Surgical Artificial Intelligence

World Summit Al Americas Montréal, Canada – April 20, 2023

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Assistant Professor of Surgery - Harvard Medical School Massachusetts General Hospital





ISAIIL @Oz_Meireles







Digital Surgical DATA generation

Strategy for developing a new field

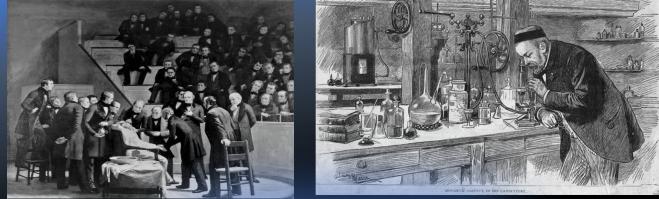
• The role that surgeons play





Surgical Revolutions (in the last 200 years)

- General Anesthesia 1840s
- Antiseptic Surgery 1860s
- Endoscopic Procedures 1960s
- Cognitive Computing 2010s













Artificial intelligence: The study of algorithms that give machines the ability to reason and perform cognitive functions - **1956**

Machine Learning: Algorithms that improve automatically through data analysis and experience

Computer Vision: Machine understanding of images and videos

Source: KPMG

Bellman R. (1978).







Consciousness: The awareness of internal and external existence.

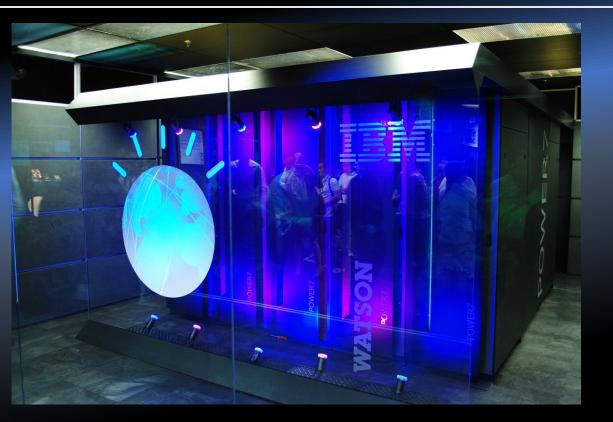
The state of being aware of and responsive to one's surroundings.

Collective Consciousness:

The set of shared beliefs, ideas, and moral attitudes which operate as a <u>unifying force within society</u>. In general, it does not refer to the specifically moral conscience, but to a <u>shared understanding of social</u> <u>norms and concepts.</u>

Collins Dictionary of Sociology, p93.

Reality - IBM and Tesla









General and Super Al



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Conceptually AI could develop Consciousness.

What is happening in the Operating Room now ?



HARVARD

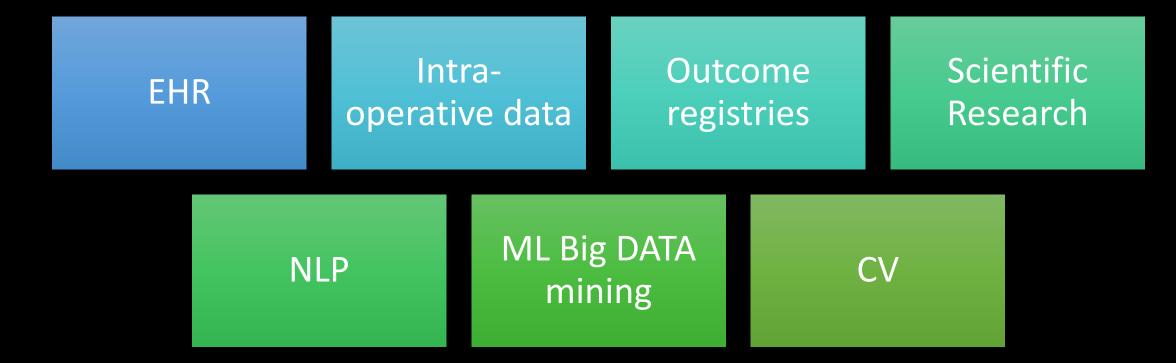
MEDICAL SCHOOL



OR Data Generation

Hardware (instruments, Robotics)	Software (Data, Algorithms)	Human Operators (MD, RN, Biomed, IT,)	Telecom
Human (professional preparedness)	Economics (business plan)	Governance	Data ownership

Data sources and Analytics



Video DATA

More computing power





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More powerful/efficient techniques

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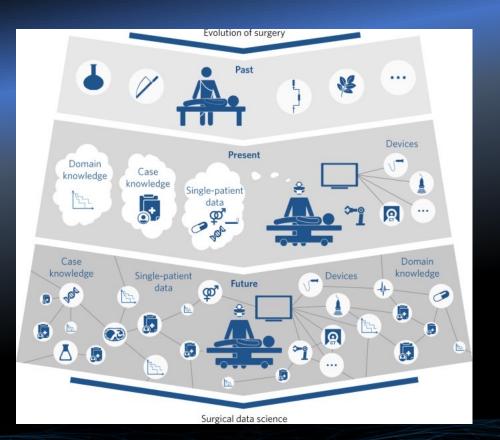


MASSACHUSETTS GENERAL HOSPITAL

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Large amount of DATA



BIG DATA IN FORMULA ONE



Formula One cars generate terabytes of data during a race. Dozens of engineers at the track and as far away as the U.K. comb over the data during a race in near real-time, looking for any adjustment that could win or lose a race.

RACE TEAMS COMBINED TO GENERATE 243 TERABYTES OF DATA FROM THEIR VEHICLES AT THE 2014 U.S. GRAND PRIX IN AUSTIN, TX.

243 TERABYTES OF DATA COMPARED TO ...



EQUIPPED WITH HUNDREDS OF SENSORS, F1 CARS PROVIDE A STREAM OF DATA THAT'S ANALYZED THOUSANDS OF MILES AWAY IN NEAR REAL-TIME

.170 secs	.300 secs	.600 secs	1.923 secs
Round trip for race data	Round trip for race data	Difference between 1st	World record fastest
to transfer between UK	to transfer between UK	and 2nd place at 2014	F1 pitstop, set by Red
and U.S.	and Australia	Spanish Grand Prix	Bull in Austin 2013

RACE FANS GENERATED MORE THAN 2.3 TERABYTES OF AT&T MOBILE DATA DURING THE U.S. GRAND PRIX BY SHARING PHOTOS AND SENDING TWEETS, LESS THAN 1% COMPARED TO THE RACING TEAMS.



SOURCES: Infiniti Red Bull Flacing, AT&T, Library of Congress, Twit





The global market size of artificial intelligence in healthcare was estimated at US\$ 11.06 billion in 2021 and is expected to surpass around US\$ 187.95 billion by 2030, growing at a CAGR of 37% during the forecast

PRECEDENCE ARTIFICIAL INTELLIGENCE IN HEALTHCARE MARKET SIZE, 2021 TO 2030 (USD BILLION)



Precedence Research - Artificial Intelligence (AI) in Healthcare Market Size 2022-2030



period 2022 to 2030.



Deloitte.

Healthcare in 2065

Patient centred healthcare: Everything from diagnosis, drugs to devices will be custom designed to seamlessly integrate into a patient's daily life.

Wearables at the forefront: Always on and constantly collecting data, these peripherals are the basis of the medicalised quantified self.

Digitised and decentralised doctors: Improved connectivity and miniaturised diagnostic technology means accessibility and convenience for future medical consultations.

Rise of the machines: Medical robots and artificial intelligence create more efficient healthcare platforms that are powered by the insights of data analytics.

Evolved healthcare provision: Services will now be consumed continuously lending itself to a subscription based business model that focuses on high productivity and asset light strategies.

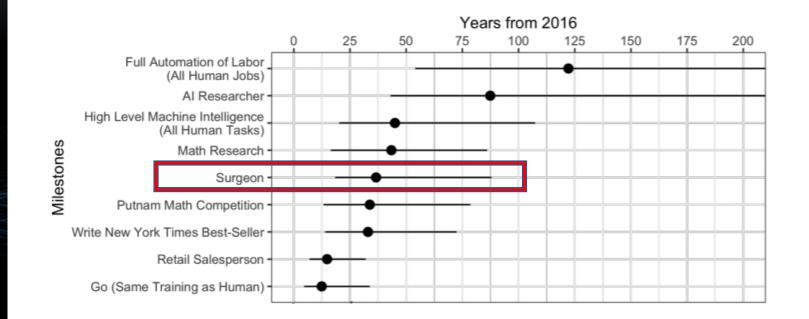






Researchers from Oxford University and Yale predict that all industries, including healthcare, could become significantly more reliant on machine intelligence by the middle of the century – and that machines may be able to automate all human jobs in less than 120 years







MASSACHUSETTS

GENERAL HOSPITAL

Scientific publications

PubMed_Timeline_Results_by_Year

Search query: Artificial intelligence surgery	
Year	Count
2023	1627
2022	5496
2021	4671
2020	3259
2019	1982
2018	1239
2017	919
2016	770



Advanced Create alert Create RSS **User Guide** Display options 🗱 Email Send to Sorted by: Best match Save **RESULTS BY YEAR** of 2.910 29,093 results Page 1963 2023 MY NCBI FILTERS Artificial Intelligence in Surgery: Promises and Perils. Hashimoto DA, Rosman G, Rus D, Meireles OR. TEXT AVAILABILITY Ann Surg. 2018 Jul;268(1):70-76. doi: 10.1097/SLA.000000000002693. Cite PMID: 29389679 Free PMC article. Review. Abstract Share OBJECTIVE: The aim of this review was to summarize major topics in artificial intelligence (AI), Free full text including their applications and limitations in surgery. ...Their current and future applications to surgical practice were introduced, including big data ... Full text



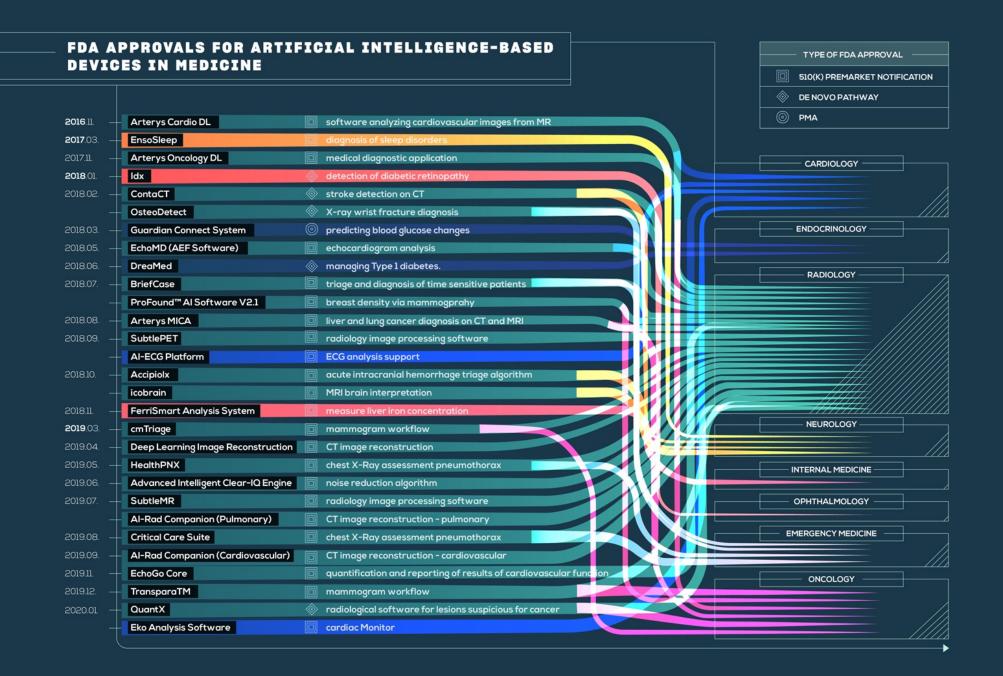


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Search

Search performed on April 12, 2023

Artificial intelligence surgery



AI + Big DATA = Cognitive Augmentation

Information, Guidance, and Intervention





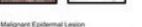


CNN Clinical Application



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Malignant Dermal Lesion







f. Benign Dermal Lesion

d. Benigh Melanocytic Lesion





. Genodermatosis

Cutaneous Lymphom



129,450 clinical images2,032 different diseasesTested performance against 21 boardcertified dermatologists on biopsy-proven clinical images.

The CNN achieves performance on par with all tested experts across both tasks,

demonstrating an artificial intelligence capable of classifying skin cancer with a level of competence comparable to dermatologists

Esteva A, Kuprel B, Novoa RA, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature 2017; 542(7639):115-118.







Computer Vision and Endoscopy

Cadens - Imagia - Satis © 2016 - all rights reserved



a joint development from **Cadens, Imagia, Satis**



AI4GI Video and copy rights





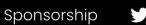
Experimental Phase

Research : Intraoperative decision support

- Shrinking data for surgical training
- Technique that reduces video files to one-tenth their initial size enables speedy analysis of laparoscopic procedures.









MGH 1811

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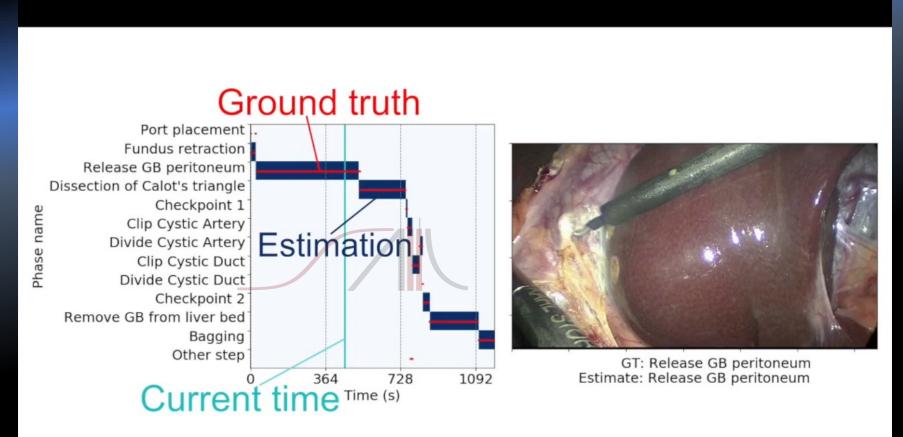
Surgical Artificial Intelligence and Innovation Laboratory

Established in 2017, Boston, USA





Real Time Phase Detection



Surgical Artificial Intelligence & Innovation Laboratory - Massachusetts General Hospital





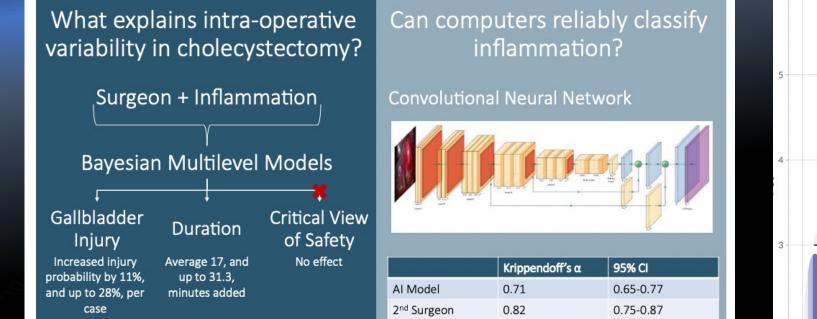


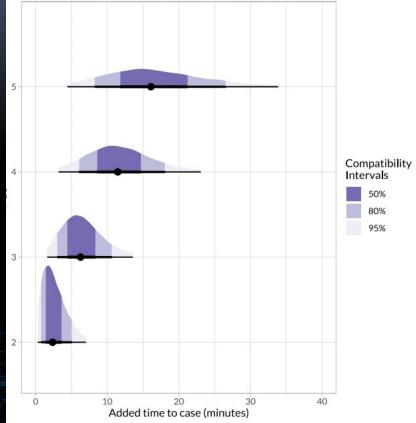


Experimental Phase

Artificial intelligence prediction of cholecystectomy operative course from automated identification of gallbladder inflammation

Thomas M. Ward¹ · Daniel A. Hashimoto¹ · Yutong Ban^{1,2} · Guy Rosman^{1,2} · Ozanan R. Meireles¹









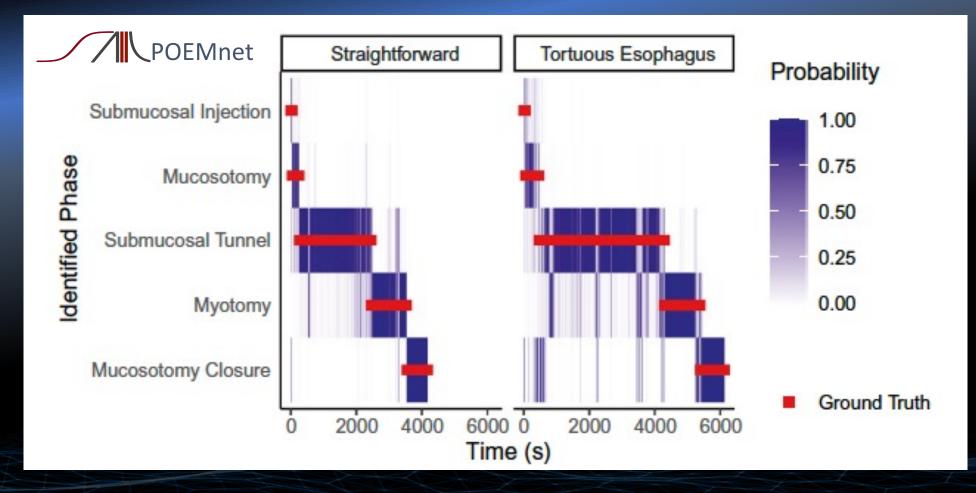




Experimental Phase

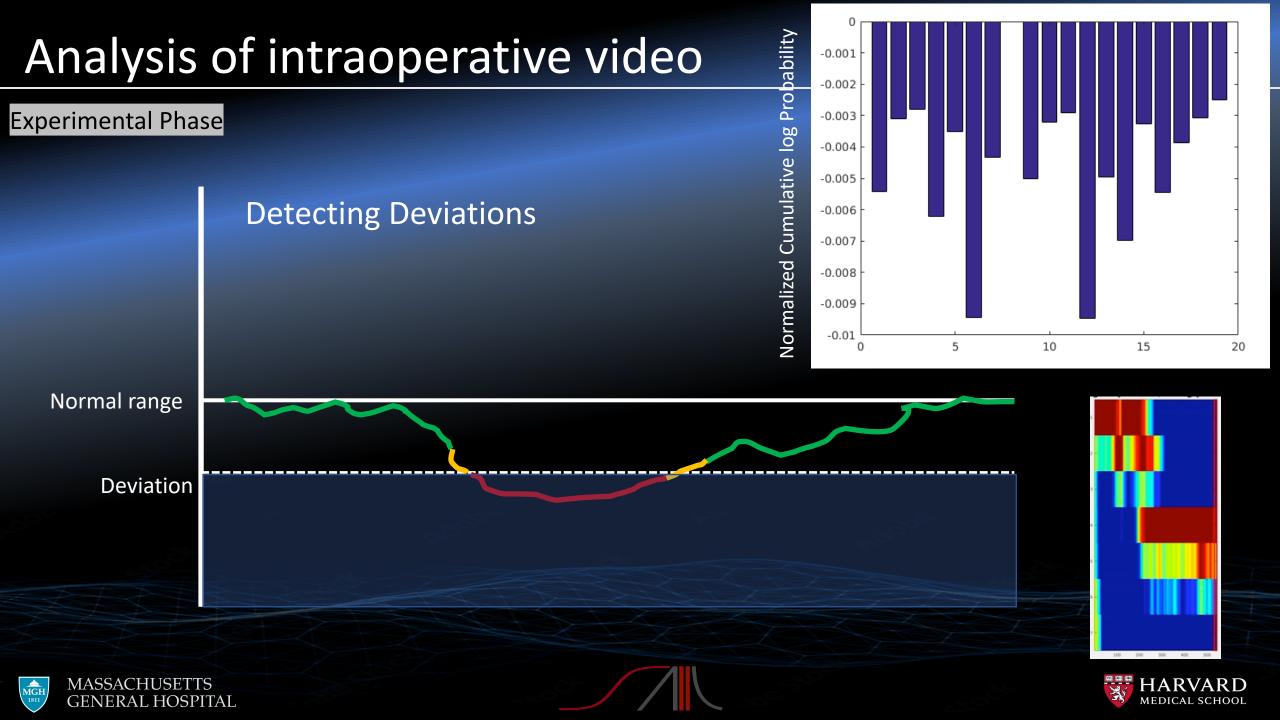


Surgical Fingerprint – POEM

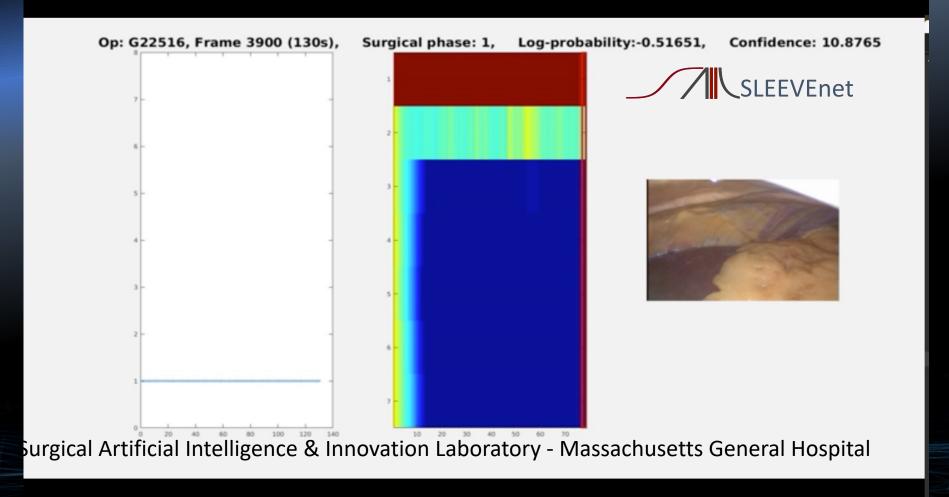








Deviation Analysis and Detection









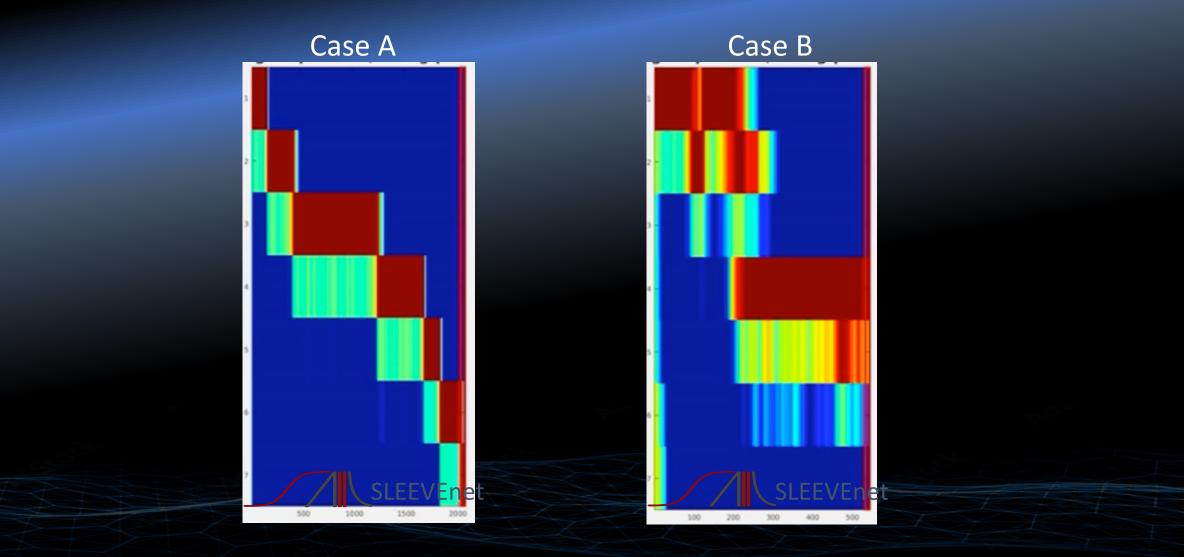








Surgical Fingerprint – Sleeve Gastrectomy



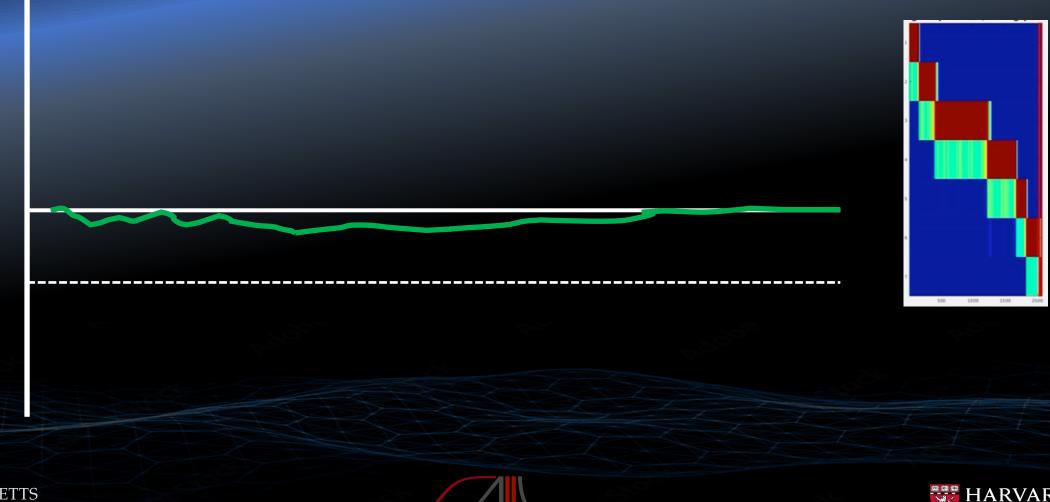




Analysis of intraoperative video

Experimental Phase





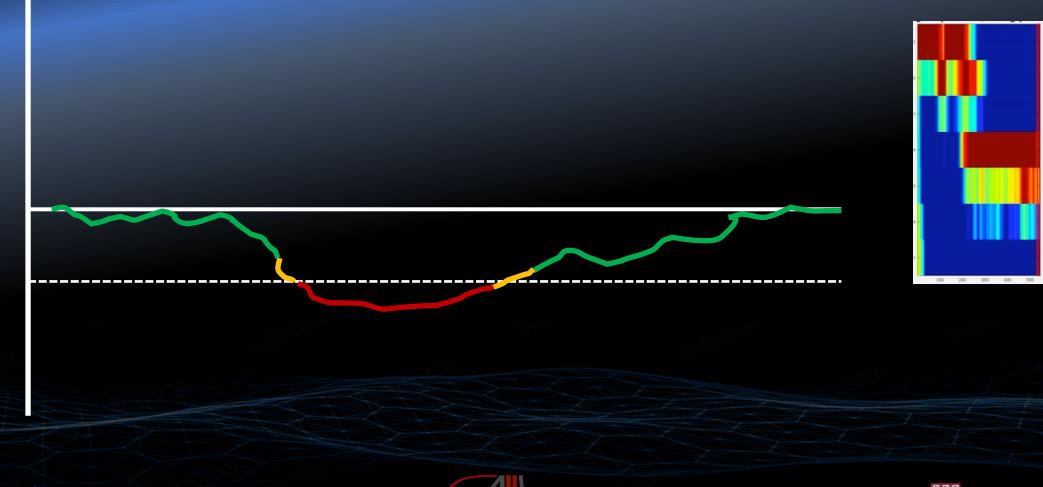




Analysis of intraoperative video

Experimental Phase

Case 2 – Detecting Complication







Potential applications

- Attending notification system
 - Notify attendings if the trainees are nearing critical portions of the operation.

Peer Review

- Augmented Morbidity and Mortality meetings
- Board certification
- Hospital credentialing and recredentialing

Tele-mentoring

- Establish automated communication link to human mentor when error is predicted or identified.
- Battlefield and Rural Areas support, to medical staff who may not have the necessary specialty specific knowledge





Automation

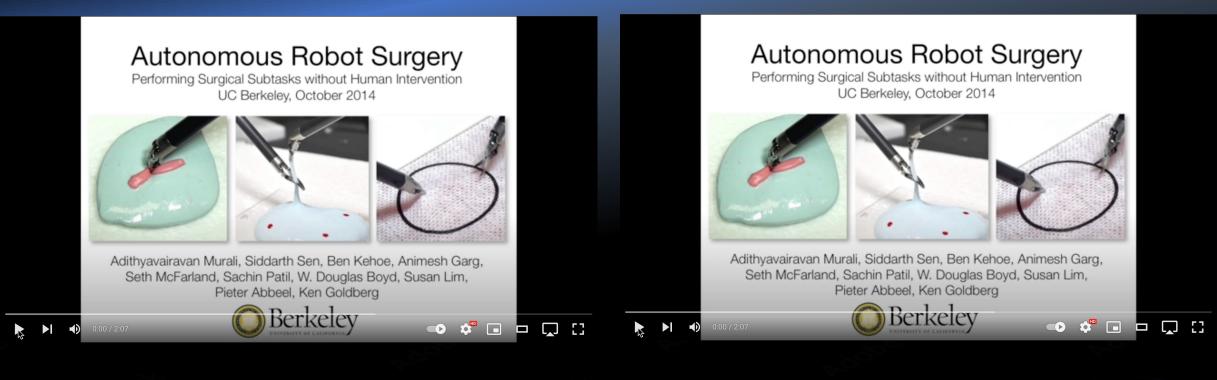






Al and Mechanical Automation

Experimental Phase

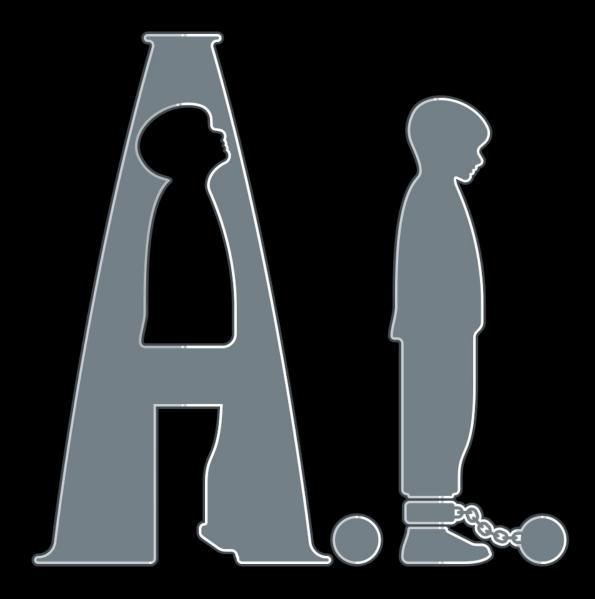


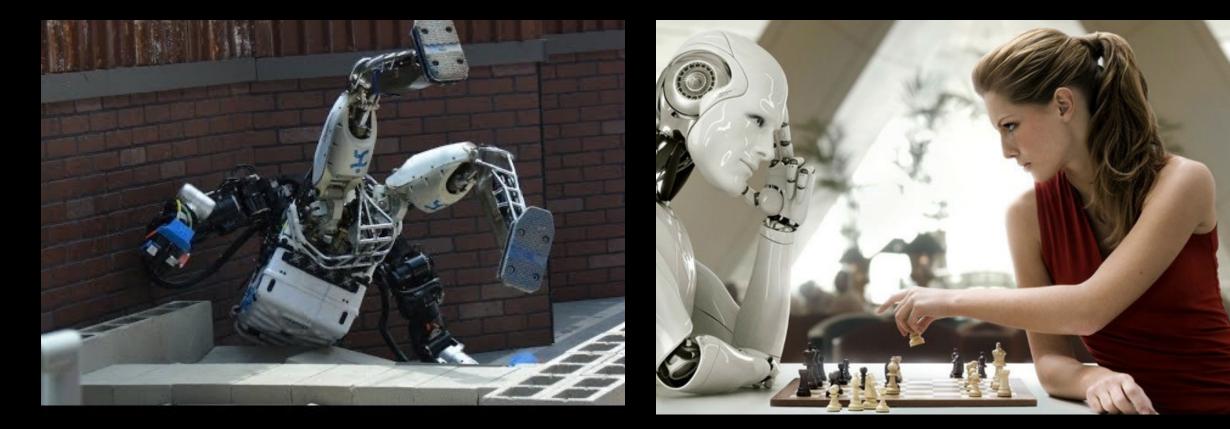


Professor, Industrial Engineering and Operations Research William S. Floyd Jr. Distinguished Chair in Engineering, UC Berkeley









Moravec's Paradox

- "Robots find the difficult things easy and the easy things difficult" •
- "Contrary to traditional assumptions, high-level <u>reasoning</u> requires relatively little computation power, whereas low-level sensorimotor skills require enormous computational resources"





MGH

Potential Failures

4) Explainability



7 REVEALING WAYS AI FAIL

IEEE Spectrum



2) Embedded Bias





https://spectrum.ieee.org/ai-failures

- Brittleness
- Embedded Bias
- Catastrophic Forgetting
- Explainability
- Quantifying Uncertainty
- Common Sense







Real life examples of AI Failures

HANDS ON THE WHEEL -

Another Tesla with Autopilot crashed into a stationary object—the driver is suing

Fail: Microsoft's AI Chatbot Corrupted by Twitter Trolls

Google Home outage hits users, '100 percent failure rate' reported

Apple's Face ID Defeated by a 3D Mask

IBM's Watson supercomputer recommended 'unsafe and incorrect' cancer treatments, internal documents show







Obstacles and Limitations

Data

- Limited access
- Limited annotation
- Regulation
- Systemic biases

Clinician

- Limited time
- Productivity pressure
- Culture

Researcher

- Limited exposure
- Innovation pressure



- Market pressure
- Culture

Patient

- Privacy
- Healthcare pressure
- Clinician relationship





Solution

Foundational work

- Annotation 🗹
- Data Structure and Use
- Governance Policies, Regulations, and Oversight

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 $X^{2} - 4X < 0$

Structural needs

- Video Data Acquisition Framework
- Management through data lifecycle

Knowledge creation and dissemination

- Scientific Research
- Education 🗸
- Cultural Transformation

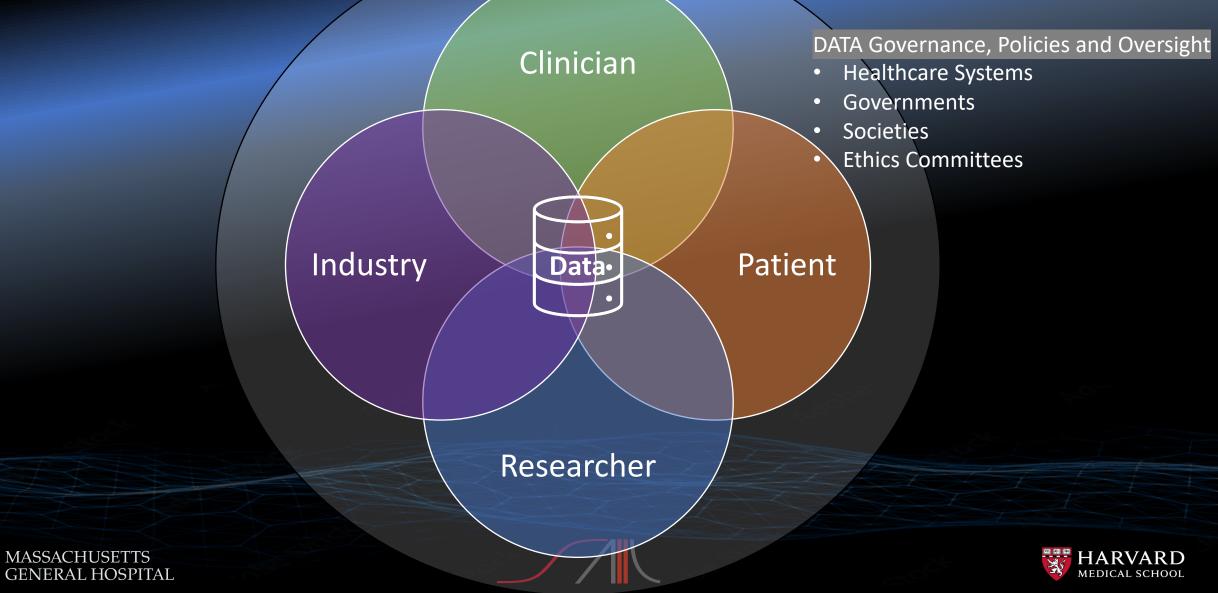
DATA collection







Surgical DATA





Consensus Recommendations on an Annotation Framework for Surgical Video

Surgical Endoscopy (2021) 35:4918–4929 https://doi.org/10.1007/s00464-021-08578-9

CONSENSUS STATEMENT



SAGES consensus recommendations on an annotation framework for surgical video

Ozanan R. Meireles¹ · Guy Rosman^{1,2} · Maria S. Altieri³ · Lawrence Carin⁴ · Gregory Hager⁵ · Amin Madani⁶ · Nicolas Padoy^{7,8} · Carla M. Pugh⁹ · Patricia Sylla¹⁰ · Thomas M. Ward¹ · Daniel A. Hashimoto¹ · the SAGES Video Annotation for AI Working Groups

Received: 25 April 2021 / Accepted: 26 May 2021 / Published online: 6 July 2021 © The Author(s), under exclusive licence to Springer Science+Business Media, LLC, part of Springer Nature 2021

Abstract

Background The growing interest in analysis of surgical video through machine learning has led to increased research efforts; however, common methods of annotating video data are lacking. There is a need to establish recommendations on the annotation of surgical video data to enable assessment of algorithms and multi-institutional collaboration.

Methods Four working groups were formed from a pool of participants that included clinicians, engineers, and data scientists. The working groups were focused on four themes: (1) temporal models, (2) actions and tasks, (3) tissue characteristics and general anatomy, and (4) software and data structure. A modified Delphi process was utilized to create a consensus survey based on suggested recommendations from each of the working groups.

Results After three Delphi rounds, consensus was reached on recommendations for annotation within each of these domains. A hierarchy for annotation of temporal events in surgery was established.

Conclusions While additional work remains to achieve accepted standards for video annotation in surgery, the consensus recommendations on a general framework for annotation presented here lay the foundation for standardization. This type of framework is critical to enabling diverse datasets, performance benchmarks, and collaboration.







Annotation Framework Hierarchical Structure with Expandable Granularity



Temporal Events

Phase (generic)

Step (procedure-specific)

Task (generic)

Action (generic)



Spatial Events

Anatomic region

Specific anatomy

General anatomy

Tissue characteristics





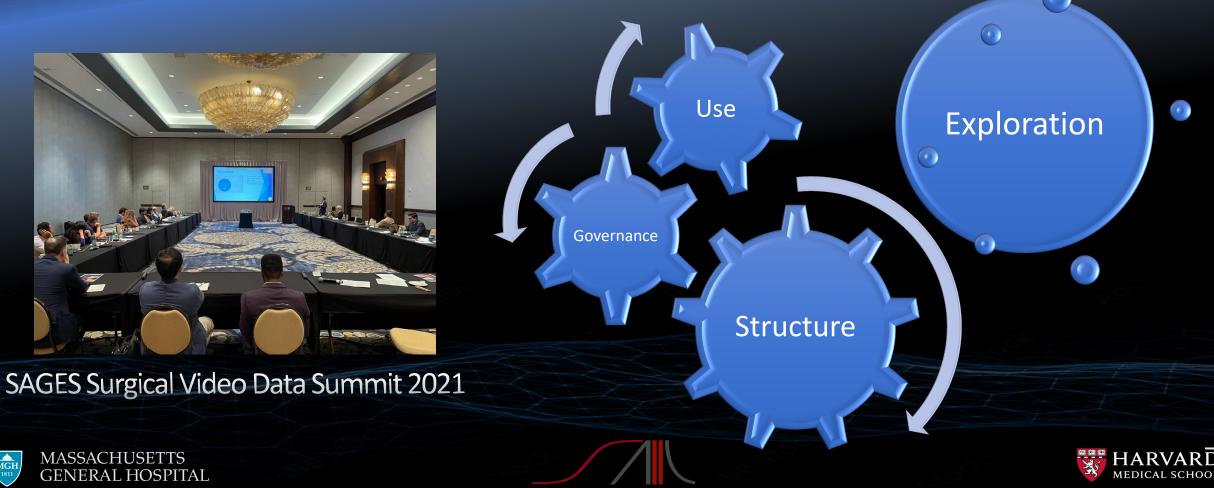






DATA Use and Structure

Objective: Establish a **framework for video data use in surgery** to improve collaboration and proposed methods to structure the use of surgical video for **clinical use**, education, and research applications.



Surgical Operating System Framework

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- Open Access Model to Promote Collaboration
- Standardization
 - Annotation
 - Data Structure
- Clear Policies and Regulations
- Transparency and Oversight
- Address Ownership Issues

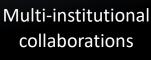




Computer Vison

Challenges





Academia and Industry partnership Standards for Publications Validation Studies

Promote Diversity











What is Computer Vision Challenge?



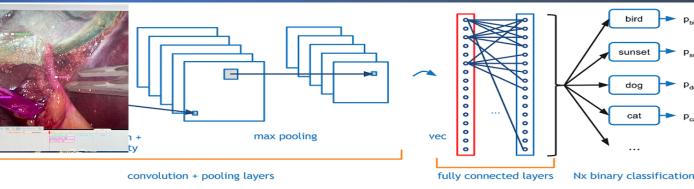
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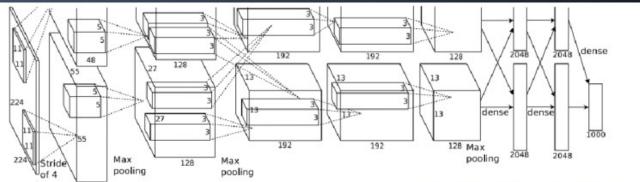
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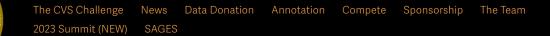
Classification Results (CLS)







MEDICAL SCHOOL



The Critical View of Safety Challenge

A SAGES Initiative

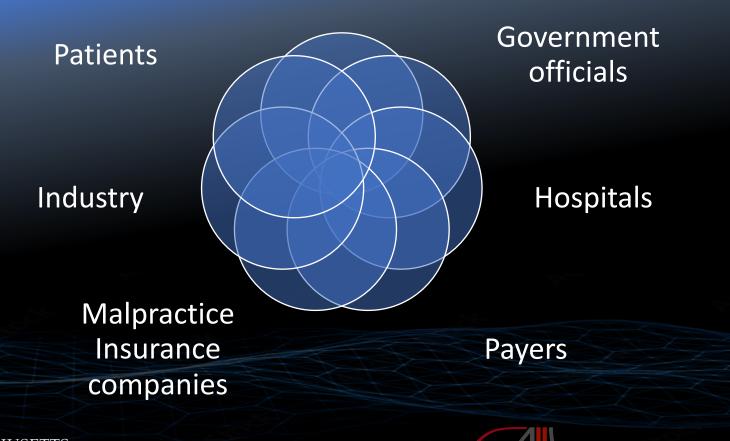






Surgical Al Governance Regulations, Policies and Oversight

Surgeons





2023





Education and Training





Medical School Curriculum



Publications







SAIIL-Net Login

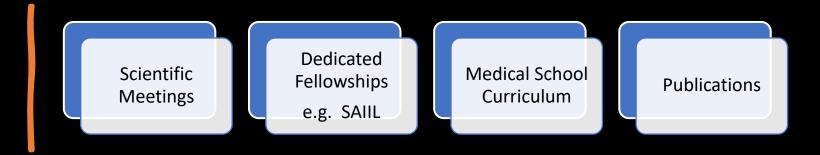
Welcome to SAIL Public

At the

At the Surgical Artificial Intelligence and Innovation Laboratory (SAIIL), we are committed to fostering a collaborative and open research community. We understand the value of sharing resources, datasets, tools, and insights with other researchers, students, and individuals interested in the field of surgical AI. To accelerate innovation and improve patient care worldwide, we are in the process of gradually making these resources available to the public. earch

Junio

Education and Training





Professional Preparation

Computer science

Ethics

Programing

Work force

Training

Credentialing

Simulations

RAL HOSPITAL







Cultural Transformation



SHARING DATA

SHARING KNOWLEDGE

CULTURAL DIFFERENCES



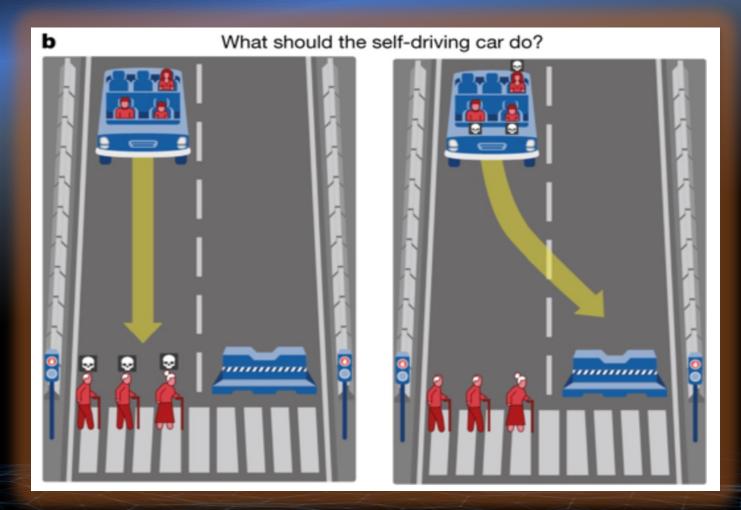




Ethical considerations

The Moral Machine

http://moralmachine.mit.edu

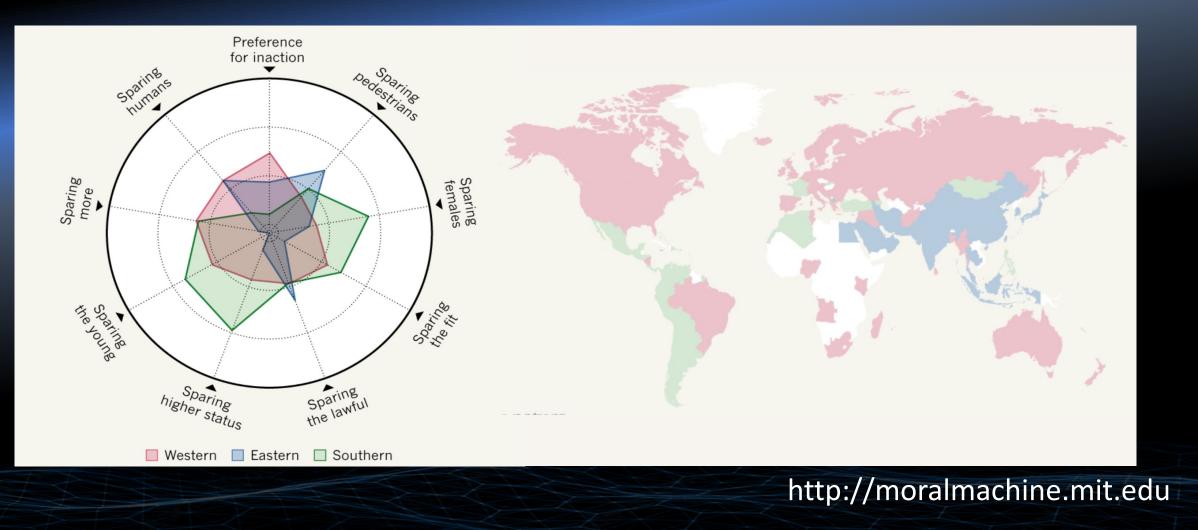


Awad et al. 2018. Nature

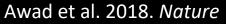




Ethical according to whom?









Other Considerations

Who owns the data?	Patient, Provider,
	Hospital, Payor
Who gets the credit?	Who gets the blame ?

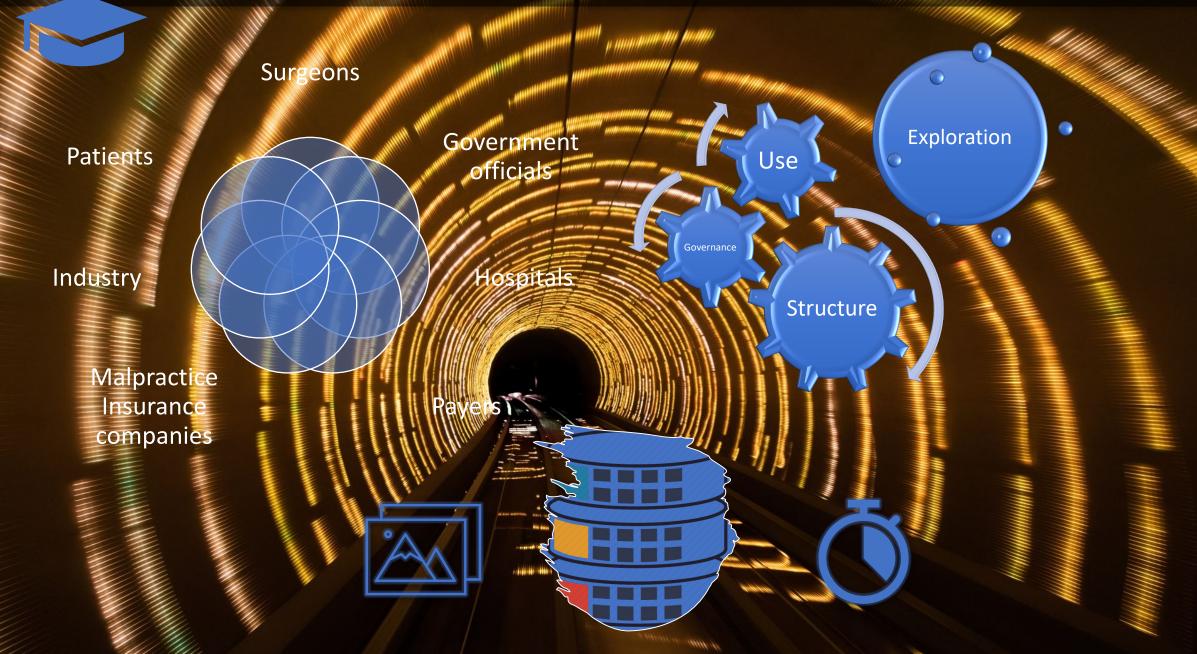
How do you explain Al-driven decisions to patients?

Can you challenge the decision ?





Surgical AI



Faculty and Fellows



Ozanan Meireles, MD Director, MGH SAIIL



Guy Rosman, PhD Assoc Director, Engineering



SAIIL Team

Daniela Rus, PhD Director, MIT CSAIL



Alumni

Daniel Hashimoto, MD MS Former Fellow



Yutong Ban, PhD Postdoctoral Fellow



Jennifer Eckhoff, MD AI & Innovation Fellow





Thomas Ward, MD **Former Fellow**









Thank you!

OzMeireles@MGH.Harvard.edu





www.SAIIL.org

Ozanan Meireles

GET INVOLVED









