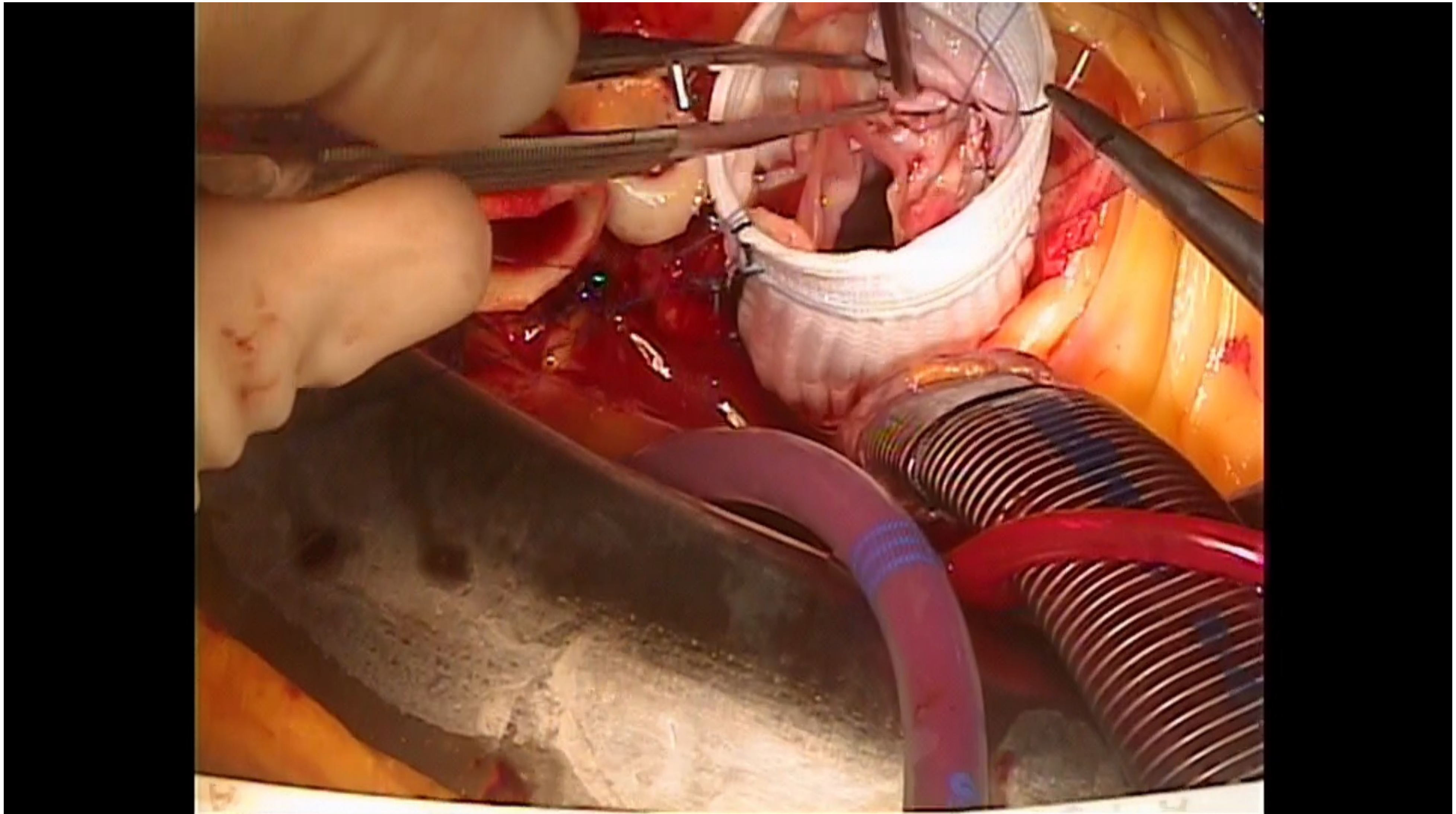
AI Coach / AI for Decision Making in Surgery

Marco A. Zenati, M.D.
Professor of Surgery, Harvard Medical School

ECML-HLDM 2023 Workshop, Turin, Italy September 22, 2023

I am a heart surgeon-scientist in Boston

“David V” Procedure
Aortic Valve-Sparing Root Replacement



My Pioneering Experience with Robotic Surgery

AESOP & ZEUS System (*Computer Motion*)

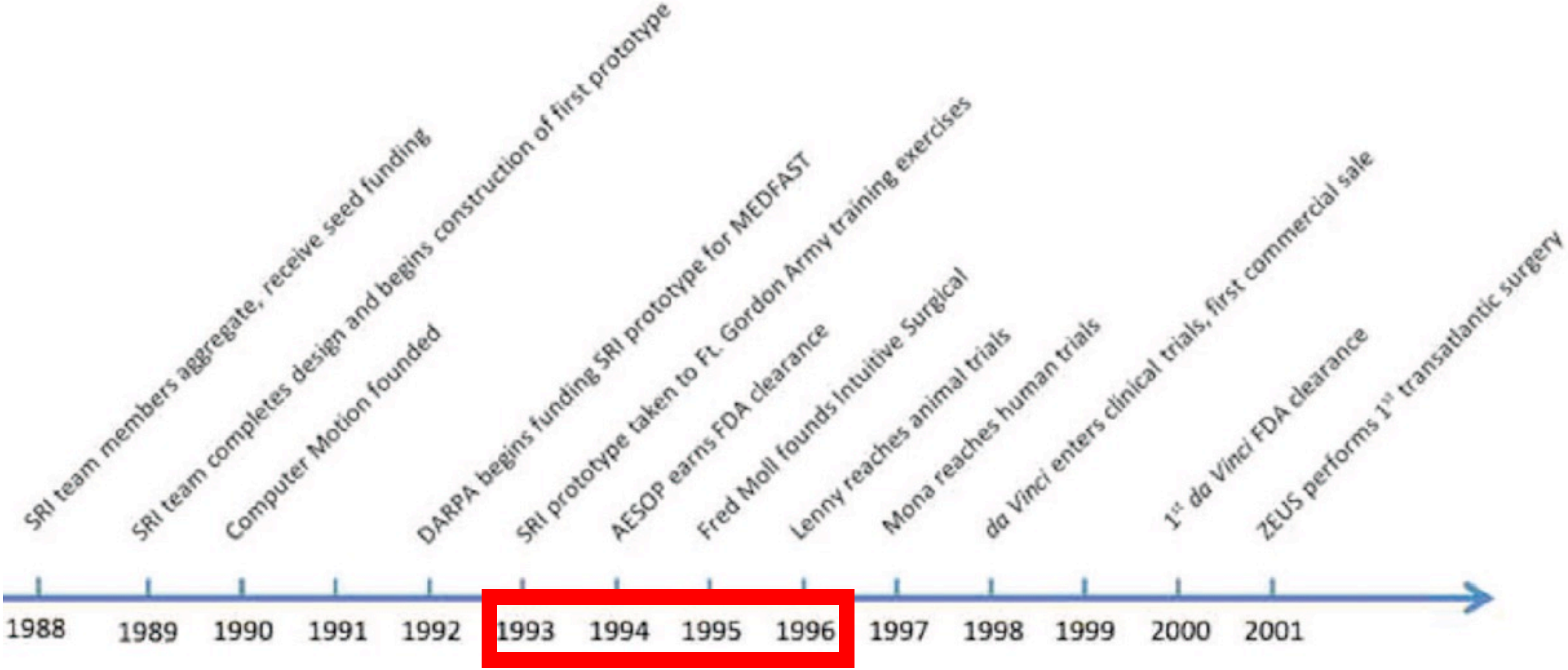
1994 - 2002

DaVinci System (*Intuitive Surgical*)

2003 - 2010

First U.S. Beating-Heart Robotic CABG
In 2000

Timeline of Surgical Robotics Development



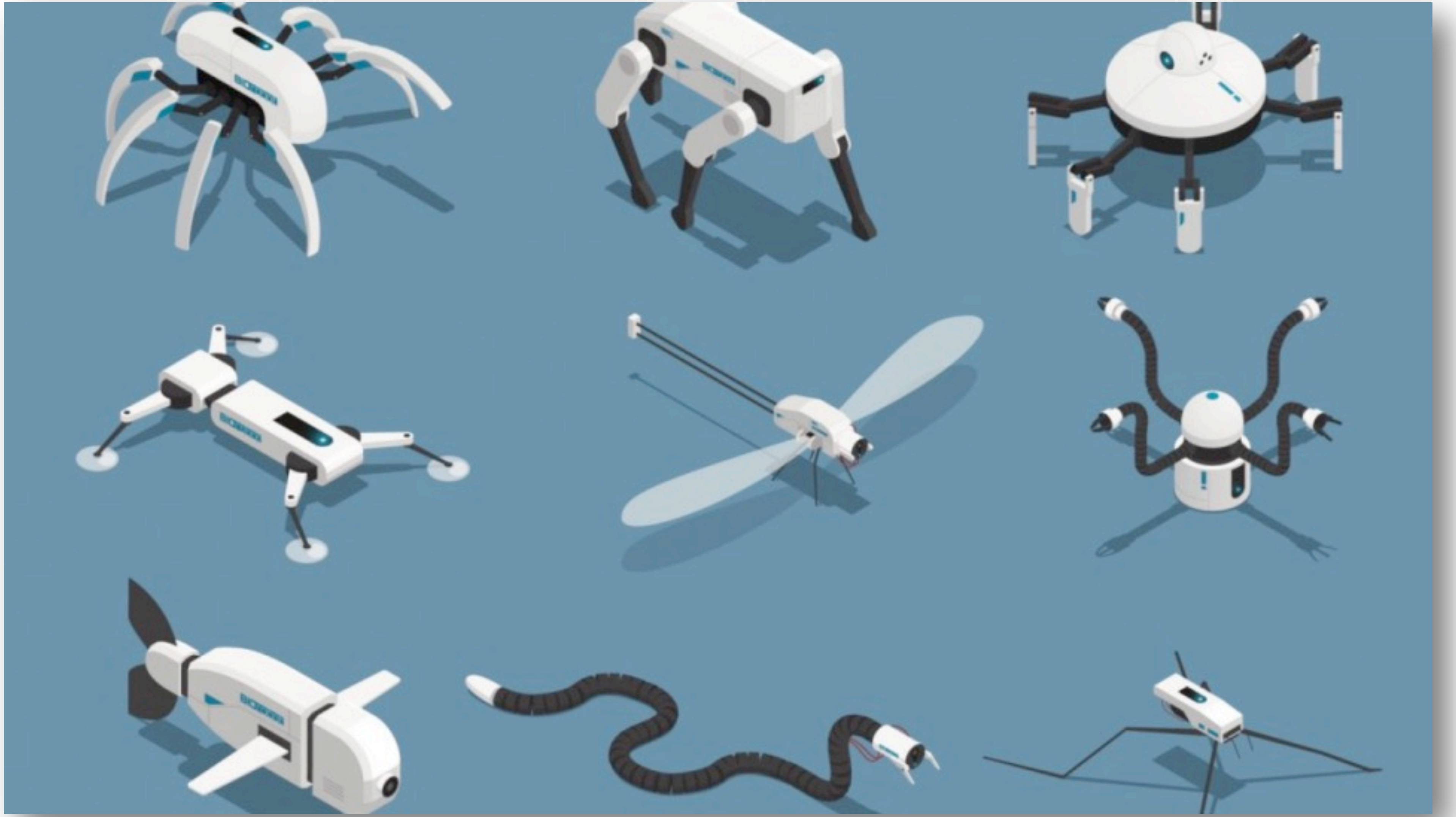
Welcome to the Medical Robotics and Computer Assisted Surgery (MRCAS) Lab website!

https://projects.iq.harvard.edu/mrcaslab/home

MISSION: To Support, Improve, and Develop Human Performance in Surgery.

The MRCAS Lab of Harvard Medical School and the VA Boston led by Dr. Marco Zenati is known for its inter-disciplinary and multi-institutional research occurring at the intersection of complex surgery, cognitive engineering, and computer science.

BioRobotics



US Patent 9,011,318

STEERABLE, FOLLOW THE LEADER DEVICE

INVENTORS: Howie Choset, Alon Wolf, Marco Zenati

(12) **United States Patent**
Choset et al.

(10) **Patent No.: US 9,011,318 B2**
(45) **Date of Patent: Apr. 21, 2015**

(54) **STEERABLE, FOLLOW THE LEADER DEVICE**

(75) Inventors: **Howard M. Choset**, Pittsburgh, PA (US); **Alon Wolf**, Haifa (IL); **Marco A. Zenati**, Pittsburgh, PA (US)

(73) Assignee: **Carnegie Mellon University and University of Pittsburg—Of the Commonwealth System of Higher Education**, Pittsburg, PA (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 1425 days.

(21) Appl. No.: **11/630,279**

(22) PCT Filed: **Jun. 24, 2005**

(86) PCT No.: **PCT/US2005/022442**
§ 371 (c)(1), (2), (4) Date: **Dec. 20, 2006**

(87) PCT Pub. No.: **WO2006/083306**
PCT Pub. Date: **Aug. 10, 2006**

(65) **Prior Publication Data**
US 2009/0171151 A1 Jul. 2, 2009

Related U.S. Application Data

(60) Provisional application No. 60/583,094, filed on Jun. 25, 2004.

(51) **Int. Cl.**
A61B 1/00 (2006.01)
A61B 1/005 (2006.01)
(Continued)

(52) **U.S. Cl.**
CPC ***A61B 1/00006*** (2013.01); ***A61B 1/0052*** (2013.01); ***A61B 1/0055*** (2013.01); ***A61B 19/22*** (2013.01); ***A61B 1/0016*** (2013.01); *A61B 19/201* (2013.01); *A61B 2017/3445* (2013.01)

(58) **Field of Classification Search**
USPC 600/114–115, 139–142, 146, 149
See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

3,060,972	A	10/1962	Sheldon
3,643,653	A	2/1972	Takahashi et al.

(Continued)

FOREIGN PATENT DOCUMENTS

JP	S6048294	A	3/1985
WO	03073920	A2	9/2003

(Continued)

OTHER PUBLICATIONS

Shammas et al., "New Joint Design for Three-dimensional Hyper Redundant Robots," International Conference on Robots and Systems, Las Vegas, NV, Oct. 2003.

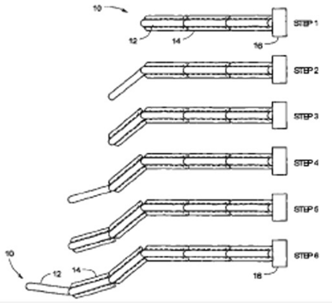
(Continued)

Primary Examiner — Matthew J Kasztejna
(74) *Attorney, Agent, or Firm* — Fox Rothschild LLP

(57) **ABSTRACT**

A highly articulated robotic probe (HARP) is comprised of a first mechanism and a second mechanism, one or both of which can be steered in desired directions. Each mechanism can alternate between being rigid and limp. In limp mode the mechanism is highly flexible. When one mechanism is limp, the other is rigid. The limp mechanism is then pushed or pulled along the rigid mechanism. The limp mechanism is made rigid, thereby assuming the shape of the rigid mechanism. The rigid mechanism is made limp and the process repeats. These innovations allow the device to drive anywhere in three dimensions. The device can "remember" its previous configurations, and can go anywhere in a body or other structure (e.g. jet engine). When used in medical applications, once the device arrives at a desired location, the inner core mechanism can be removed and another functional device such as a scalpel, clamp or other tool slid through the rigid sleeve to perform. Because of the rules governing abstracts, this abstract should not be used to construe the claims.

11 Claims, 22 Drawing Sheets

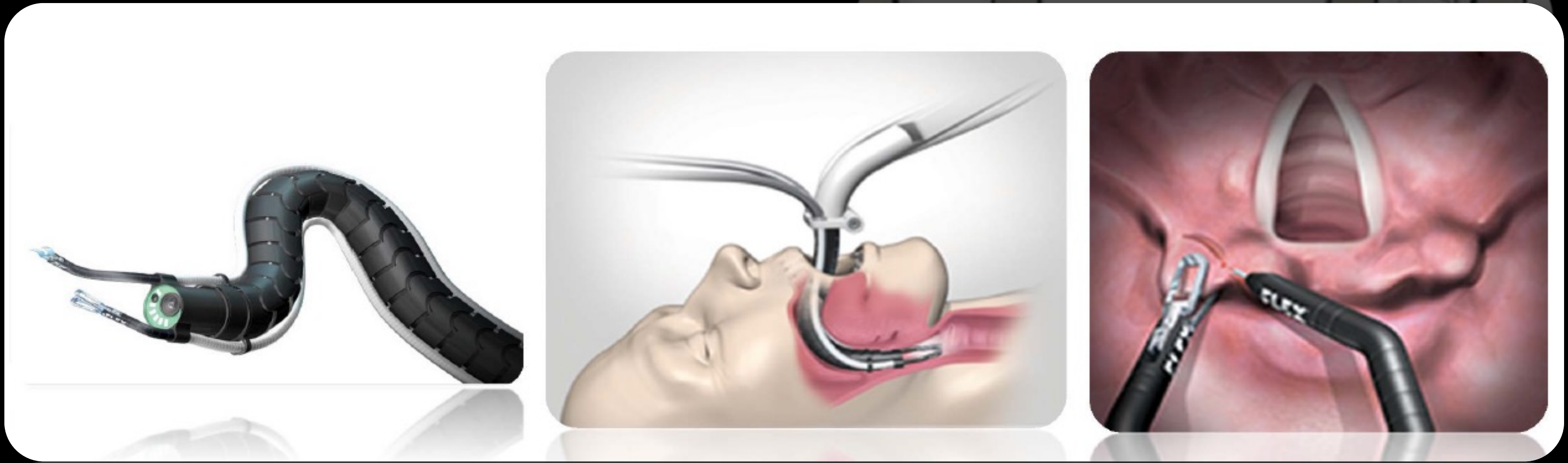


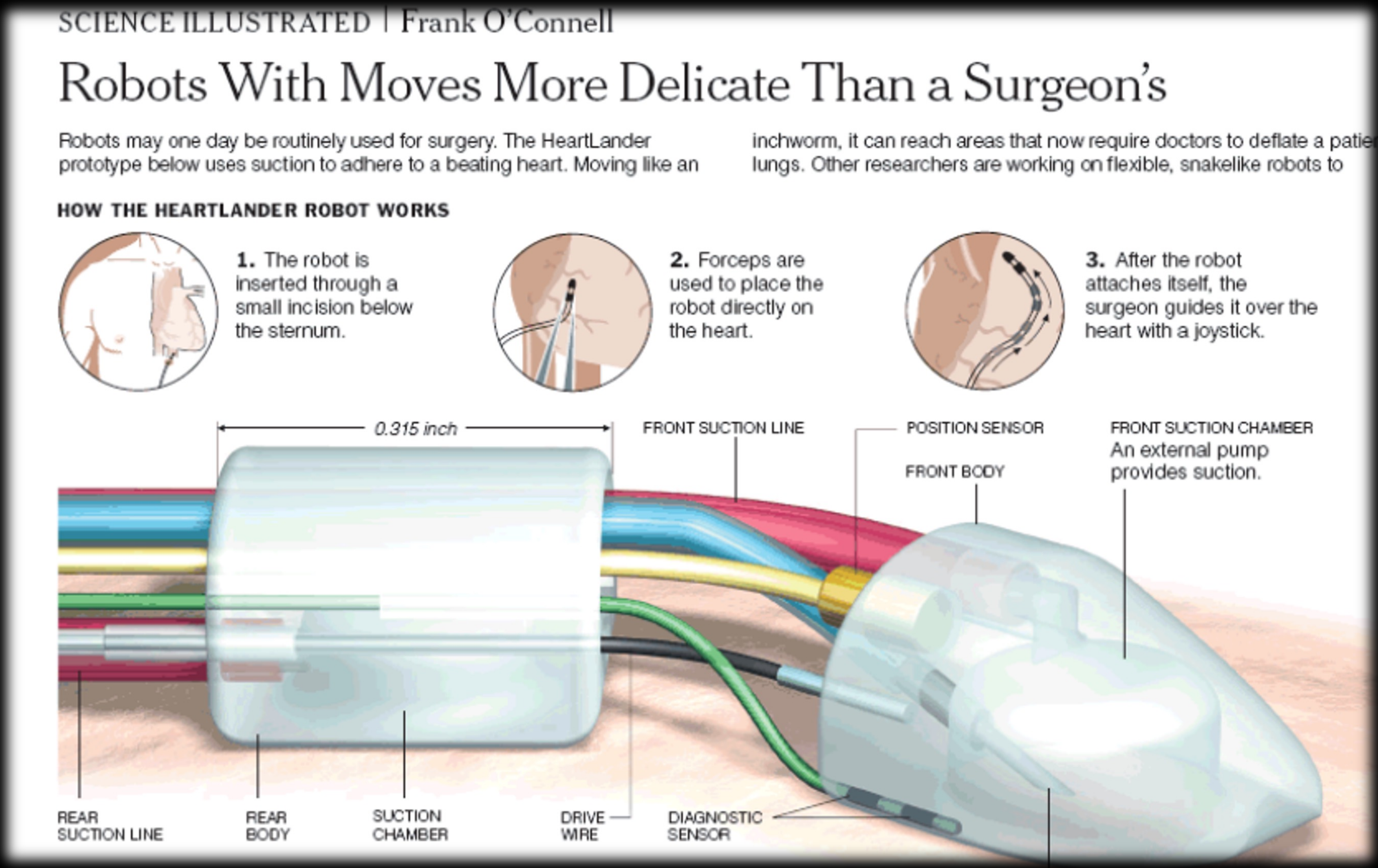
Co-FOUNDER in 2005

Medrobotics

Expanding the reach of surgery ®

FLEX®





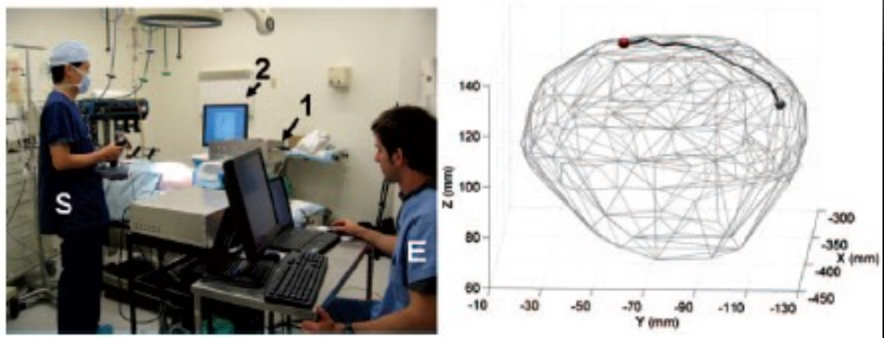
The New York Times 2011

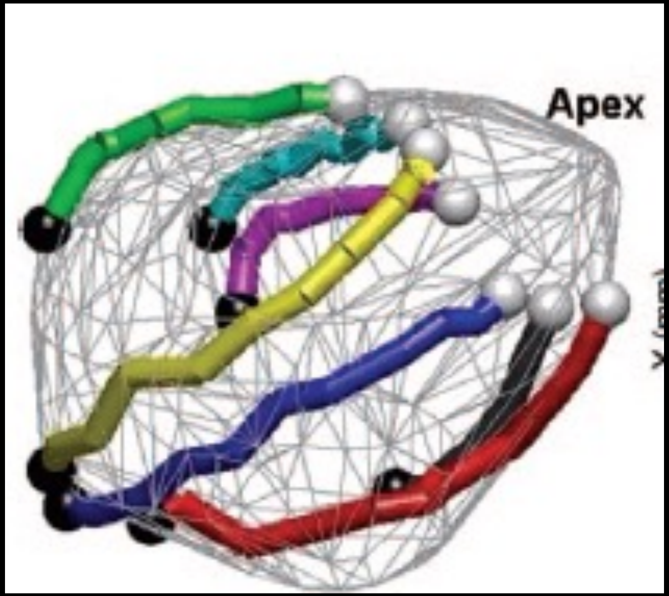
Cell Transplantation and Tissue Regeneration

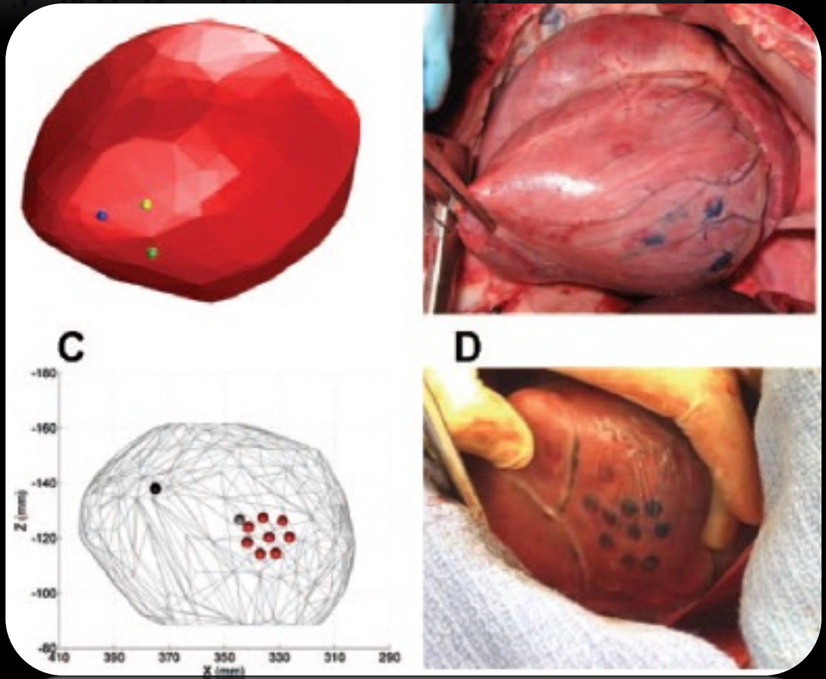
Minimally Invasive Epicardial Injections Using a Novel Semiautonomous Robotic Device

Takeyoshi Ota, MD, PhD; Nicholas A. Patronik, PhD; David Schwartzman, MD; Cameron N. Riviere, PhD; Marco A. Zenati, MD

2006







Ota…Zenati. Circulation 2008

Current Federal Funding - Zenati Lab

- U.S. **National Institutes of Health (NIH)**/National Heart, Lung & Blood Institute (NHLBI)
  - **R01-HL126896** Title: "*A Novel **Cognition-based Guidance System** to Improve Surgical Safety*"
  - **R01-HL157457** Title: "*A **Robot-assisted Perfusion System** to Improve Patient Safety in the Cardiac Operating Room*"
- U.S. **National Science Foundation (NSF)**/Division of Information and Intelligent Systems (IIS)
  - Smart & Connected Health Award No. **2205000** (09/01/2022 – 08/31/2026) Title: "*An **Artificial Intelligence Coach** for Enhancing Teamwork in the Cardiac Operating Room*"

The Problem

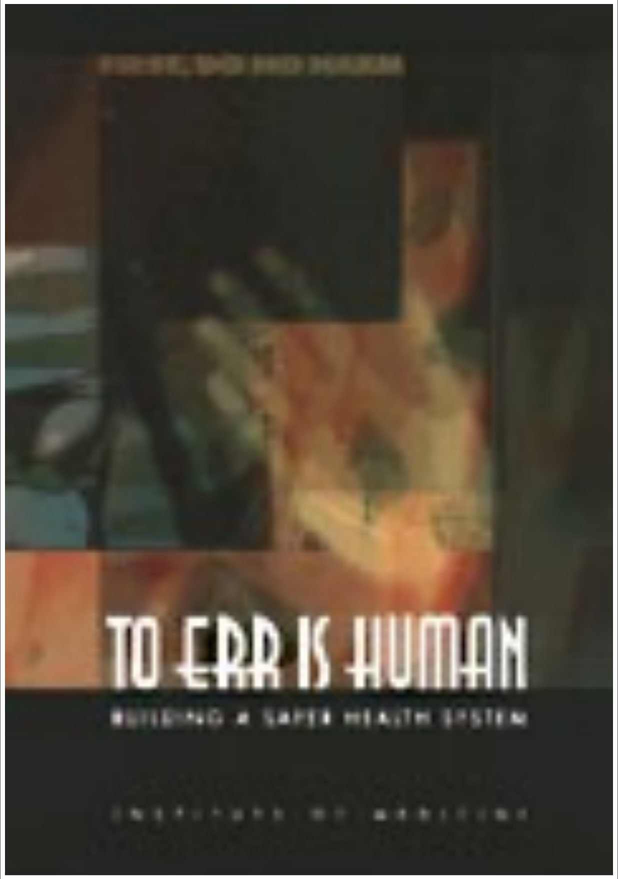
“Hospitals are not the safe places we would like them to be.”

De Vries New Engl J Med 2010

Landmark 1999
U.S. Institute of Medicine Safety Report

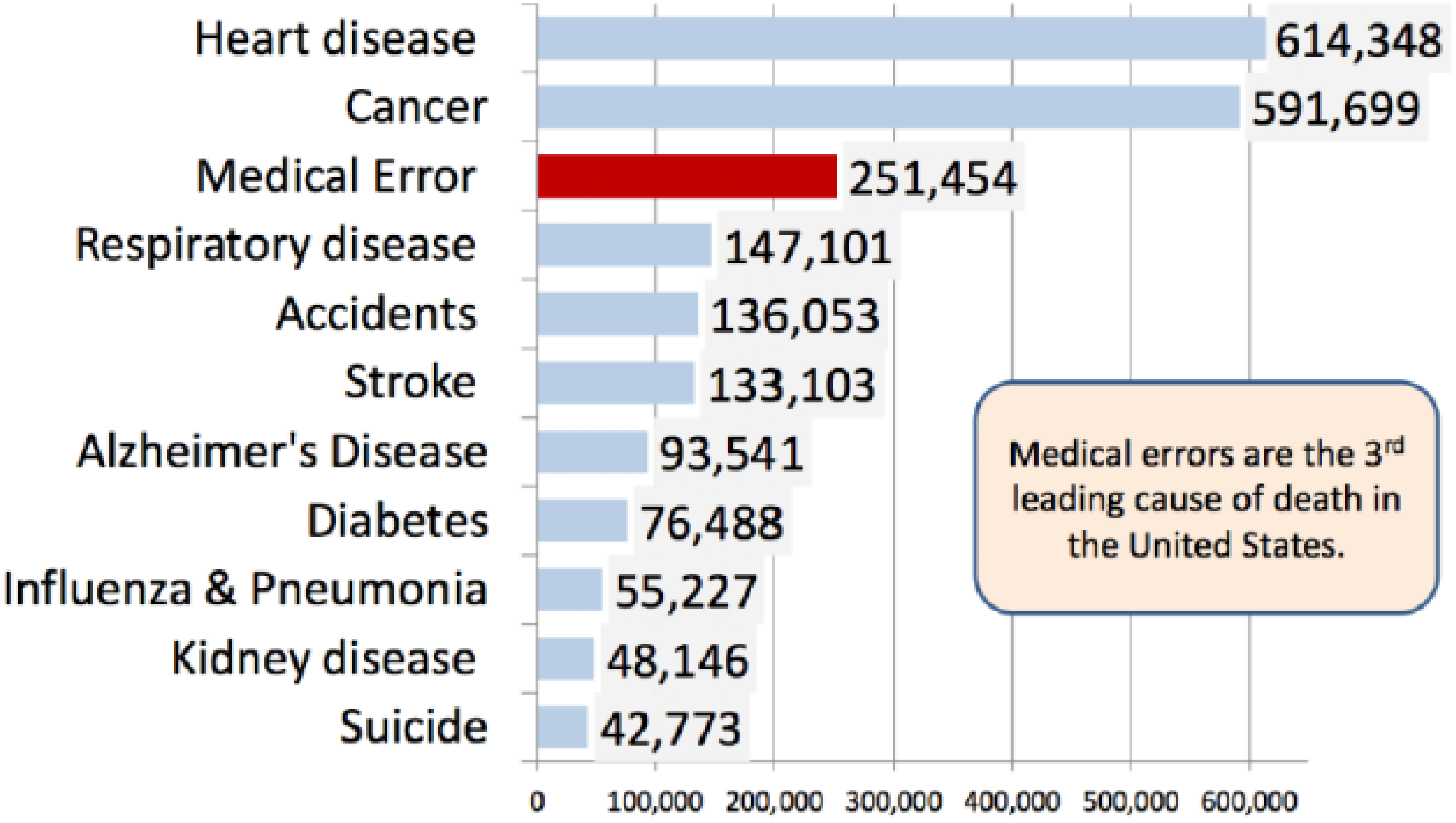
U.S. alone/year:

- 98,000 deaths caused by Preventable Adverse Events
- 1 million injuries
- 1/150 patients die because of injuries



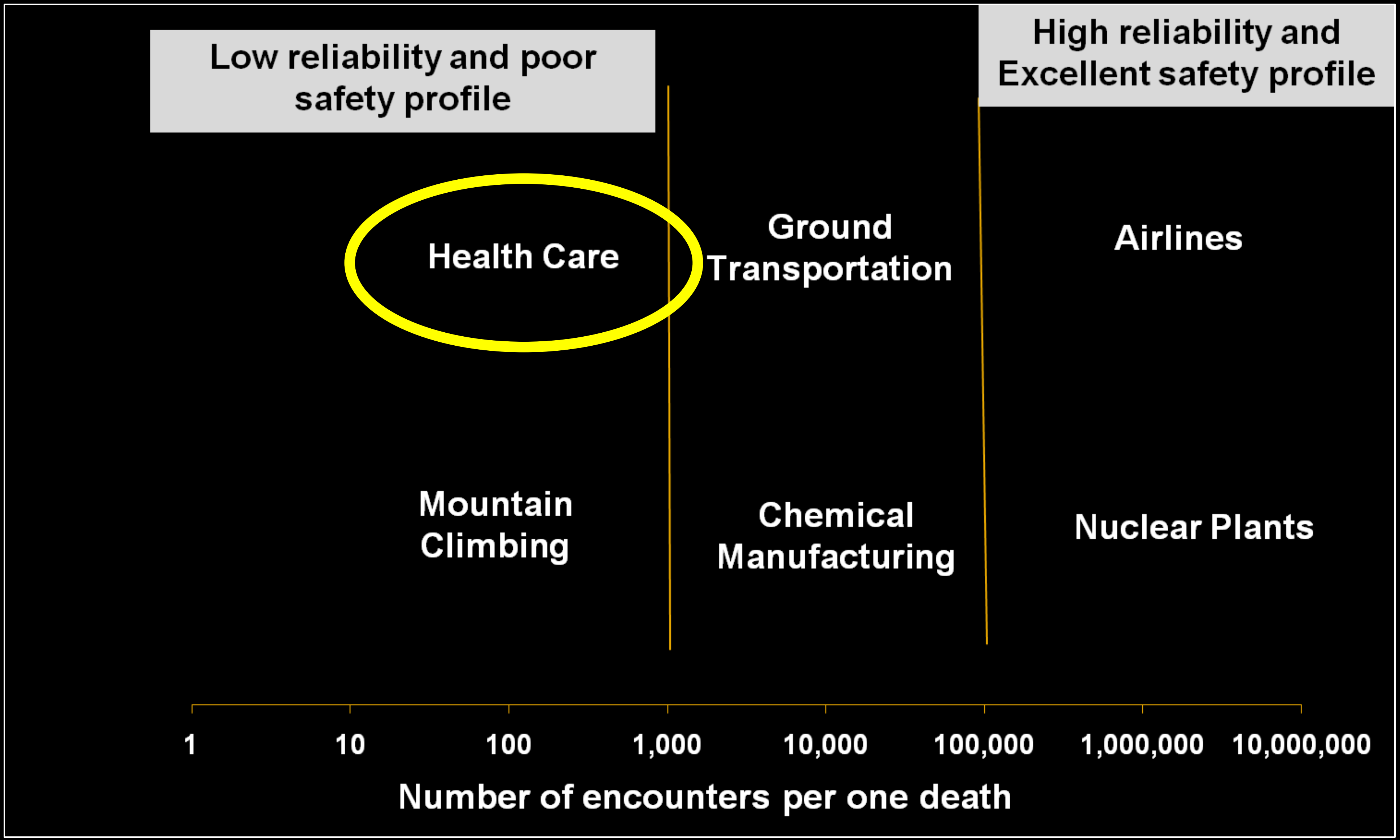
Kohn LT et al. **To Err is Human: Building a Safer Health System**. Washington, DC, U.S. Institute of Medicine

Number of Deaths in the United States



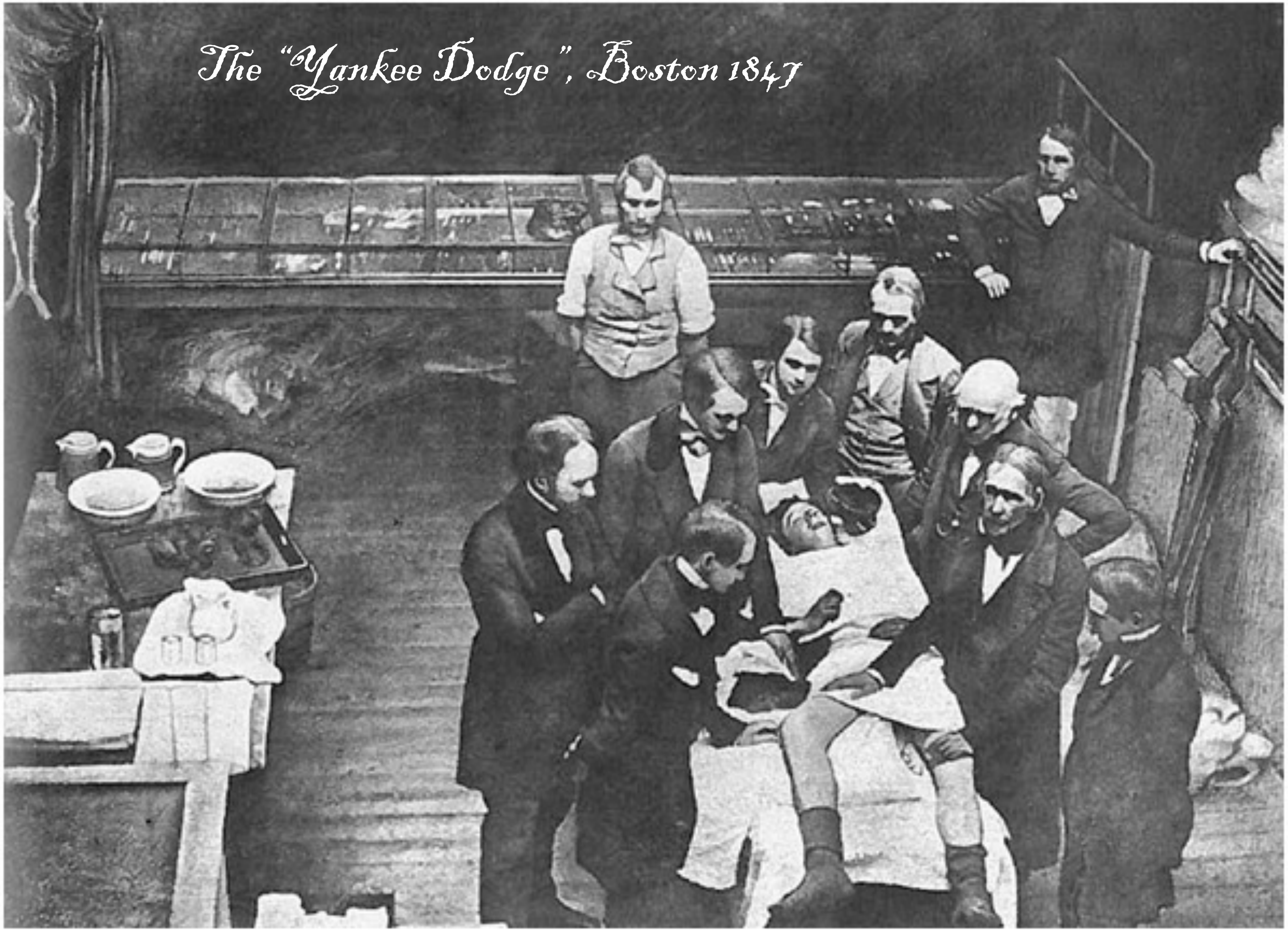
Sources: CDC. National Center for Health Statistics. Number of deaths for leading causes of death, 2014.

Health Care vs. Other High-Reliability Organizations



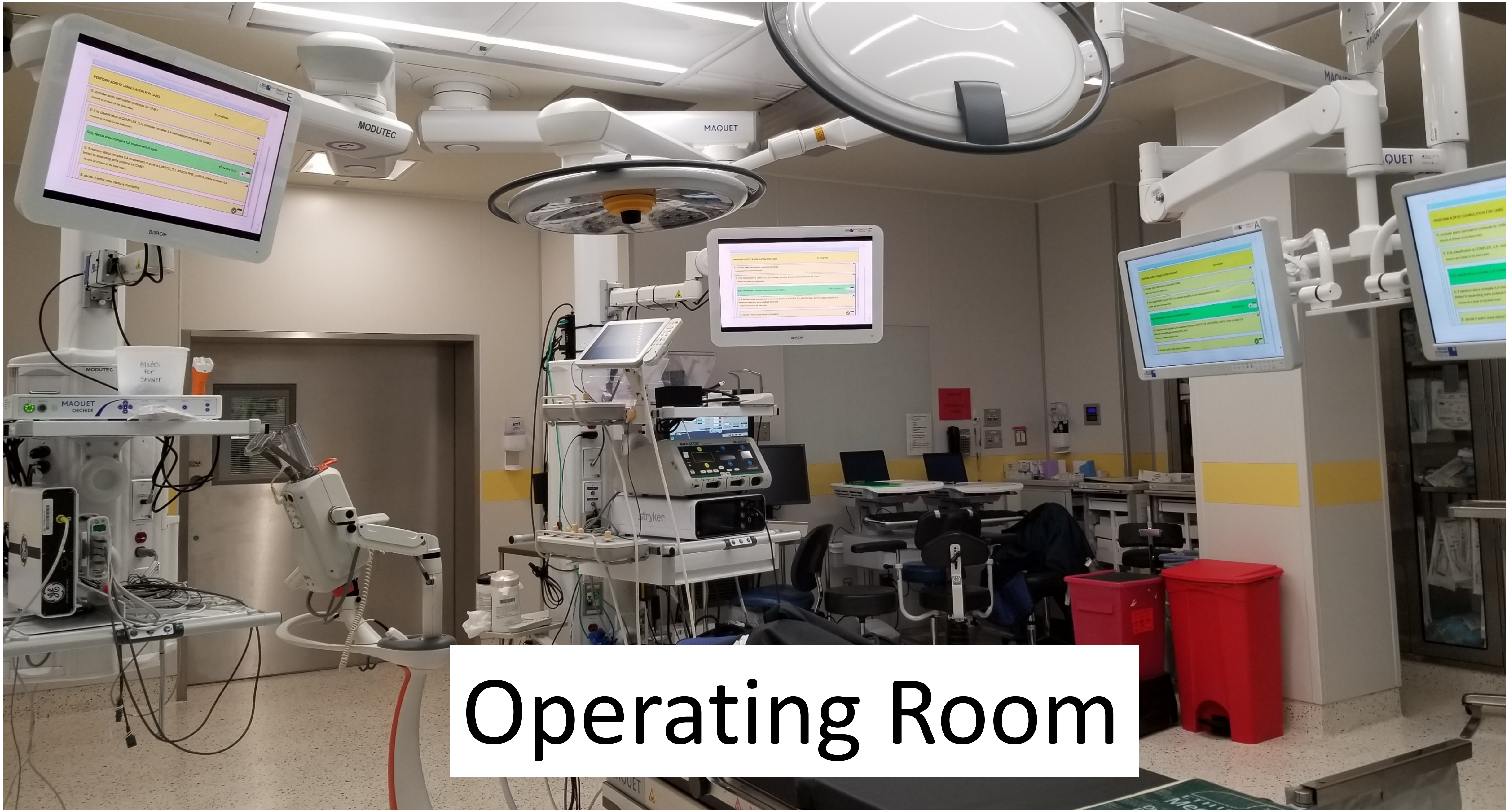
Surgery

- Among most challenging activities performed by humans
- Require years of training and learning
  - Cardiac Surgeon
    - 4 years of Medical School,
    - 5 years of General Surgery
      - 1-2 year of research
    - 2-3 years of Thoracic Surgery
    - >12 years of post-college training!


The "Yankee Dodge", Boston 1847


Domain knowledge
PubMed
Case knowledge
Patient individual data
Devices
CT
...
PRESENT

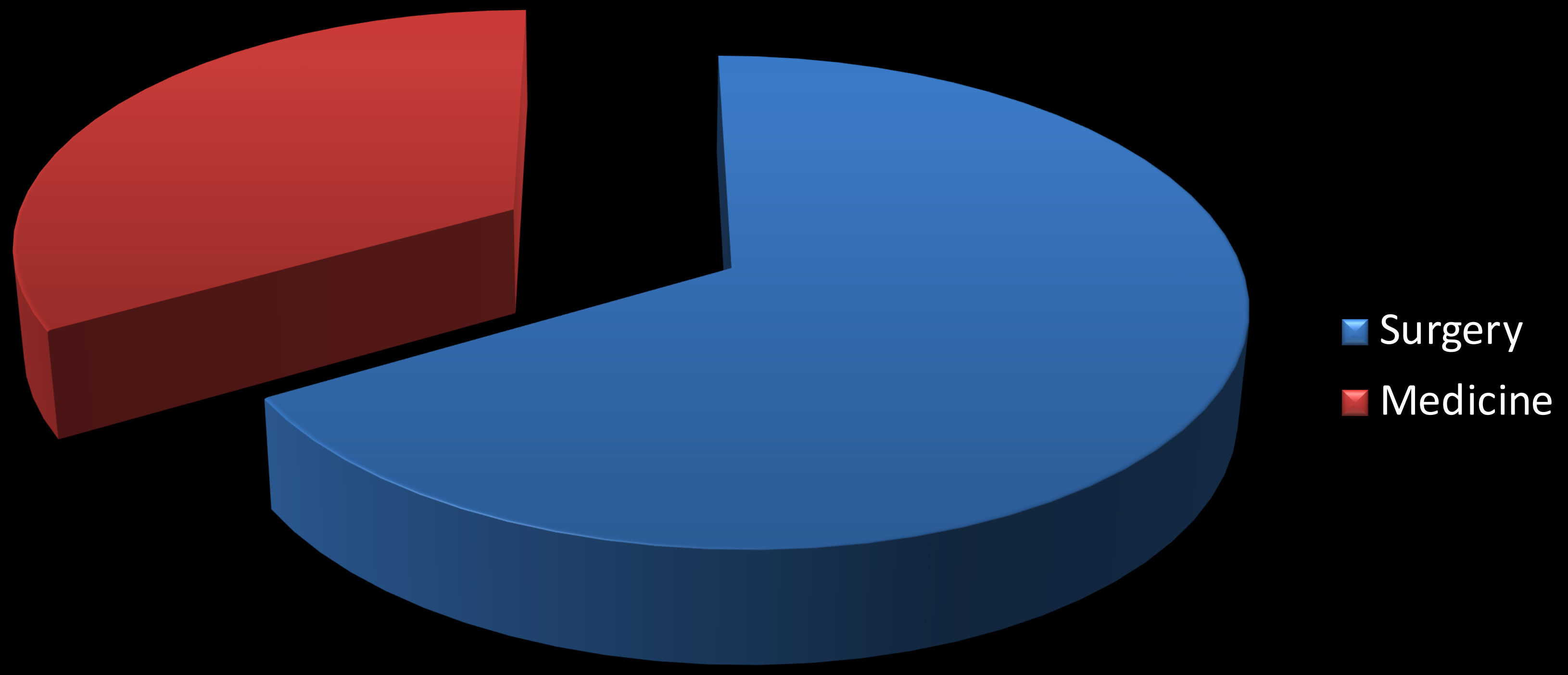

Artis
zeego



Operating Room

A Complex and Vulnerable Socio-technical System

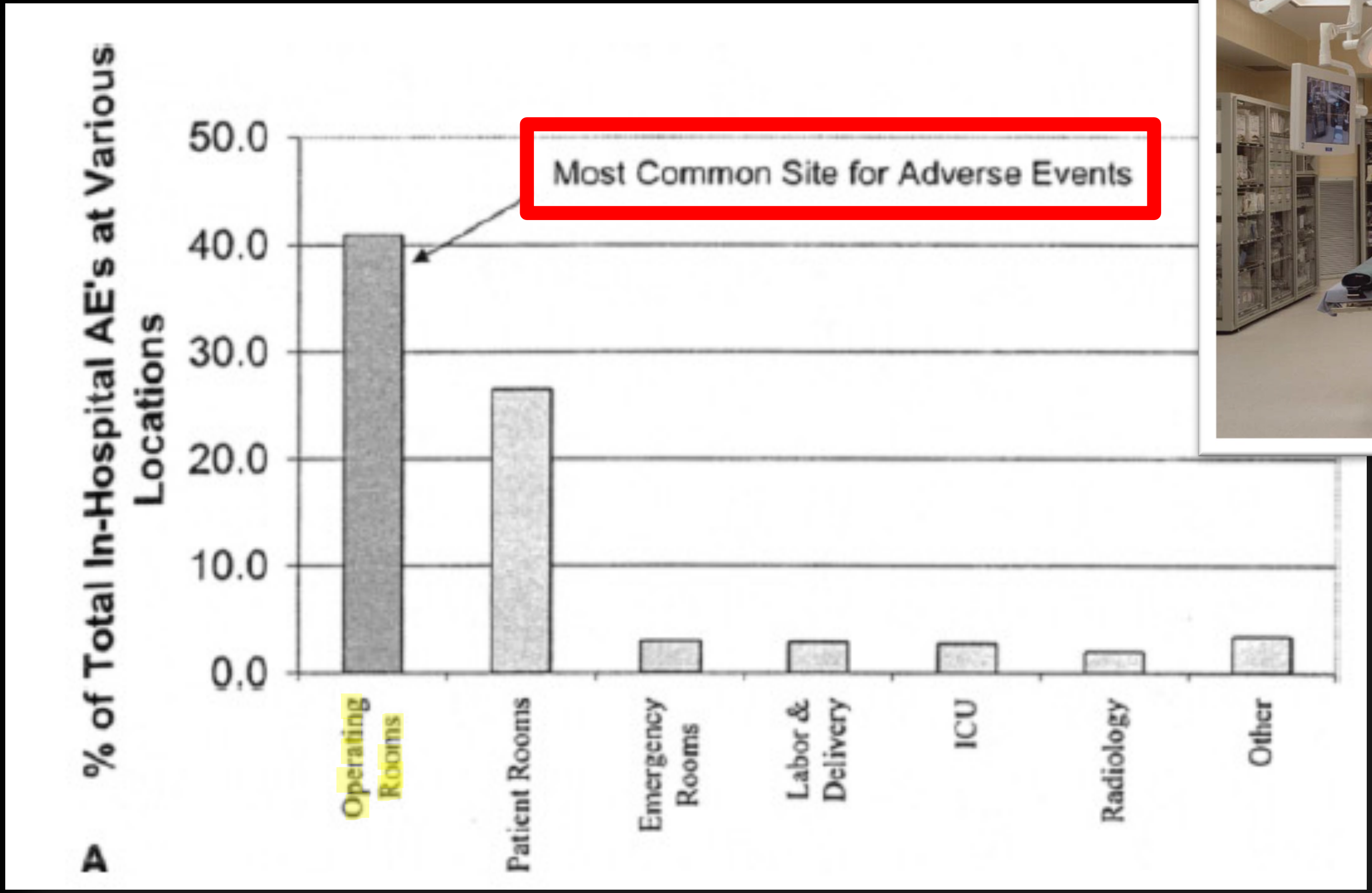
2/3 of Adverse Events in Hospitals are **Surgical**



50% of AEs are preventable!

Gawande AA 1999, Leape LL 1991

Locations of Adverse Events in Surgery



Calland 2002

Human Errors as Mental Workload Problems

THEORETICAL POPULATION BIOLOGY 9, 129–136 (1976)

Optimal Foraging, the Marginal Value Theorem

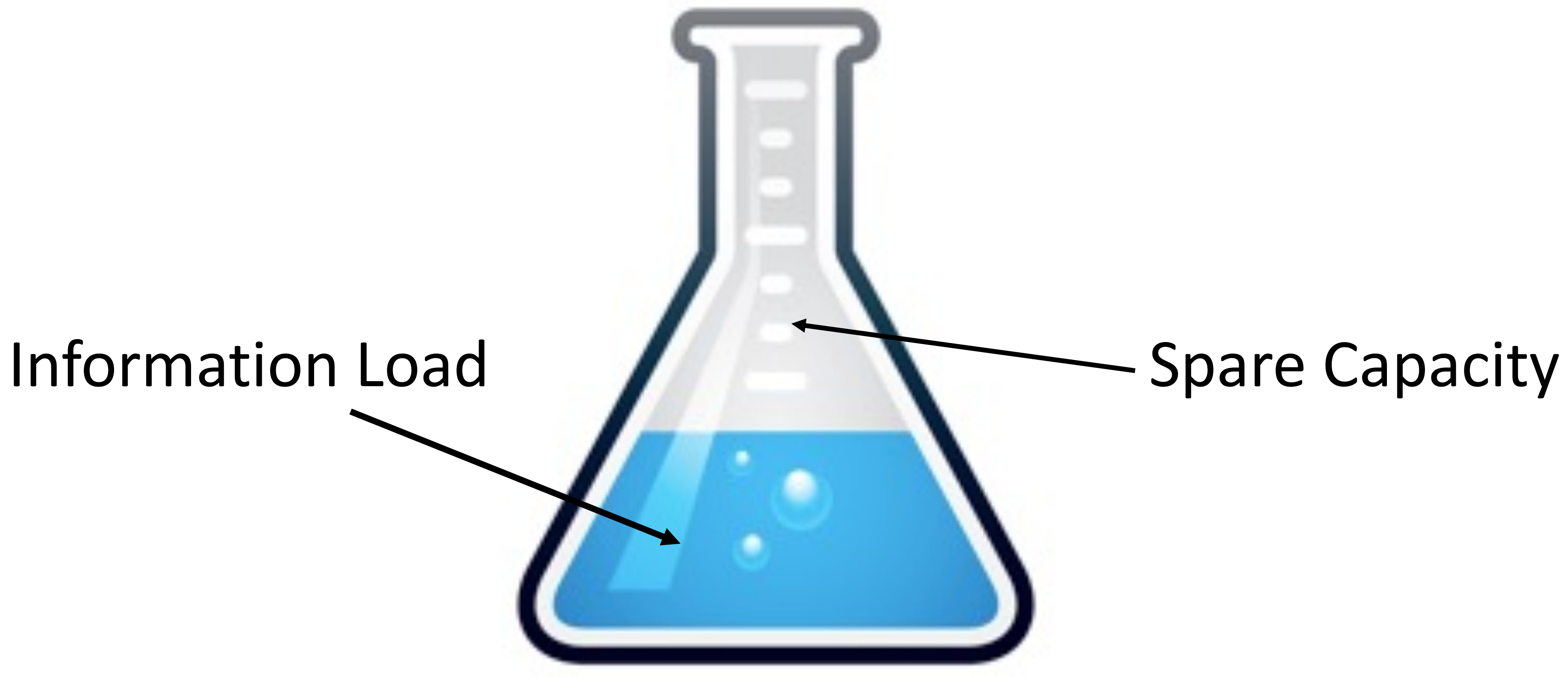
ERIC L. CHARNOV*

Center for Quan. Science in Forestry, Fisheries, and Wildlife, University of Washington, Seattle, Washington 98195; and Institute of Animal Resource Ecology UBC, Vancouver 8, Canada

Received December 26, 1974

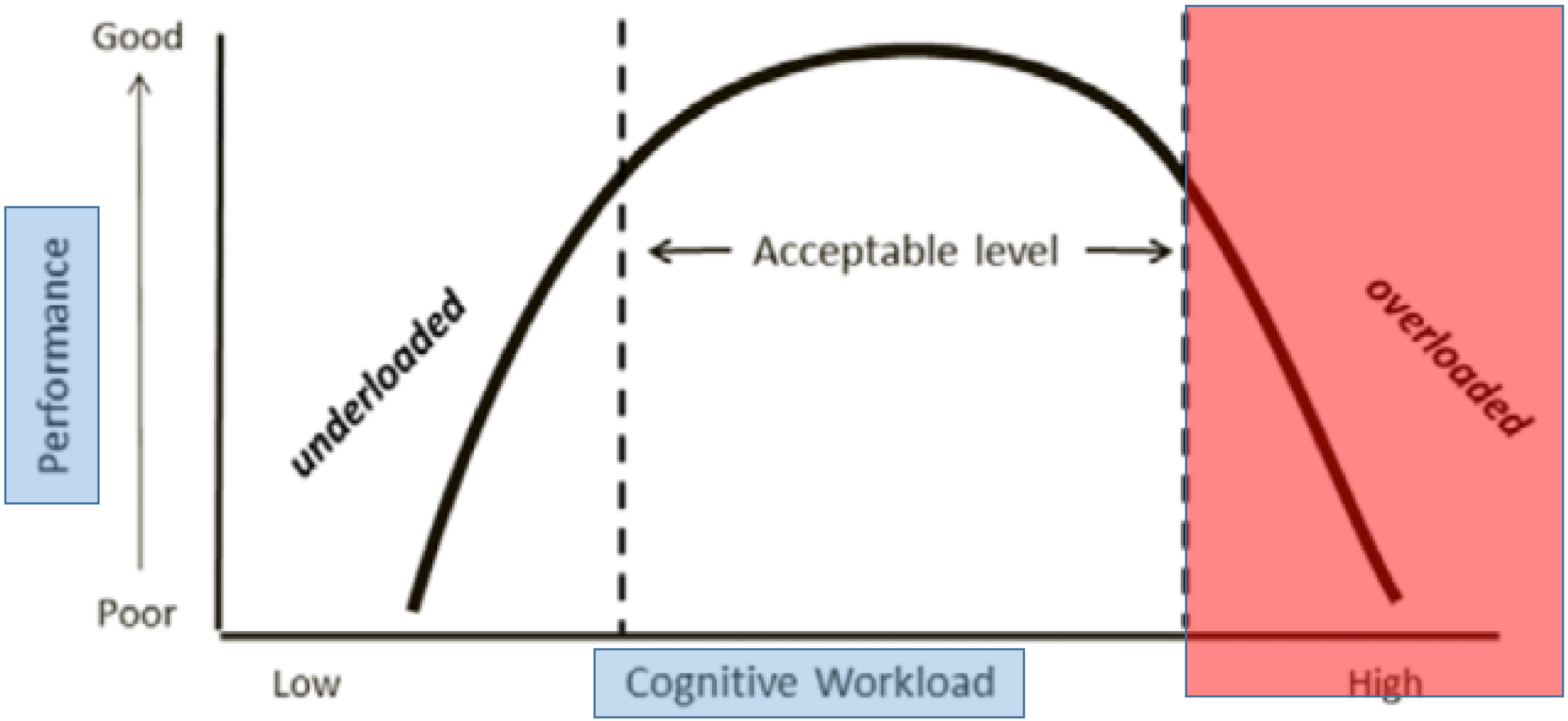
ANIMAL FORAGING		INFORMATION FORAGING
Food	**Goal**	Information
A site containing one or more potential sources of food	**Patch**	A website (or other source of information)
Search for food	**Forage**	Search for information
The animal's assessment of how likely it is that a given patch will provide food	**Scent**	How promising a potential source of information appears to the user
The totality of food types that an animal may consider in order to satisfy hunger	**Diet**	The totality of the information sources that a user may consider in order to satisfy an information need

Limited Human Working-Memory Capacity



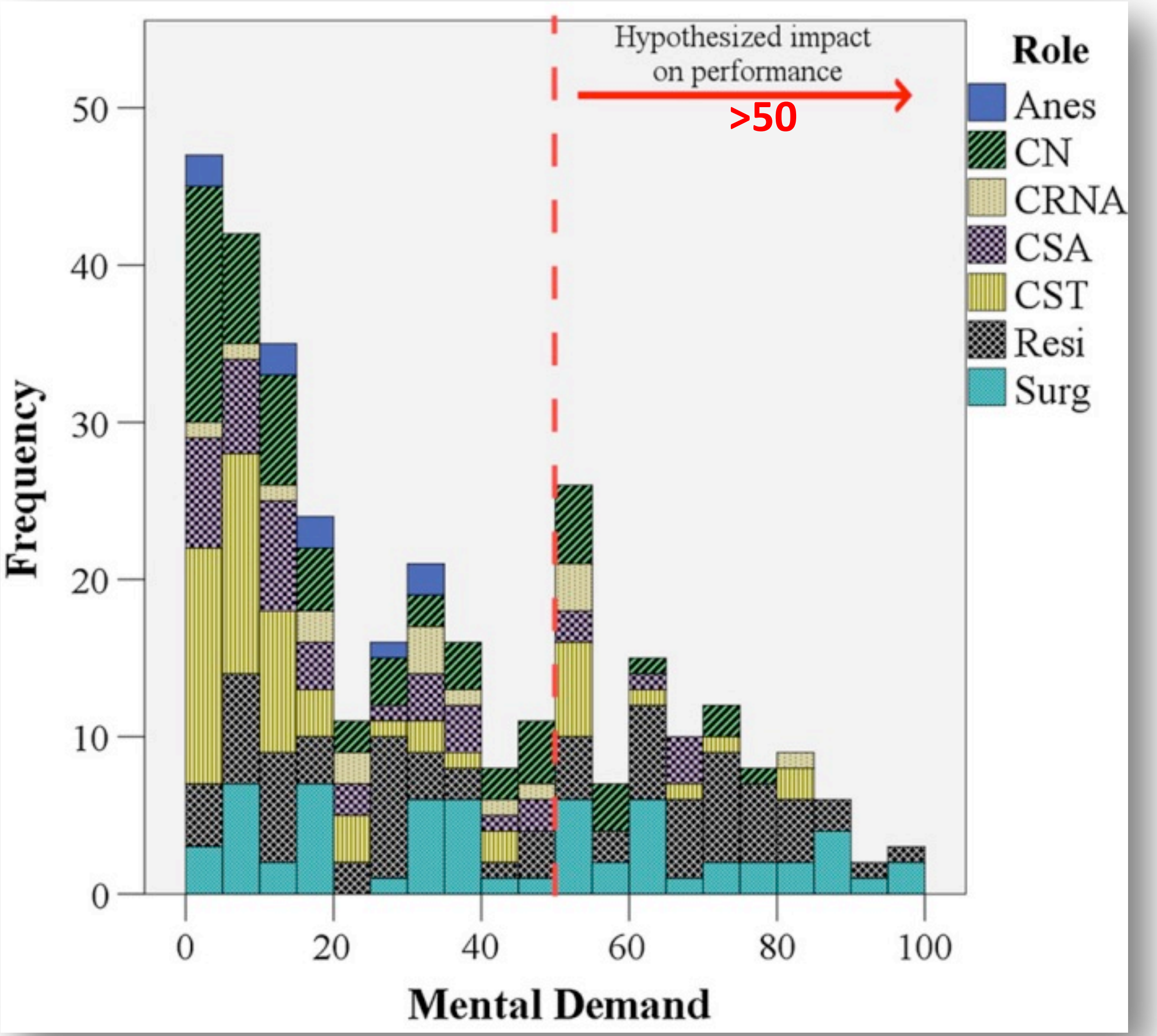
- Surgeon working through a series of steps in a procedure uses working memory store to hold the information.
- Information contained in distractions/interruptions erases the material that the working memory store was holding

Cognitive Load and Performance in Complex Socio-technical Systems



Hebb-Yerkes-Dodson Law 1910

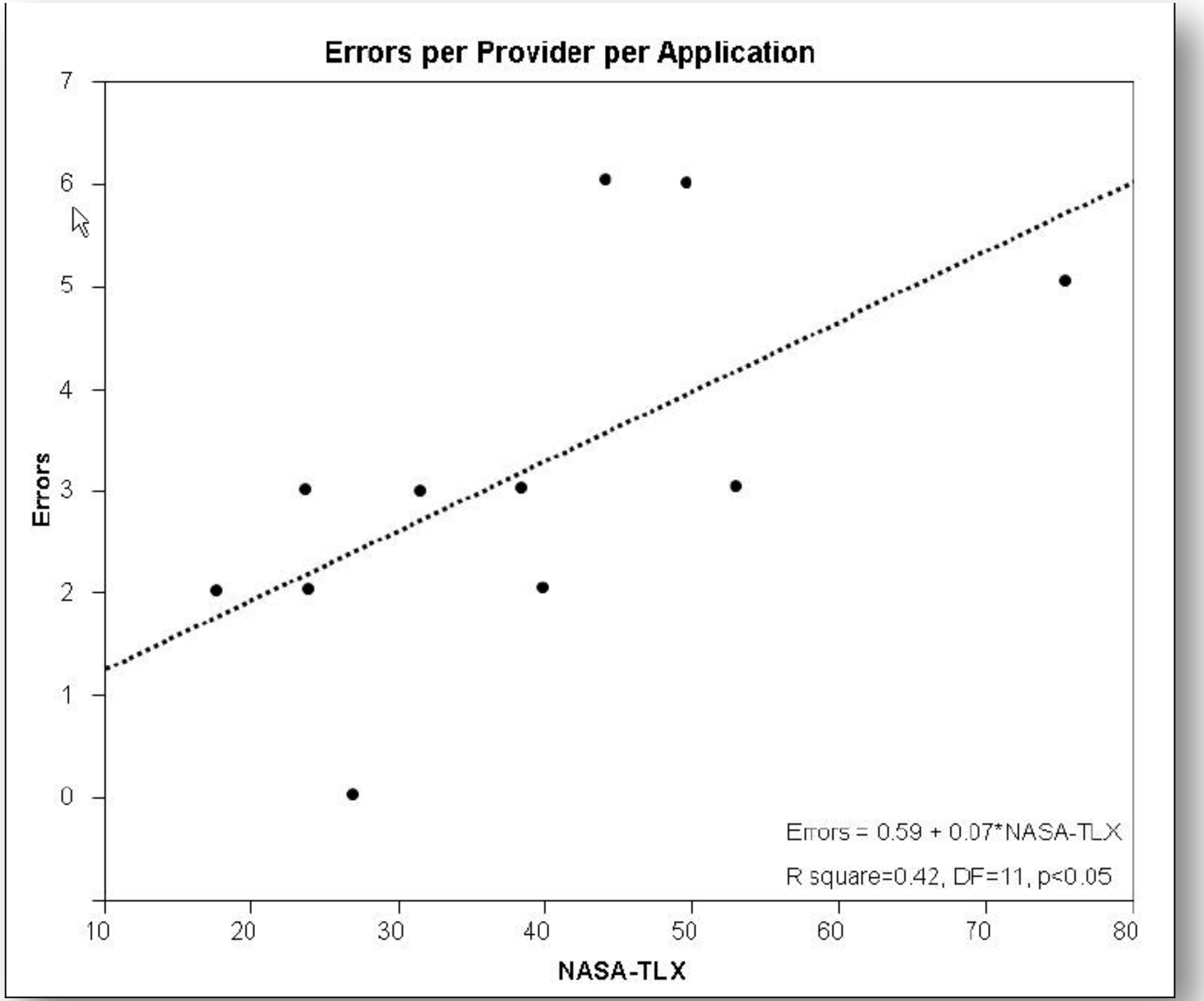
Surgical Team Routinely Cross Mental "Red Zone"



Reckless!?

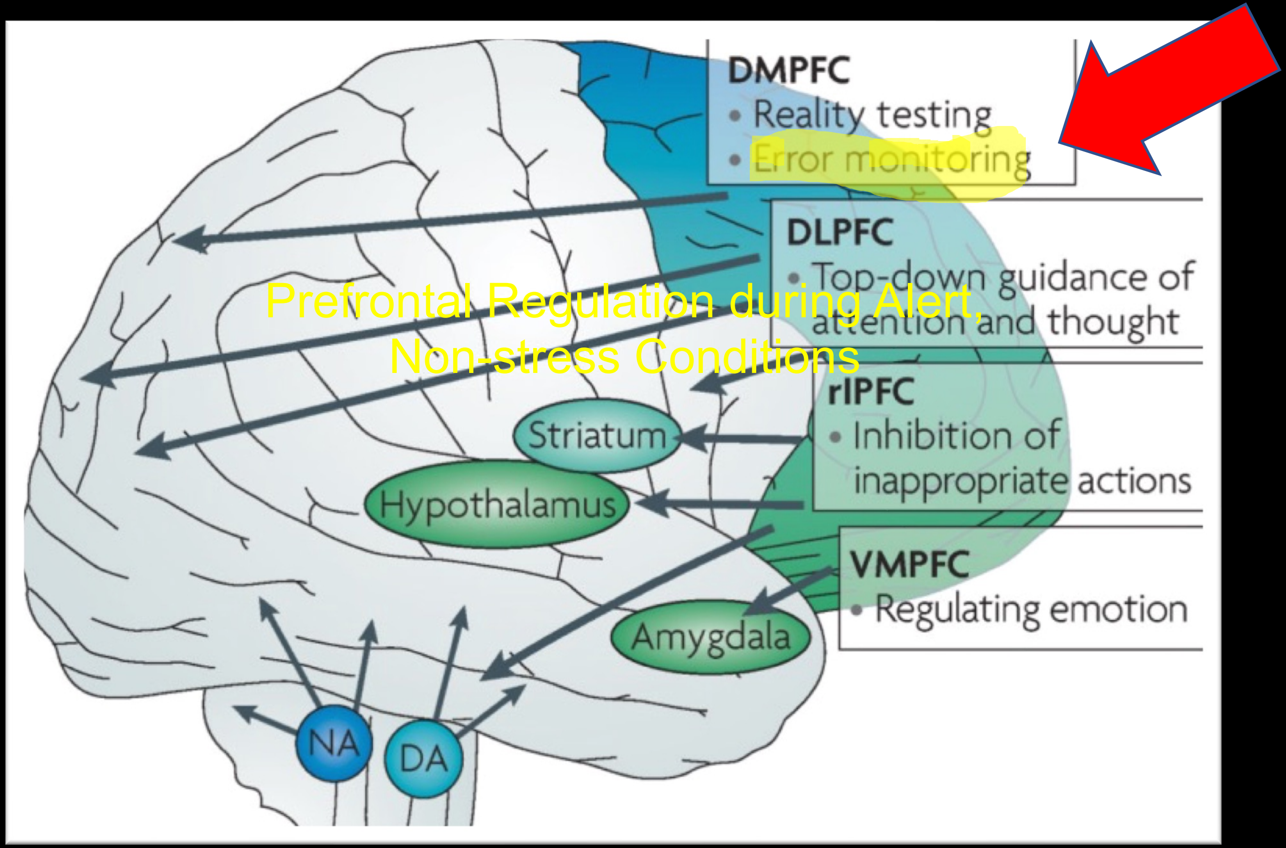
Yu…Hallbeck (Mayo) 2016

Linear Fit Model of Cognitive Load and Medical Error



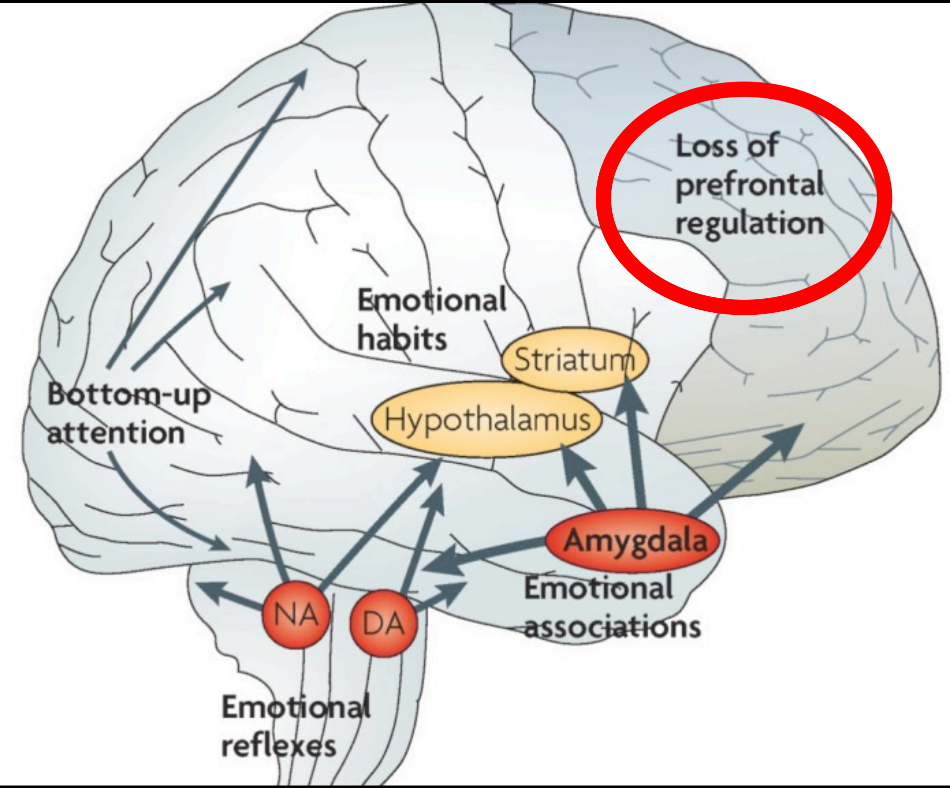
Pickering 2010

Prefrontal Regulation during Alert, Non-stress Conditions

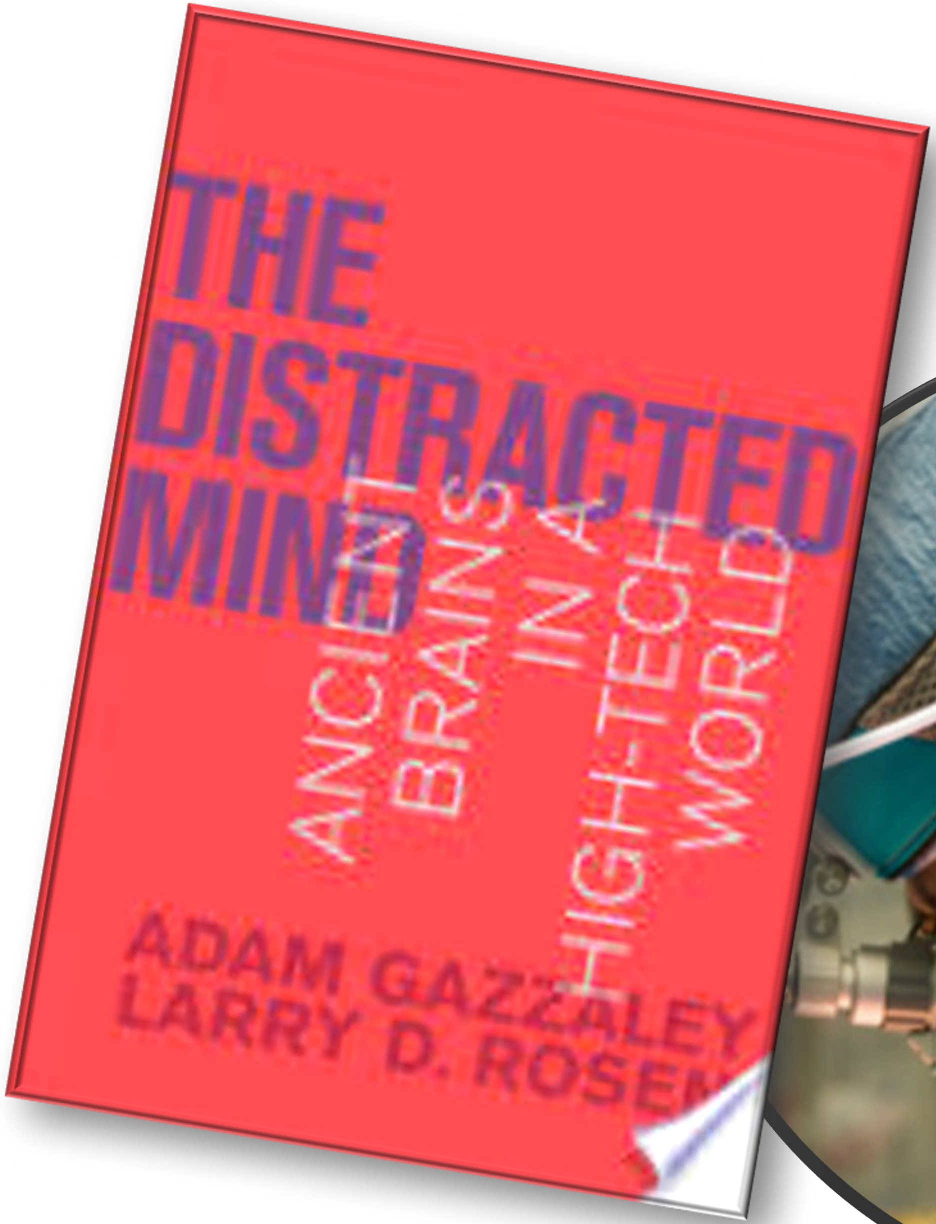


Prefrontal Regulation during Alert,
Non-stress Conditions

Amygdala Hijack during Stress Conditions



Avoidance of PAIN as a driver of human behavior…



MIT Press 2016

Cognitive Engineering

ADULT – State of the Art

Cognitive Engineering to Improve Patient Safety and Outcomes in Cardiothoracic Surgery

Marco A. Zenati, MD,[*,†,‡,§] Lauren Kennedy-Metz, PhD,[*,†,‡,§] and Roger D. Dias, MD, MBA, PhD[‡,¶]

Improved understanding of the cognitive basis of preventable medical errors offers the opportunity to develop new strategies to prevent and mitigate human errors in cardiothoracic surgery.

- Task shedding
- Intelligent interruption system[35]
- Sterile cockpit[36]
- Short breaks[15]
- Team strengthening[15]
- Preincision time-out[37]
- Safety system for device interoperabilty[38]
- Workload-adaptive associate systems
- Cognitive aids for high-risk/low-frequency situations[39]

Zenati et al. Semin Thorac Cardiovasc Surg 2019

The Need

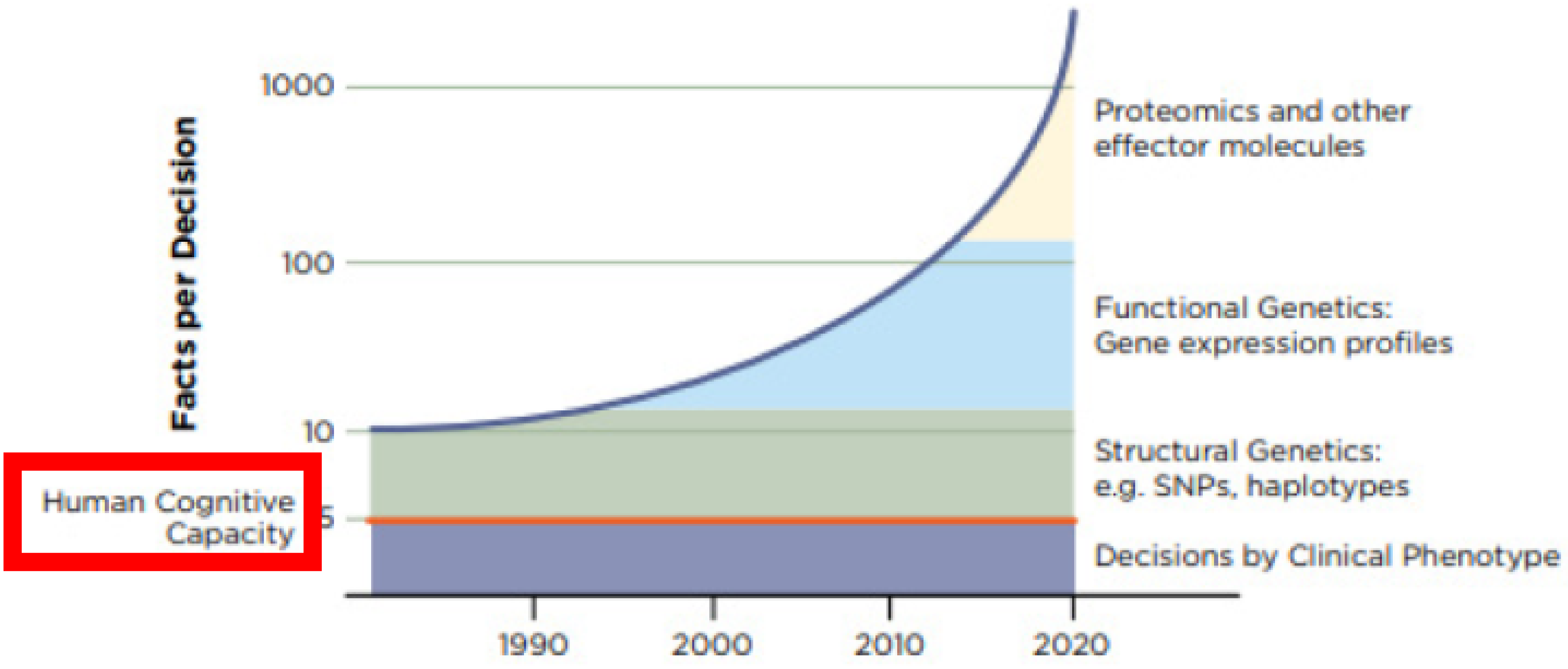
Diagnostic and judgment errors are the second most common cause of preventable harm incurred by surgical patients.

Healey et al 2002

Surgeons report that *lapses in judgment* are the most common cause of their major errors.

Loftus et al. JAMA Surg 2019

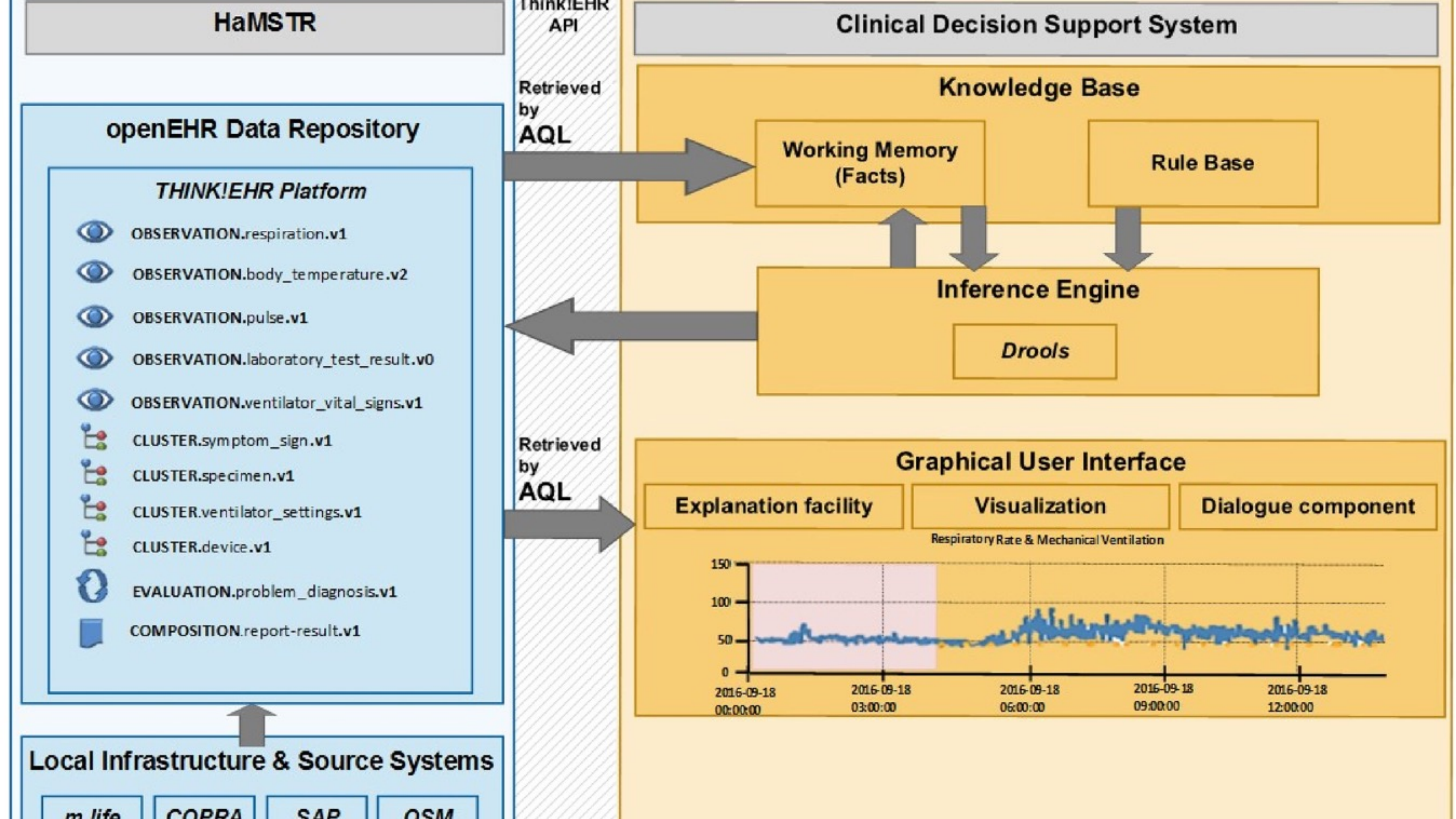
Growth in medical facts affecting provider decision vs. human cognitive capacity



Human Agents Managing Increasingly Complex Work Systems

CDSS - Computerized Decision Support Systems

Support	On Top	Concern	Underlying
• Support processing of large volumes of information facilitating effective decision-making	• On top of EHR, mostly for prescribing and medication management	• Concern for variable clinical impact and alert fatigue	• Underlying knowledge engines need to be maintained as they can quickly become out of date


HaMSTR
Think!EHR API
Clinical Decision Support System
Retrieved by AQL
Knowledge Base
openEHR Data Repository
Working Memory (Facts)
Rule Base
THINK!EHR Platform
OBSERVATION.respiration.v1
OBSERVATION.body_temperature.v2
OBSERVATION.pulse.v1
OBSERVATION.laboratory_test_result.v0
OBSERVATION.ventilator_vital_signs.v1
CLUSTER.symptom_sign.v1
CLUSTER.specimen.v1
CLUSTER.ventilator_settings.v1
CLUSTER.device.v1
EVALUATION.problem_diagnosis.v1
COMPOSITION.report-result.v1
Inference Engine
Drools
Retrieved by AQL
Graphical User Interface
Explanation facility
Visualization
Dialogue component
Respiratory Rate & Mechanical Ventilation
150
100
50
0
2016-09-18 00:00:00
2016-09-18 03:00:00
2016-09-18 06:00:00
2016-09-18 09:00:00
2016-09-18 12:00:00
Local Infrastructure & Source Systems

“Static”* CDSS

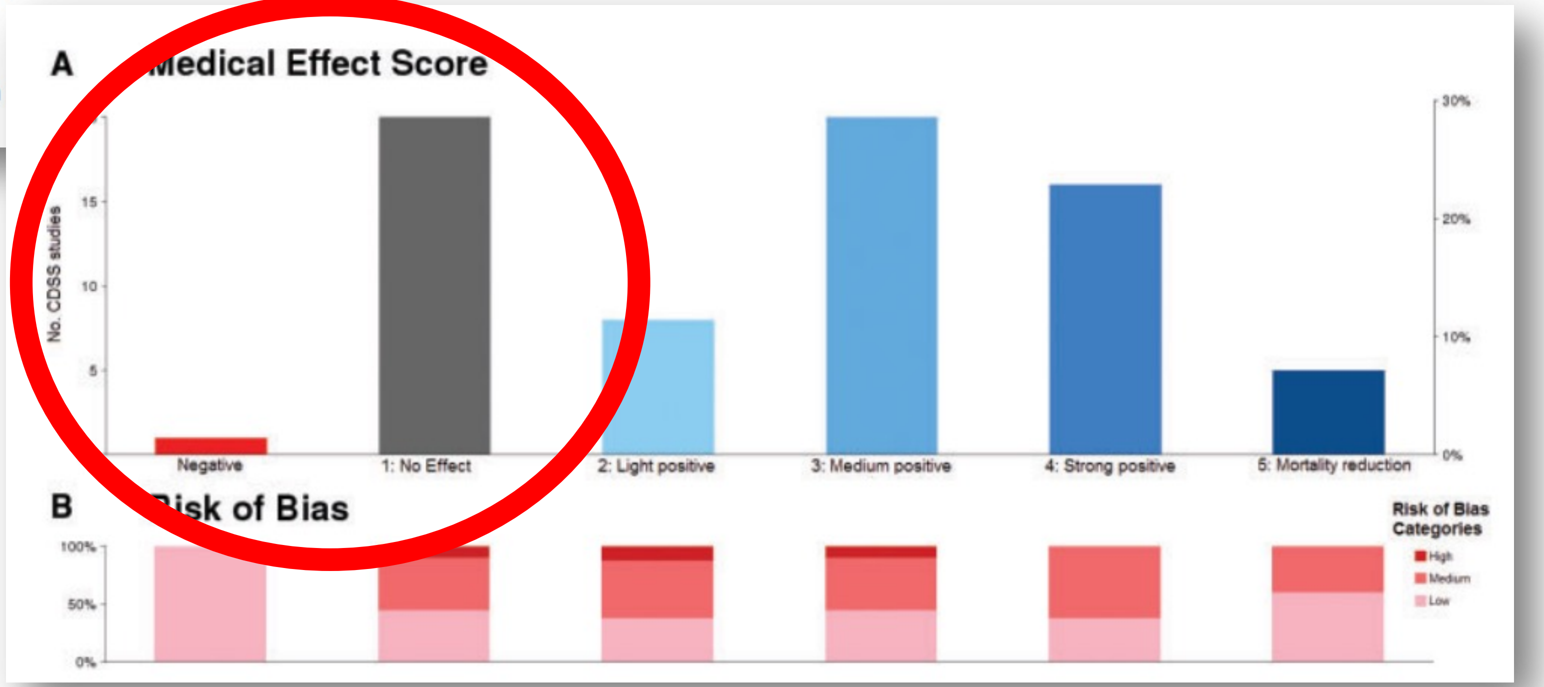
Journal of the American Medical Informatics Association, 25(5), 2018, 593–602
doi: 10.1093/jamia/ocx100
Advance Access Publication Date: 23 September 2017
Review

Review

Effects of computerized decision support system implementations on patient outcomes in inpatient care: a systematic review

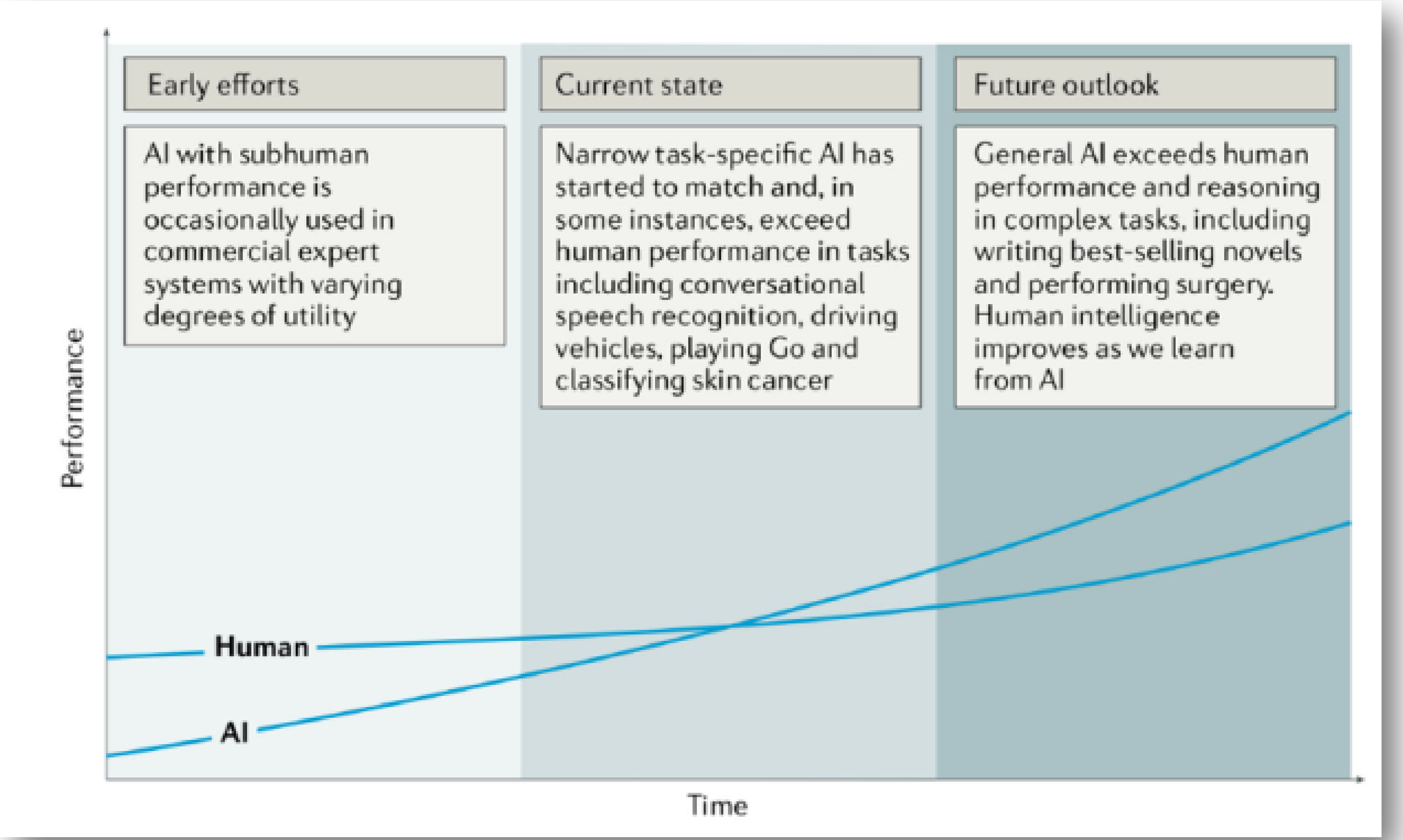
Julian Varghese,[1] Maren Kleine,[2] Sophia Isabella Gessner,[1] Sarah Martin Dugas[1,3]

- ✓ Blood Glucose Management
- ✓ Blood Transfusion Management
- ✓ Physiologic Deterioration Prevention
- ✓ Pressure Ulcer Prevention
- ✓ AKI Prevention
- ✓ VTE Prophylaxis



*CDSS output does not change with use

JAMIA 2018



Hosny et al. Nature Rev Cancer 2018

Challenges in Surgical Decision Making

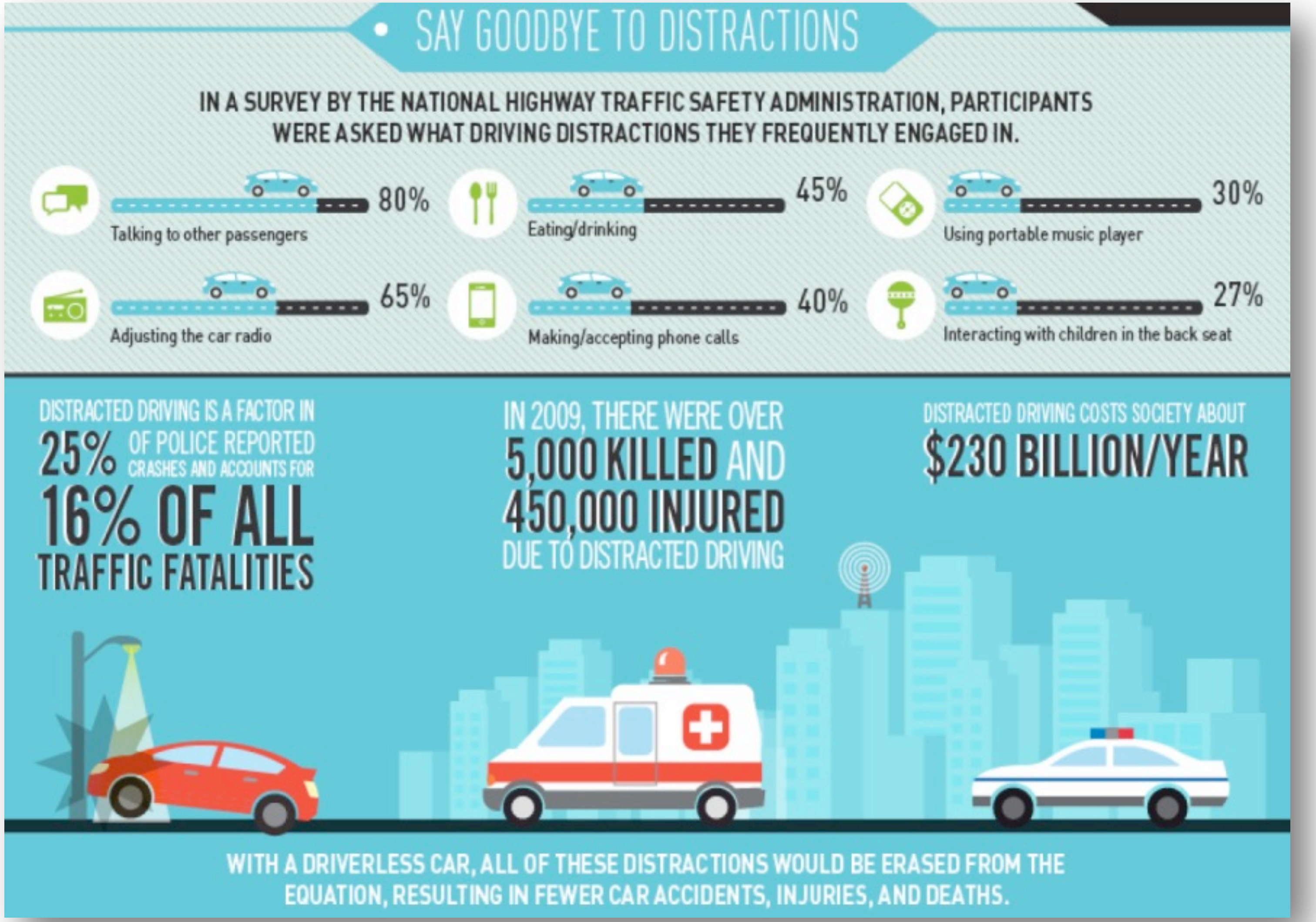
- ✓Complexity
- ✓Values and Emotions
- ✓Time Constraints and Uncertainty
- ✓Heuristics and bias

Source of Bias	Examples
Framing effect	A clinician presents a clinical scenario to a surgeon in different context than the surgeon would have perceived during an independent assessment
Overconfidence bias	A surgeon falsely perceives that weaknesses and failures disproportionately affect their peers
Commission bias	A surgeon tends toward action when inaction may be preferable, especially in the context of overconfidence bias
Anchoring bias	Patients are informed of expected outcomes using data from aggregate patient populations without adjusting for their personalized risk profile
Recall bias	Recent experiences with a certain patient population or operation disproportionately affect surgical decision-making relative to remote experiences
Confirmation bias	Outcomes are predicted using personal beliefs rather than evidence-based guidelines

The Solution


ORIGINAL
U.S. RESTAURANT
U.S. RESTAURANT
UNIONE SPORTIVA
ORIGINAL U.S. RESTAURANT
CUCINA ITALIANA
BIORDI
BIORDI ART IMPORTS
420
WAYMO
JAGUAR

Rationale for Autonomous Vehicles (AV)



SAFETY

Perceptions of General Surgeons on AI

17% I have made clinical use of AI

27% I follow AI developments

Which application of AI in the OR has the greatest potential?

58% Image processing

24% Guidance

Who should be liable if an AI tool is used?

83% The Surgeon

Would you have a fully autonomous gallbladder surgery in the future?

69% Yes

Survey sent to Dutch Association of Surgeons. 313 surgeons responded (17%). % rounded to nearest whole number.

AIS *Artificial Intelligence Surgery*

Voskens et al., Jan 2022

AI/ML-flown uncrewed aircraft solving a tactically relevant "*challenge problem*" during airborne operations

Artificial Intelligence agents (algorithms) controlling a **XQ-58A Valkyrie uncrewed aircraft**.
USAF July 2023

CCA: Collaborative Combat Aircraft

Advances in both *data capture in the operating room* and explainable artificial intelligence (XAI) techniques to process these data open the way for

REAL-TIME CLINICAL DECISION SUPPORT
AI (Adaptive)-CDSS

that can help surgical teams anticipate, understand, and prevent intraoperative events.

WINDOW of OPPORTUNITY

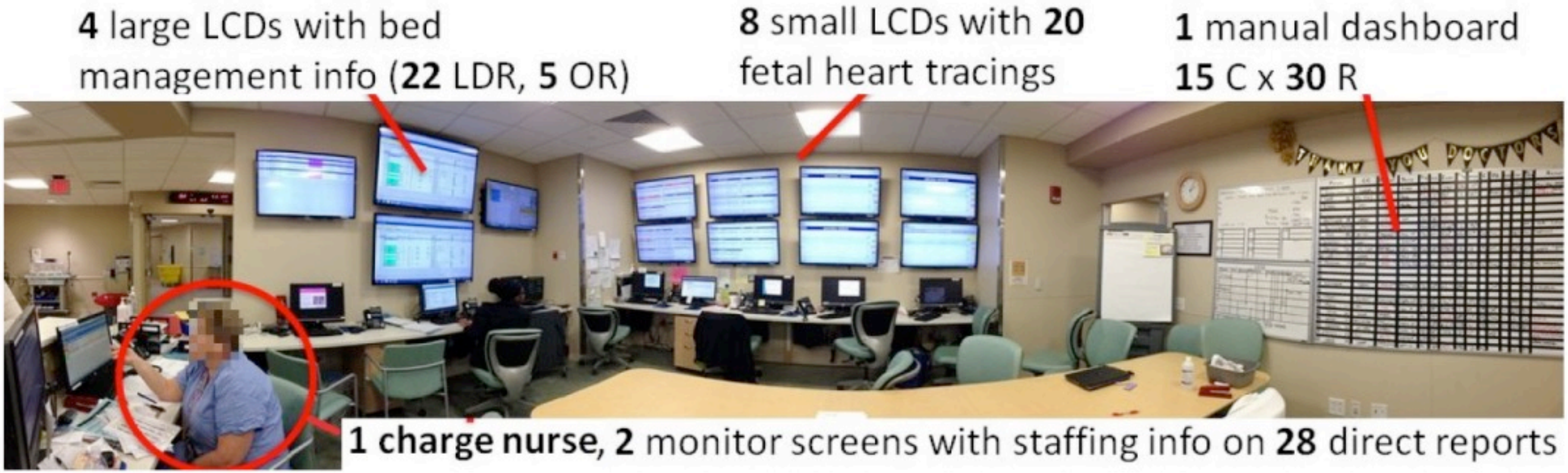
Surgical “**Hybrid Decision Support System**”

AI models, fed with live-streaming data, would:

(*a*) *obviate* human surgical decision-making weaknesses and

(b) should be *integrated* with human intuition to *augment* surgical decision-making

OBGYN/Labor&Delivery Unit
Resource Nurse solving an NP-hard problem



- Stochasticity of patient progression
- Upper and lower-bound temporal constraints

Gombolay et al. 2016

e coordination of

The International Journal of
Robotics Research
2018, Vol. 37(10) 1300–1316

DOI: 10.1177/0278364918778344
journals.sagepub.com/home/ijr
SAGE

g[1], Bradley Hayes[1], Nicole Seo[1],
a Yu[1], Neel Shah[2], Toni Golen[2] and Julie Shah[1]

Gombolay et al. Int J Robotics Research 2018

Apprenticeship Scheduling: Learning to Schedule from Human Experts

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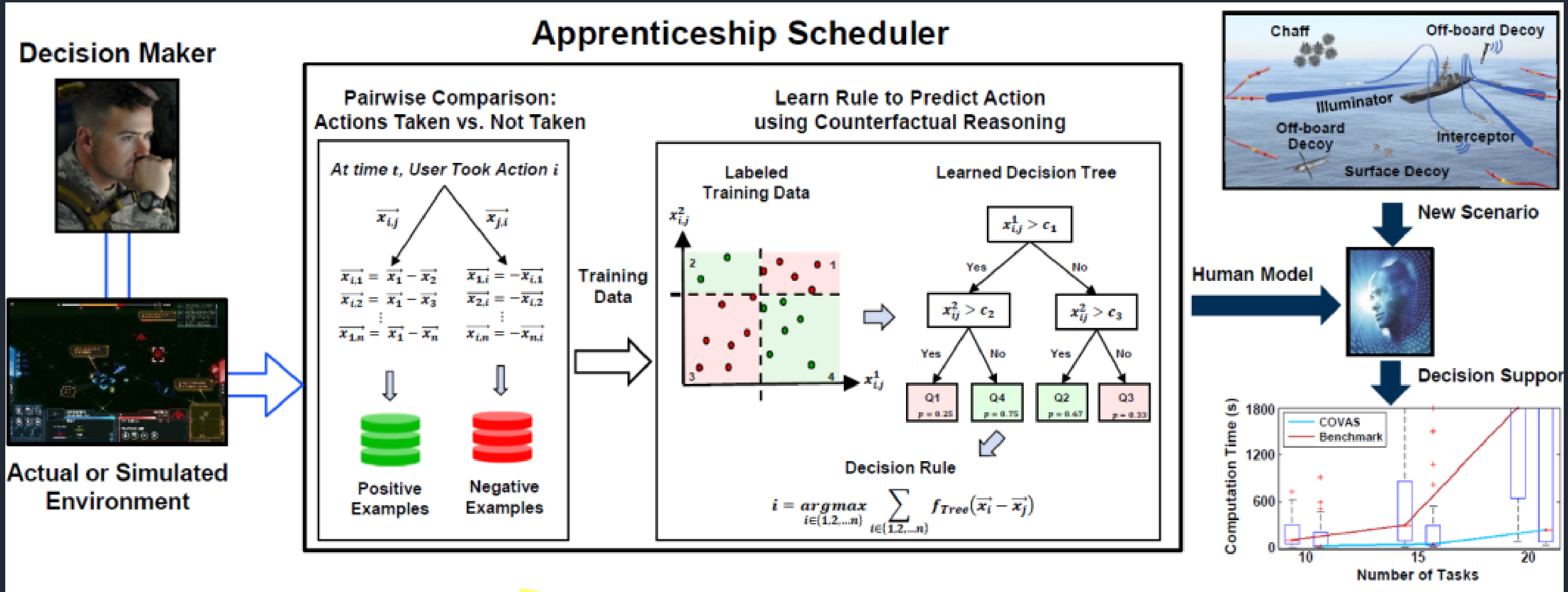


Learn from imperfect human demonstration on simpler problems to optimally solve more complex problems 10x faster

Learning from Human Demonstrations

Classic Learning Paradigm

- Domain experts & engineers work together
- Transfer domain knowledge, then design algorithm

Challenge: domain expertise is **hard to verbalize**.

Challenge: **not enough engineers to code every use case**.

Reinforcement Learning (RL)

- Domain experts and engineers design cost function
- Allow the AI/robot to learn by itself

Challenge: cost function is HIGHLY non-trivial to design

Challenge: RL's learning from trial&error in healthcare??

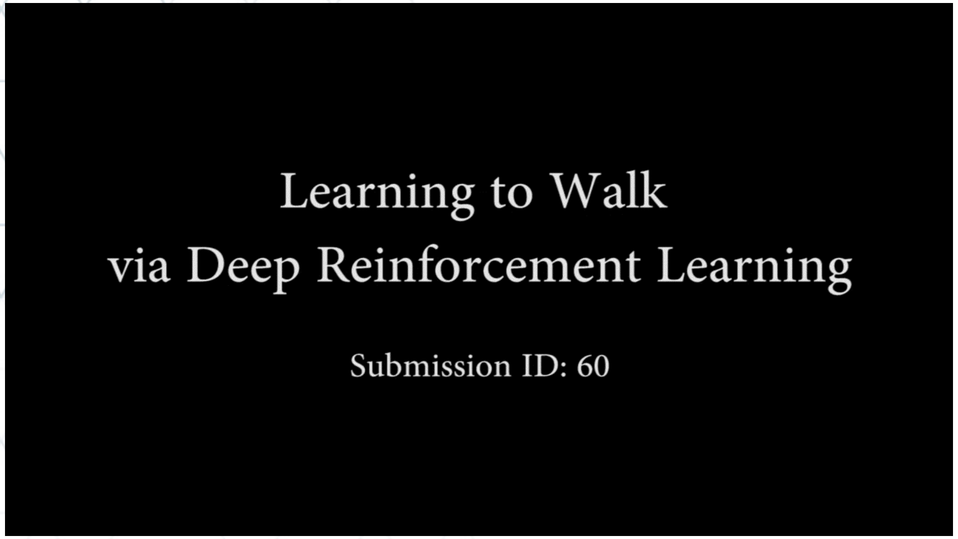


Figure Credit: https://www.zdnet.com/article/yes-robots-have-taken-over-so-why-dont-we-care/, Haarnoja, T., Ha, S., Zhou, A., Tan, J., Tucker, G., & Levine, S. (2018). Learning to walk via deep reinforcement learning. arXiv preprint arXiv:1812.11103.

Learning from Human Demonstrations

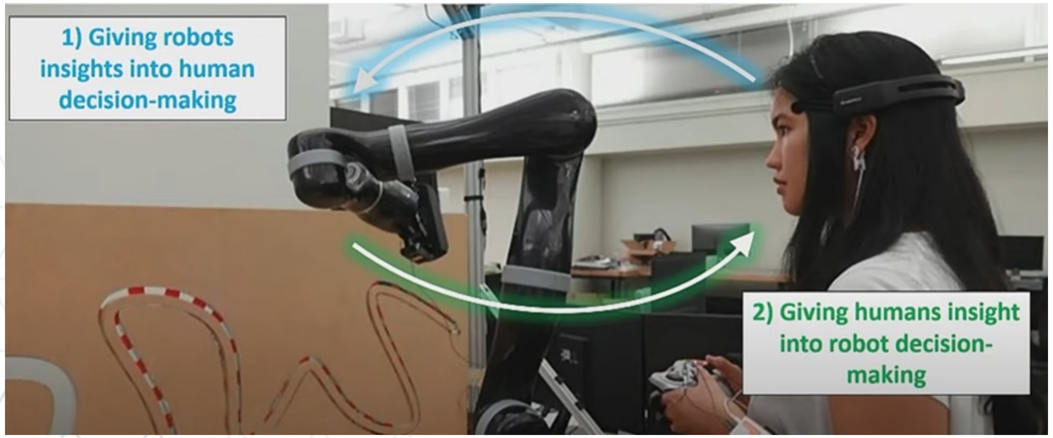
Learning from Demonstration (LfD)

- Allow domain experts to directly program AI/robots through demonstrations
- Intuitive, scalable, and personalizable

Solution: Domain knowledge is easier to demonstrate!

Three forms for LfD

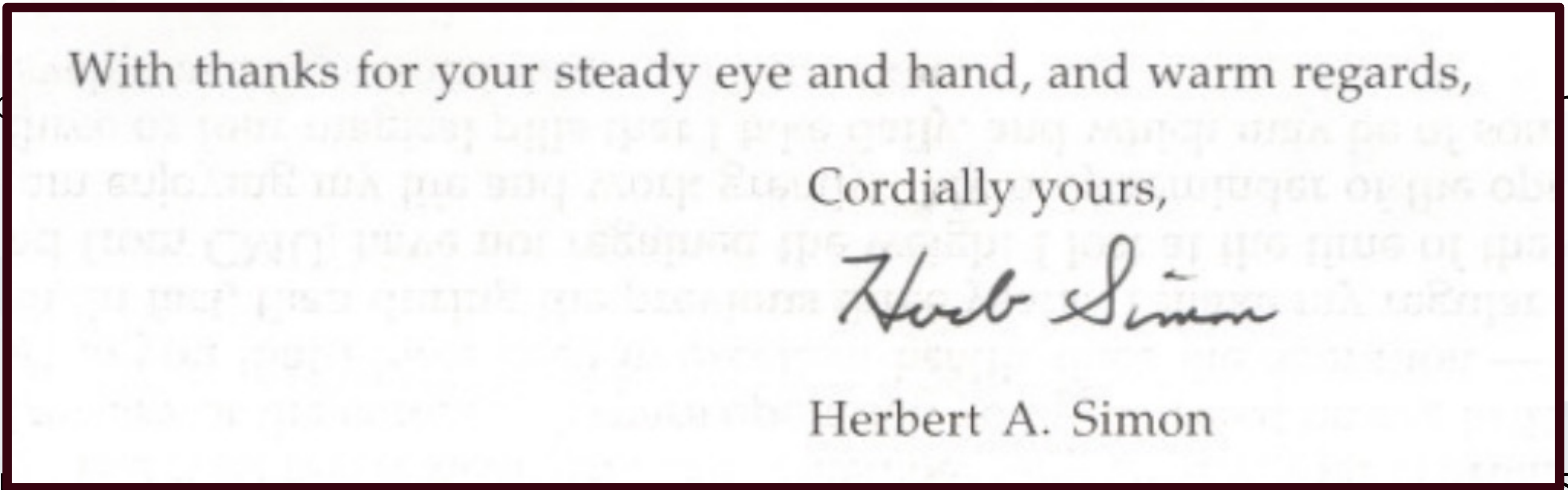
- **Mimicry** – Supervised Learning
- **Emulation** – Goal inference and planning
- **Imitation learning** – **Inverse Reinforcement Learning**



Human demonstrations are not ideal!

Variable, suboptimal demonstrations

- Humans often adopt heuristics due to limited cognitive abilities (Herb Simon 1972)



With thanks for your steady eye and hand, and warm regards,

Cordially yours,

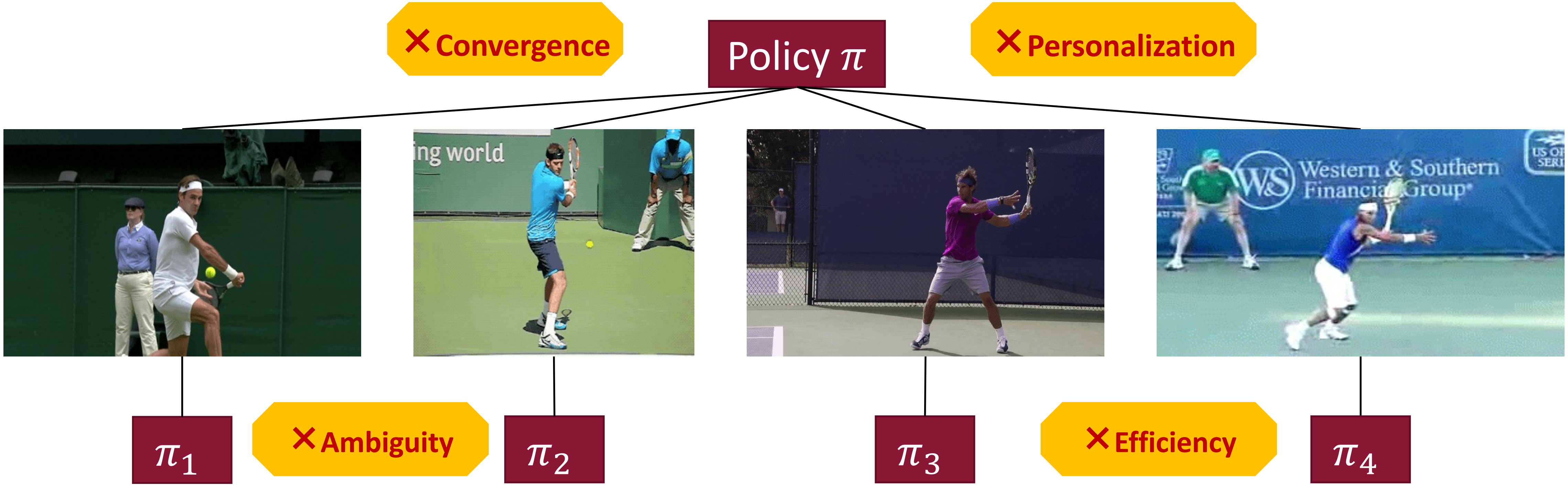
Herb Simon

Herbert A. Simon

- Variab … he goal
- Subop … stics

Learning from Variable Demonstrations

- Ignore the variability -> learned model may not perform well, lose personalization

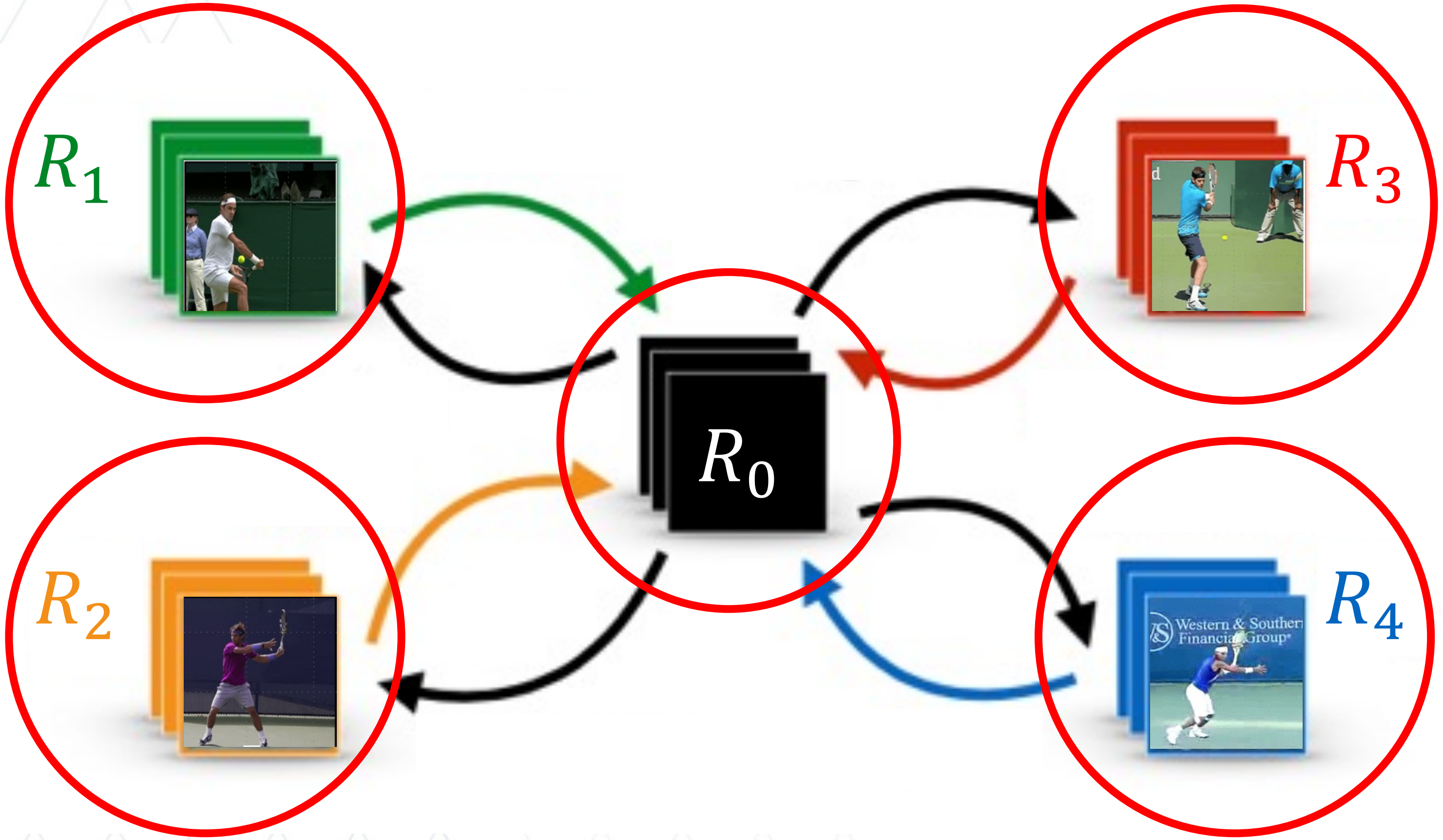


- **Learn a policy for each demonstration separately** -> a single demo conveys an ambiguous intention and learning from scratch is not efficient.

Learning from Variable Demonstrations

- **Multi-Strategy Reward Distillation (MSRD)**
  - $\boldsymbol{R_0}$: shared task reward
  - $\boldsymbol{R_i}$: specific strategy $\boldsymbol{i}$'s reward

L. Chen, R. Paleja, M. Ghuy, and **M. Gombolay**, "*Joint goal and strategy inference across heterogeneous demonstrators via reward network distillation*," in Proceedings of International Conference on Human-Robot Interaction (HRI), 2020



AI Coach in OBGYN Labor&Delivery

- Formulation of the "*Resource Nurse Decision Making Problem*"
- Role of the Resource Nurse
- Learning from Resource Nurse

$$\min fn\left(\{{}^{t}A^{a}_{\tau_i^j}\},\{{}^{t}G^{a}_{\tau_i^j}\},\{{}^{t}R^{r}_{\tau_i^j}\},\{H_{\tau_i}\},\{s_{\tau_i^j},f_{\tau_i^j}\}\right)$$

$$\sum_{a\in A}{}^{t}A^{a}_{\tau_i^j}\geq 1-M\left(1-H_{\tau_i}\right),\forall\tau_i^j\in\boldsymbol{\tau},\forall t$$

$$M\left(2-{}^{t}A^{a}_{\tau_i^j}-H_{\tau_i}\right)\geq -U_{\tau_i^j}+{}^{t}G^{a}_{\tau_i^j}\geq$$
$$M\left({}^{t}A^{a}_{\tau_i^j}+H_{\tau_i}-2\right),\forall\tau_i^j\in\boldsymbol{\tau},\forall t$$

$$\sum_{\tau_i^j\in\boldsymbol{\tau}}{}^{t}G^{a}_{\tau_i^j}\leq C_a,\forall a\in A,\forall t$$

$$\sum_{r\in R}{}^{t}R^{r}_{\tau_i^j}\geq 1-M\left(1-H_{\tau_i}\right),\forall\tau_i^j\in\boldsymbol{\tau},\forall t$$

$$\sum_{\tau_i^j\in\boldsymbol{\tau}}{}^{t}R^{r}_{\tau_i^j}\leq 1,\forall r\in R,\forall t$$

$$ub_{\tau_i^j}\geq f_{\tau_i^j}-s_{\tau_i^j}\geq lb_{\tau_i^j},\forall\tau_i^j\in\boldsymbol{\tau}$$

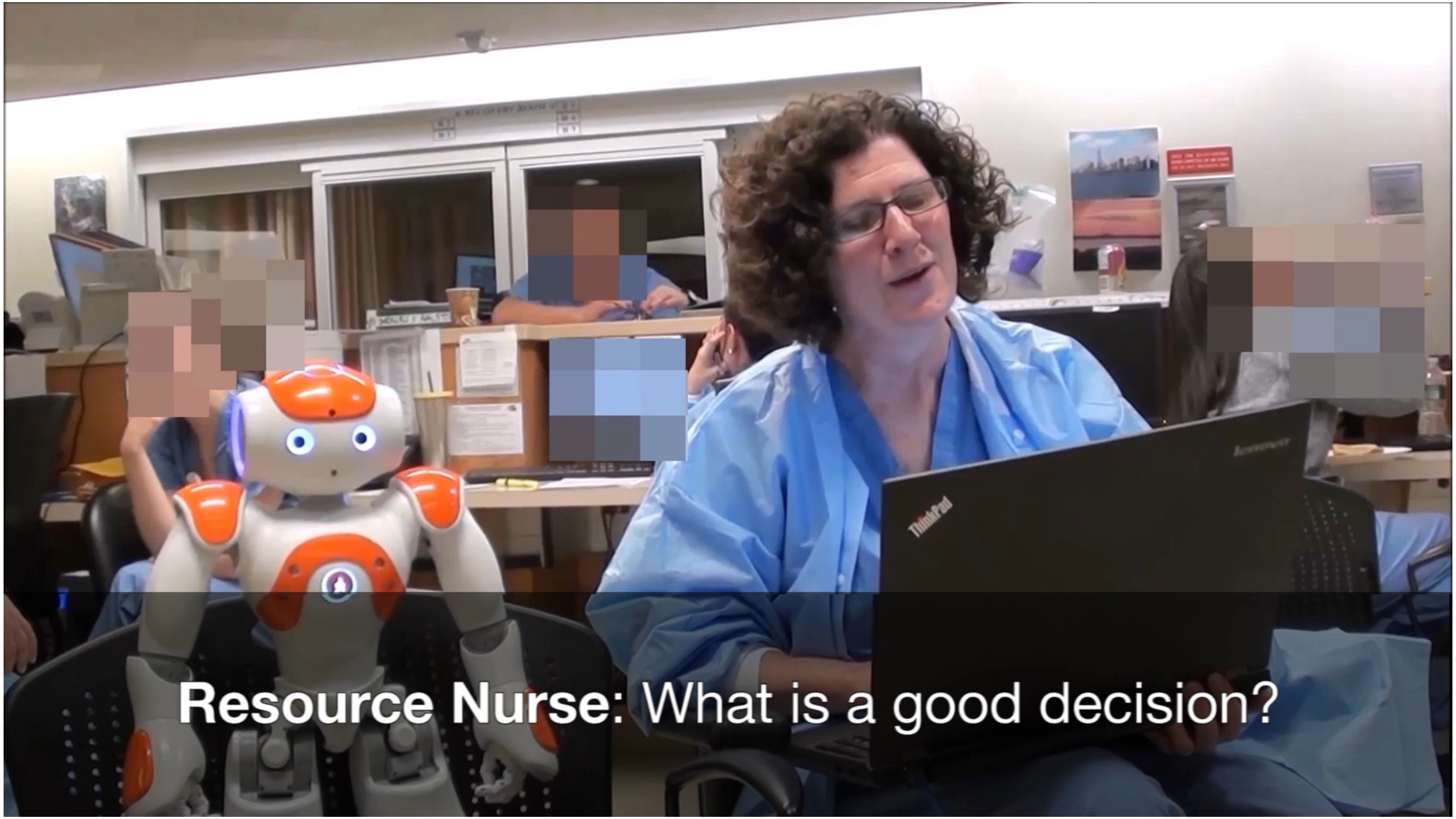
$$s_{\tau_x^y}-f_{\tau_i^j}\geq W_{\langle\tau_i,\tau_j\rangle},\forall\tau_i,\tau_j\in\boldsymbol{\tau}|,\forall W_{\langle\tau_i,\tau_j\rangle}\in\boldsymbol{TC}$$

$$f_{\tau_x^y}-s_{\tau_i^j}\leq D^{rel}_{\langle\tau_i,\tau_j\rangle},\forall\tau_i,\tau_j\in\boldsymbol{\tau}|\exists D^{rel}_{\langle\tau_i,\tau_j\rangle}\in\boldsymbol{TC}$$

$$f_{\tau_i^j}\leq D^{abs}_{\tau_i},\forall\tau_i\in\boldsymbol{\tau}|\exists D^{abs}_{\tau_i}\in\boldsymbol{TC}$$

Gombolay et al. 2016

Robotic Coordination of Patient Care in OBGYN



Courtesy of Julie Shah MIT

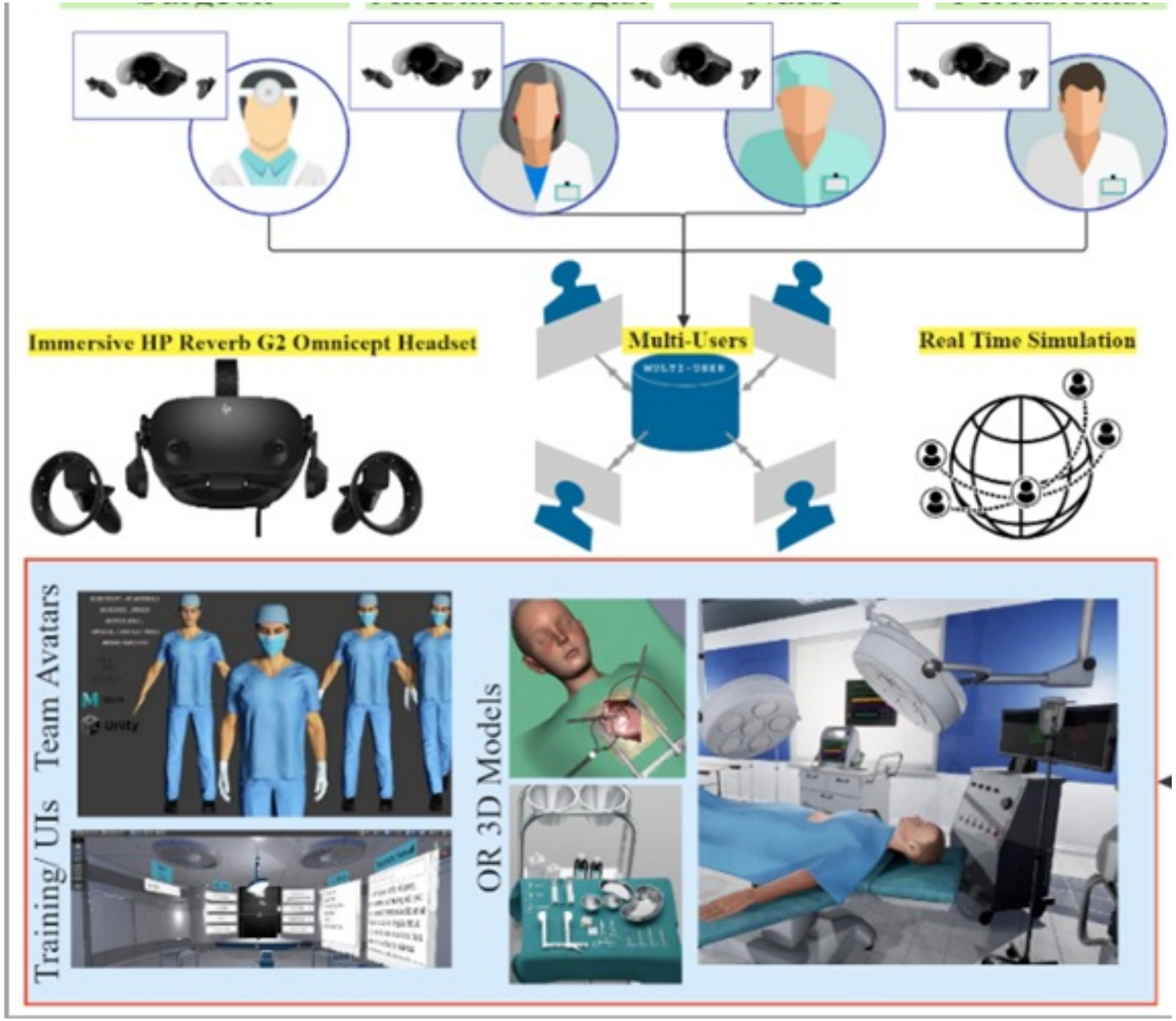
Nao: A humanoid robot

Created by Aldebaran Robotics in France (2008)
https://www.softbankrobotics.com/us/NAO

Digital Human Avatars

https://www.youtube.com/shorts/rRgPOx1aJdQ

Project SOAR: Simulation of Operating Room Non-Technical Skills in Immersive Virtual Environments (AHRQ R18 Zenati/Ebnali 2023)



OR/VR Team:
Mix of Human Avatars + Digital Avatar Agent

Teamwork in the Cardiac Operating Room

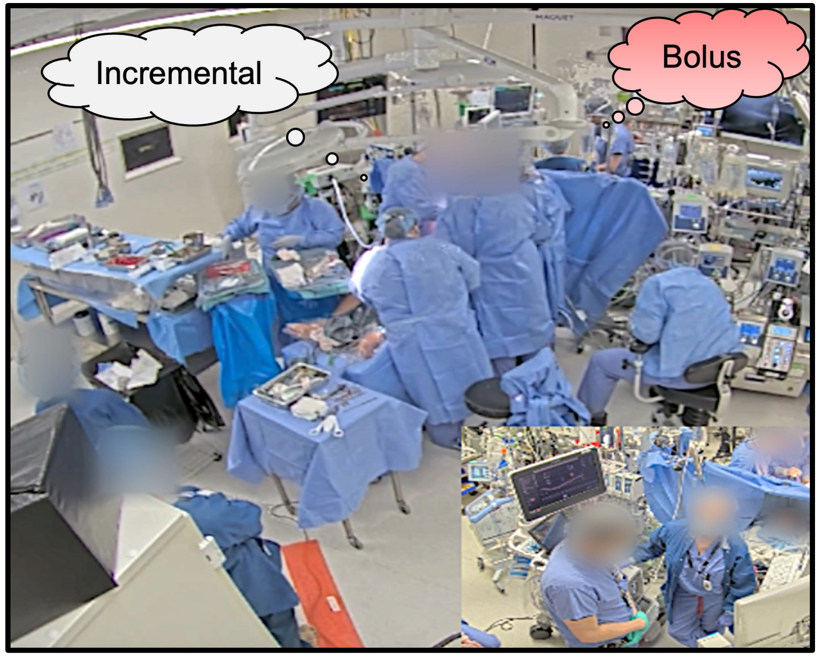
Status Quo and Opportunities for AI

Enhancing Teamwork in the Cardiac OR

Opportunities for Artificial Intelligence

We envision an AI-enabled assistant (called **AI Coach**) that can provide **automated real-time assessment of surgical teamwork** to enhance teamwork and mitigate preventable errors.

- Observe team behavior using multi-modal sensors.
- Model teamwork using the recorded data.
- Assess teamwork using the team model and data.
- Generate interventions to improve teamwork.



Predict misalignment in team members' mental models from sensed multi-modal data.

References:

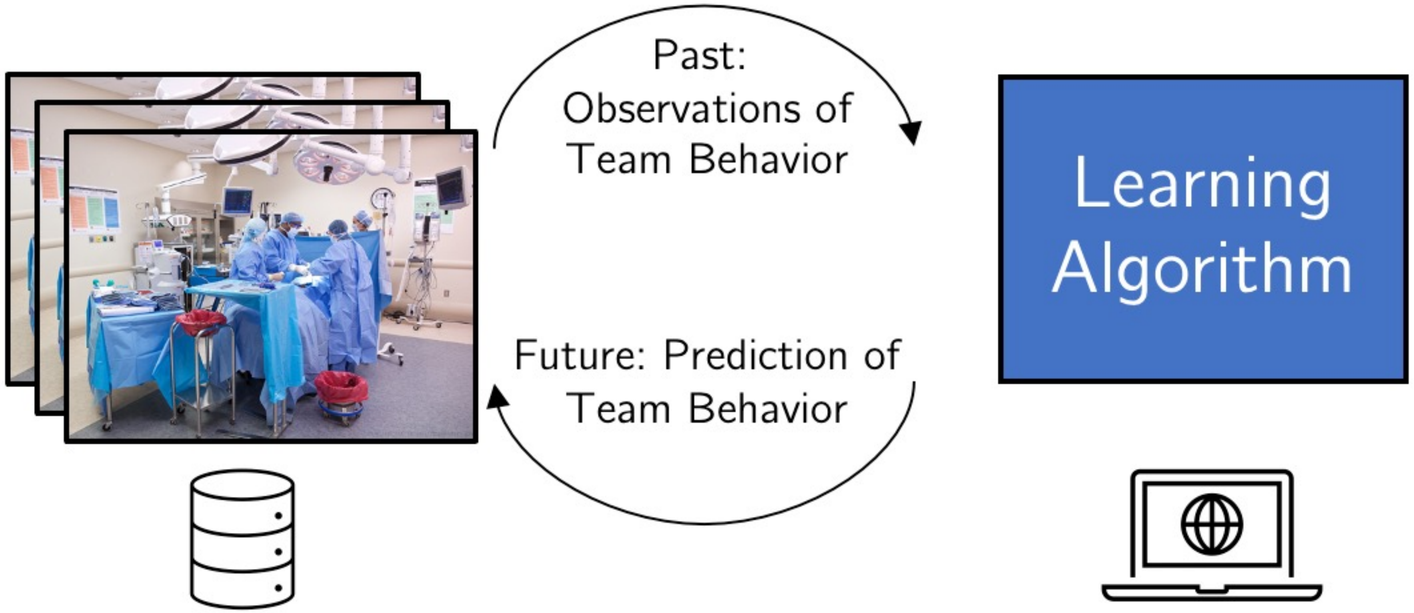
Seo, S., Kennedy-Metz, L. R., Zenati, M. A., Shah, J. A., Dias, R. D., & Unhelkar, V. V. (2021, May). Towards an AI coach to infer team mental model alignment in healthcare. In *2021 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA)* (pp. 39-44).

Generative Models of Surgical Teamwork

Multi-Modal Team Imitation Learning

Research Problem

Learning Generative Models of Surgical Team Behavior



Multi-Modal Measurements of Teamwork

Desiderata: Informative, Unintrusive, Privacy Preserving

References:

1. Kennedy-Metz, L. R., Dias, R. D., Srey, R., Rance, G. C., Furlanello, C., & Zenati, M. A. (2020).
   Sensors for continuous monitoring of surgeon's cognitive workload in the cardiac operating room. *Sensors*, *20*(22), 6616.

2. Dias, R. D., Kennedy-Metz, L. R., Yule, S. J., Gombolay, M., & Zenati, M. A. (2022, June).
   Assessing Team Situational Awareness in the Operating Room via Computer Vision.
   In *2022 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA)* (pp. 94-96). IEEE.

Representing Team Behavior

Model: Multi-agent Markov Decision Processes

Surgical Team

Team's behavior summarized by their policy,

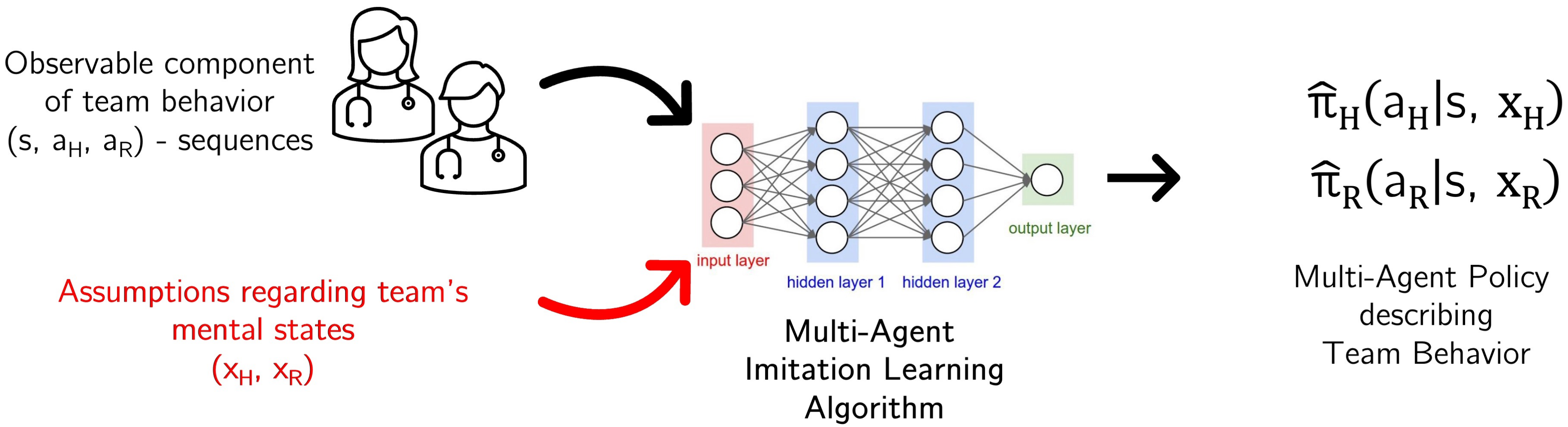
$$\pi(a|s,x)$$

Actor's
actions or decisions

Decision factors (states) that
influence the actor's behavior

Multi-Agent Imitation Learning

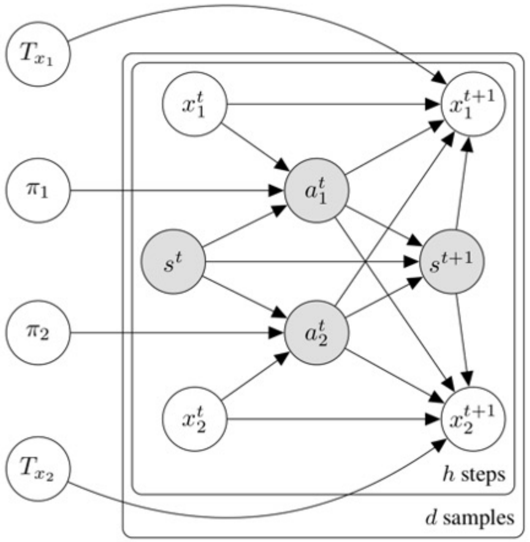
Prior Art: Learning Generative Models of Team Behavior



Prior work either does not model team members' mental states or assume the team members are always in agreement ($x_H = x_R$).

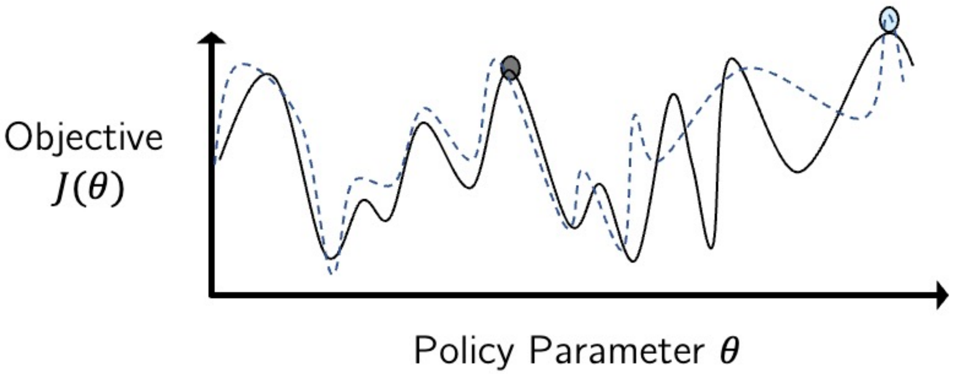
Solution: Bayesian Team Imitation Learning

Key Insights



Insight #1:
Add bias through priors
and probabilistic structure

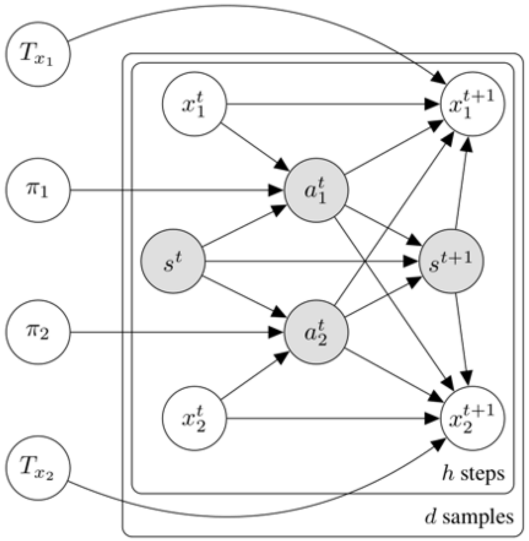
$$\Pr(\theta|s, x, a) \propto \Pr(s, x, a|\theta)\Pr(\theta)$$



Insight #2:
Enable semi-supervised learning
via Bayesian techniques

Solution: Bayesian Team Imitation Learning

Key Components



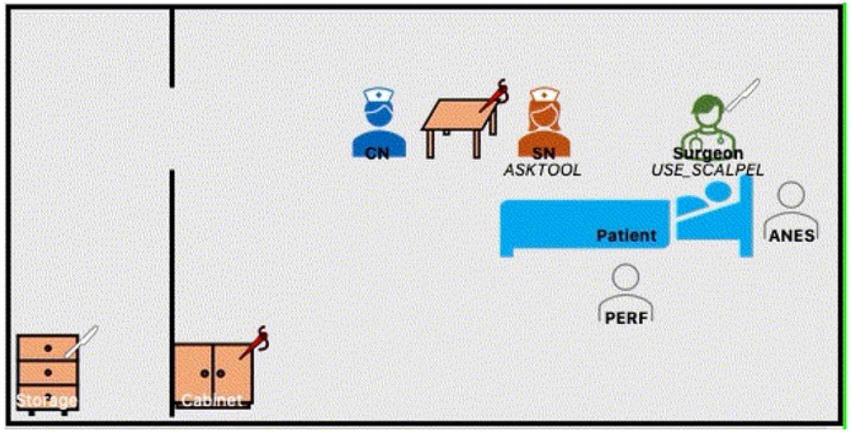
Algorithm 1 Bayesian Team Imitation Learner (BTIL)

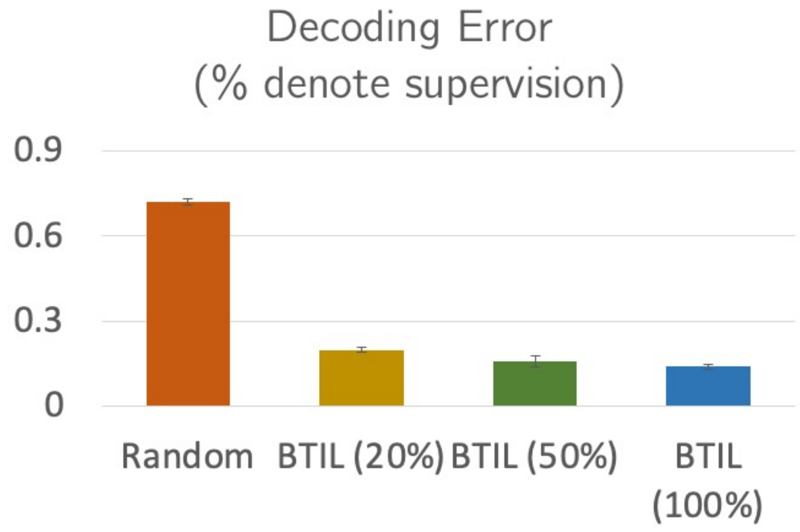
Input: $\tau_{1:d}, \chi_{1:l}$
Parameters: u^{π}, u^{T_x}, N, T_s

Initialize $w_i^{\pi}, w_i^{T_x}$ for $i = 1 : n$
Initialize posterior of all unlabeled states $q(\{x_m^{0:h}\}_{m>l})$
while $\mathcal{L}(\mathrm{q})$ converges **do**
    Update the variational parameters $w_{1:n}^{\pi}, w_{1:n}^{T_x}$
    for all τ_m **do**
        Compute forward F and backward B messages
        Update posterior of all unlabeled states $q(\{x_m^{0:h}\}_{m>l})$
    end for
end while
Compute the policy posterior $q(\pi) \sim \mathrm{Dir}(w_i^{\pi})$
return $\arg\max_{\pi} q(\pi)$

Our solution includes a generative model of team behavior (left) and a Bayesian multi-agent learning algorithm (right) to learn team policies from semi-supervised and suboptimal demonstrations.

Experimental Results





BTIL can effectively utilize available partial annotation of latent features to learn policies.

Results on human subject data collected in silico on a benchmark teaming task. More details available in:

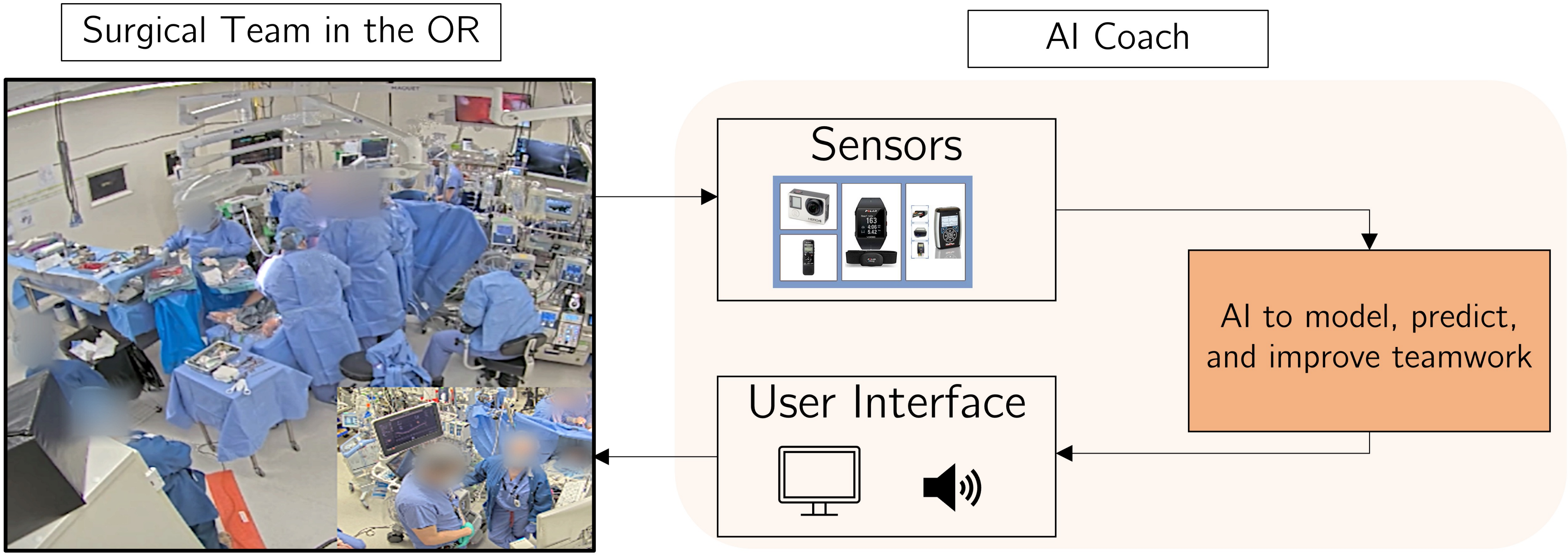
1. Seo, S., Kennedy-Metz, L. R., Zenati, M. A., Shah, J. A., Dias, R. D., & Unhelkar, V. V. (2021, May). Towards an AI coach to infer team mental model alignment in healthcare. In *2021 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA)* (pp. 39-44).
2. Seo, S., & Unhelkar, V. V. Semi-Supervised Imitation Learning of Team Policies from Suboptimal Demonstrations. In 2022 *International Joint Conference on Artificial Intelligence (IJCAI).*

Towards Automated Team Assessment and Training

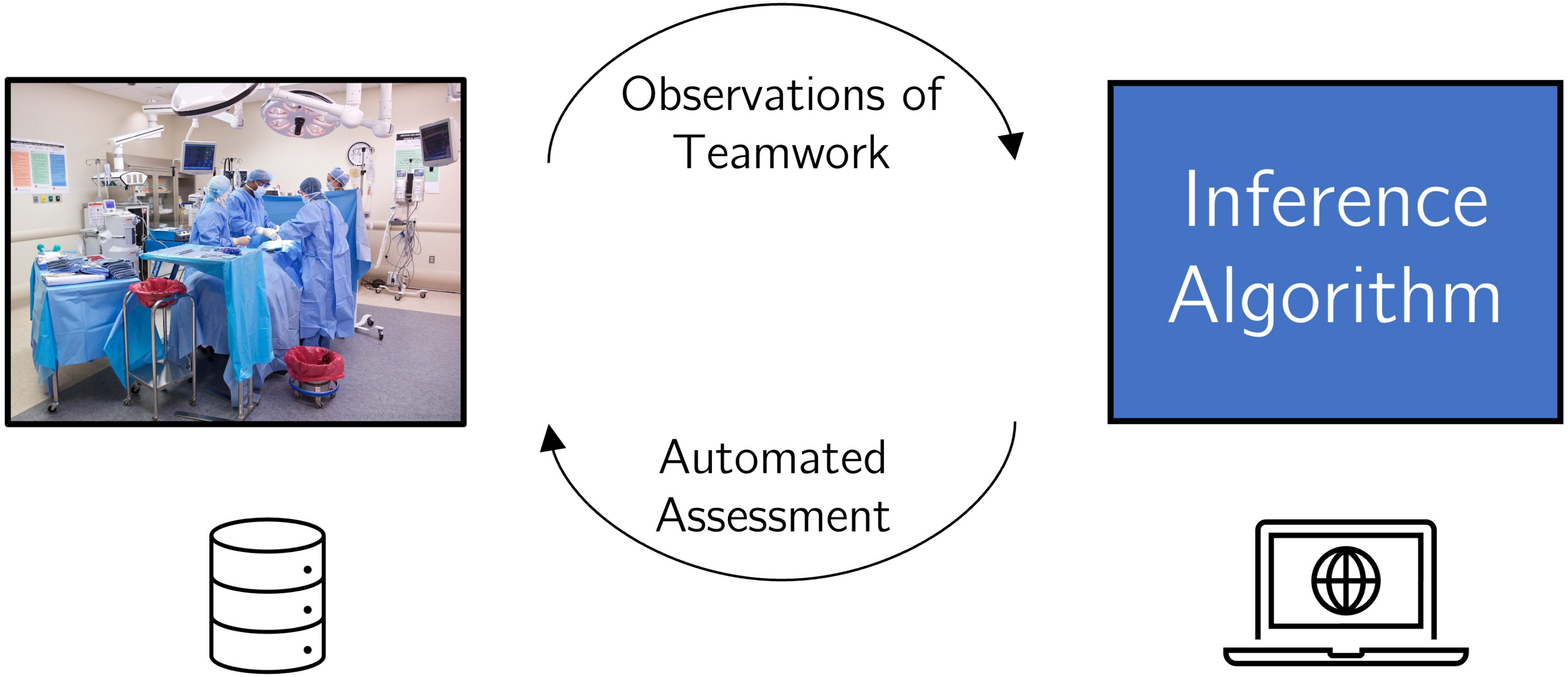
On-going Research and Next Steps

AI Coach for the Cardiac OR

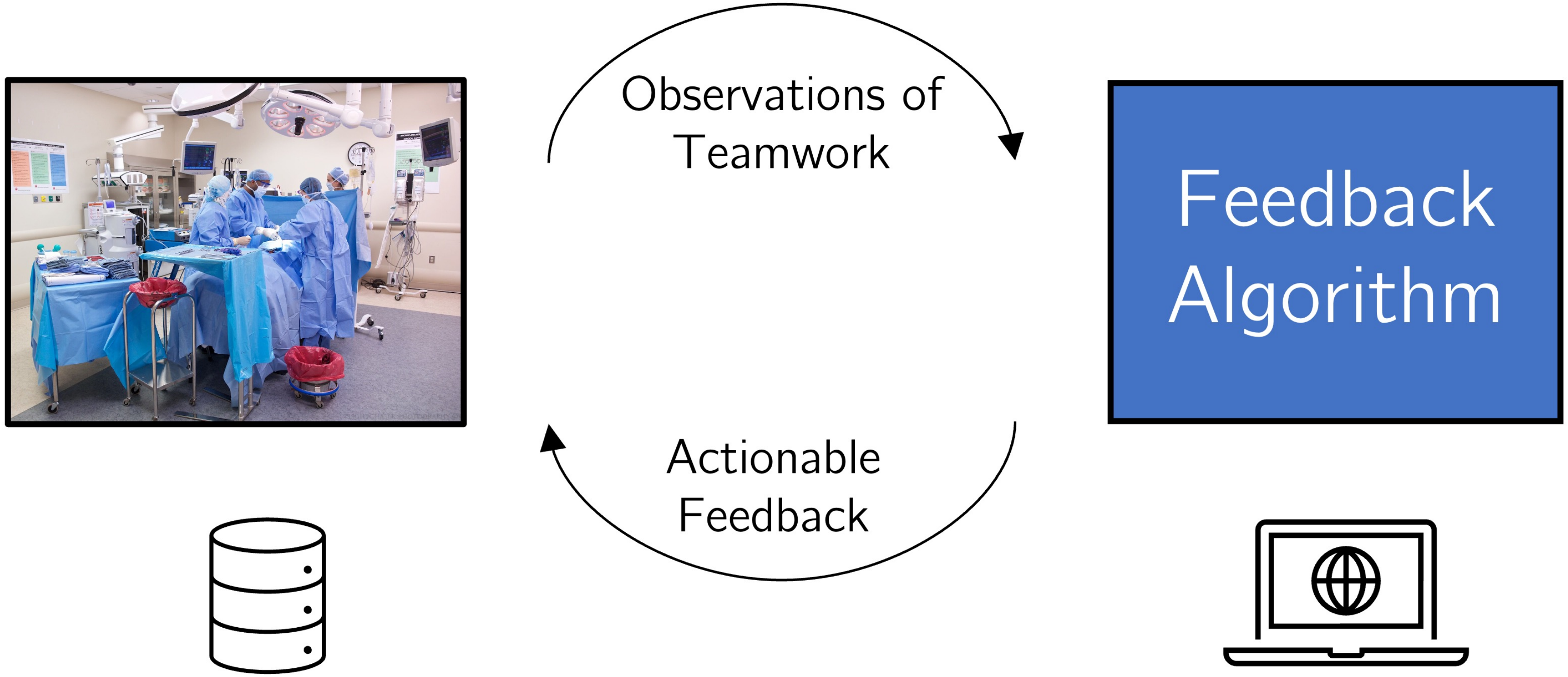
Towards Automated Assessment of Surgical Teamwork



Automated Team Assessments



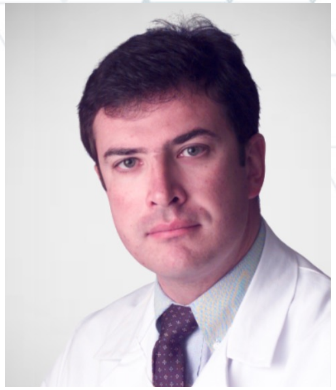
Automated Team Interventions



Collaborative Multidisciplinary Science

Supported by **NSF/NIH Smart Health and Biomedical Research in the Era of Artificial Intelligence and Advanced Data Science Program**'s Award #2205454.

This work is a collaborative effort involving researchers from Harvard, Rice University, Brigham and Women's Hospital, Massachusetts Institute of Technology.



Eduardo Salas

~~“Black Box” Predictions~~

Models which simply provide predictions without explanation, are difficult for physicians to trust and provide little insight into how they should respond.

nature biomedical engineering

ARTICLES

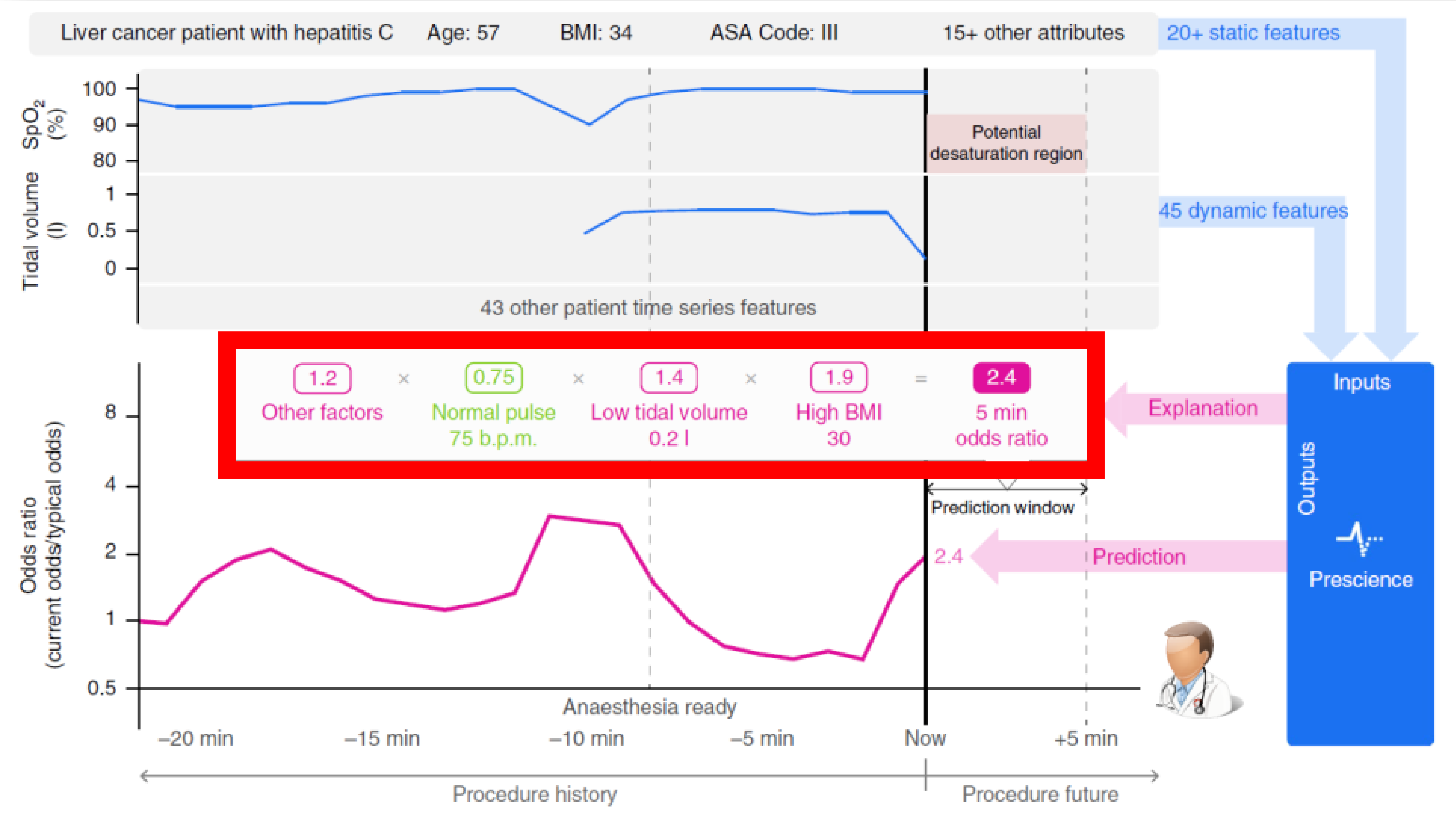
https://doi.org/10.1038/s41551-018-0304-0

Explainable machine-learning predictions for the prevention of hypoxaemia during surgery

Scott M. Lundberg[1], Bala Nair[2,3,4], Monica S. Vavilala[2,3,4], Mayumi Horibe[5], Michael J. Eisses[2,6], Trevor Adams[2,6], David E. Liston[2,6], Daniel King-Wai Low[2,6], Shu-Fang Newman[2,3], Jerry Kim[2,6] and Su-In Lee[1*]

NATURE BIOMEDICAL ENGINEERING | VOL 2 | OCTOBER 2018 | 749-760 | www.nature.com/natbiomedeng

Prescience: ensemble-based-model ML



Need for Higher Standards in Artificial Intelligence-enabled Decision Support in Surgery

- AI models should incorporate explainability mechanisms to convey the relative importance of input features in determining outputs.
- A **clinical implementation** framework should be presented in developmental work and tested in subsequent work
- Model **precision** (e.g., area under the precision-recall curve, positive predictive value, or F1 score) should be reported.
- Confidence intervals should be reported for all performance metrics.
- Model performance across **vulnerable populations** (e.g., by race, sex, age, socioeconomic indicators) should be reported.
- Artificial intelligence-enabled decision support should include **patient-centered outcomes**.
- Small sample sizes (less than 1,000-2,000 per class) should be accompanied by model learning curves illustrating change in predictive performance as the sample size increases.
- Internal validation alone is inadequate unless the modeling approach or application is novel.

Loftus T et al. Annals of Surgery 2023

Measures for Evaluating Human-AI Teams

Team Performance

- Quality
  - Decision Making
  - Performance Outcomes
- Time on Task
- Operations Under Failure or Unanticipated Conditions
  - Recovery Time
  - Recovery Quality
  - Resilience
  - Bias Propagation
  - Adaptability
- Safety

Team Sustainability

- Human
  - Job Satisfaction
  - Skill Retention
- System
  - Maintainability & Auditability
  - Vulnerability
  - Suitability

Team Knowledge

- Situation Awareness (Models)
  - Team
  - Shared
- Mental Models
  - Team
  - Shared
- Knowledge
  - Teamwork
  - Taskwork

Team Processes

- Team Situation Awareness Processes
- Team Trust
- Team Distrust
- Teamwork Quality
  - Cohesion
  - Coordination
  - Cooperation
- Communications
- Behaviors

Team Efficiency

- Training Time
- Team Organization Optimality
  - Effectiveness of Resource Utilization
  - Mutual Performance Monitoring
  - Coordination Efficiency
  - Flexibility
  - Time to Resolve Uncertainty (TRU)
- Workload
- System
  - Usability
  - Understandability
  - Predictability
  - Controllability
  - Trustworthiness
  - Responsivity
  - Reliability
  - Robustness
  - Over-Promise Rate (OPR)
  - Bias

The Risks

Should Humans Team with AI?

Machines as Teammates (MaT)

“We shape our tools, and thereafter, our tools shape us”**.**

Marshall McLuhan

IBM Watson Health™

SOLUTION BRIEF

Elevate cancer care with the Watson Oncology Suite

IBM's Watson recommended 'unsafe and incorrect' treatments for cancer patients, investigation reveals

10:00 AM - July 27, 2018

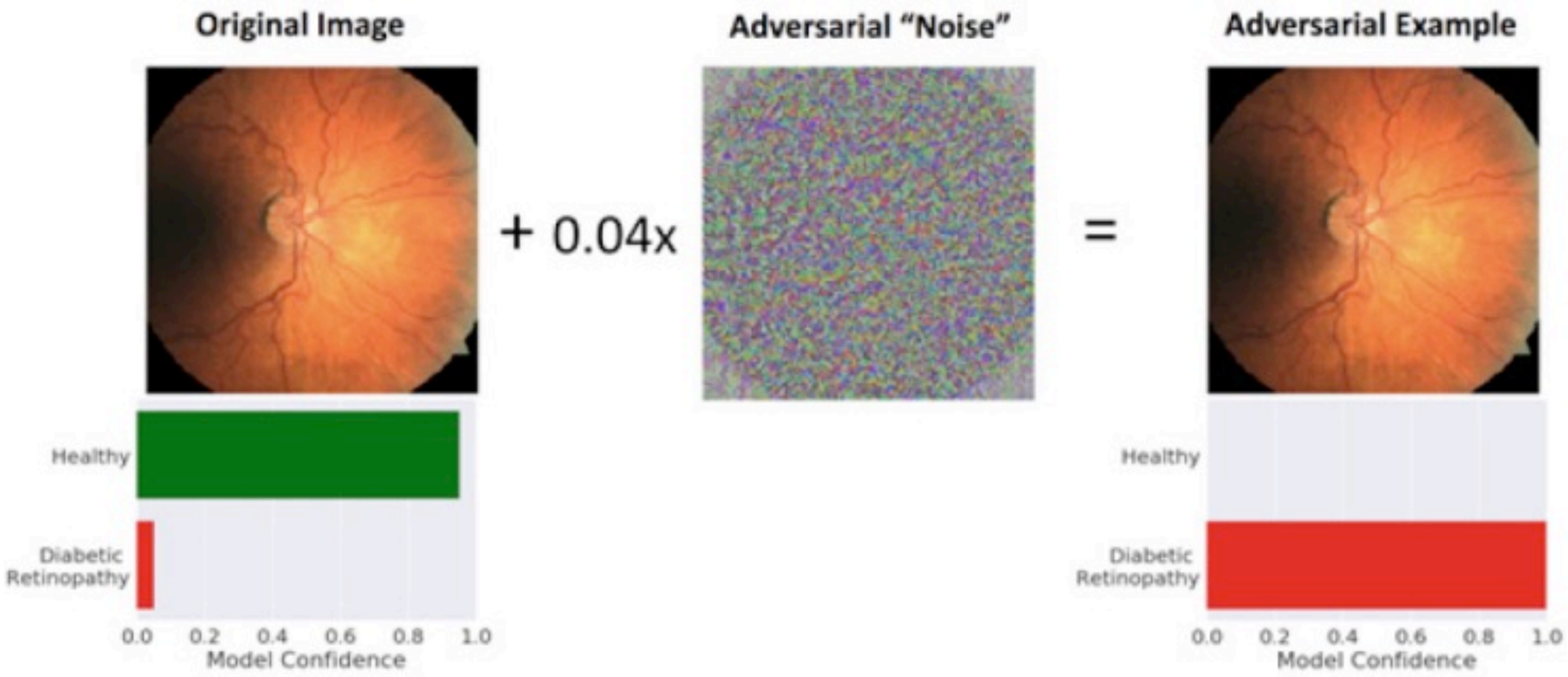
HARVARD | BUSINESS | SCHOOL

9-621-022
REV: APRIL 16, 2021

SHANE GREENSTEIN
MEL MARTIN
SARKIS AGAIAN

IBM Watson at MD Anderson Cancer Center

AI vulnerability to adversarial attacks



Harvard Business Review

DECISION MAKING

Want Less-Biased Decisions? Use Algorithms.

by Alex P. Miller

JULY 26, 2018

Human Beings Are Remarkably Bad Decision Makers

A not-so-hidden secret behind the algorithms mentioned above is that they actually *are* biased. But the humans they are replacing are *significantly more biased*. After all, where do institutional biases come from if not the humans who have traditionally been in charge?

Risk of “Skill rot”

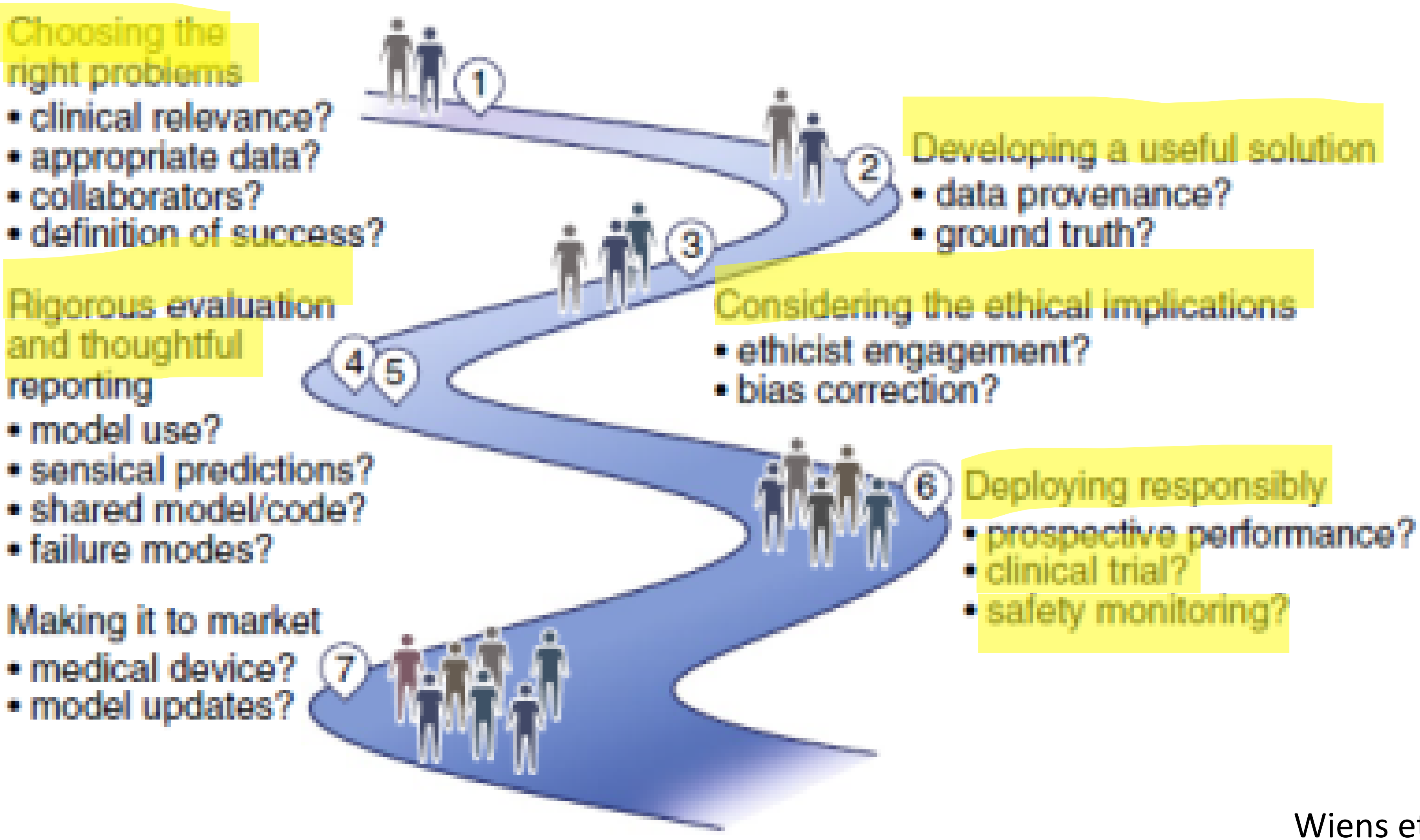
The Costs

Consumption CO_2e (lbs)

Air travel, 1 passenger, NY ↔️SF 1,984
Human life, avg, 1 year 11,023
American life, avg, 1 year 36,156
Car, avg incl. fuel, 1 lifetime 126,000
Training one model (GPU) NLP pipeline (parsing, SRL) 39 w/ tuning & experimentation **78,468**
Transformer (big) 192 w/ neural architecture search **626,155**

Conclusion

Roadmap for Developing Effective Machine Learning Systems in Healthcare



Wiens et al. Nat Med 2019

Interdisciplinary Teams of Stakeholders

Stakeholder categories	Examples
Knowledge experts	• Clinical experts • ML researchers • Health information and technology experts • Implementation experts
Decision-makers	• Hospital administrators • Institutional leadership • Regulatory agencies • State and federal government
Users	• Nurses • Physicians • Laboratory technicians • Patients • Friends and family (framily)

Business And Society

AI Won’t Replace Humans — But Humans With AI Will Replace Humans Without AI

August 04, 2023

“Humans in the Loop” for Everything

- **Trainers:** Teaching AI systems how to perform will require deliberate effort to evaluate and stress test them. AI systems can automate tasks and find patterns in data, but still require humans to provide meaning, purpose, and direction.
- **Explainers:** Advancing AI algorithms often have a “black box” nature, making suggestions without clear explanations, requiring humans versed in both the technical and application domains to explain how such algorithms can be trusted to drive practical decisions.
- **Sustainers:** The intelligence needs of human endeavors will continually evolve, preventing the advent of “completed” AI systems. Humans must continue to maintain, interpret, and monitor the behavior and unintended consequences of AI systems.

We may need 20 people to do the job that was previously done by 10…

AI is a strategic technology that offers many benefits for society as a whole

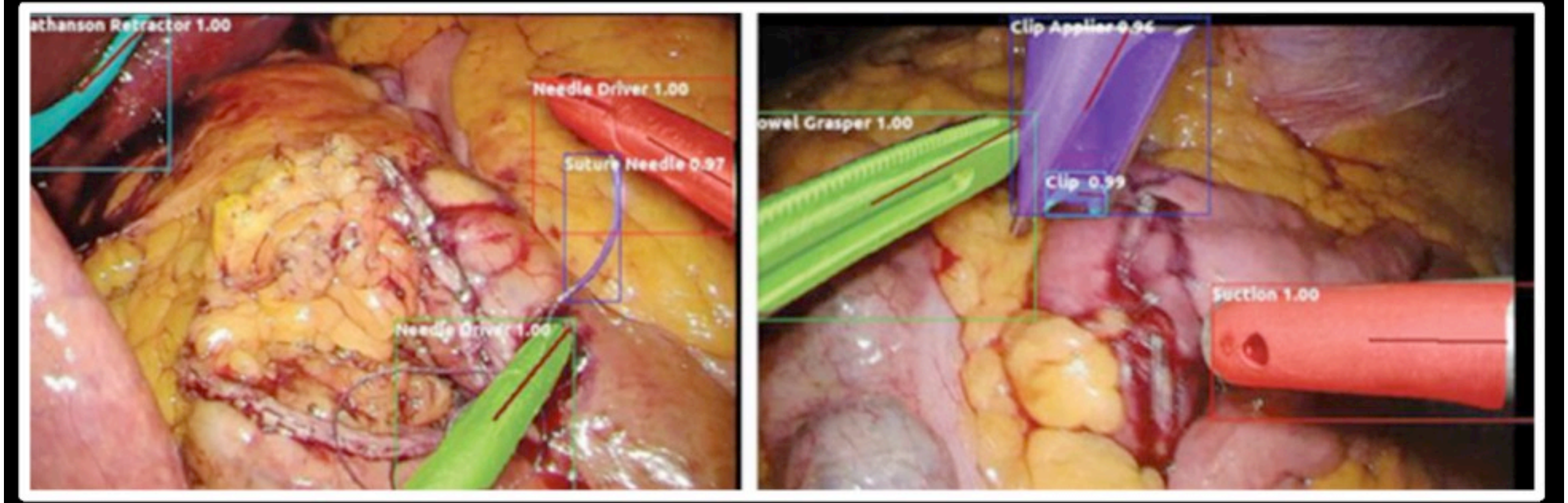
provided that it is

human-centric, ethical, sustainable and respects fundamental rights and values.

Thank you!

Marco_Zenati@hms.harvard.edu
@MarcoZenatiMD

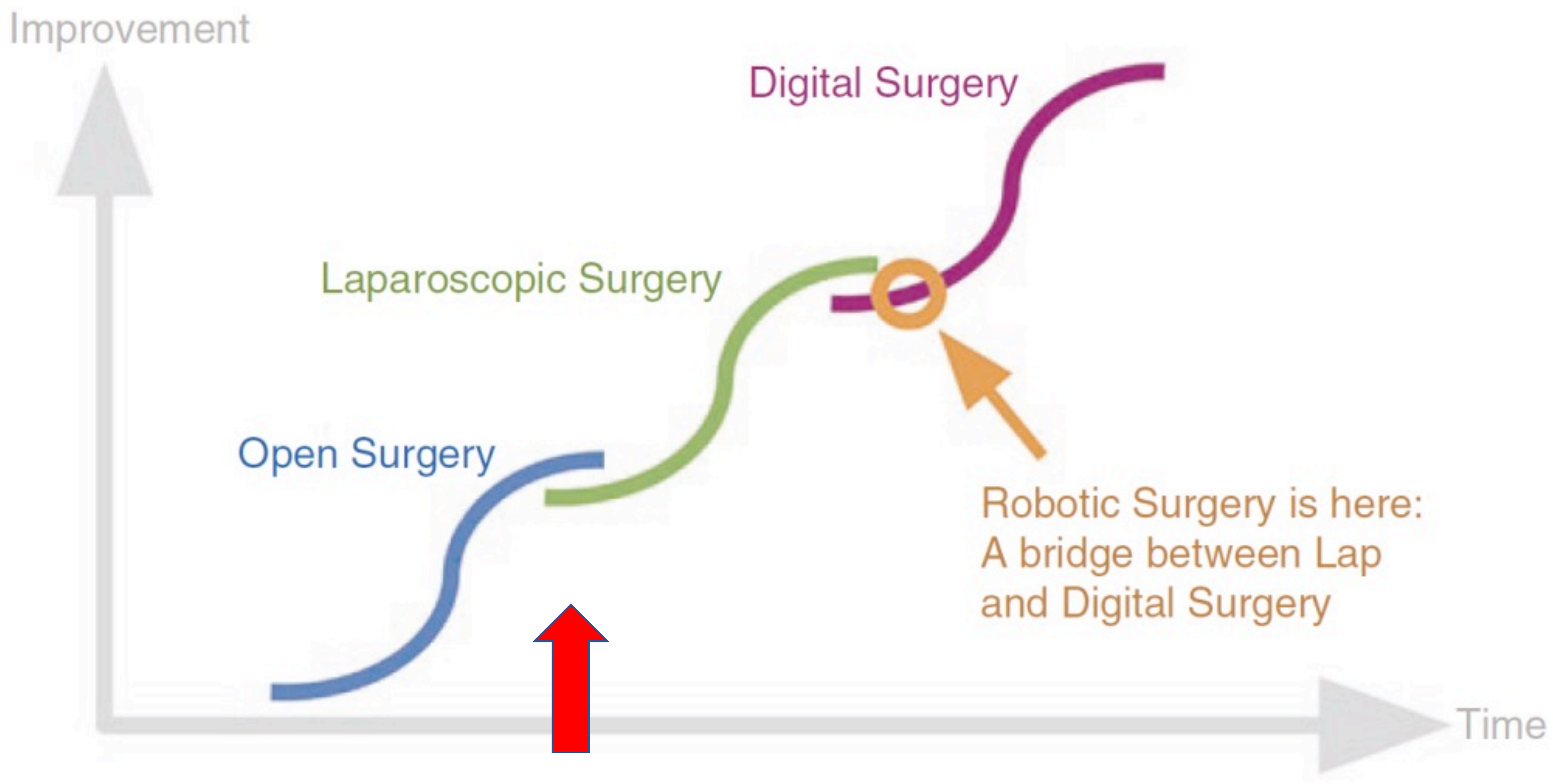
Labeles Indicating Presence of Surgical Instruments in Images



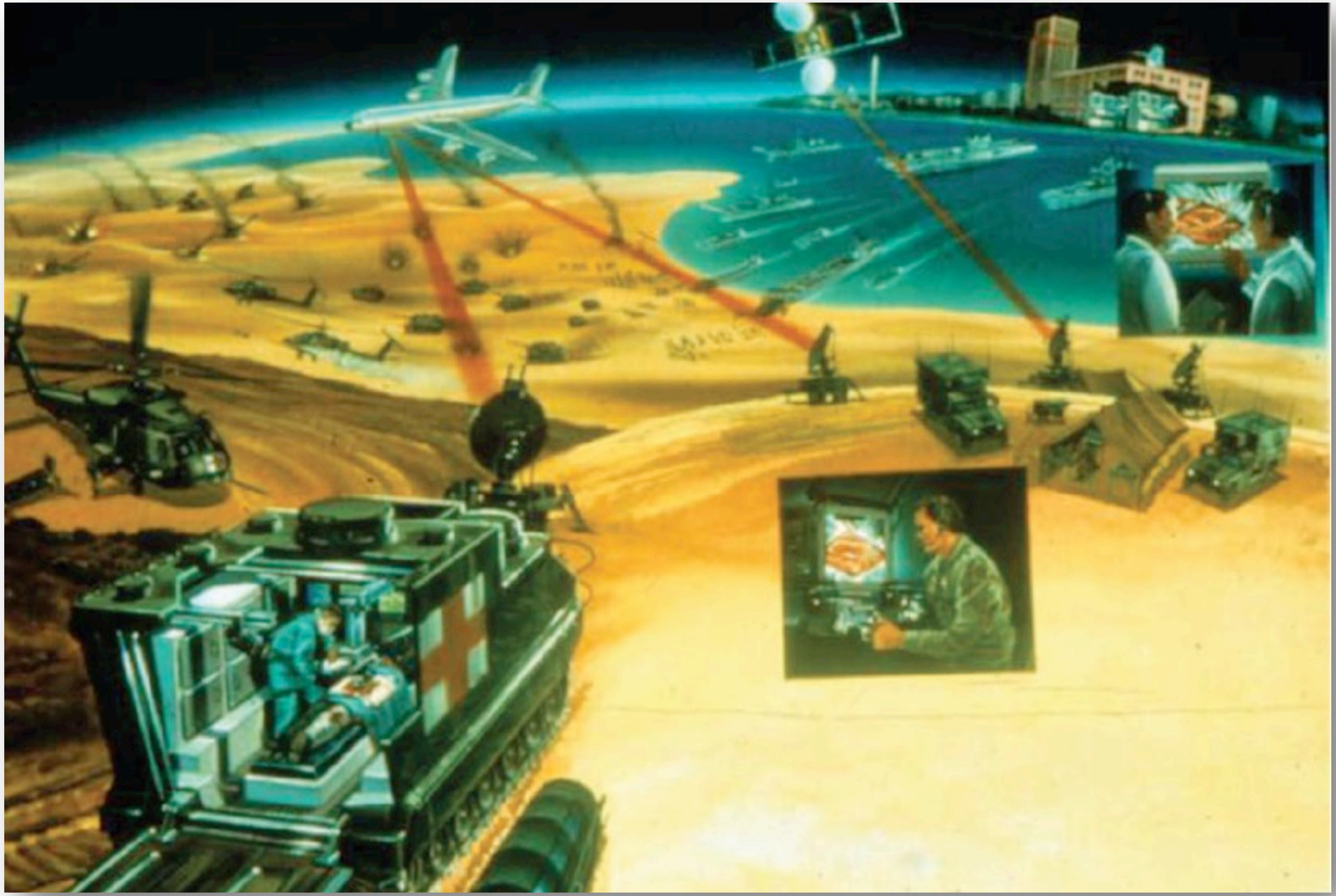
Barriers to Digital Surgery

Development	Deployment	Monitoring
Lack of digitisation in hospitals Legacy Hospital IT systems unfit for purpose Insufficient data availability Lack of shared ontology for annotation Lack of data registry and platform standards Lack of standards in data formatting methods Lack of data quality standards Insufficient expertise in surgical AI Poor interoperability between AI systems and embedded technology in the Operating room Difficulties in sharing data between multiple centres	Costs of setting up infrastructure Hindering of process due to bureaucratic processes Challenges in getting contractual relationships established Reimbursement or business model not clearly defined Institutional aversion to sharing patient data Inability to demonstrate safety or clinical benefit to stakeholders Difficulties of integrating AI systems with existing IT infrastructure Variation in hospital IT systems Regulatory requirements are unclear at present Lack of framework for consenting and obtaining data	Clarity on responsibility for data monitoring Lack of resource and personnel dedicated to task Costs associated with monitoring Lack of standardised outcome measures for monitoring Difficulties in quantifying improvement Lack of prioritisation given to monitoring at present Divide between those monitoring and developing surgical AI systems

MOON
SURGICAL

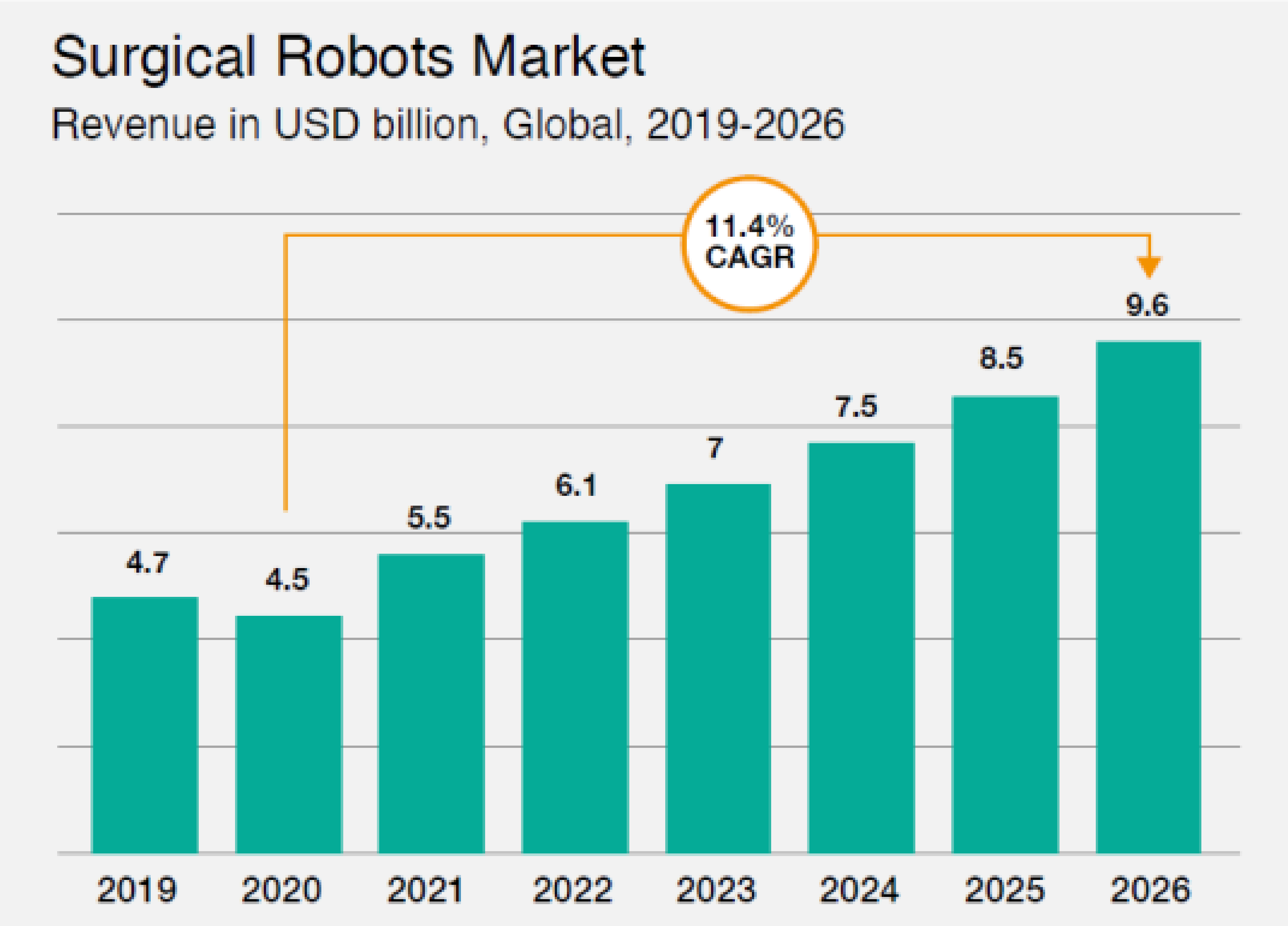

Improvement
Digital Surgery
Laparoscopic Surgery
Open Surgery
Robotic Surgery is here:
A bridge between Lap
and Digital Surgery
Time

DARPA/DOD's MEDFAST Surgical Unit



1980s


da Vinci Xi

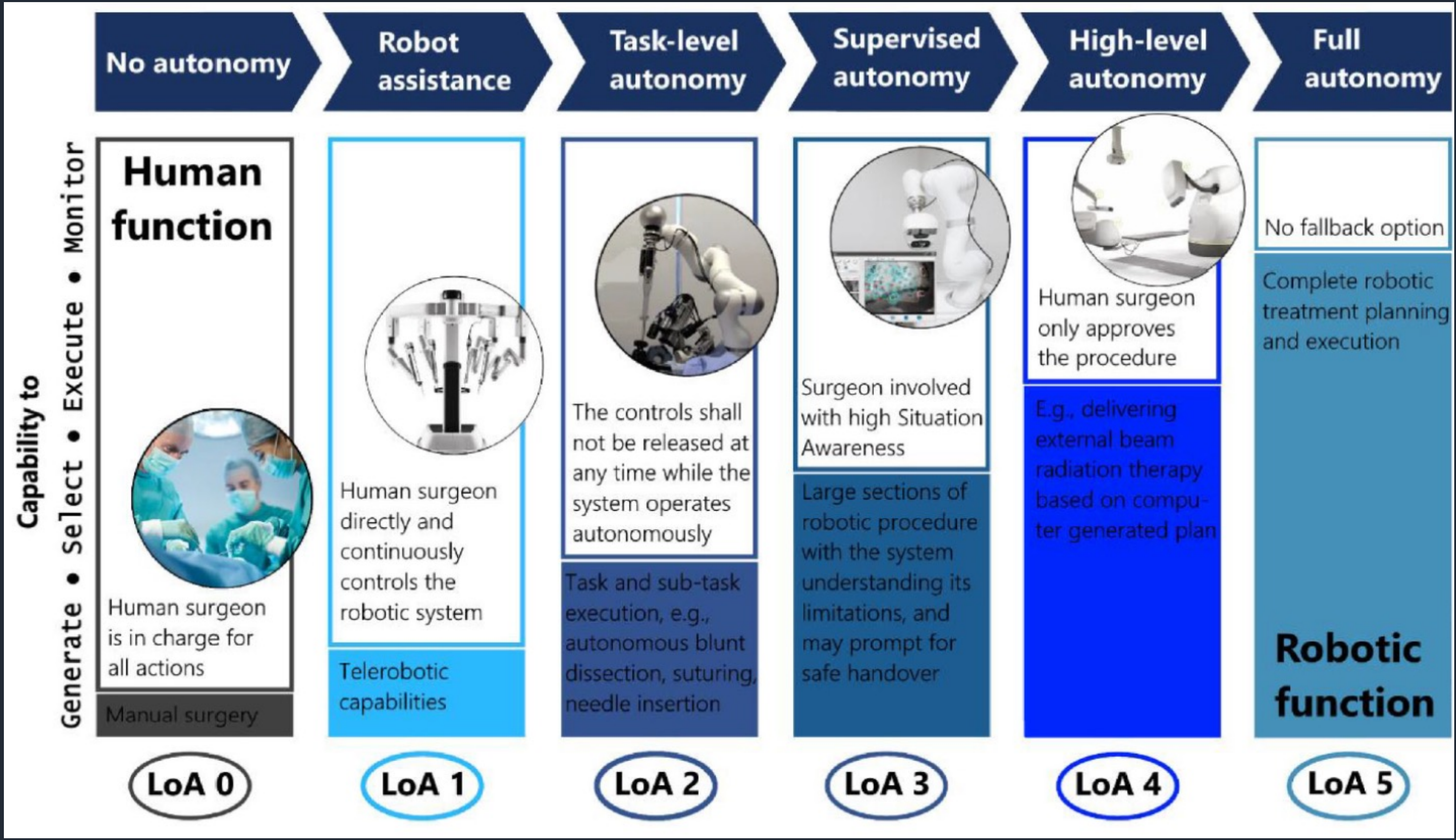


Surgical Robots Market
Revenue in USD billion, Global, 2019-2026
11.4% CAGR
4.7
4.5
5.5
6.1
7
7.5
8.5
9.6
2019
2020
2021
2022
2023
2024
2025
2026

“Million Dollar Needle Holder”

Jim Moser, Robotic Surgeon @BIDMC

From Tools to Teammates



T. Haidegger IEEE Transactions in Medical Robotics and Bionics 2019

Science Translational Medicine AAAS

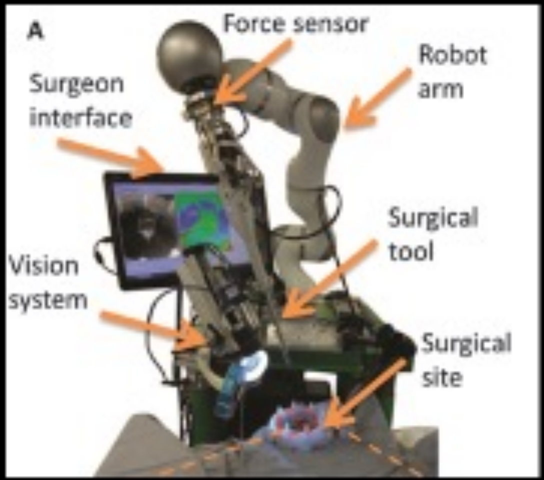
Supervised autonomous robotic soft tissue surgery

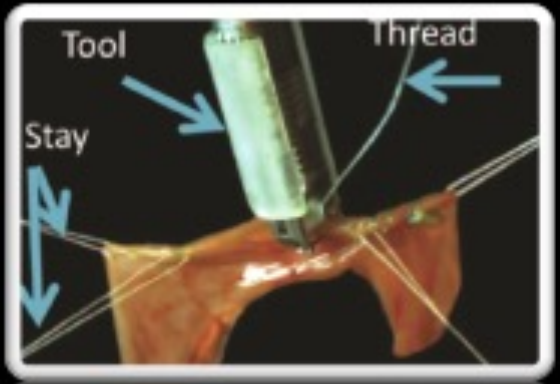
Azad Shademan, Ryan S. Decker, Justin D. Opfermann, Simon Leonard, Axel Krieger and Peter C. W. Kim (May 4, 2016)
Science Translational Medicine **8** (337), 337ra64. [doi: 10.1126/scitranslmed.aad9398]

Editor's Summary

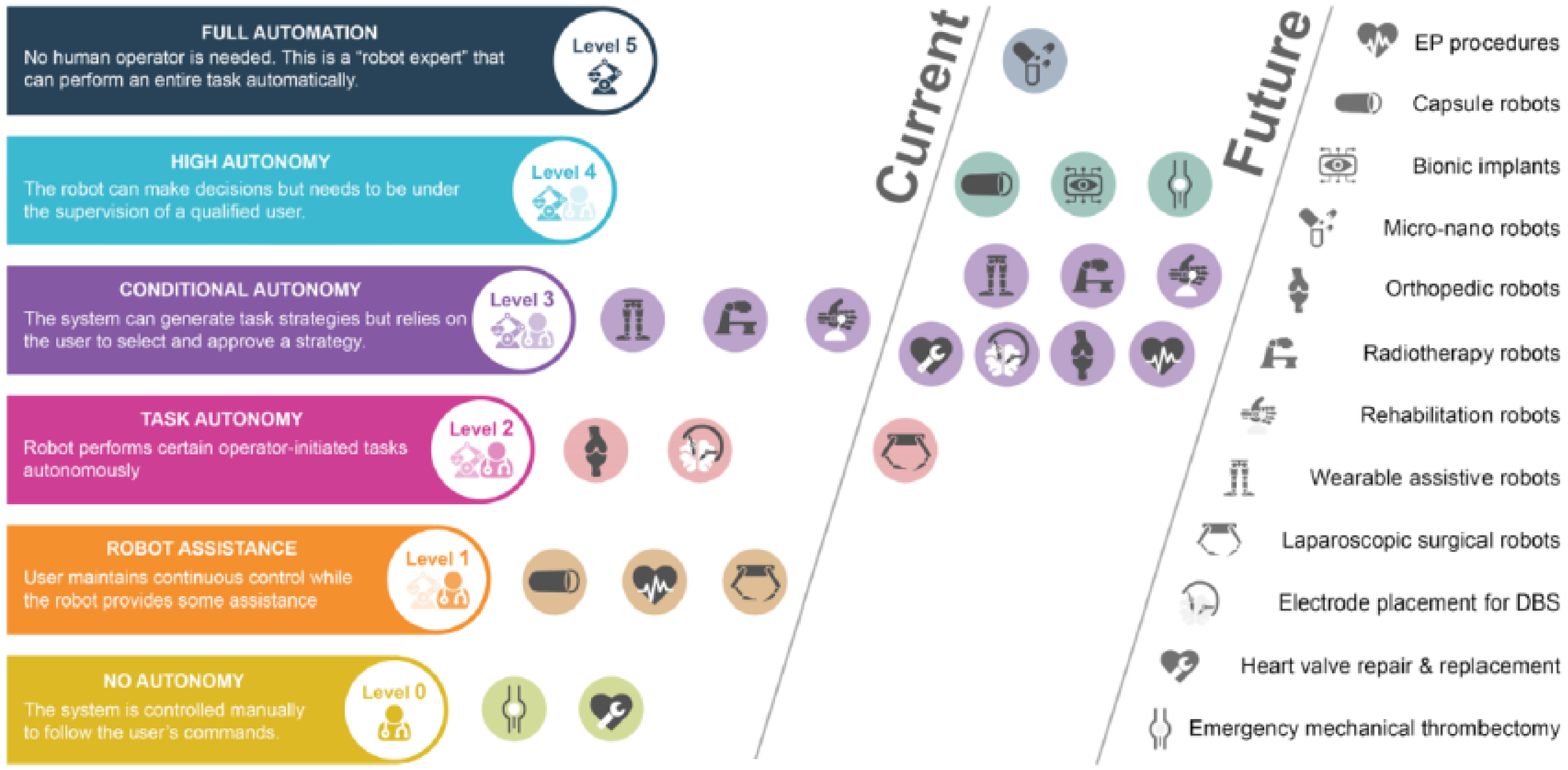
Hands-free

The operating room may someday be run by robots, with surgeons overseeing their moves. Shademan *et al*. designed a "Smart Tissue Autonomous Robot," or STAR, which consists of tools for suturing as well as fluorescent and 3D imaging, force sensing, and submillimeter positioning. With all of these components, the authors were able to use STAR for soft tissue surgery—a difficult task for a robot given tissue deformity and mobility. Surgeons tested STAR against manual surgery, laparoscopy, and robot-assisted surgery for porcine intestinal anastomosis, and found that the supervised autonomous surgery offered by the STAR system was superior.





Shademan et al. Science Translational Medicine May 2016



Dupont *et al.*, *Sci. Robot.* **6**, eabi8017 (2021) 10 November 2021

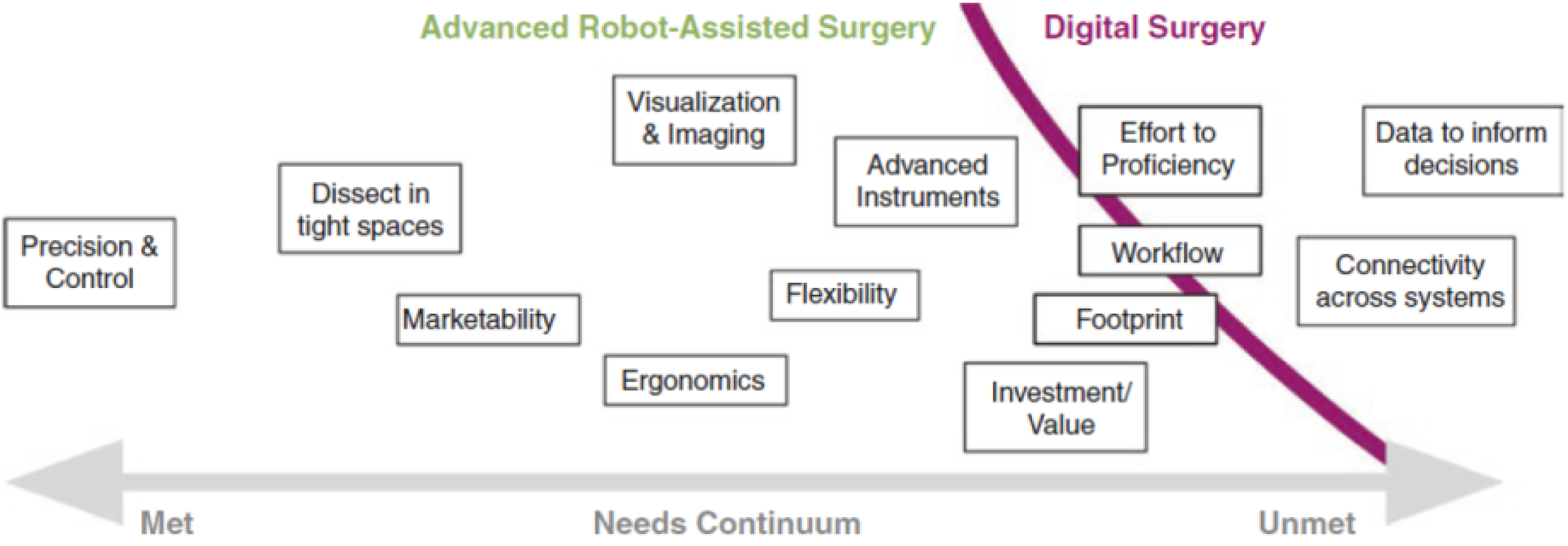
The Automation Conundrum

The more automation is added to a system, and the more reliable and robust that automation is…

…the less likely that human operators overseeing the automation will be aware of critical information and …

…able to take over manual control when needed.

Endsley 2017

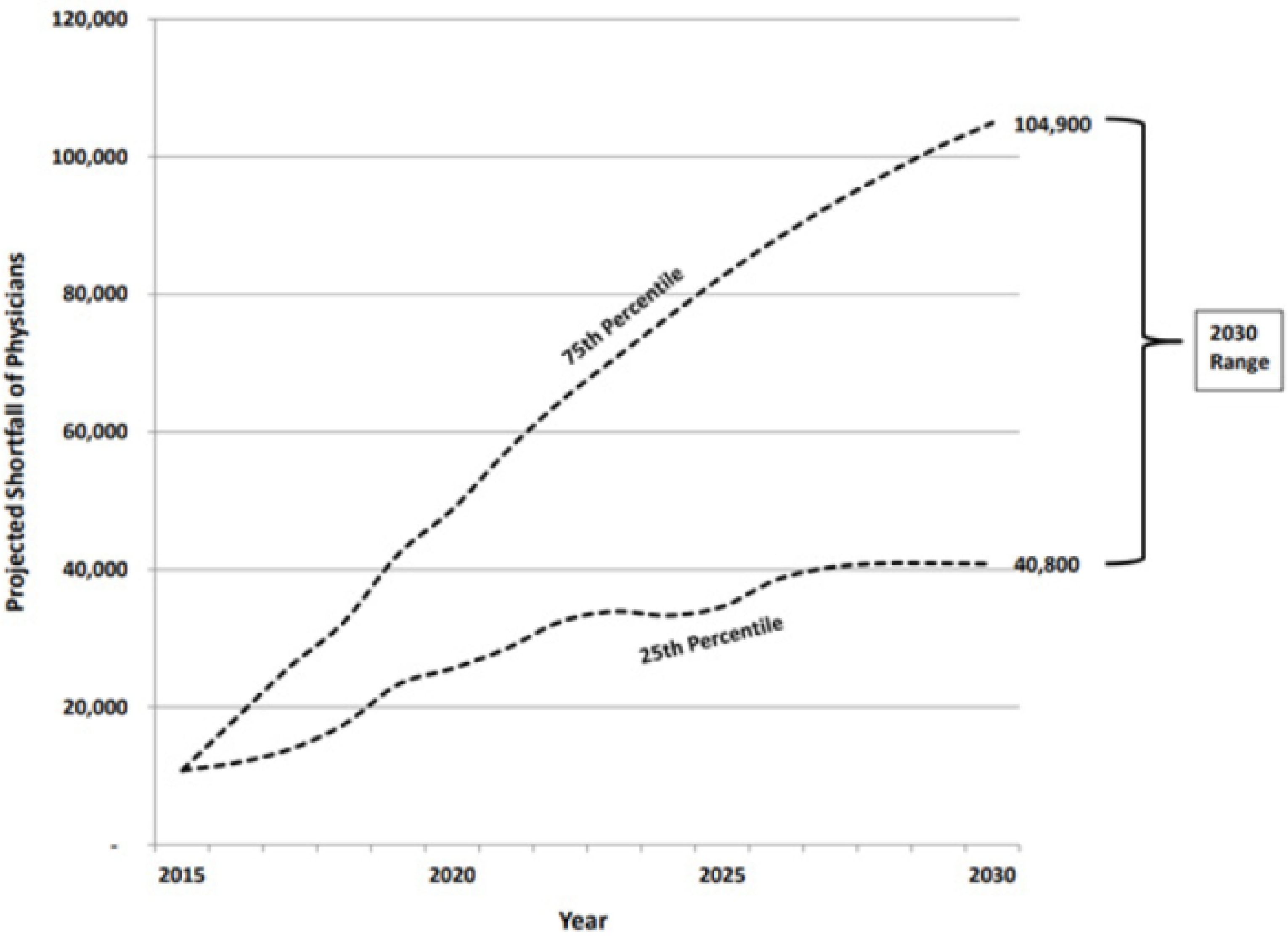


Advanced Robot-Assisted Surgery
Digital Surgery
Visualization & Imaging
Dissect in tight spaces
Precision & Control
Marketability
Ergonomics
Flexibility
Advanced Instruments
Effort to Proficiency
Workflow
Footprint
Investment/ Value
Data to inform decisions
Connectivity across systems
Met
Needs Continuum
Unmet

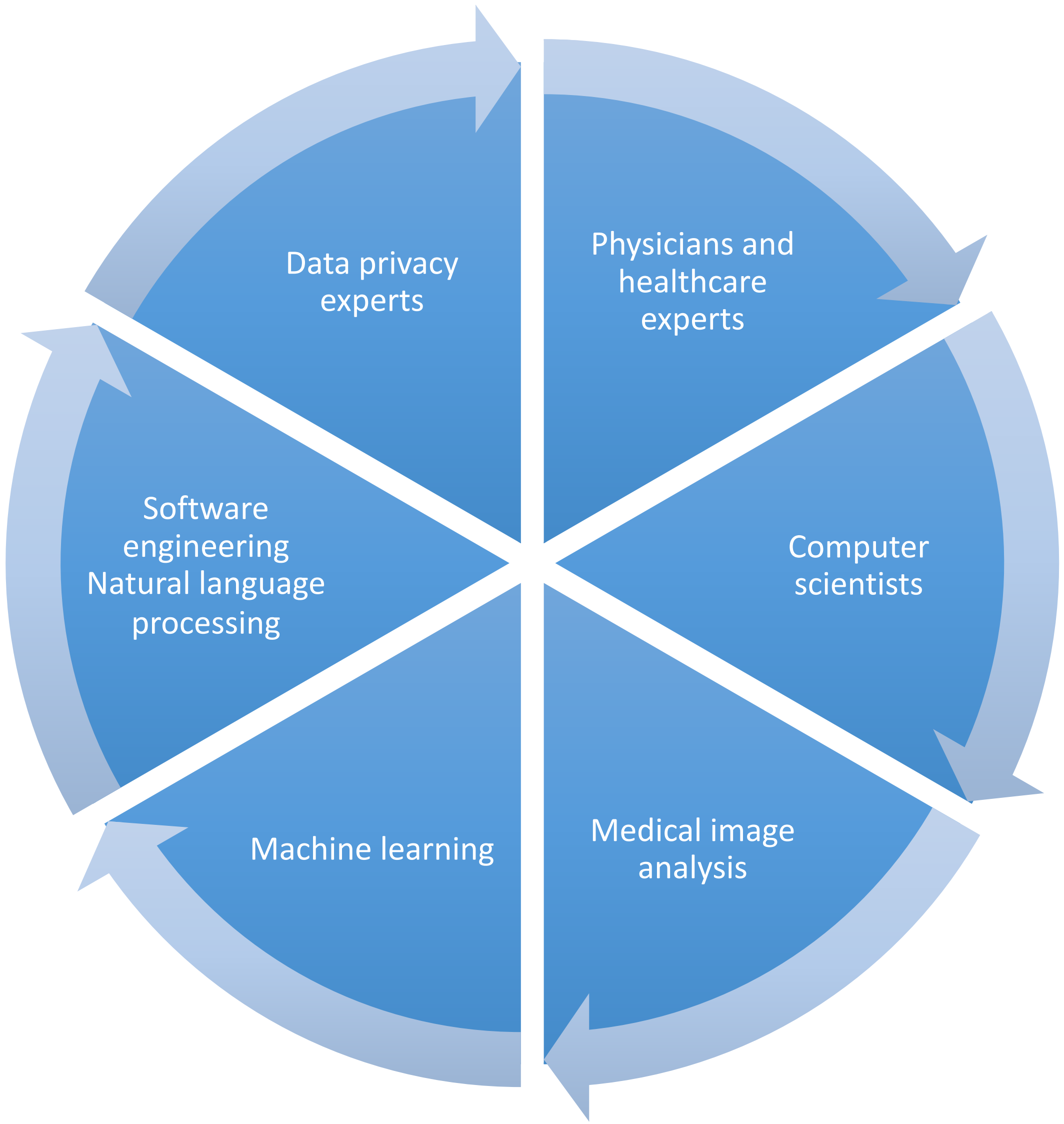
Ethical Dilemmas of AI for Health Care “AI Bioethics”

- How do algorithms arrive at a particular conclusion?
- Risk of exacerbation of human bias and discrimination
- Tension between profit and delivery of health in U.S.
- AI as a “Luxury item” (ie, does nothing to democratize expertise)
- Patients give up a lot of privacy
- How AI will interact with health insurance reimbursement? (eg, provider may not be allowed to use discretional power if insurance only reimburses what AI recommends)
- Excessive control of provider decision and workflows (eg, CDSS)
  - Good to reduce errors, bad if only geared to increase profit or finessing evaluation metrics
- Can providers challenge algorithmic recommendations? (already an issue in non-healthcare contexts – higher standard)
- Current medical education system not preparing to practice in an AI-augmented environment (eg, need to be critical users and need to learn data science = Human-capital pipeline)
- Need expertise in “ML for Oncology” (vs ML and oncology)
- Black box algorithms, transparency, explainable AI (clinicians order MRI but don’t know exactly how an MRI scanner works, but someone does)
- We don’t know how many therapies work in medicine but we can demonstrate that it reliably produces the desired effect
- Important that AI works vs how it works

Projected physician shortfall into 2030



Comprehensive Network of Experts



We Need More Collaborative Science!

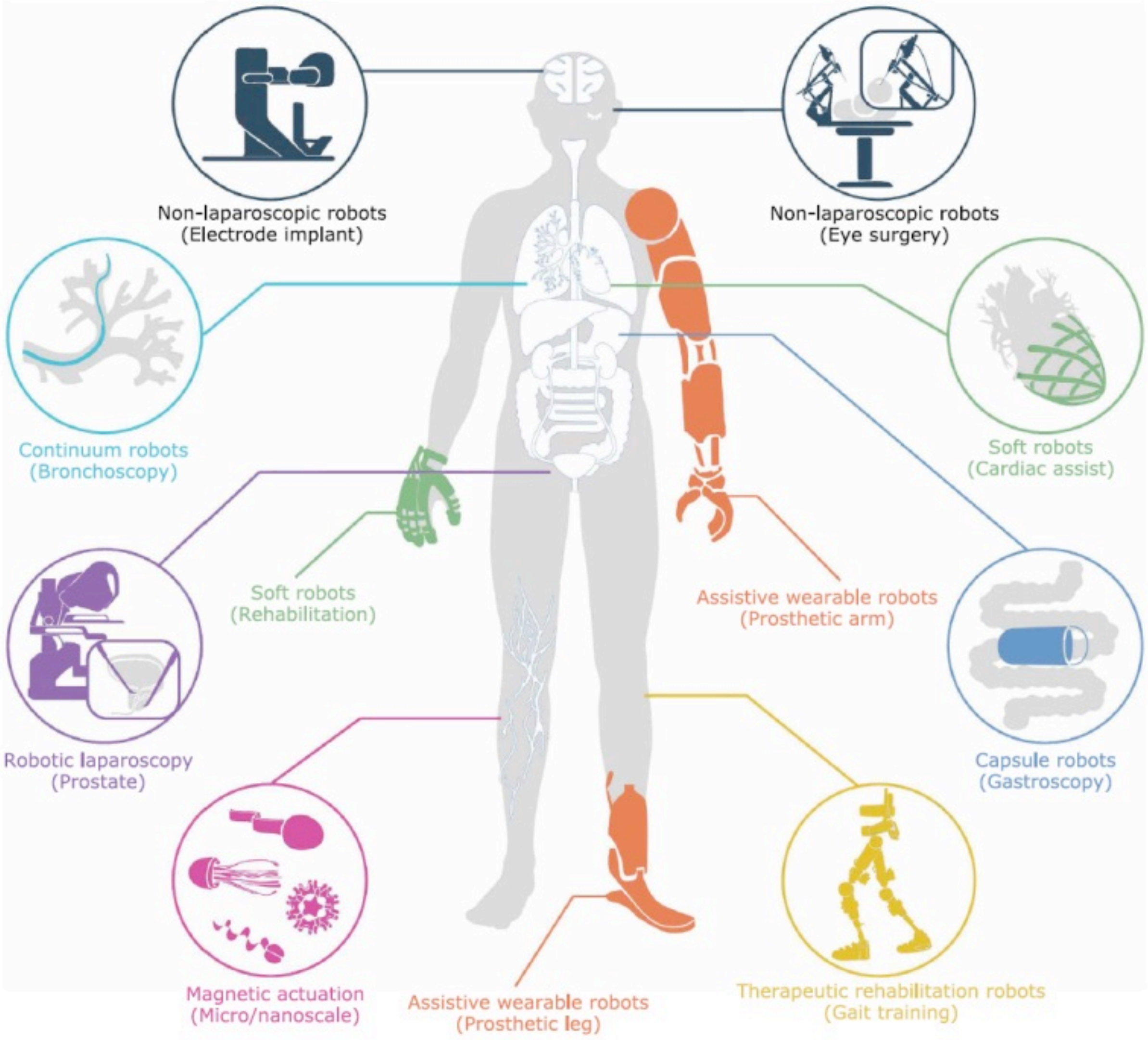
- ***Inside* Medicine/Multidisciplinary**
  - Cardiology, anesthesia, vascular surgery, etc
- ***Outside* Medicine/Interdisciplinary**
  - Computer science, robotics, mechanical engineering, human factors, computer modeling, simulation science, statistics, computer vision, AI/ML, etc

Future Research Goals for Digital Surgery

Technical	Clinical	Organisational
Standardisation of surgical data science platforms for data sharing and annotation	Define most suitable use cases/applications for surgical AI	Demonstrate impact of surgical AI systems
Shared ontology for data annotation	Develop core outcomes, reporting and measurement sets relevant to AI in surgery	Improve public trust and education in AI
Improving explainability of AI algorithms	Develop framework for introduction and evaluation of AI in surgery	Legal framework for introduction and monitoring of AI surgical systems
Dealing with unlabelled or weakly labelled data	Determine trial methodology for assessment of surgical AI	Encourage interdisciplinary education
Identifying inequalities in underlying datasets	Standardisation of processes	Organisation of task force involving all relevant stakeholders to define best practices for surgical AI
Effective data collection systems	Encourage surgeons to share data	Define impact of surgical AI systems on litigation and liability
Uptake of common communication standard for surgical data		Establish a model business plan with industry
Generation of open source datasets		
Interoperability between different devices and systems		

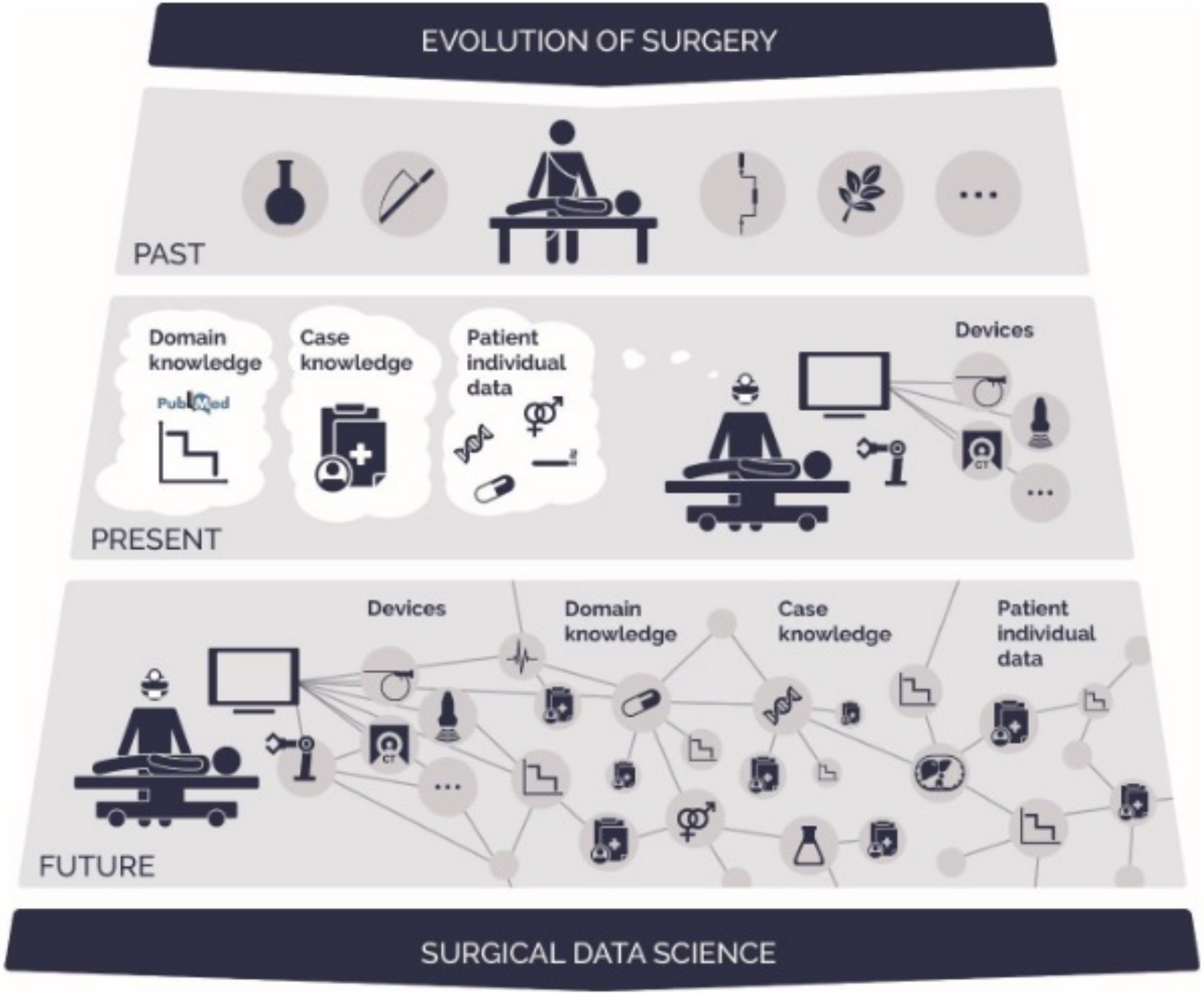
Cognitive Automation

- Software bringing intelligence to information-intensive processes.
- Commonly associated with Robotic Process Automation (RPA) as the conjunction between Artificial Intelligence (AI) and Cognitive Computing


Non-laparoscopic robots
(Electrode implant)
Non-laparoscopic robots
(Eye surgery)
Continuum robots
(Bronchoscopy)
Soft robots
(Cardiac assist)
Soft robots
(Rehabilitation)
Assistive wearable robots
(Prosthetic arm)
Robotic laparoscopy
(Prostate)
Capsule robots
(Gastroscopy)
Magnetic actuation
(Micro/nanoscale)
Assistive wearable robots
(Prosthetic leg)
Therapeutic rehabilitation robots
(Gait training)

“Spaghetti Syndrome”

Catchpole 2012

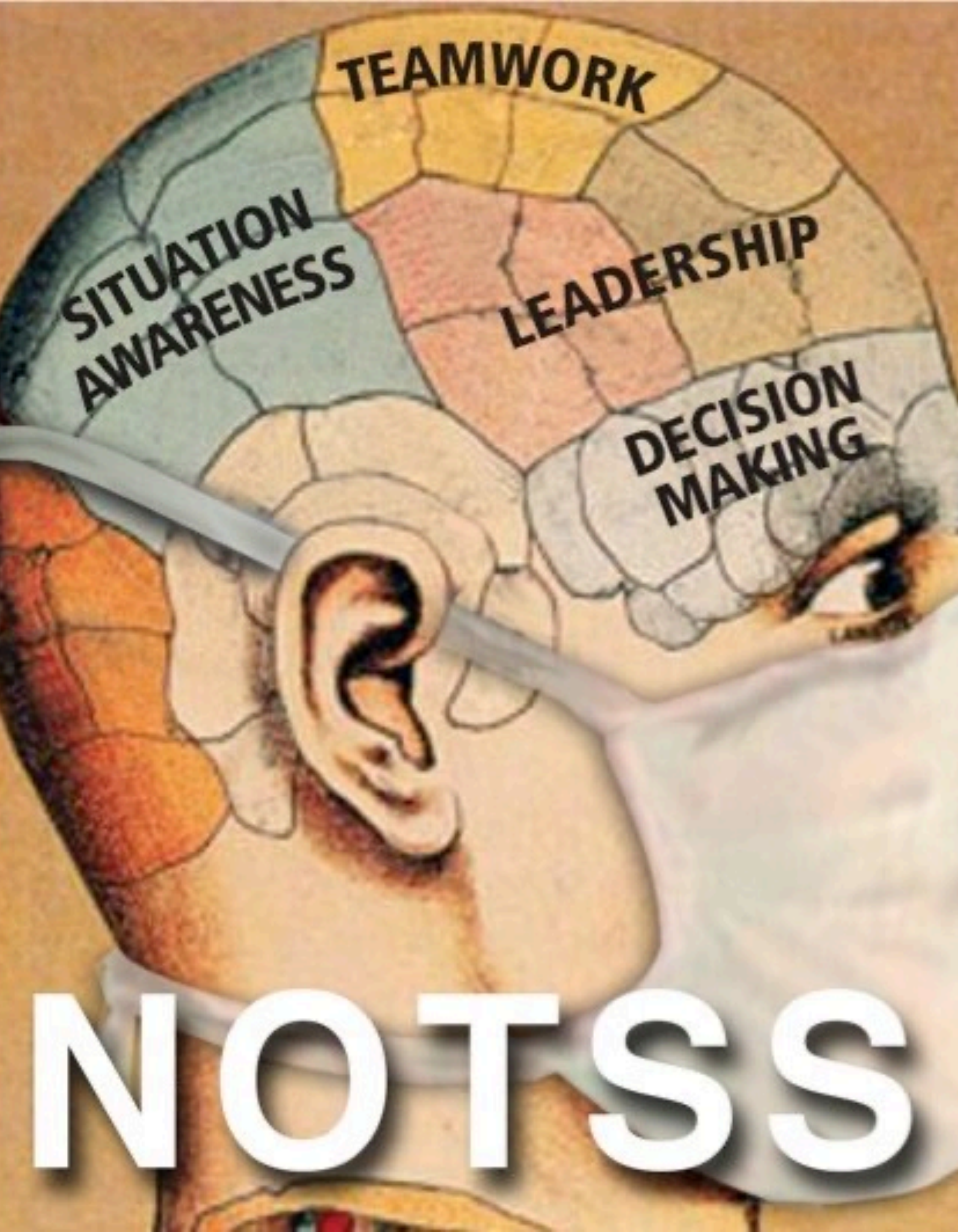


Maier-Hein L et al. (2017) Surgical Data Science: Enabling Next-Generation Surgery.

MRCAS Lab

- To quantify, predict, and support mental states of ***surgical team members*** through novel, multi-modal, and unobtrusive methods in the OR
  - Measuring and assessing behaviors
  - Physiological data capture
  - Machine learning and computer vision approaches

- We envision a context-aware cognitive aid that can function to support OR personnel when cognitive demands become excessive



Measuring and assessing behaviors

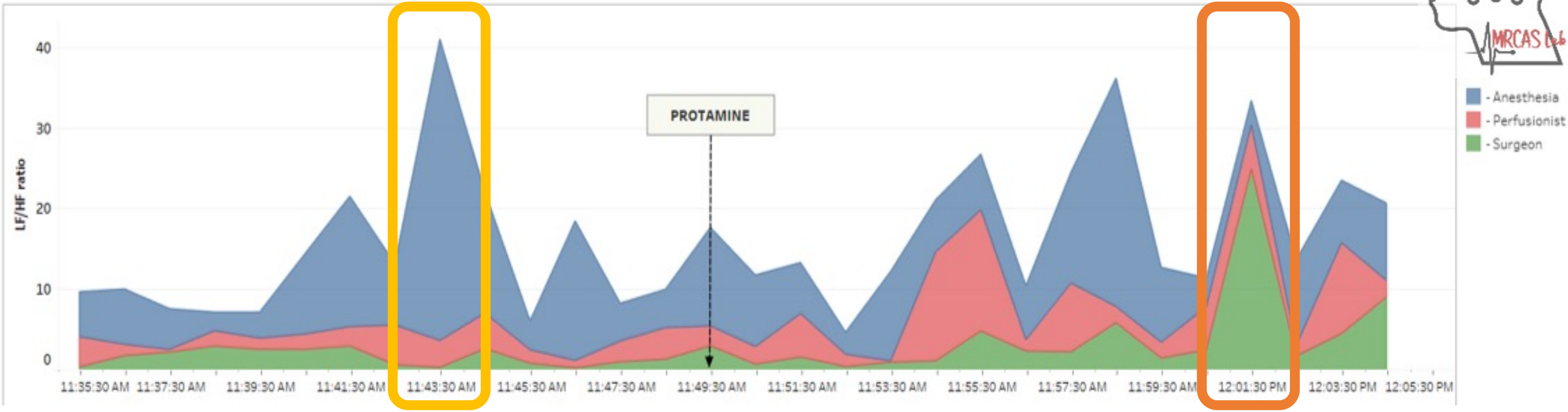
Category	Elements
Situation Awareness	• Gathering information • Understanding information • Projecting and anticipating future state
Decision Making	• Considering options • Selecting and communicating option • Implementing and reviewing decisions
Communication and Teamwork	• Exchanging information • Establishing a shared understanding • Co-ordinating team activities
Leadership	• Setting and maintaining standards • Supporting others • Coping with pressure

Flin R *et al.* (2012) The Non-Technical Skills for Surgeons (NOTSS) System Handbook v1.2: Structuring observation, rating and feedback of surgeons' behaviours in the operating theatre, *Aberdeen University*.

Physiological data capture

Machine learning and computer vision

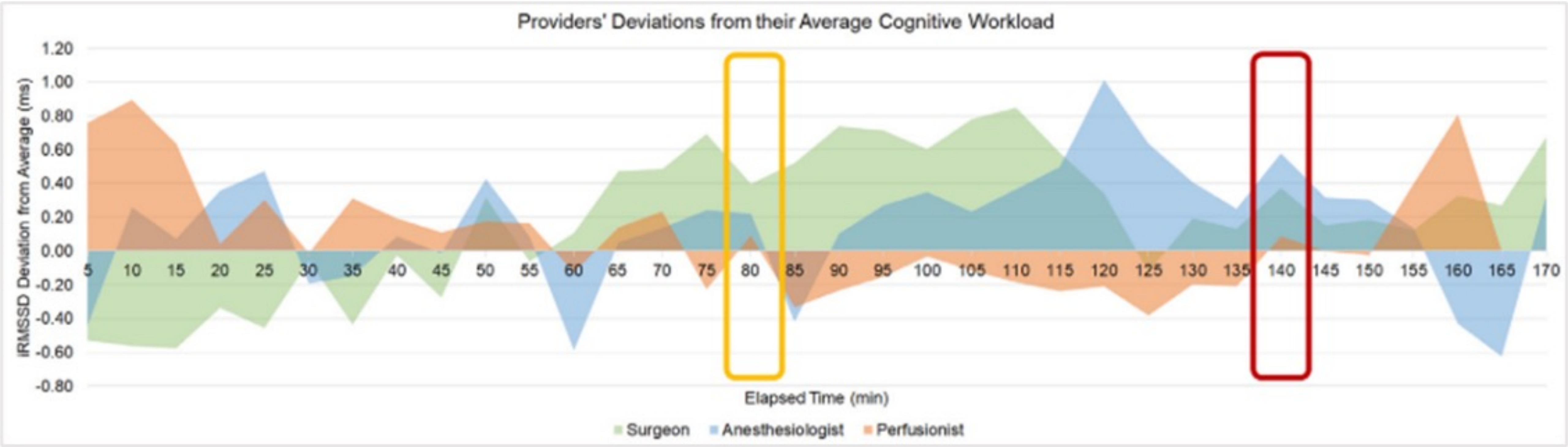
Automated Assessment of Intraoperative Performance



Prior to the error (labeled “Protamine”), isolated **cognitive overload state** can be observed (HRV LF/HF ratio of 37; normal is <2.5) for the anesthesiologist. Following the error, the cognitive workload of all 3 team members **rises synchronously**.

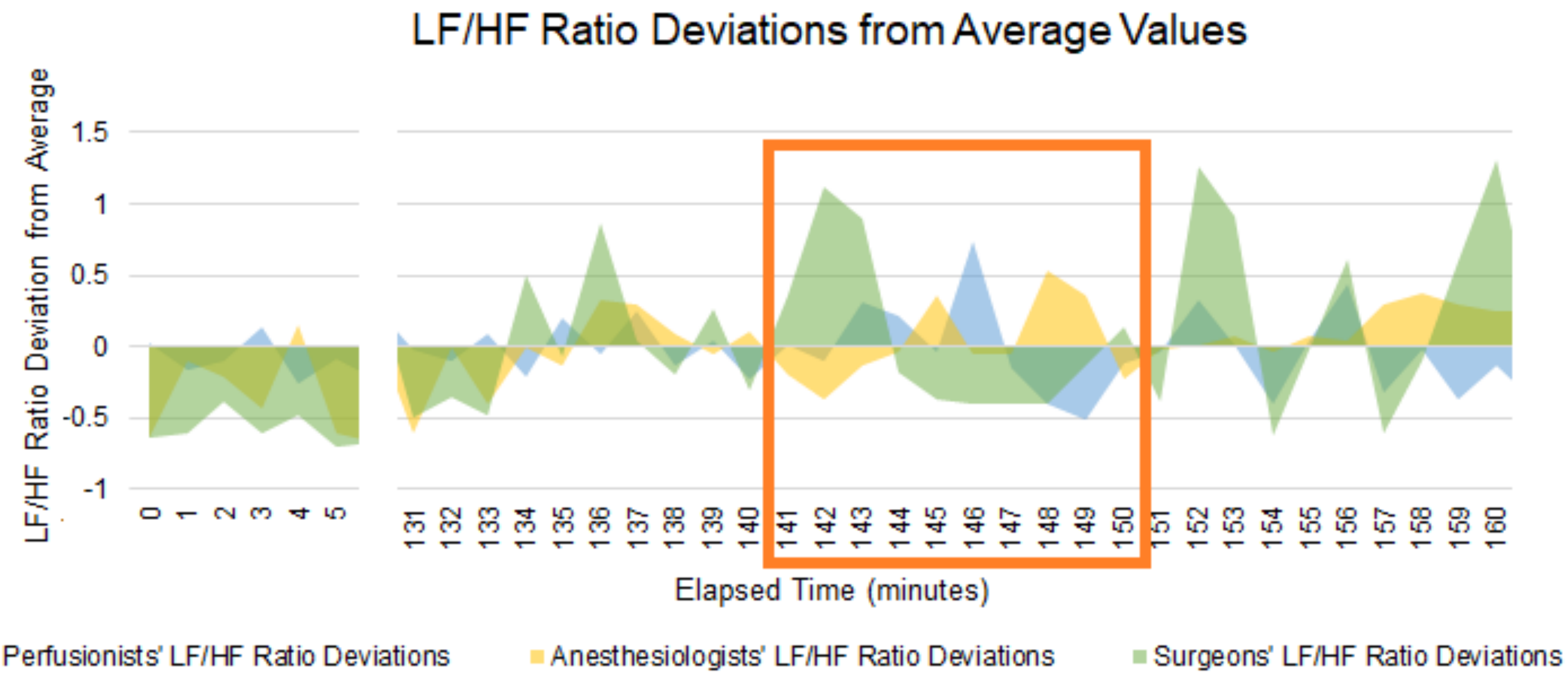
Zenati M et al. (2019) First Reported Use of Team Cognitive Workload for Root Cause Analysis in Cardiac Surgery. *Seminars in Thoracic and Cardiovascular Surgery*

Periods of mirrored physiological levels across team members occur most commonly during highly **technically demanding** stages



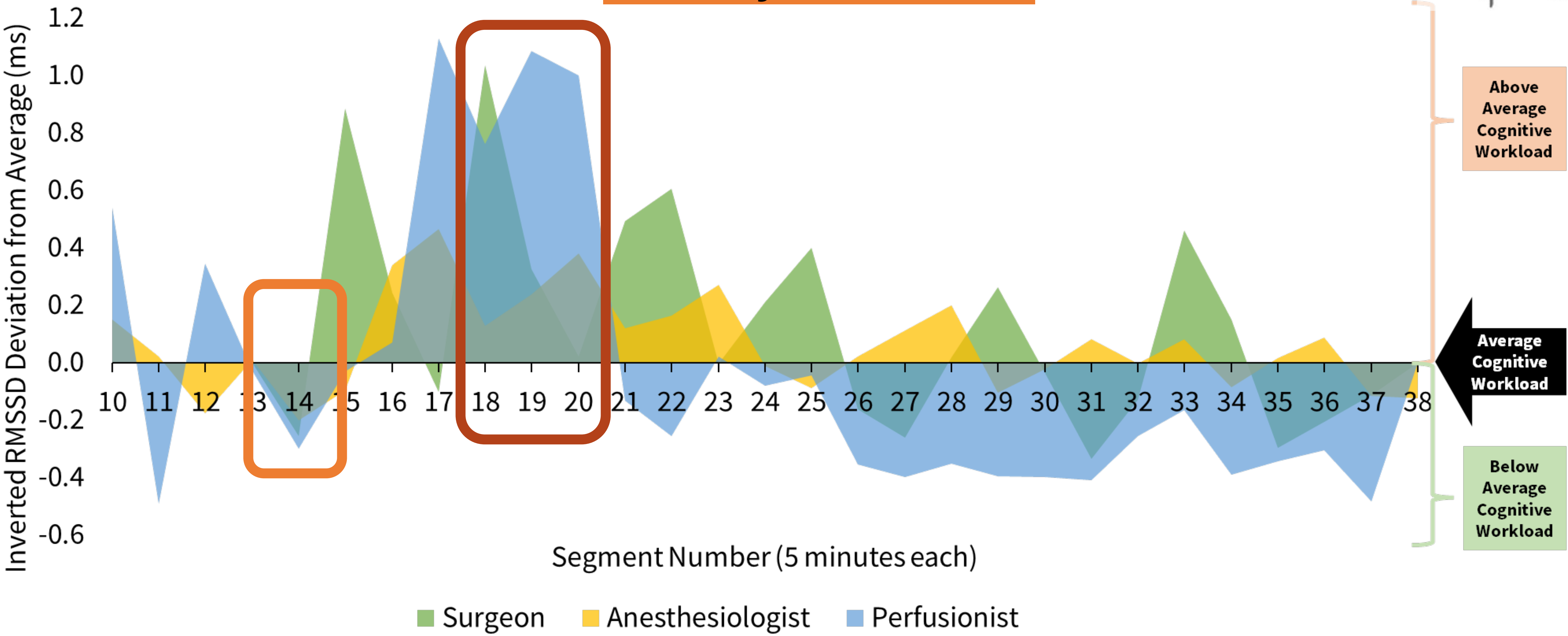
Kennedy-Metz LR et al. (2020) Analysis of Mirrored Psychophysiological Change of Cardiac Surgery Team Members During Open Surgery. *Journal of Surgical Education.*

Consecutive peaks in physiological levels occur during deviations from standard care, most often reflecting **teaching burden**



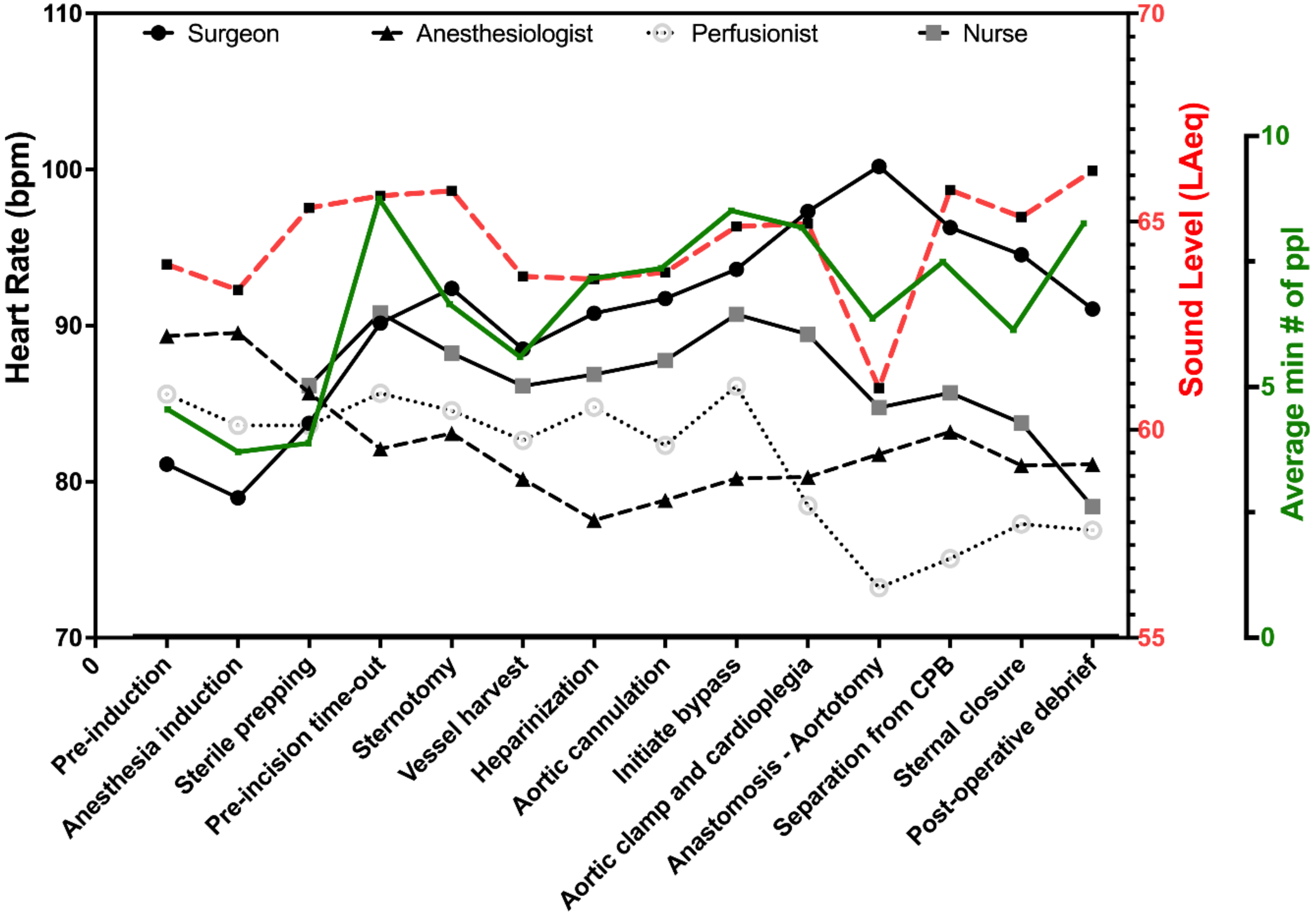
Kennedy-Metz LR et al. (2021) *Cognitive implications of high teaching burden in academic cardiac surgery*. Abstract for podium presentation. Academic Surgical Conference

High team physiological levels are more strongly associated with **cognitive distractions** and low team physiological levels with **auditory distractions**

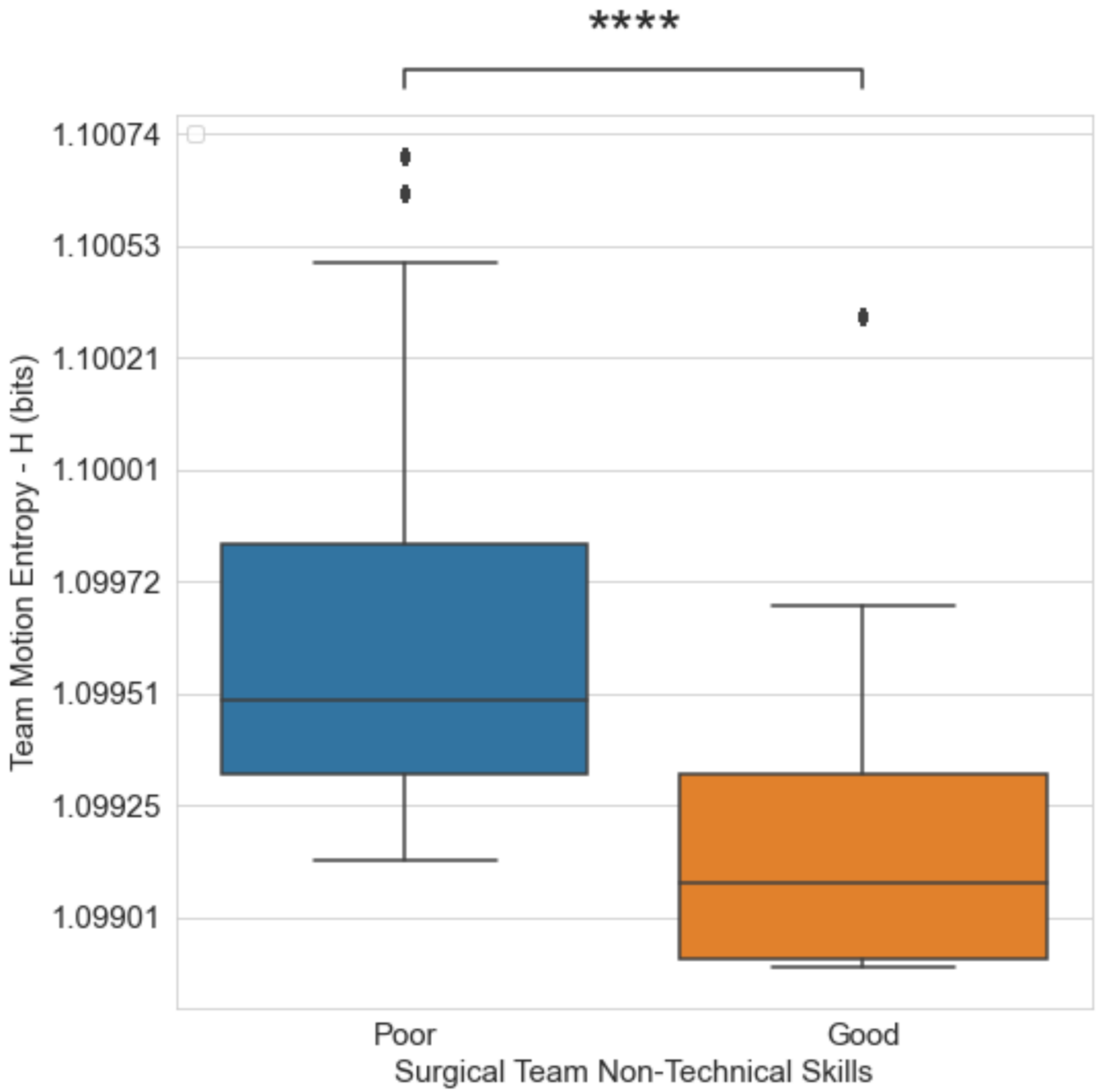


Kennedy-Metz LR et al. (2021) Prevalence of Surgical Flow Disruptions Across Intra-operative High- and Low-Workload Phases in Cardiac Surgery. Conference proceedings of the International Symposium on Human Factors and Ergonomics in Health Care.

Lowest noise levels and surgeon's highest heart rate occur during **anastomosis/aortotomy**



Kennedy-Metz LR et al. (2022) *Systematic assessment of perioperative indicators affecting team performance and noise levels in cardiac surgery*. Abstract for poster presentation. American Association for Thoracic Surgery.



Merging non-technical skills assessment and computer vision approaches, recent work has demonstrated that teams with **higher non-technical skills** exhibited less motion entropy while separating the patient from bypass, suggesting greater coordination

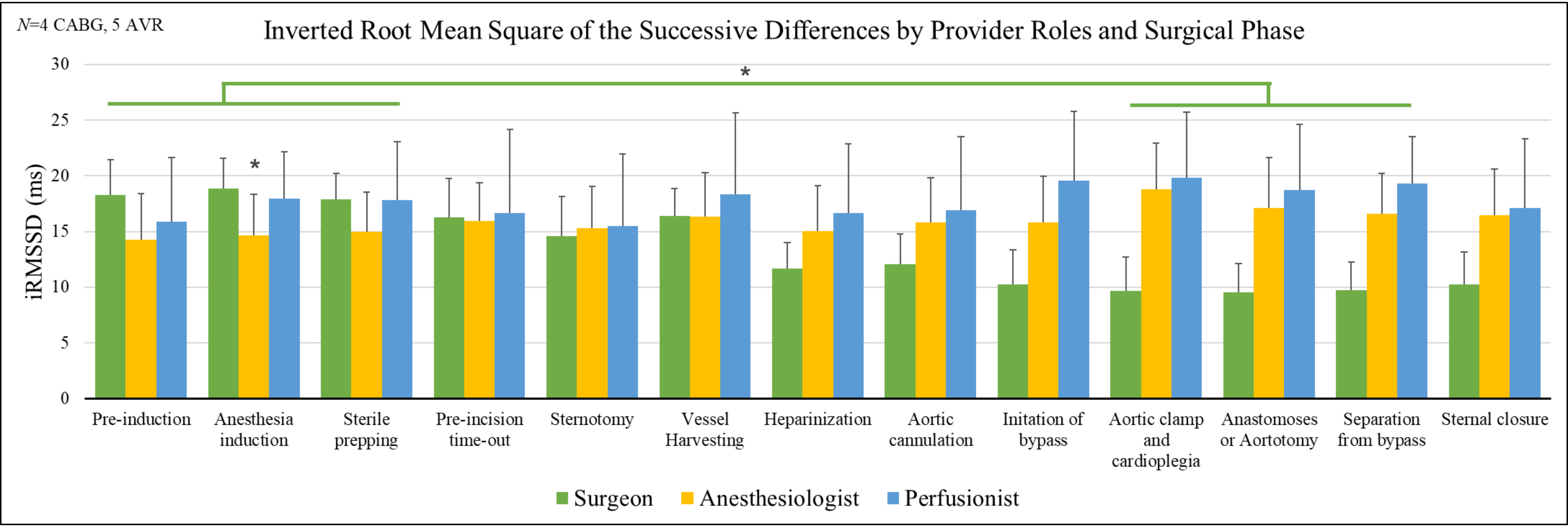
Ebnali M et al. (2022) Using computer vision for automated assessment of non-technical skills during a critical phase of cardiac surgery. Abstract under review, 18th Annual Academic Surgical Congress.

Cardiac surgery process models

3	Stage	Step N	Step Name	Sub-step Number	Sub-step Name	Sub-step order	Agent Resources	Resources/Inputs
79	Pre-op	4	Perform Pre-incision Time Out			Sequential		
80				4.1	Confirm all team members have introduced themselves by name and role		Anesthesiologist, Surgeon, Nurse, Perfusionist	
81				4.2	Discuss crisis checklists	Sequential		
82					4.2.1 Confirm all team members know how to locate/access crisis checklists		Anesthesiologist, Surgeon, Nurse, Perfusionist	
83					4.2.2 Identify designated reader of crisis checklists		Anesthesiologist, Surgeon, Nurse, Perfusionist	
84				4.3	IF (TEE probe in place) THEN Perform TEE		Anesthesiologist	TEE probe, TEE scanner
85				4.4	Verbally confirm updated procedure		Anesthesiologist, Surgeon, Nurse, Perfusionist	
86				4.5	Perform review of anticipated critical events	In Any Order		
87					4.5.1 Perform surgeon team review of anticipated critical events		Surgeon	
88					4.5.2 Perform anesthesiologist team review of anticipated critical events		Anesthesiologist	
89					4.5.3 Perform nursing team review of anticipated critical events		Nurse	
90				4.6	Administer prophylactic antibiotics		Anesthesiologist	Patient
91								
92	IntraO	5	Perform Sternotomy			Sequential		
93				5.1	Make First Skin Incision		Surgeon	Patient, Scalpel, Electroca
94				5.2	Divide Sternum		Surgeon	Patient, Sternal saw
95								
96	IntraO	6	Perform Vessel Harvesting			Sequential		
97				6.1	Lift Sternum		Surgeon	Patient
98				6.2	Turn on CO2 monitor on cardiac tower		Nurse	Cardiac tower
99				6.3	Harvest conduits	In Any Order		
100					6.3.1 Harvest LIMA, RIMA, or both		Surgeon	Patient
101					6.3.2 Prepare for and then harvest saphenous vein or radial artery	Sequential		Patient
102					6.3.2.1 IF (Endoscopic vein harvest AND (Decision to administer low dose heparin = YES)) THEN Administer low dose heparin		Anesthesiologist	Endoscopic or open vein
103					6.3.2.2 Harvest saphenous vein or radial artery		Surgeon	Patient
104								
105	IntraO	7	Perform Heparinization			Sequential		
106				7.1	IF (HDR Recommended Heparin Dose > 400 u/kg) THEN Report Suspicion of Heparin Resistance		Perfusionist	HDR Recommended Hepa
107				7.2	Administer HDR Recommended Heparin Then Verify ACT	Sequential		
108					7.2.1 Administer Heparin		Anesthesiologist	HDR Recommended Hepa
109					7.2.2 Verify Target ACT Achieved	Sequential		
110					7.2.2.1 Determine Post-Heparin ACT	Sequential		

Isolated CABG | Cannulation

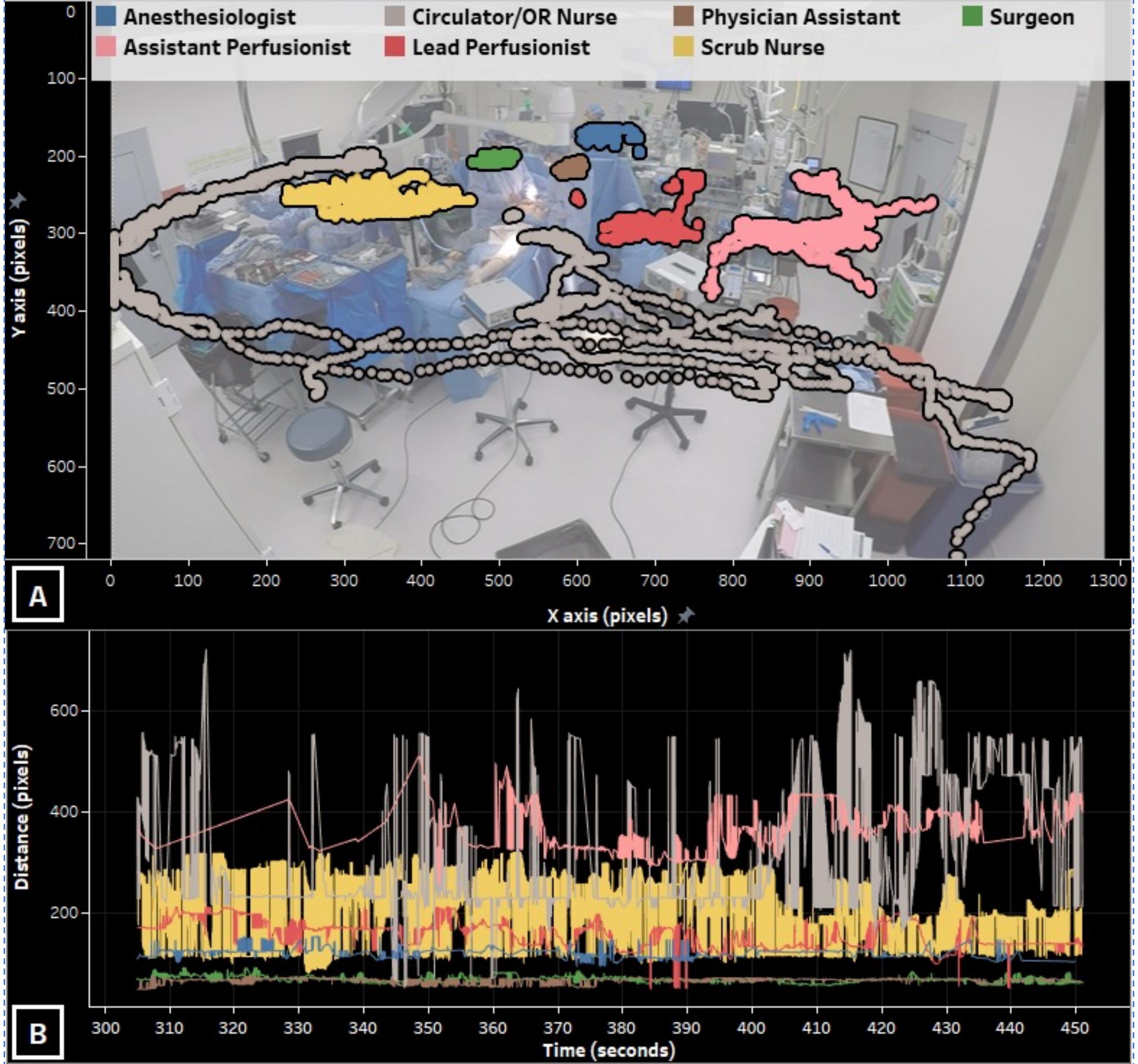
Cognitive workload levels vary according to provider role and surgical phase

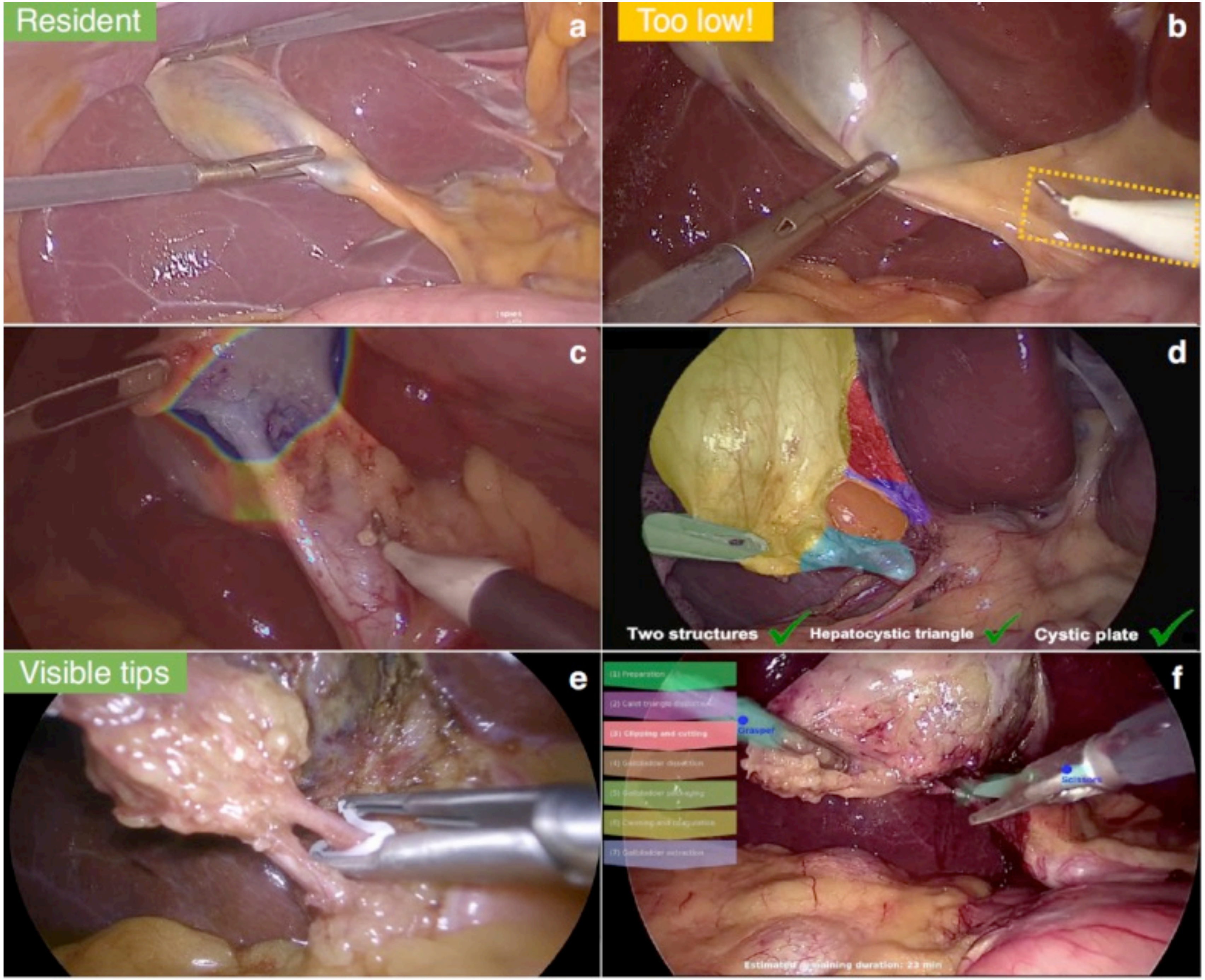


Computer vision for motion tracking

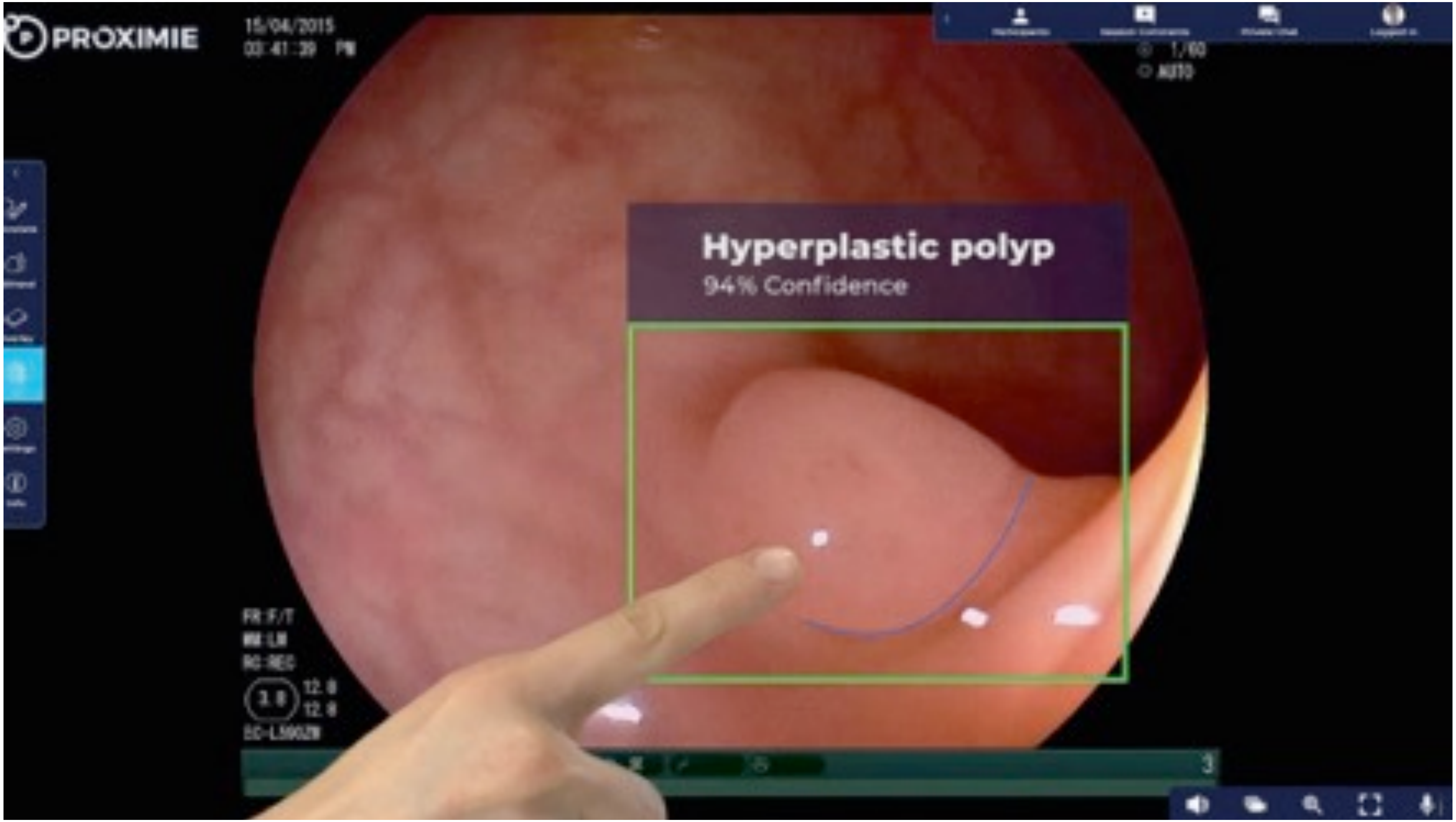
A: Density of individual's position over time

B: Team centrality over time



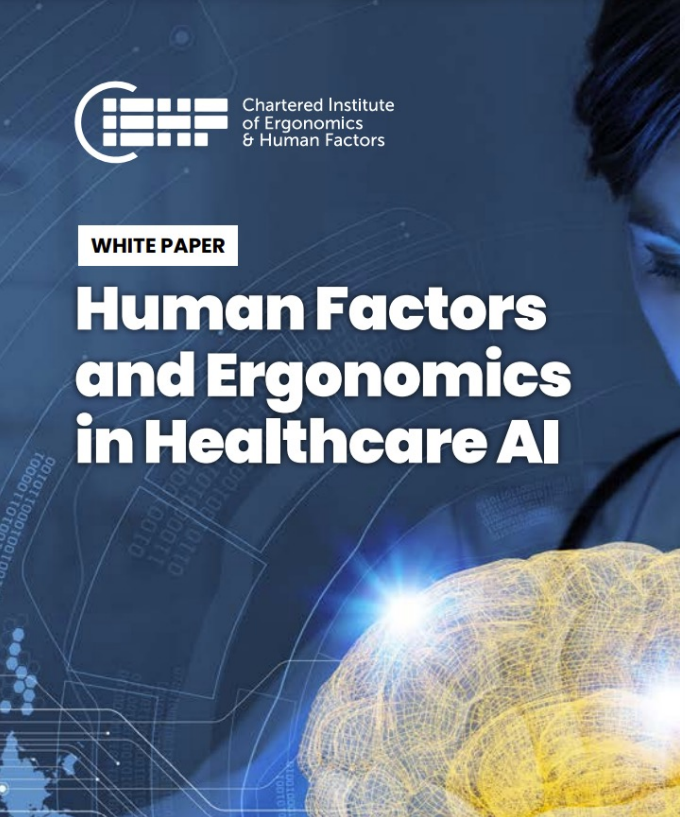


Resident
a
Too low!
b
c
d
Two structures
Hepatocystic triangle
Cystic plate
Visible tips
e
f
(1) Preparation
(3) Clipping and cutting
Grasper
Scissors


PROXIMIE
15/04/2015
03:41:39 PM
1/60
AUTO
Hyperplastic polyp
94% Confidence

Next questions…

- Has the machine learned enough? Or should the intervention be allowed to continue learning (and improving)?
- Is the supporting suite of implementation strategies (eg, hardware configuration and reliability, information display, or user education) optimized? Or are some elements redundant or missing?
- Is the information provided by the SaMD of homogeneous accuracy and utility? Or do some instructions “work” better than others?
- What characteristics of the healthcare delivery environment (eg, clinician knowledge and attitudes, existing care patterns) influence the incremental benefit?
- What characteristics of the patient population influence the incremental benefit?
- How do these features interact to influence the effect of the SaMD on the proximate (eg, intra operative hypotension) and more important distal (eg, post operative recovery) patient outcomes?



This White Paper has identified eight HF/E principles that should be taken into consideration in the successful use of AI in healthcare. These are:

SITUATION AWARENESS
Design options need to consider how AI can support, rather than erode, people's situation awareness

WORKLOAD
The impact of AI on workload needs to be assessed because AI can both reduce as well as increase workload in certain situations.

AUTOMATION BIAS
Strategies need to be considered to guard against people relying uncritically on the AI, e.g., the use of explanation and training.

EXPLANATION AND TRUST
AI applications should explain their behaviour and allow users to query it in order to reduce automation bias and to support trust.

HUMAN-AI TEAMING
AI applications should be capable of good teamworking behaviours to support shared mental models and situation awareness.

TRAINING
People require opportunities to practise and retain their skill sets when AI is introduced, and they need to have a baseline understanding of how the AI works.

RELATIONSHIPS BETWEEN STAFF AND PATIENTS
The impact on relationships needs to be considered, e.g., whether staff will be working away from the patient once more and more AI is introduced.

ETHICAL ISSUES
AI in healthcare raises ethical challenges including fairness and bias in AI models, protecting privacy, respecting autonomy, providing benefits and minimising harm.

npj | digital medicine www.nature.com/npjdigitalmed

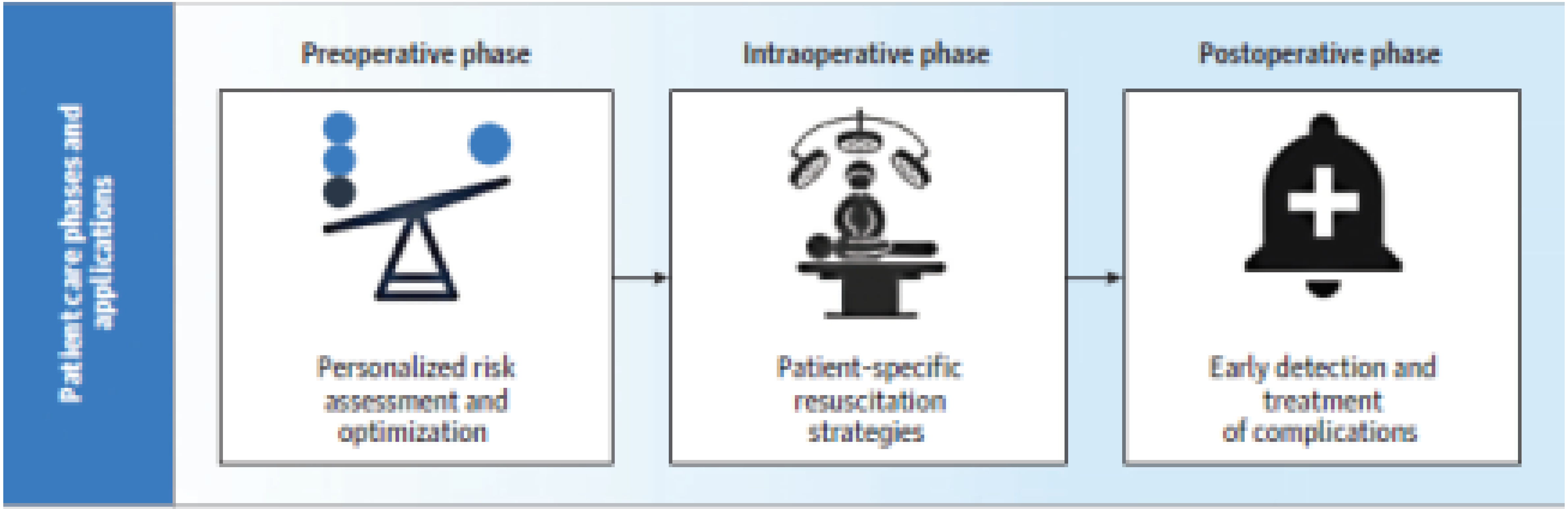
ARTICLE OPEN Check for updates

A Delphi consensus statement for digital surgery

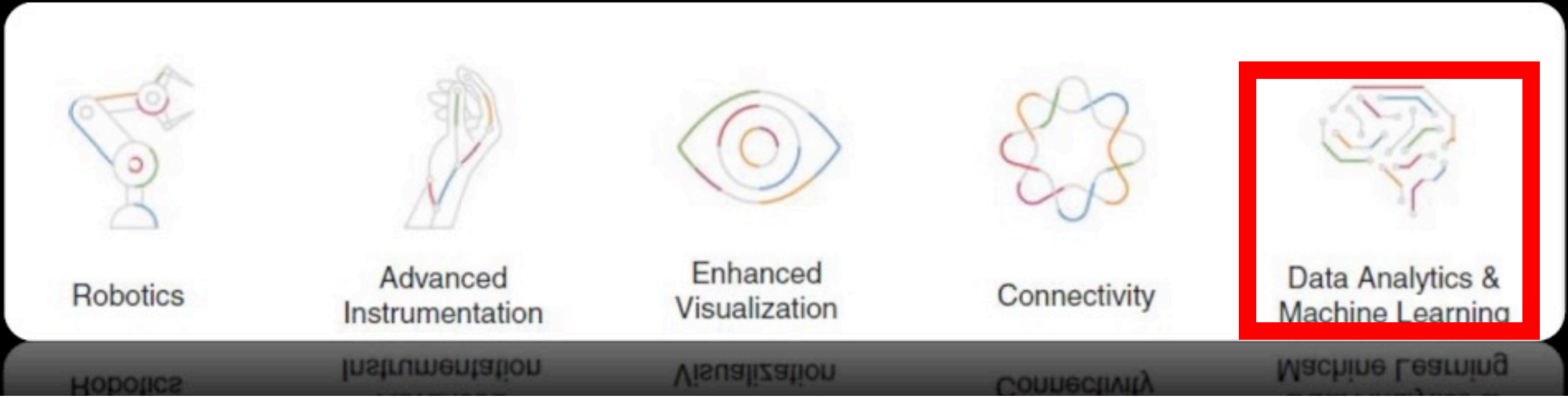
Digital Surgery

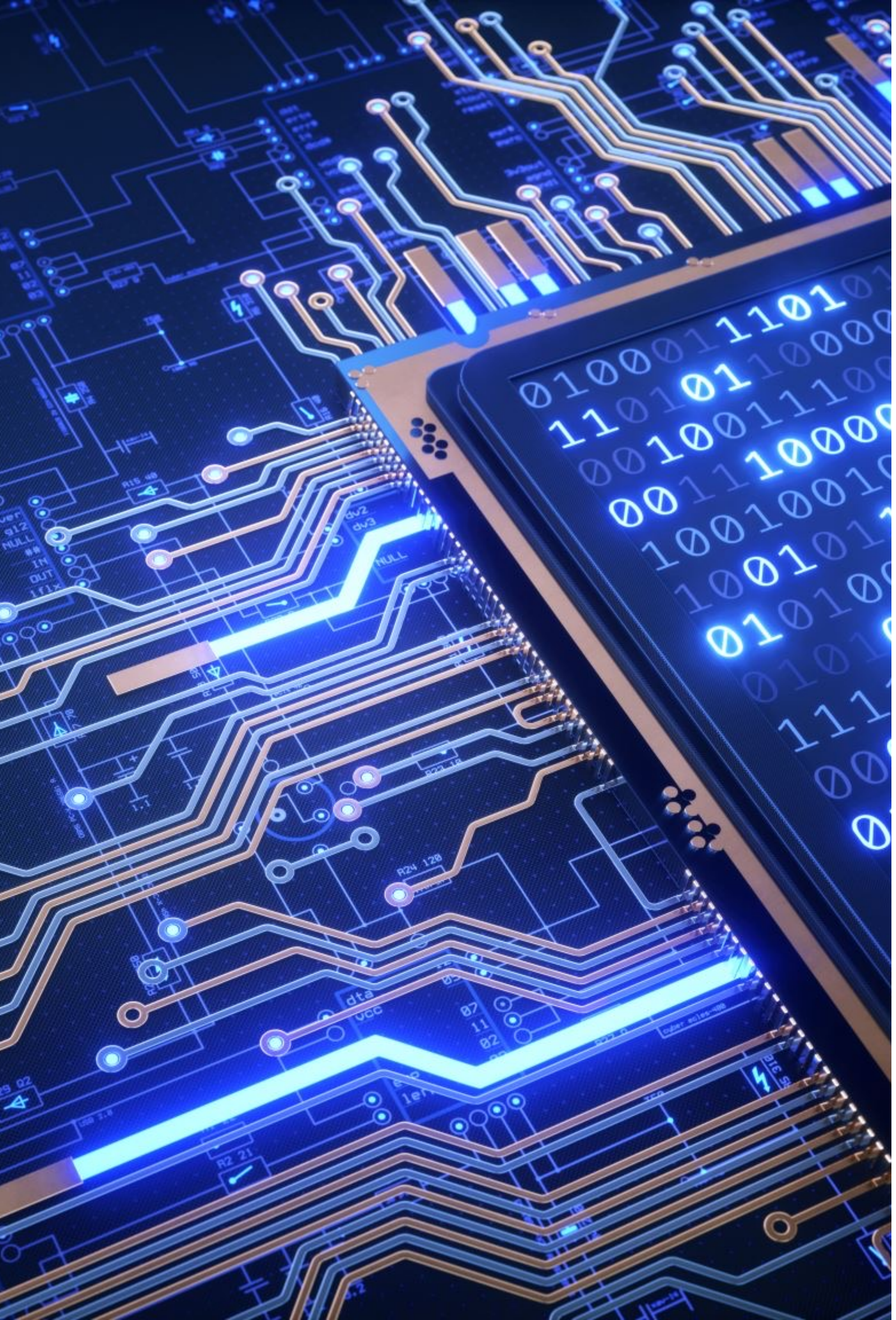
- “The use of technology for the enhancement of preoperative planning, surgical performance, therapeutic support or training, to improve outcomes and reduce harm”

Lam et al. npj Digital Medicine (2022)5:100

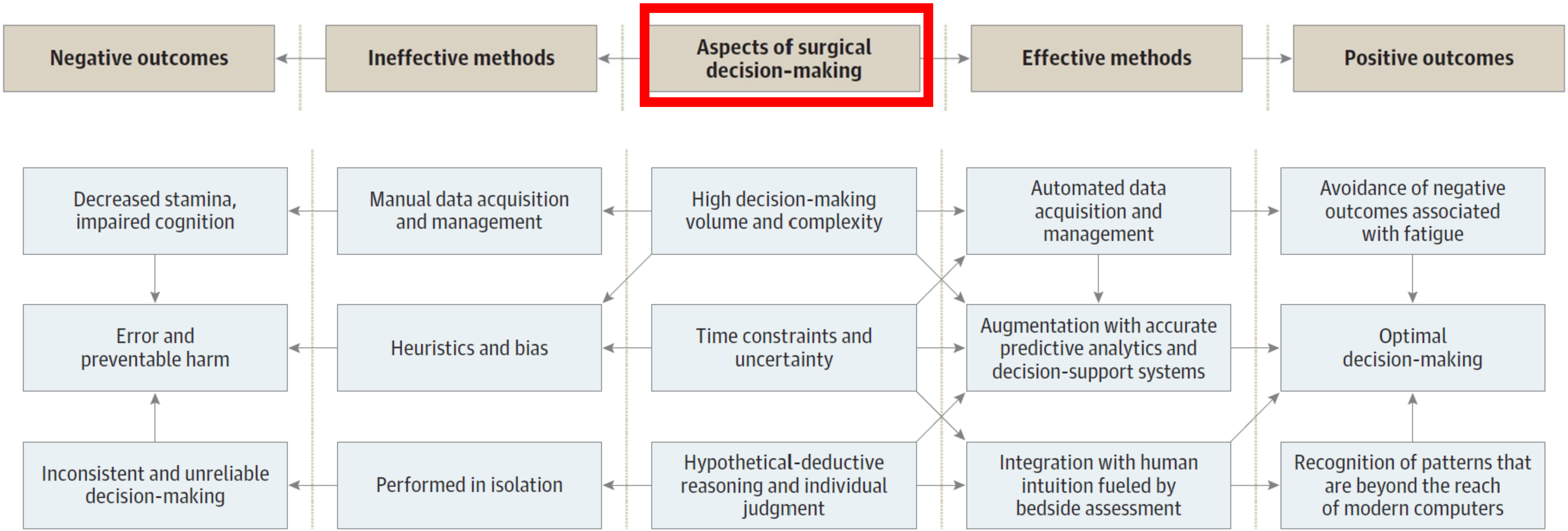

Patient care phases and applications
Preoperative phase
Personalized risk assessment and optimization
Intraoperative phase
Patient-specific resuscitation strategies
Postoperative phase
Early detection and treatment of complications

Five Pillars of Digital Surgery

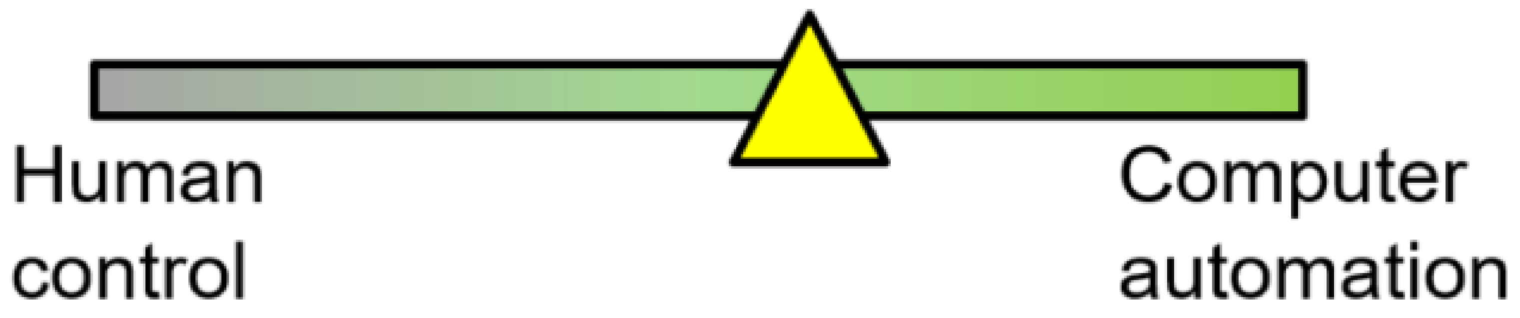




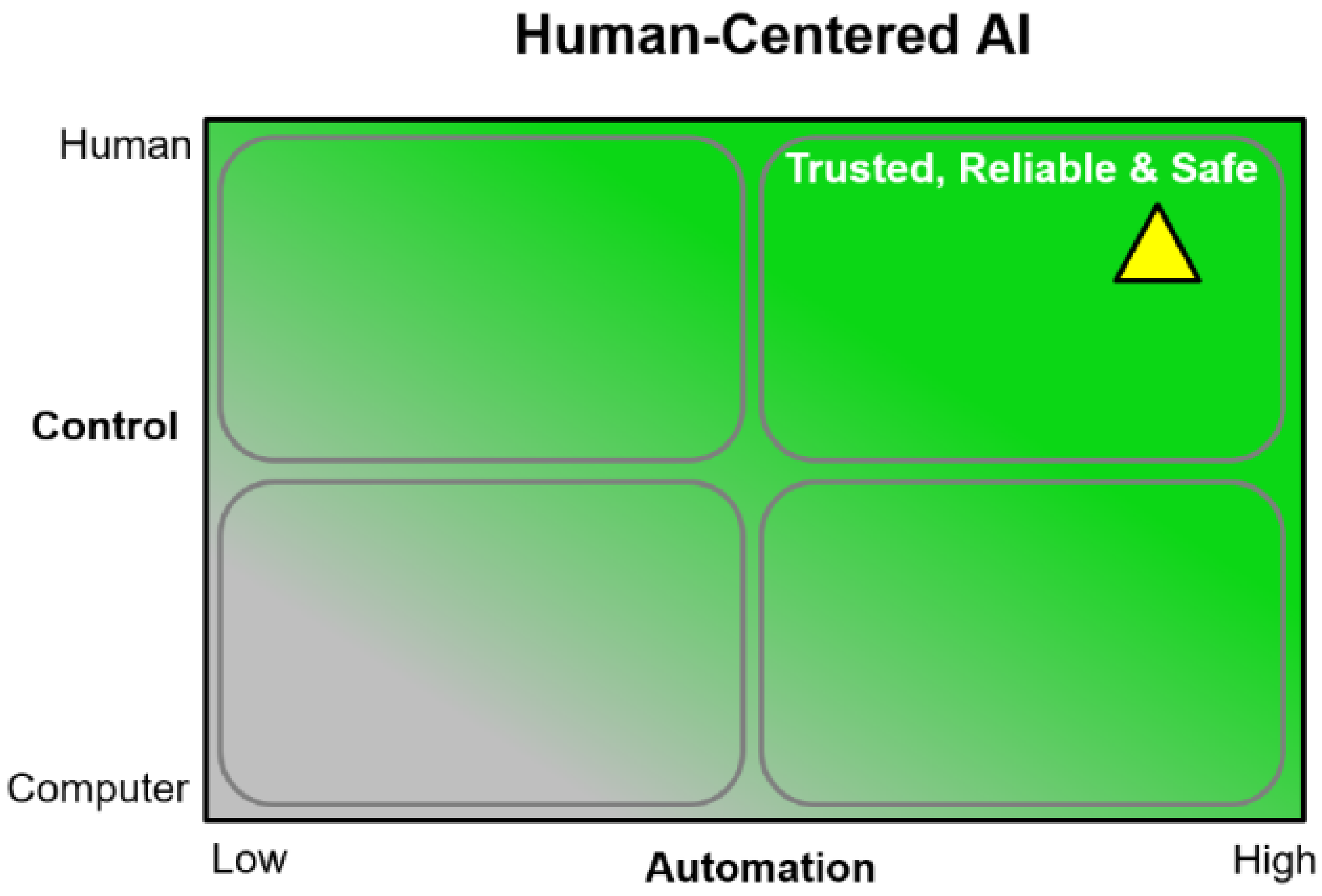
AI, Autonomous Operations, and Human-Machine Teaming continue to evolve at an unprecedented pace


Negative outcomes
Ineffective methods
Aspects of surgical decision-making
Effective methods
Positive outcomes
Decreased stamina, impaired cognition
Manual data acquisition and management
High decision-making volume and complexity
Automated data acquisition and management
Avoidance of negative outcomes associated with fatigue
Error and preventable harm
Heuristics and bias
Time constraints and uncertainty
Augmentation with accurate predictive analytics and decision-support systems
Optimal decision-making
Inconsistent and unreliable decision-making
Performed in isolation
Hypothetical-deductive reasoning and individual judgment
Integration with human intuition fueled by bedside assessment
Recognition of patterns that are beyond the reach of modern computers

One-dimensional thinking on automation



Two-dimensional AI



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Explanations of autonomous teammates acting counter to human expectations

- A viable means to remedying and resolving misunderstanding or expectation violations produced by autonomous agents