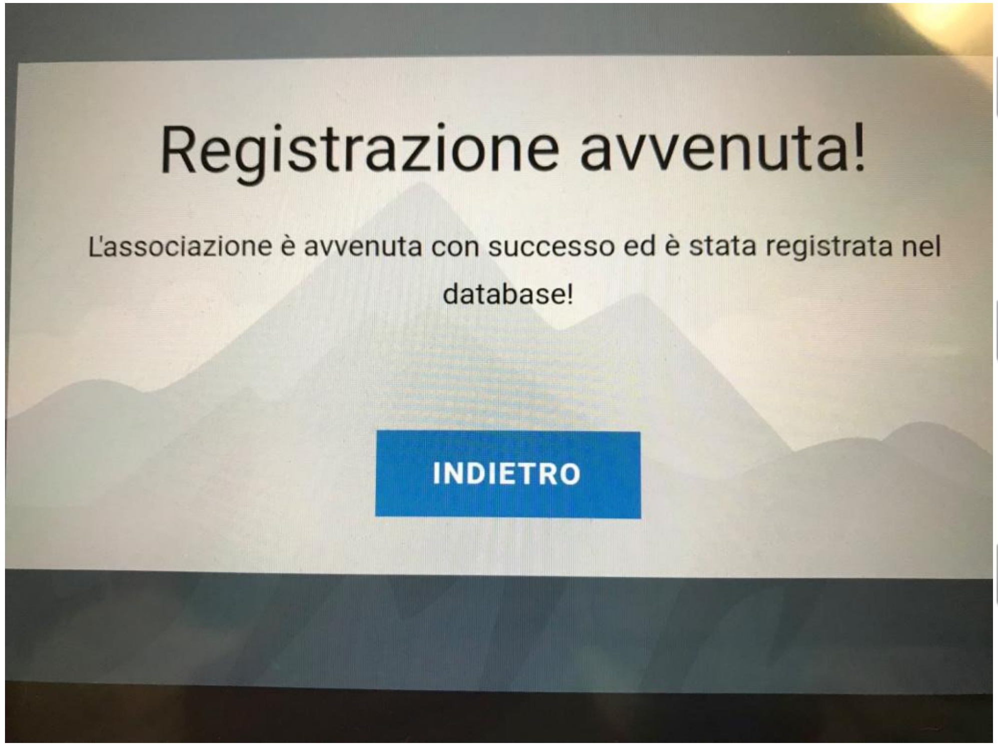
FASE OPERATIVA

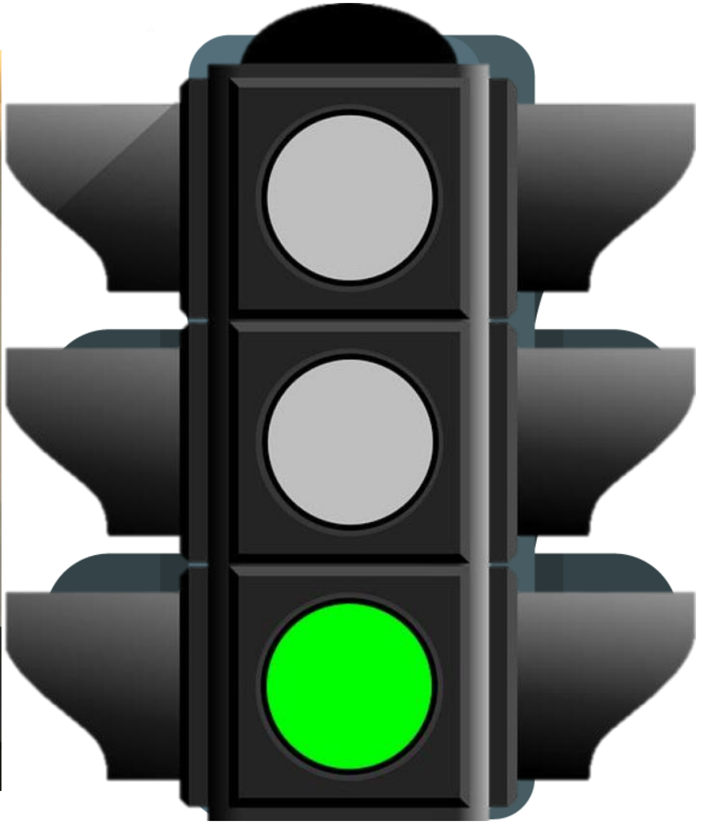
FASE OPERATIVA

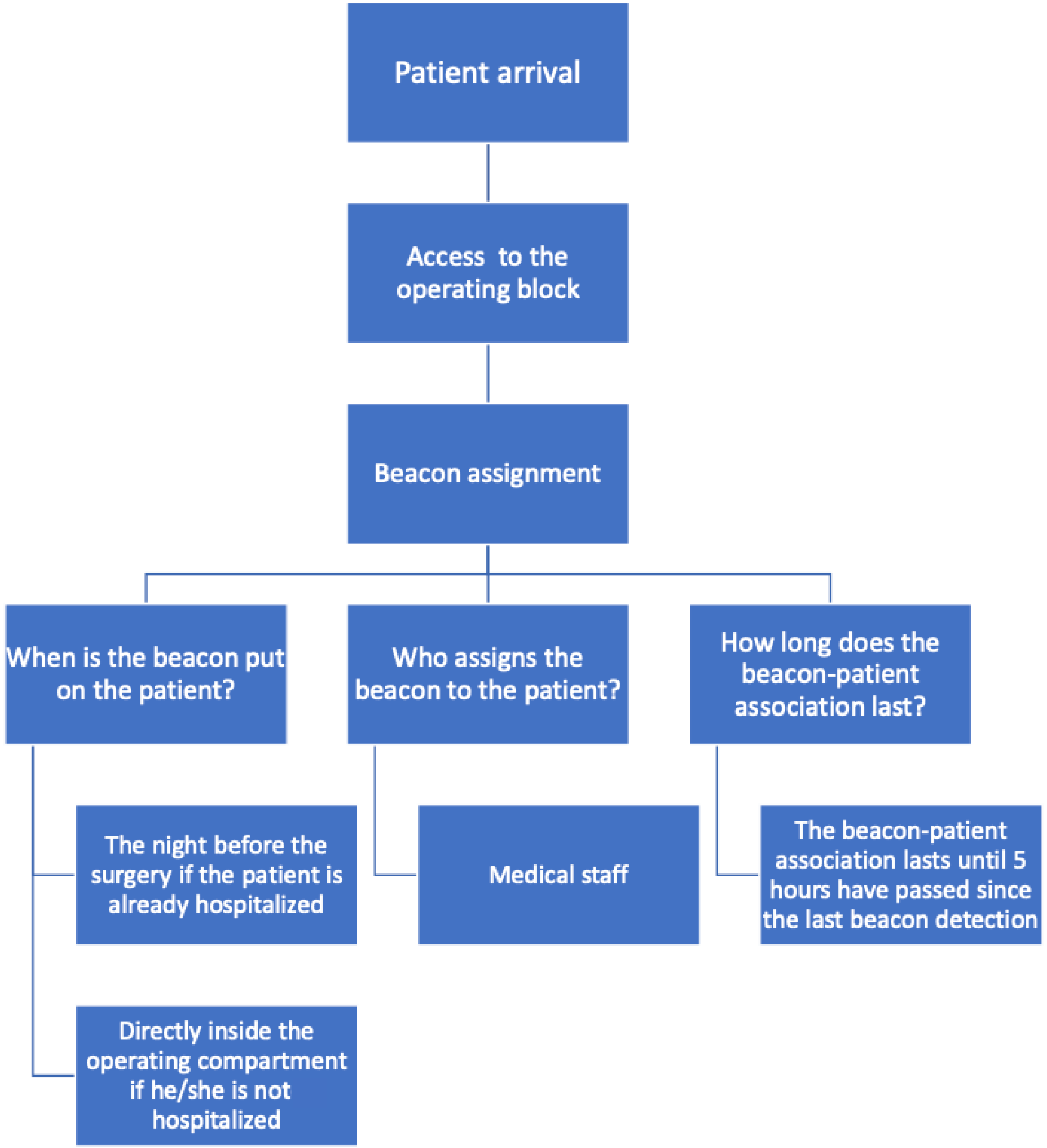




FASE OPERATIVA






Patient arrival
Access to the operating block
Beacon assignment
When is the beacon put on the patient?
Who assigns the beacon to the patient?
How long does the beacon-patient association last?
The night before the surgery if the patient is already hospitalized
Medical staff
The beacon-patient association lasts until 5 hours have passed since the last beacon detection
Directly inside the operating compartment if he/she is not hospitalized

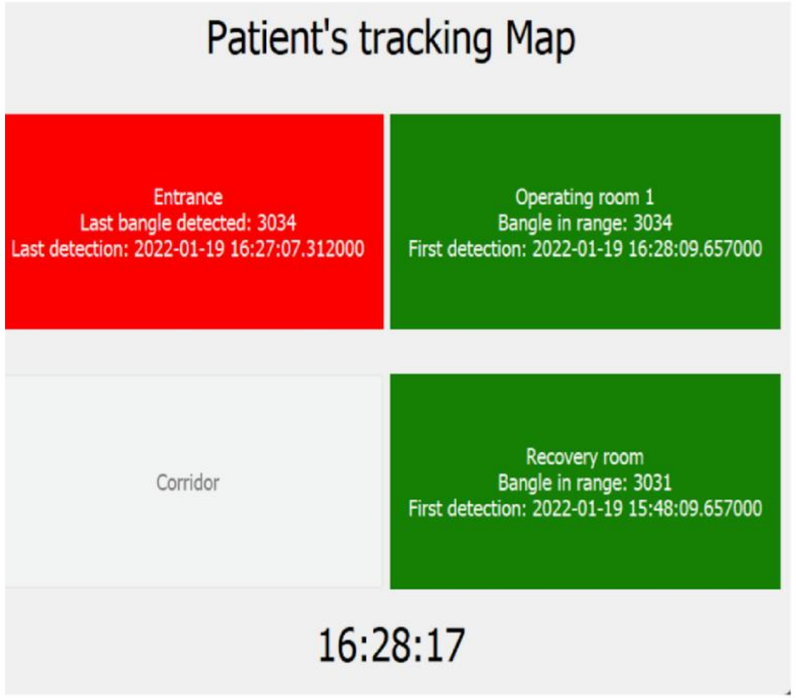

Patient's tracking Map
Entrance
Last bangle detected: 3034
Last detection: 2022-01-19 16:27:07.312000
Operating room 1
Bangle in range: 3034
First detection: 2022-01-19 16:28:09.657000
Corridor
Recovery room
Bangle in range: 3031
First detection: 2022-01-19 15:48:09.657000
16:28:17

Figure1:

Fig. 1A: Surgical block staying. In blue time (min) recorded by the watch (min). In green time (min) recorded on OrmaWeb. In orange the difference (min) between the two records.

The mean difference between the two records is 19.3 minutes with a mean % difference of 6.9%.

Fig. 1B: Operating room staying. In blue time (min) recorded by the watch (min). In green time (min) recorded on OrmaWeb. In orange the difference (min) between the two records.

The mean difference between the two records is 17.1 minutes with a mean % difference of 11.1%.

Fig. 1C: Recovery room staying. In blue time (min) recorded by the watch (min). In green time (min) recorded on OrmaWeb. In orange the difference (min) between the two records.

The mean difference between the two records is 24.5 minutes with a mean % difference of 27.8%.

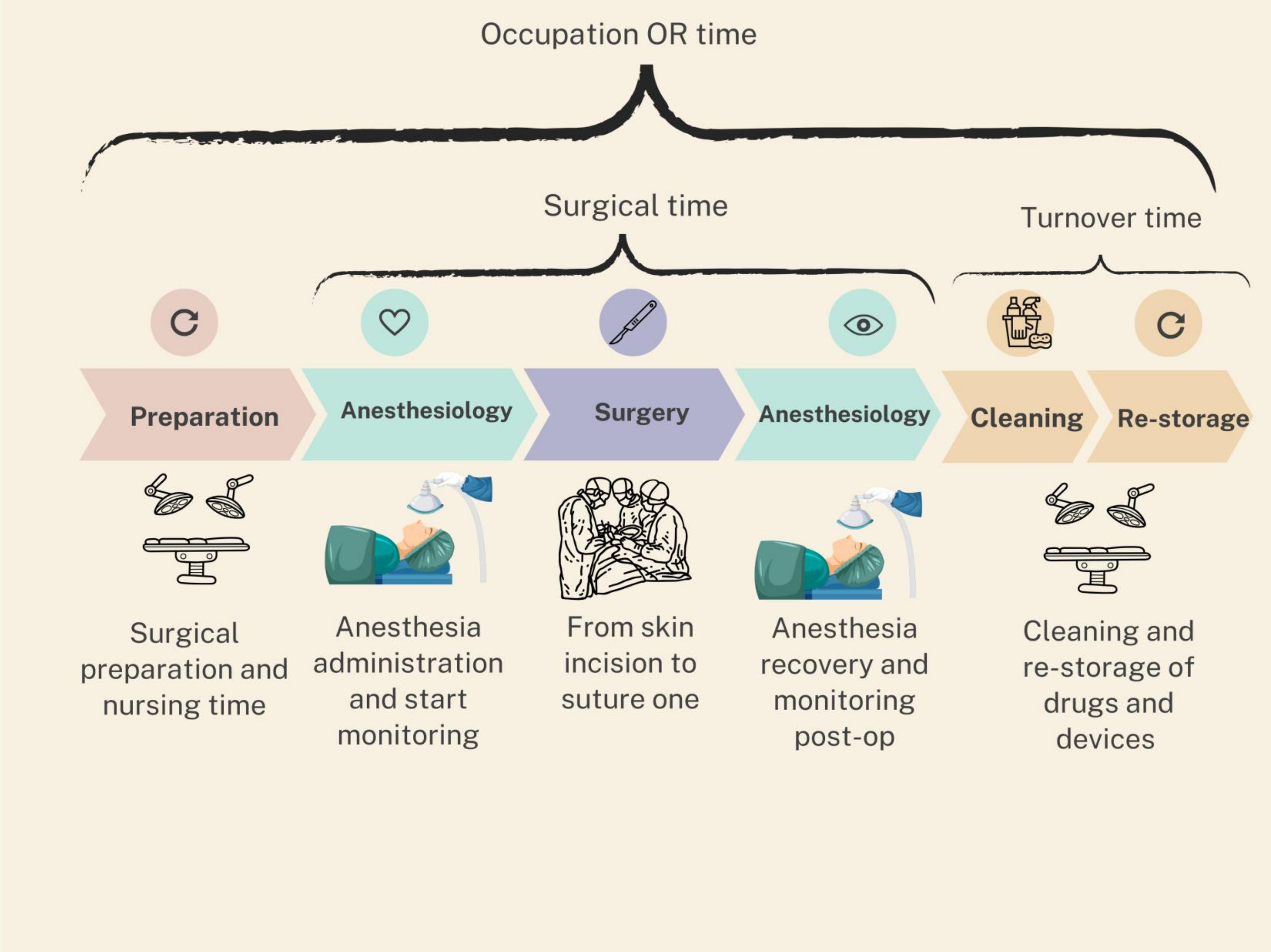
Risultati delle prime analisi

LA DIFFERENZA TRA IL TEMPO STIMATO DI OCCUPAZIONE DI SO E IL TEMPO EFFETTIVO MISURATO TRAMITE L'IoT APPARE VARIARE SECONDO ALCUNE VARIABILI:

- **Numero di comorbidità ($p < 0.01$)**
- **L'età del paziente ($p = 0.03$)**
- **BMI ($p < 0.01$)**

Innovative Technologies for Smarter and Efficient Operating Room Scheduling

Valentina Bellini[1] · Tania Domenichetti[1] · Elena Giovanna Bignami[1]



ORIGINAL ARTICLE

MAYO CLINIC

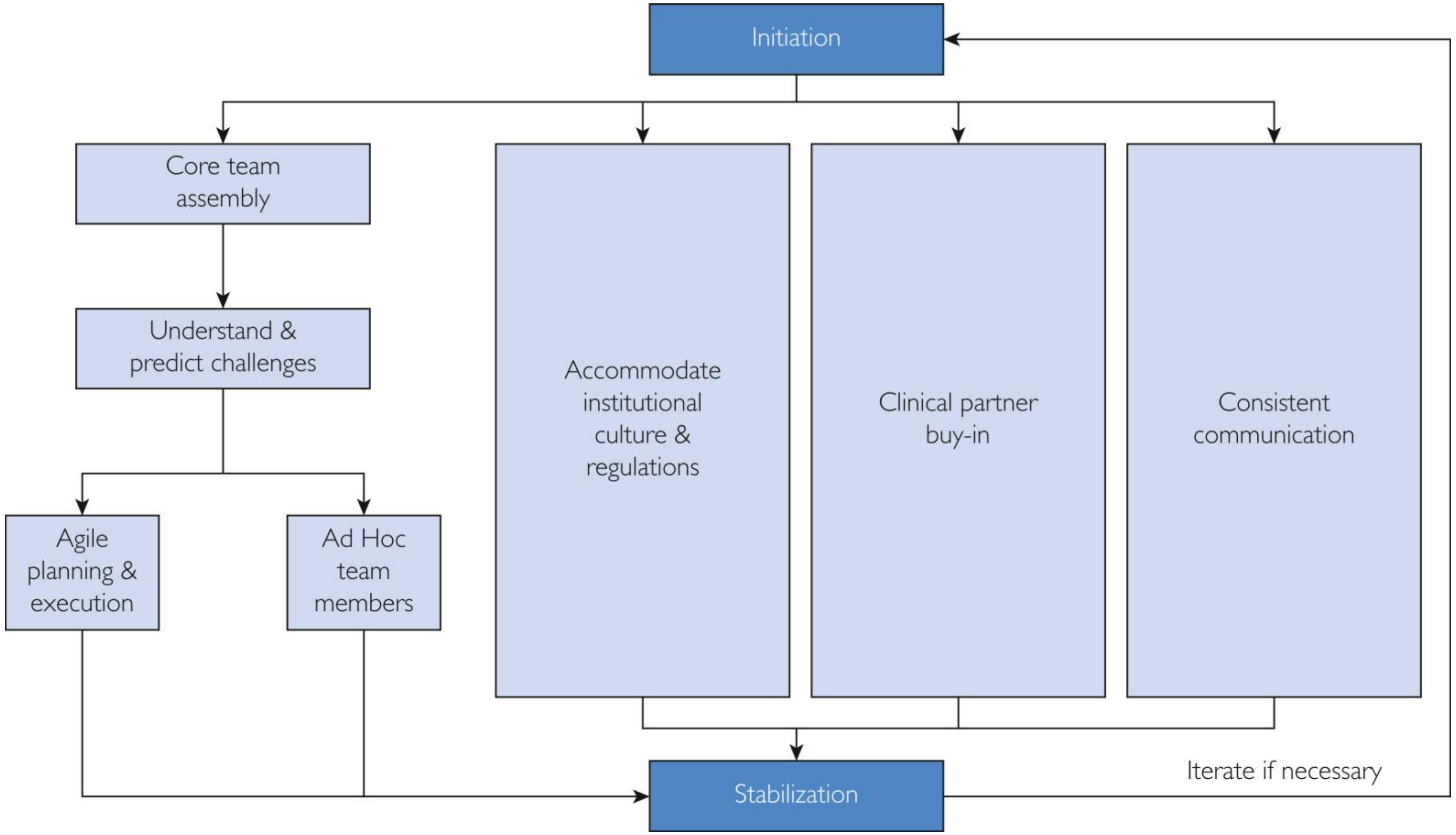
Creating a Practical Transformational Change Management Model for Novel Artificial Intelligence—Enabled Technology Implementation in the Operating Room

Tianqi G. Smith, PhD; Hamid Norasi, PhD; Kelly M. Herbst, BEd; Michael L. Kendrick, MD; Timothy B. Curry, MD, PhD; Teodor P. Grantcharov, MD, PhD; Vanessa N. Palter, MD, PhD; M. Susan Hallbeck, PhD; and Sean P. Cleary, MD

Gestione del Cambiamento per l’Implementazione di Tecnologie Innovative in Sala Operatoria

- Identificare strategie efficaci di Change Management (CM) per l’introduzione di tecnologie innovative (es. AI) in sala operatoria
- Creare un nuovo modello CM personalizzabile per progetti futuri

Nuovo modello CM creato e personalizzabile per esigenze specifiche di istituti e progetti



Mayo Clin Proc Inn Qual Out n December 2022;6(6):584-596 n https://doi.org/10.1016/j.mayocpiqo.2022.09.004

Journal of Medical Systems (2025) 49:8
https://doi.org/10.1007/s10916-025-02141-y

RESEARCH

Development of Predictive Model of Surgical Case Durations Using Machine Learning Approach

Jung-Bin Park[1] · Gyun-Ho Roh[2] · Kwangsoo Kim[3,4] · Hee-Soo Kim[1]

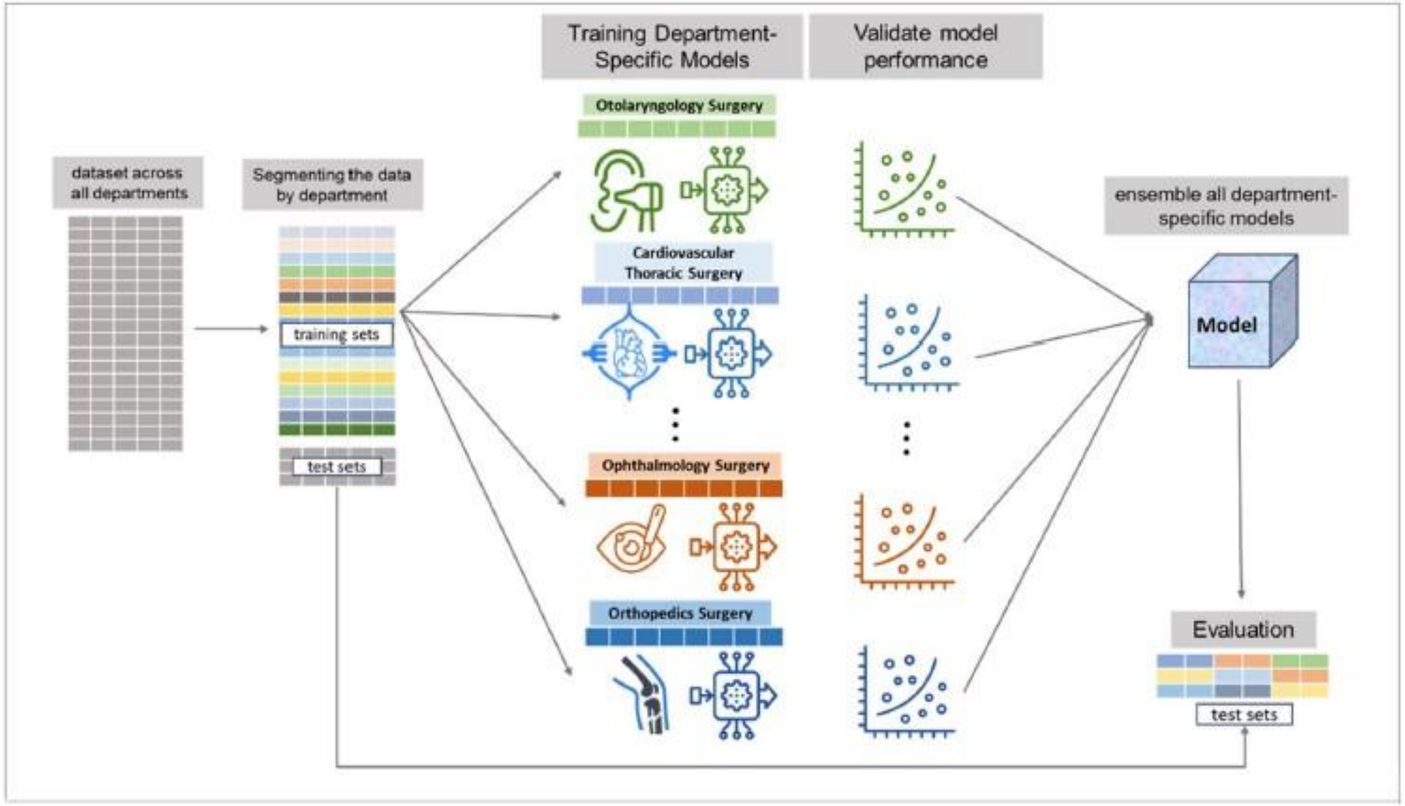


Fig. 2 Department-Specific Modeling Approach

Modelli ML personalizzati per reparto migliorano la precisione nella pianificazione chirurgica e aumentano l'efficienza operativa

Strategia chiave: **modelli su misura per i dati e le esigenze di ciascun reparto.**

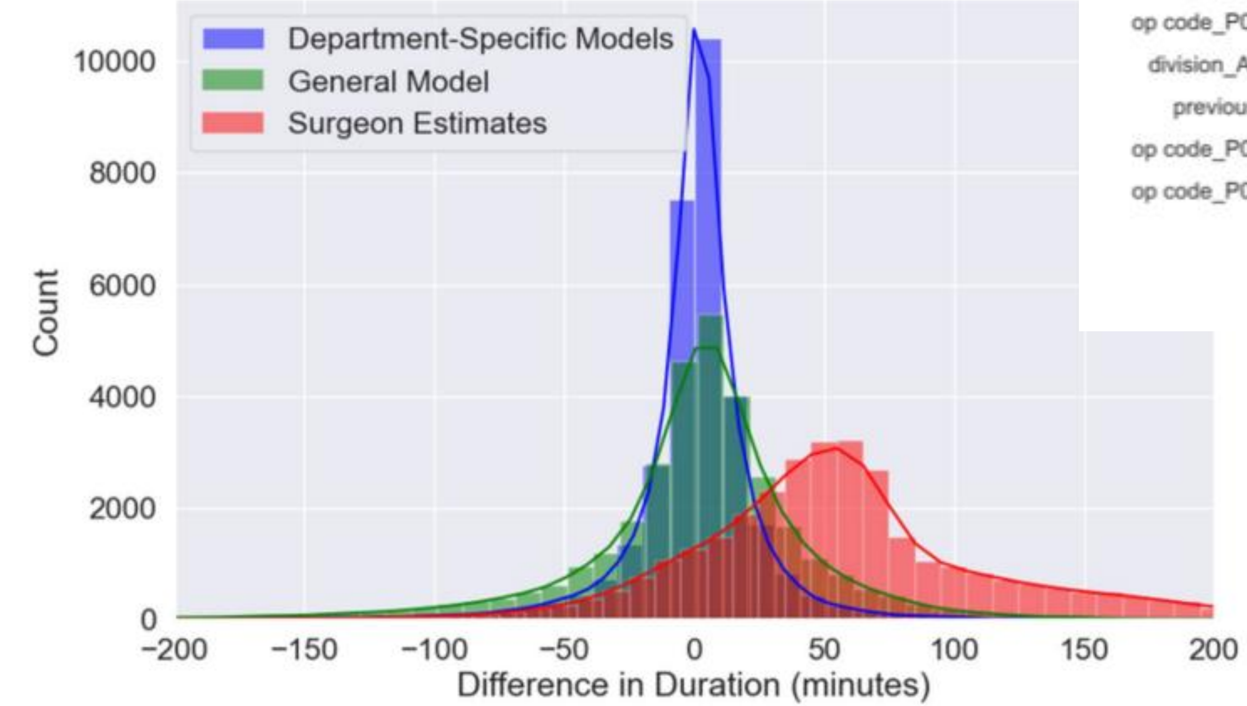
Migliorare la previsione della durata degli interventi chirurgici per ottimizzare la gestione delle sale operatorie

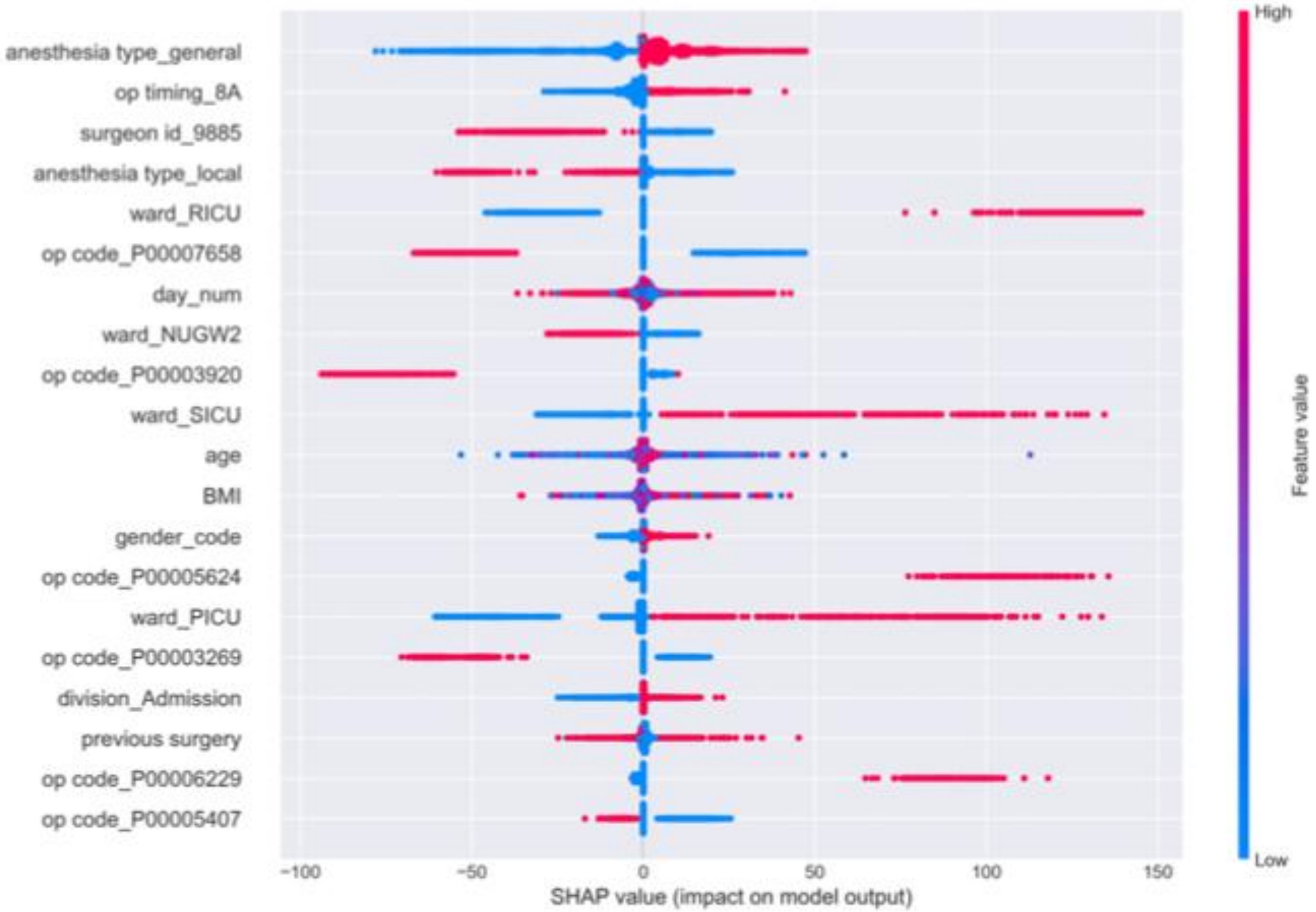
Journal of Medical Systems (2025) 49:8
https://doi.org/10.1007/s10916-025-02141-y

RESEARCH

Development of Predictive Model of Surgical Case Durations Using Machine Learning Approach

Jung-Bin Park[1] · Gyun-Ho Roh[2] · Kwangsoo Kim[3,4] · Hee-Soo Kim[1]





- Tempi anestesiologici e infermieristici: FISSI, attribuiti e non misurati
- Ripristino OR: NON contemplato

Natural Language Processing (NLP)- and Machine Learning (ML)-Enabled Operating Room Optimization: A Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Systematic Review Anchored in Project Planning Theory

1° gennaio 2020 e il 15 marzo 2025

Balaiah Chamarthi [1], Omkar Reddy Polu [2], Sathish Krishna Anumula [3], Azhar Ushmani [4], Pratik Kasralikar [5], Abdul Aleem Syed [6]

2025 Chamarthi et al. Cureus 17(4): e82796. DOI 10.7759/cureus.82796

using ML models such as ensemble learning, neural networks, and regression-based algorithms. Several studies demonstrated that ML models significantly outperformed traditional scheduling and prediction approaches, while NLP, particularly ClinicalBERT, improved accuracy when analyzing unstructured clinical texts. Risk of bias assessment using the Prediction model Risk Of Bias ASsessment Tool (PROBAST) revealed that five studies were of low risk, eight moderate risk, and six high risk, primarily due to limitations in analysis and external validation. Overall, integrating NLP and ML with project planning principles presents

analysis and external validation. Overall, integrating NLP and ML with project planning principles presents
a promising approach to optimizing OR workflows, enhancing efficiency, reducing costs, and improving patient outcomes. However, broader clinical adoption will require cross-institutional validation, improved interpretability, and ethical artificial intelligence (AI) governance.

Natural Language Processing (NLP)- and Machine Learning (ML)-Enabled Operating Room Optimization: A Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Systematic Review Anchored in Project Planning Theory

Balaiah Chamarthi [1], Omkar Reddy Polu [2], Sathish Krishna Anumula [3], Azhar Ushmani [4], Pratik Kasralikar [5], Abdul Aleem Syed [6]

- Diciannove studi, osservazionali retrospettivi
- 1° gennaio 2020 e il 15 marzo 2025
- miglioramenti nella previsione della durata chirurgica, durata della degenza in unità di terapia post-anestesia (PACU) e nell'efficienza della programmazione delle sale operatorie

- modelli di ML hanno superato significativamente gli approcci tradizionali di programmazione e previsione,
- NLP ha migliorato l'accuratezza nell'analisi di testi clinici non strutturati.
- La valutazione del rischio di bias utilizzando il Prediction Model Risk Of Bias ASSessment Tool (PROBAST) ha rivelato che cinque studi erano a basso rischio, otto a rischio moderato e sei ad alto rischio, principalmente a causa di limitazioni nell'analisi e nella validazione esterna.

L'integrazione di PNL e ML con i principi di pianificazione progettuale rappresenta un approccio promettente per ottimizzare i flussi di lavoro in sala operatoria, migliorare l'efficienza, ridurre i costi e migliorare i risultati per i pazienti

2025 Chamarthi et al. Cureus 17(4): e82796. DOI 10.7759/cureus.82796

AI &NT in OR…

…IMPLEMENTAZIONE CLINICA

- ✓ I dati impiegati devono essere di qualità elevata processati molto velocemente
- ✓ Sono necessari un maggior numero di studi di validazione esterna
- ✓ Gli output dovrebbero essere disponibili in sala operatoria o al letto del paziente e si devono integrare con i sistemi informativi locali
- ✓ Impiegare tecniche di explanable AI, qualora possibile, per rendere gli output maggiormente comprensibili

Digital twin

Available online at www.sciencedirect.com
ScienceDirect
Procedia Computer Science 246 (2024) 4732–4740
Procedia Computer Science
www.elsevier.com/locate/procedia

28th International Conference on Knowledge-Based and Intelligent Information & Engineering Systems (KES 2024)

Towards Digital Twins in Healthcare: Optimizing Operating Room and Recovery Room Dynamics

Mattia Pellegrino[a,*], Gianfranco Lombardo[a], Agostino Poggi[a]
[a]Department of Engineering and Architecture, Parco Area delle Scienze 181/A, Parma 43125, Italy

Multi-agent system

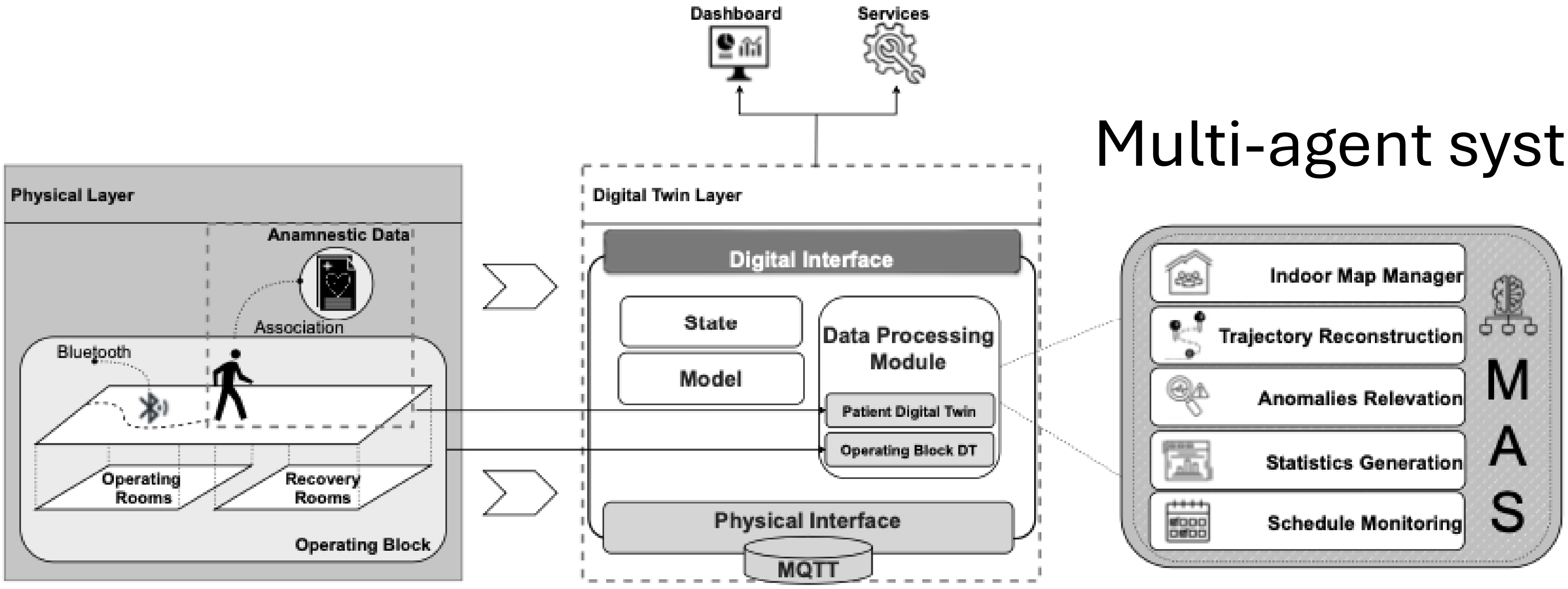


Fig. 1. A graphical illustration of our Digital Twin architecture shows real-world data integration to improve operational efficiency and patient care in operating and recovery rooms.

REALE

VIRTUALE

REALE

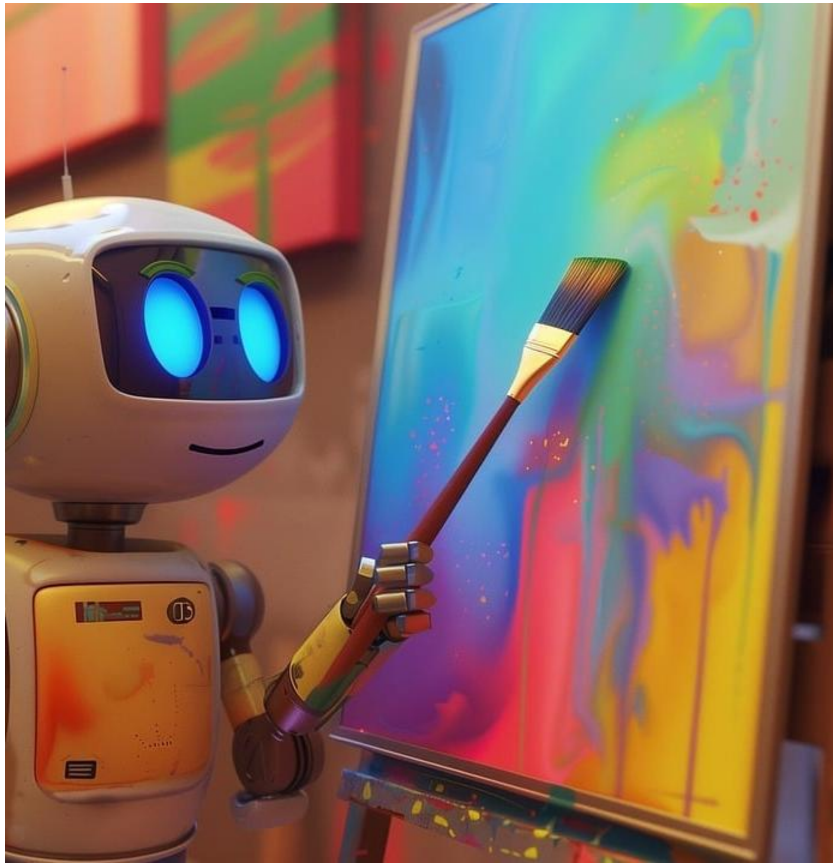
VIRTUALE

Blocco operatorio....

- Attività chirurgica: elezione o urgenza/emergenza

- Sale operatorie
- Recovery room/PACU (monitoraggio o sala di «lavoro»)

- Dimissione: reparto/ICU



Using AI to Predict Patients' Length of Stay: PACU Staff's Needs and Expectations for Developing and Implementing an AI System

Sara Lundsten,[1] **Maritha Jacobsson**,[2] **Patrik Rydén**,[3] **Lars Mattsson**,[3,4] **and Lenita Lindgren**[1]

Journal of Nursing Management
Volume 2024, Article ID 3189531, 13 pages
https://doi.org/10.1155/jonm/3189531

Table 2: Themes and comparison of benefits and drawbacks of manual planning versus the proposed ML system.

Themes	Manual planning		ML system	
	Drawbacks	**Benefits**	**Potential drawbacks**	**Possible benefits**
Controlling PACU throughput	Poor visibility Vulnerability	Better than no planning at all	Possible system miscalculation Not being in control	Enhanced trustworthiness and safety Robust planning Accessibility Lucidity
Prioritizing the patient	Risk of bed overcrowding		Patient confidentiality breach	Patient-focused care Guidance on patients' care duration
Communication strategies	Time consuming	Encourages interpersonal communication	Digital overload	Effective digital information
Adapting new technology			Others have problems with new technology, Technological malfunctions	Management support Building team spirit, User friendly Previous experience eases the transition Tailored education

Using AI to Predict Patients' Length of Stay: PACU Staff's Needs and Expectations for Developing and Implementing an AI System

Sara Lundsten,[1] **Maritha Jacobsson**,[2] **Patrik Rydén**,[3] **Lars Mattsson**,[3,4] **and Lenita Lindgren**[1]

Journal of Nursing Management
Volume 2024, Article ID 3189531, 13 pages
https://doi.org/10.1155/jonm/3189531

In healthcare, many tasks are manually executed, requiring highly skilled staff and strong, supportive leadership for effective workflows. Introducing advanced technology, like an ML-enhanced planning system, promises significant benefits. Our research indicates that for the successful de-

be optimized through digital communication. Successful adaptation to new digital systems and workflows requires management support, the cultivation of team spirit, tailored education, and the implementation of a user-friendly system. These factors are crucial for empowering staff to manage their responsibilities effectively. Successful development and implementation of such an ML system necessitates collaboration with healthcare staff, focusing on their needs, desires, and expectations.

Predicting Care Times at PACU

Lars MATTSSON[a,1], Sara D. LUNDSTEN[b], Patrik RYDÉN[a], and Lenita LINDGREN[b]

predictions. The long-term goal is to develop ML-tools enable us to optimize staffing and resources so that throughput is maximized while care quality remains high.

The data used in this study include patient medical history, preoperative data, surgical times, registered complications, and monitoring data from PACU. The data

comprises more than 170 variables from 84,000 patients, gathered over a 7 year period at *Region Västerbotten*, in northern Sweden.

Early planning at PACU requires predicting both care times and arrival times. One of the challenges is that response data are partially censored [2].

For successful implementation the ML-tool needs to be trusted by clinicians. To ensure acceptance, an ongoing study contrasts clinicians predictions of PACU care times to model predictions and observed outcomes. Furthermore, explaining model predictions through local explanation methods [3] is another way to gain acceptance.

2025, *Intelligent Health Systems – From Technology to Data and Knowledge*

Predicting Care Times at PACU

Lars MATTSSON[a,1] , Sara D. LUNDSTEN[b], Patrik RYDÉN[a], and Lenita LINDGREN[b]

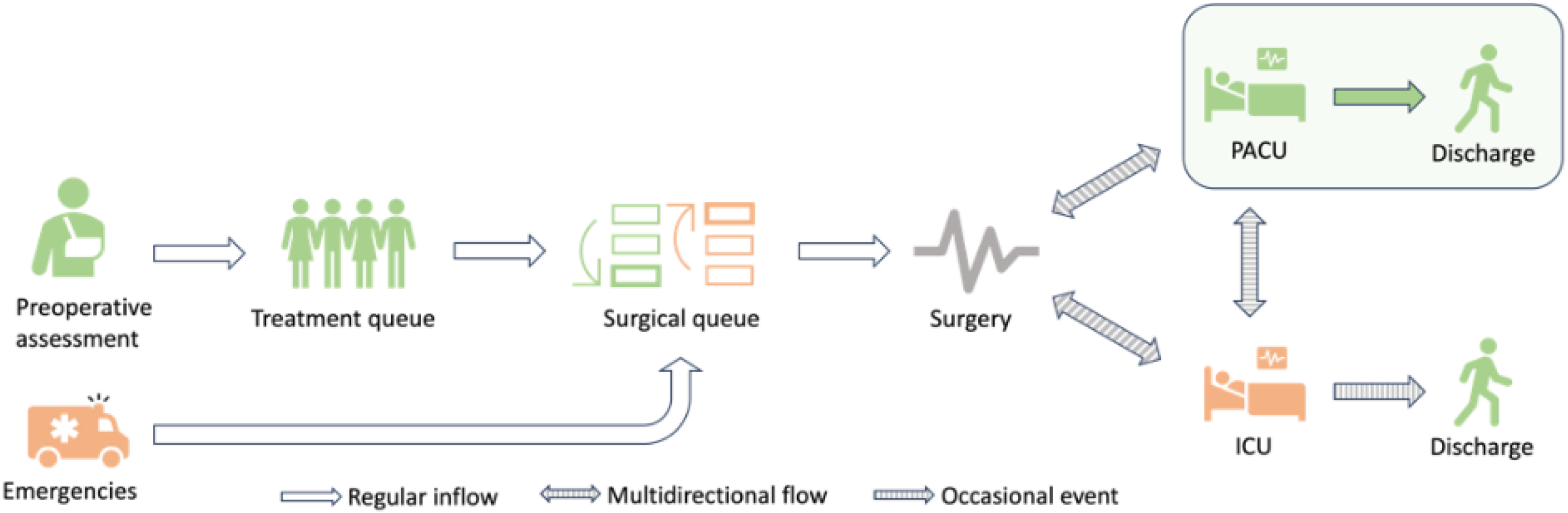
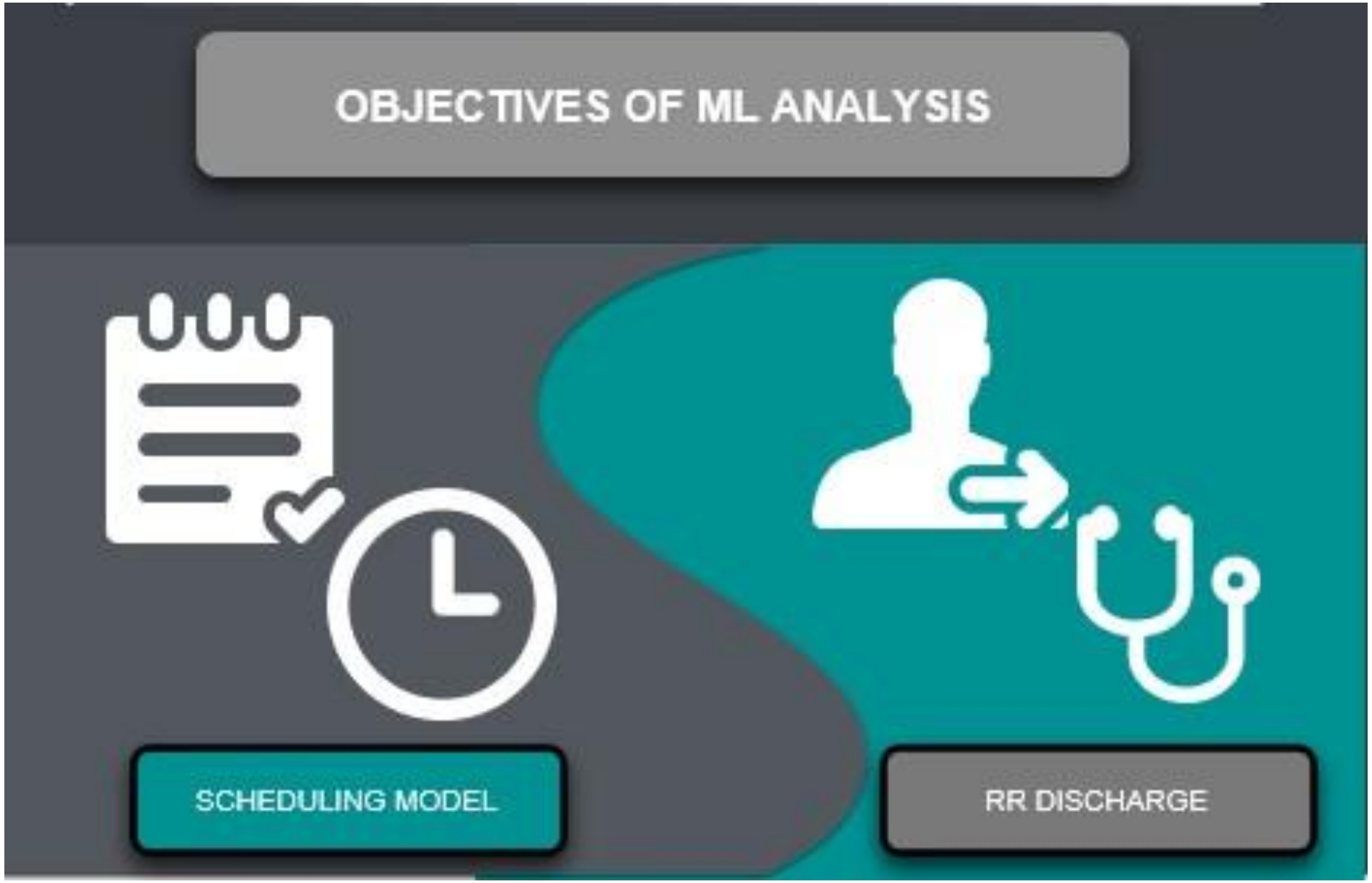


Figure 1. Interdepartmental flow of patients from preoperative assessment to the PACU.

Medical Data Recorder (MDR)®



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Medical Data Recorder (MDR)

- GCS, neurologico
- Frequenza respiratoria
- PA (MAP)
- FC
- SatO2
- Diuresi
- Sanguinamento
- PONV
- Dolore

- Tipologia di intervento

→ range di normalità e sicurezza

Ranges for alarm limits, per normal standards, used in the post anesthesia care unit from which data was acquired.

Biomedical signal	Range
SpO_2	90–100%
Systolic blood pressure	90–185 mmHg
Heart rate	45-120 beats per minute
Respiratory rate	8-30 breaths per minute

PARMAI
PERIOPERATIVE MEDICINE

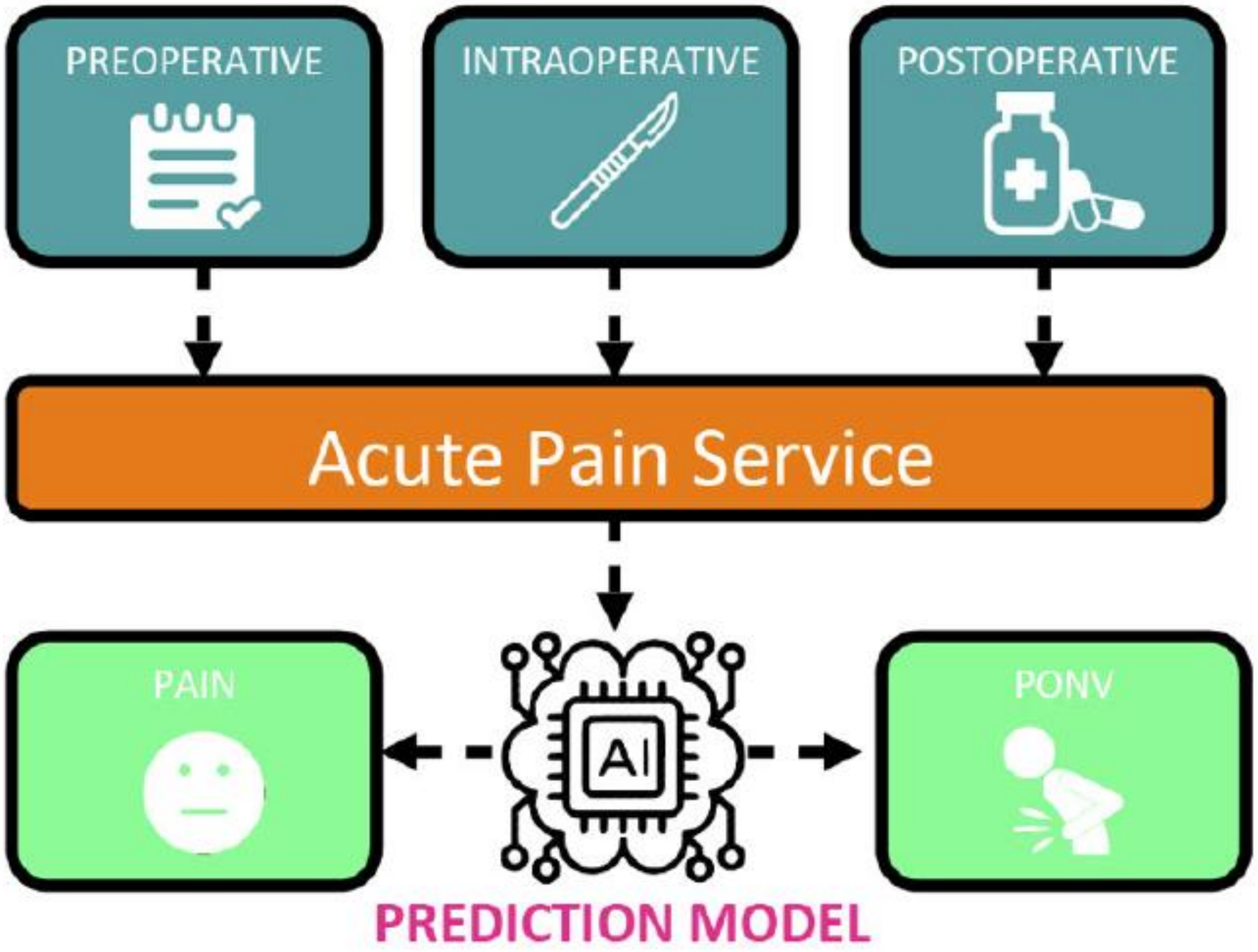
Computers in Biology and Medicine 101 (2018) 15–21

Artificial Intelligence for Perioperative Medicine: Perioperative Intelligence

Kamal Maheshwari, MD, MPH,* Jacek B. Cywinski, MD,*† Frank Papay, MD,‡
Ashish K. Khanna, MD, FCCP, FCCM, FASA,§|| and Piyush Mathur, MD, FCCM, FASA*

(Anesth Analg 2022;00:00–00)

AN INTELLIGENT MACHINE FOR THE ACUTE PAIN SERVICE (APS)®



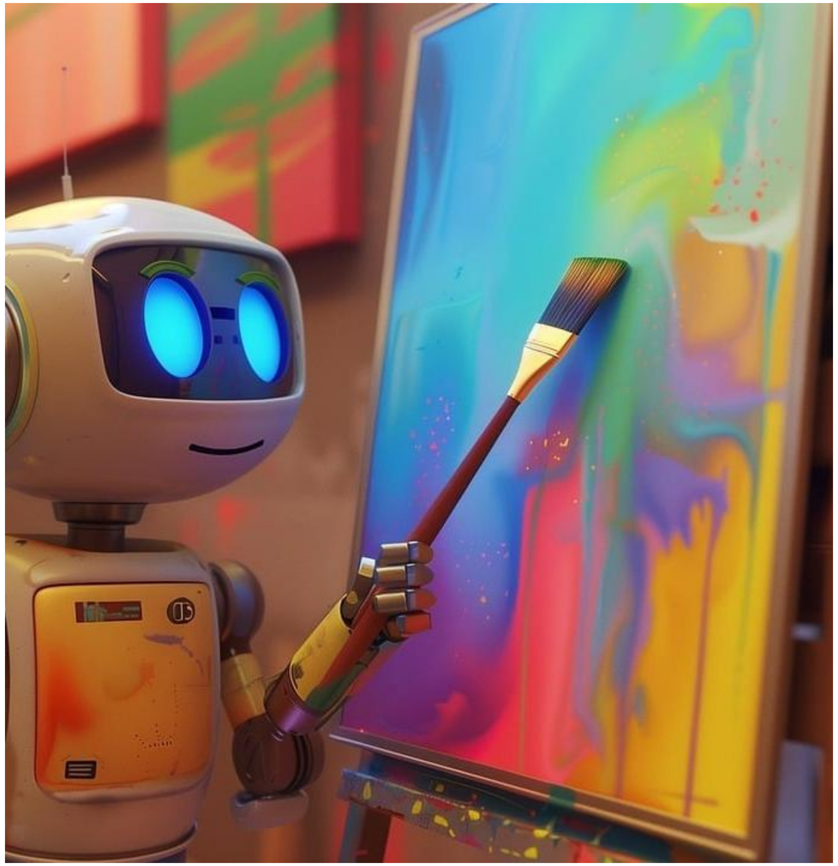
Bignami e et al, submission

Blocco operatorio....

- Attività chirurgica: elezione o urgenza/emergenza

- Sale operatorie
- Recovery room/PACU (monitoraggio o sala di «lavoro»)

- Dimissione: reparto/ICU



Trauma Surgery & Acute Care Open

Data-driven identification of urgent surgical procedures for use in trauma outcomes measurement

Matthew Miller [1,2] Louisa Jorm,[3] Blanca Gallego[4]

Trauma Surg Acute Care Open 2025;**10**:e001783.

Methods We linked perioperative and inpatient data for trauma patients with procedures booked within 24 hours of admission from a single Australian hospital (July 2018–July 2023). Surgical procedure codes were extracted where booked free-text and coded procedures matched. Procedures were labeled urgent-by-agreement if over 75% were needed within 4 hours, or urgent-by-consensus if 50–75% met this time frame with consensus below 0.7. Our method also allows adjustment for urgency time frame.

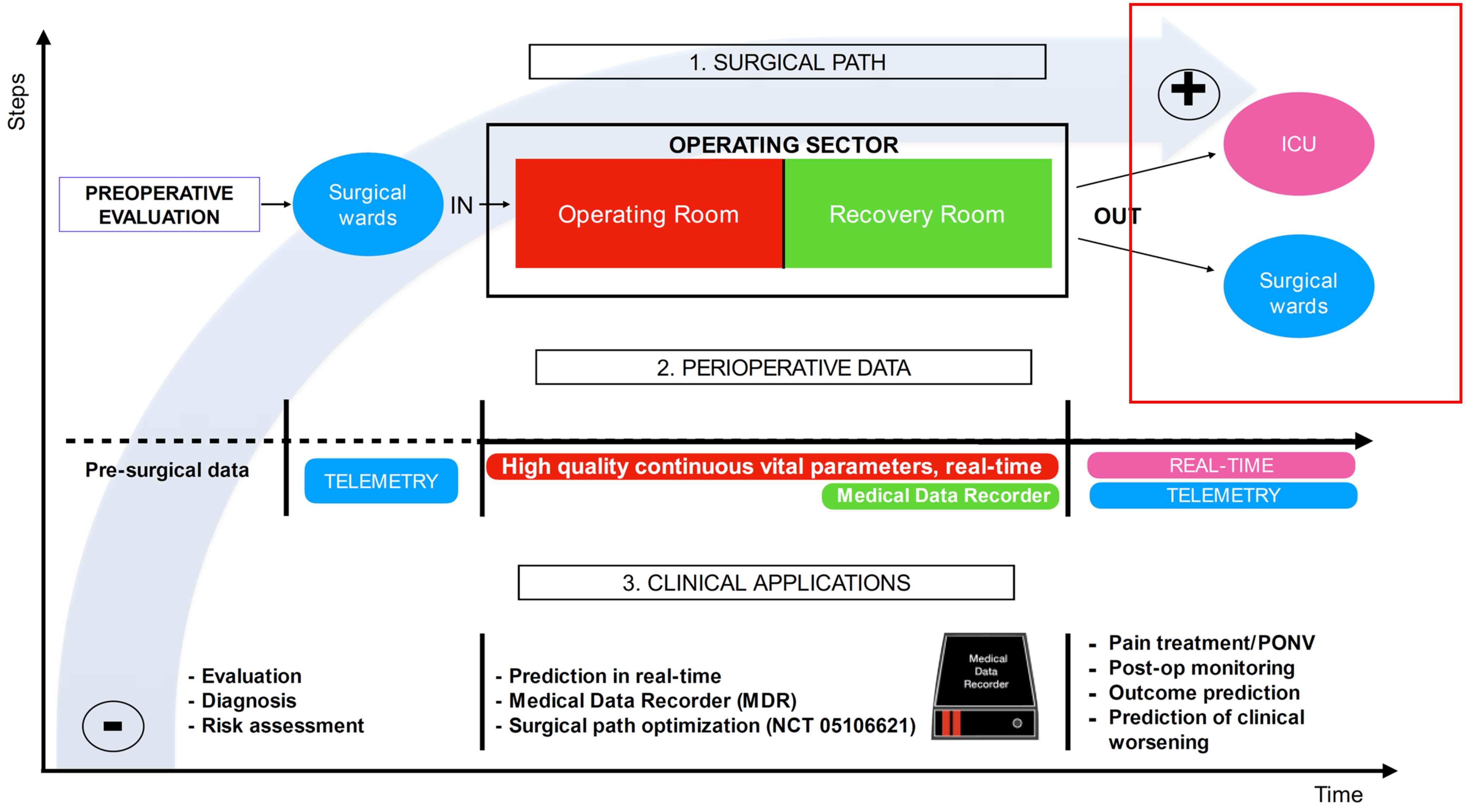
Results Of 567 unique procedures from 6,750 total in 4,737 trauma admissions, 161 were classified as urgent-by-agreement and 6 as urgent-by-consensus. 15 surgical specialties were represented on this list.

Discussion and conclusions Using routinely collected data, we outline a method for generating and updating urgent surgical procedure lists for trauma patients that could be applied at the institution level or across trauma networks. In addition, different urgency periods can be accommodated. Future work could look at further automating these processes by incorporating deep learning.

Table 1 Study demographics for those patients whose surgery v booked within 24 hours of admission

Demographics	n(%) or median (IQR, 25–75 centile, range)	At least one procedur assigned <1 hour or <4 hours priority
Number of patient episodes	4,737	
Age (years)	46 (48, 23–71, 1–103)	
Gender		
Female	1,963 (41.4)	131 (6.7)
Male	2,774 (58.6)	364 (13.1)
ASA		
1—healthy	1,772 (37.4)	106 (6.0)
2—mild systemic disease	1,323 (27.9)	100 (7.6)
3—moderate-to-severe systemic disease	1,120 (23.7)	117 (10.4)
4—severe systemic disease	340 (7.2)	126 (37.1)
5—Moribund	31 (0.7)	30 (96.8)
6—Organ donation	0	
Not recorded	151 (3.2)	18 (12.8)
Emergency priority		
<1 hour	244 (5.2)	
<4 hours	253 (5.3)	
<8 hours	330 (7.0)	
<24 hours	3626 (76.6)	
<72 hours	284 (6.0)	
Booking surgical specialty		
Orthopedic	3,111 (65.7)	88 (2.8)
Plastic	793 (16.7)	8 (1)
Neurosurgery	214 (4.5)	114 (53.3)
Gastroenterology	133 (3.0)	61 (45.9)
Ear, nose and throat	140 (2.8)	22 (15.7)
General surgery	115 (2.4)	72 (62.6)
Trauma	114 (2.4)	71 (62.3)
Urology	38 (0.8)	14 (36.8)
Vascular	22 (0.5)	14 (63.6)
Maxillofacial	17 (0.4)	4 (23.5)
Cardiothoracic	15 (0.3)	12 (80)
Hand	8 (0.2)	4 (50.0)
Radiology	8 (0.2)	7 (87.5)
Obs/gyne	7 (0.1)	5 (71.4)
Eye	1 (0.1)	1 (100)
Cardiology	1 (0.1)	0

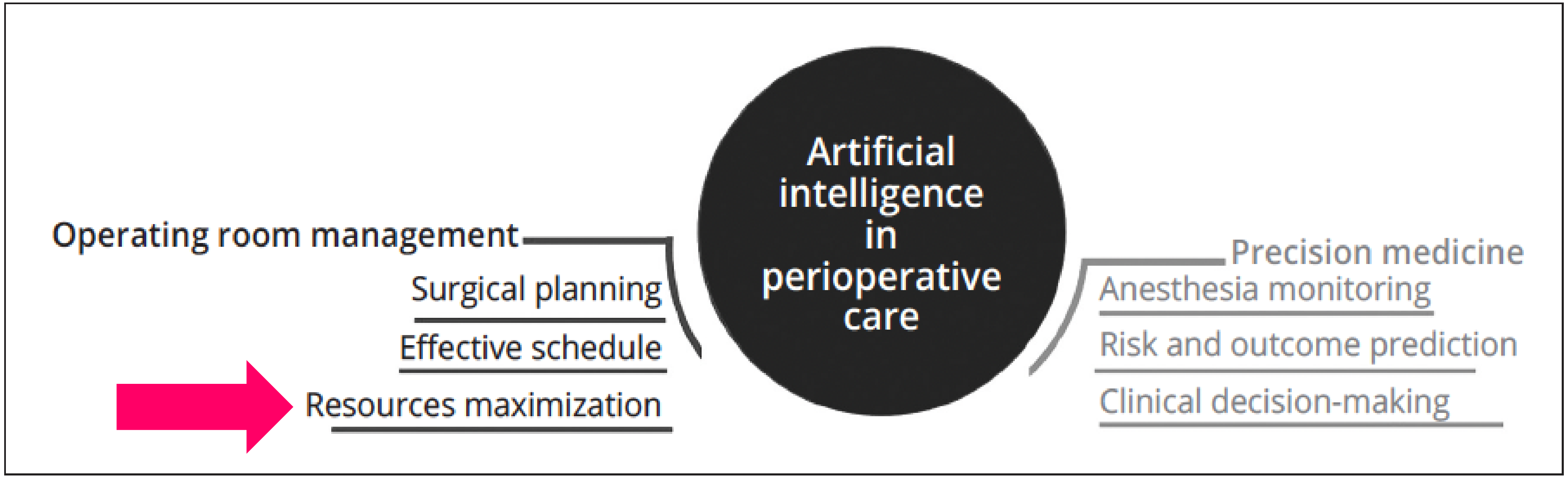
Trauma Surg Acute Care Open 2025;**10**:e001783.



Steps
1. SURGICAL PATH
PREOPERATIVE EVALUATION
Surgical wards
IN
OPERATING SECTOR
Operating Room
Recovery Room
OUT
ICU
Surgical wards
2. PERIOPERATIVE DATA
Pre-surgical data
TELEMETRY
High quality continuous vital parameters, real-time
Medical Data Recorder
REAL-TIME
TELEMETRY
3. CLINICAL APPLICATIONS
- Evaluation
- Diagnosis
- Risk assessment
- Prediction in real-time
- Medical Data Recorder (MDR)
- Surgical path optimization (NCT 05106621)
Medical Data Recorder
- Pain treatment/PONV
- Post-op monitoring
- Outcome prediction
- Prediction of clinical worsening
Time

AI e NT

Figure 1.—Role of artificial intelligence in perioperative medicine. Its role is twofold. It can be used both to optimize the organization and efficiency of the operating room, and to maximize the personalization of perioperative care.



PERIOPERATIVE MEDICINE

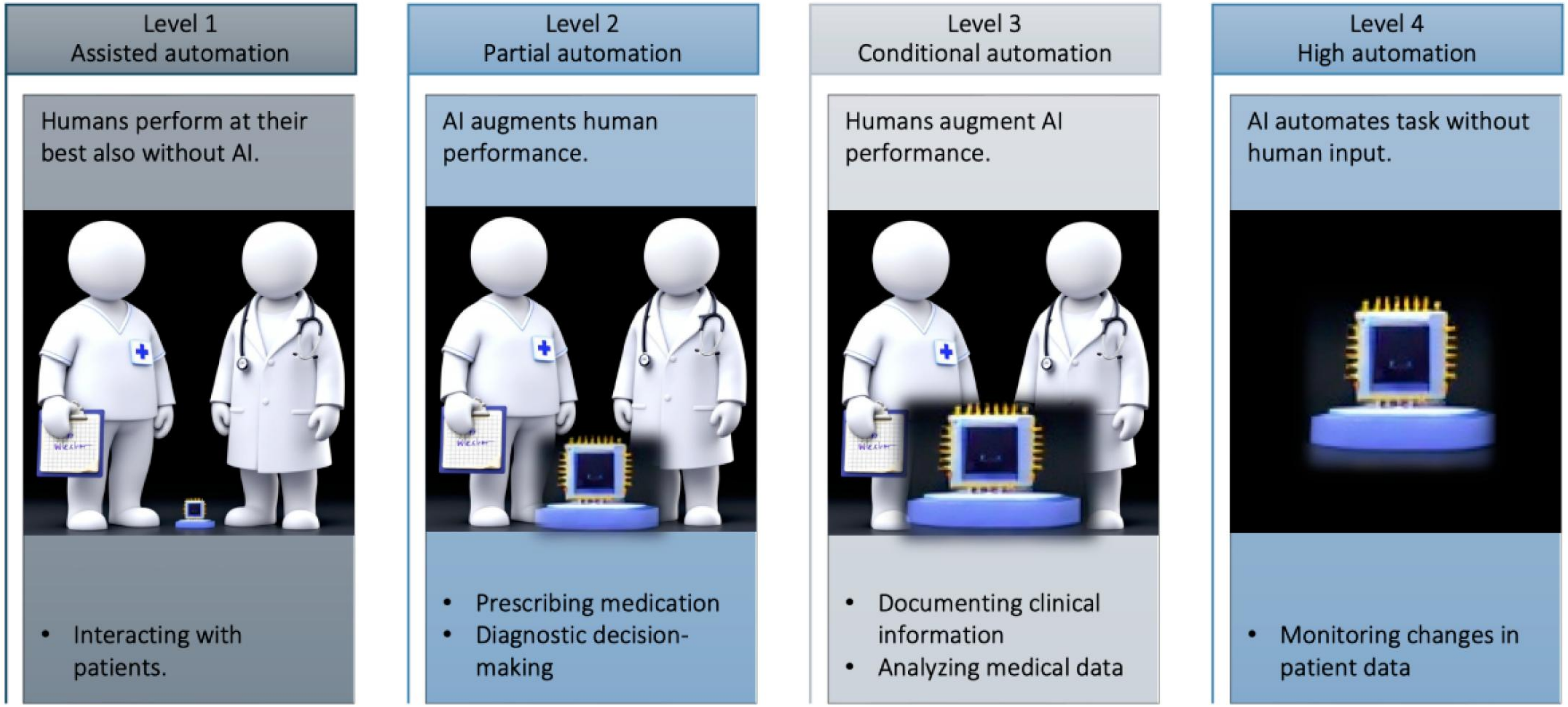
Bellini, Bignami et al. *Minerva Anest*. 2022

AI Interventions to Alleviate Healthcare Shortages and Enhance Work Conditions in Critical Care: Qualitative Analysis

Nadine Bienefeld[1], PD, PhD; Emanuela Keller[2], MD, Prof Dr; Gudela Grote[1], Prof Dr

(J Med Internet Res 2025;27:e50852)

Figure 2. Summary of results from Bienefeld et al [39], a mixed-method study identifying optimal levels of human-AI teaming in a sample of n=19 data science experts and n=61 nurses and physicians. AI: artificial intelligence.



«Naturally, the idea of synergy is evolving-and we're beginning to see that the effectiveness of *human-AI collaboration* may vary depending on the specific task being prformed»

Conclusions: This study demonstrates AI's capacity to mitigate stress and improve work conditions for ICU nurses and physicians, thereby contributing to resolving health care staffing shortages. AI solutions that are thoughtfully designed in line with the principles for good work design can enhance intrinsic motivation, learning, and worker well-being, thus providing strategic value for hospital management, policy makers, and health care professionals alike.

(J Med Internet Res 2025;27:e50852)

Intelligenza artificiale e….

Rapid diagnostics

Precision medicine

Novel therapeutics

AI driven CDSS

…e innovazione tecnologica

Intelligenza artificiale e….

Journal of Medical Systems (2025) 49:30
https://doi.org/10.1007/s10916-025-02163-6

CORRESPONDENCE

Reclaiming Patient-Centered Care: How Intelligent Time is Redefining Healthcare Priorities

Elena Giovanna Bignami[1] · Michele Russo[1] · Valentina Bellini[1]

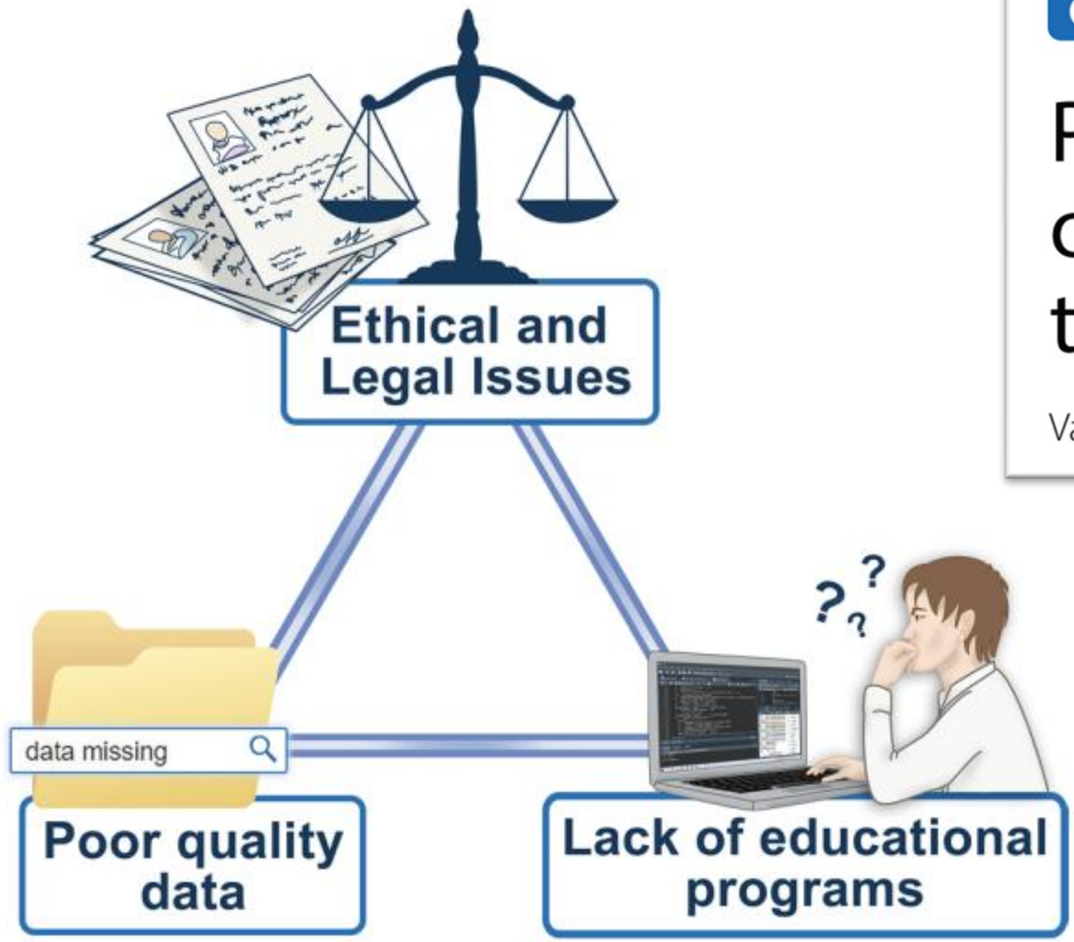
Received: 28 January 2025 / Accepted: 12 February 2025

Intelligent Time: Refocusing on Patient-Centred Care

One of the most compelling opportunities presented by GenAI lies in what we term "intelligent time recovery". The article rightly highlights GenAI's capacity to alleviate clinician burnout by automating labour-intensive tasks such as documentation, billing, and data entry. This aligns with recent insights on the rapid evolution of Large Language Models (LLMs) in medicine, emphasizing their growing role in clinical documentation management and decision support systems [2]. However, we propose extending this notion further: GenAI should not only streamline workflows but also enable clinicians to refocus on what matters most in healthcare—time spent with patients.

…Intelligent time in perioperative medicine

Triad of AI Death in Clinical Practice



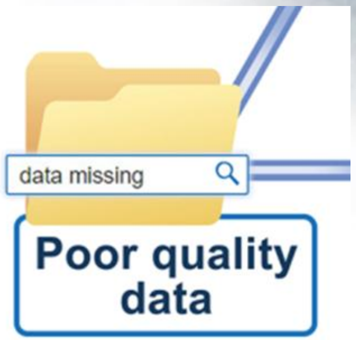
Intensive Care Med
https://doi.org/10.1007/s00134-021-06473-4

CORRESPONDENCE

Poor quality data, privacy, lack of certifications: the lethal triad of new technologies in intensive care

Valentina Bellini[1], Jonathan Montomoli[2] and Elena Bignami[1*]

Bellini et al. Intensive Care Med. 2021



the low-quality incoming data will produce poor quality output data and Is a very big problem for a correct decisions making indeed the main one it is still open

GIGO

Garbage In-Garbage out

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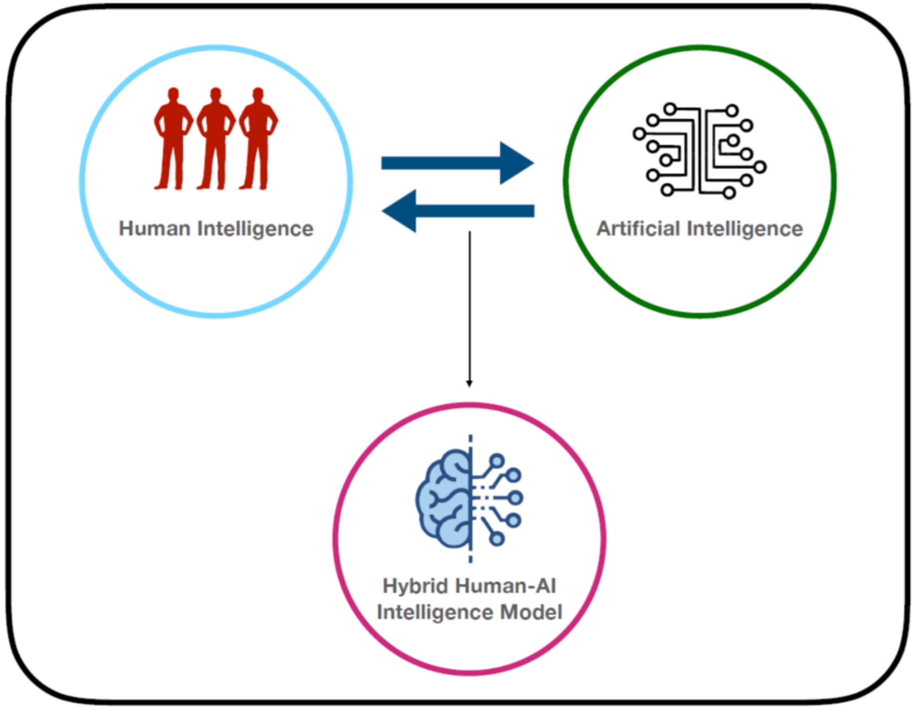
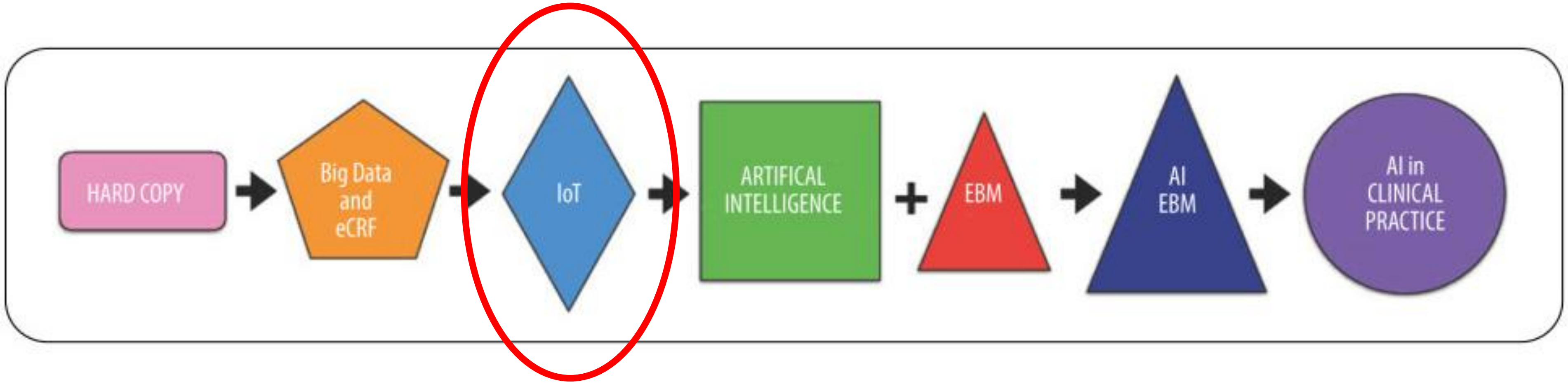
UNIVERSITÀ DI PARMA

Human and Artificial Intelligence Hybrid Model





Bellini et al Med Sci Monit, 2023; 29: e939366

Tracciabilità del paziente, process-map ping, riduzione liste d’attesa, etc.

Trasferimenti e dimissioni sicure, stratificazione del rischio, etc.

Take home message

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Expert Opinion

Literature Review

JOURNAL OF PERIOPERATIVE PRACTICE

AfPP PROGRESSING SAFER SURGERY
The Association for Perioperative Practice

A bibliometric analysis of perioperative medicine and artificial intelligence

Journal of Perioperative Practice
1–10

DOI: 10.1177/17504589251320811
journals.sagepub.com/home/ppj
Sage

Luke Kar Man Chan[1,2,3], Brooke Perrin Mao[1,2] and Rebecca Zhu[4]

Xie et al. Perioperative Medicine (2024) 13:121
https://doi.org/10.1186/s13741-024-00480-x

Perioperative Medicine

REVIEW Open Access

Artificial intelligence in anesthesiology: a bibliometric analysis

Bi-Hua Xie[1,2], Ting-Ting Li[1], Feng-Ting Ma[1,3], Qi-Jun Li[4], Qiu-Xia Xiao[5], Liu-Lin Xiong[5*] and Fei Liu[1*]

Ou et al. Perioperative Medicine (2025) 14:47
https://doi.org/10.1186/s13741-025-00531-x

Perioperative Medicine

REVIEW Open Access

Global trends in artificial intelligence research in anesthesia from 2000 to 2023: a bibliometric analysis

Yi Ou[1], Xiaoyi Hu[2*], Cong Luo[1] and Yajun Li[1]

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Week 26

Congresso Ai e NT

Parma, 29-30 gennaio 2026

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Prof. Elena Giovanna Bignami
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Gennaio 2026
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