Beyond the Algorithm Warning: AI's Impact on Modern Anesthesia Care Today and Tomorrow

Western Summit for Nurse Anesthesiology
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October 4, 2025

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AI: Who Cares?


healthcare

MDPI

Article

Adoption of Artificial Intelligence in Rehabilitation: Perceptions, Knowledge, and Challenges Among Healthcare Providers

Monira I. Aldhahi [1,*], Amal I. Alorainy [2], Mohamed M. Abuzaid [3,4], Awadia Gareeballah [5], Naifah F. Alsubaie [2], Anwar S. Alshamary [6] and Zuhal Y. Hamd [2]

Aldhahi, M. I., Alorainy, A. I., Abuzaid, M. M., Gareeballah, A., Alsubaie, N. F., Alshamary, A. S., & Hamd, Z. Y. (2025). Adoption of Artificial Intelligence in Rehabilitation: Perceptions, Knowledge, and Challenges Among Healthcare Providers. *Healthcare (Basel)*, *13*(4), 350. https://doi.org/10.3390/healthcare13040350

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Artificial Intelligence: Hype

- **GPT-1 (2018) – by OpenAI**
  - Introduction GPT (**generative pre-trained transformers**) consisting of ***117 million parameters***.
  - Demonstrated power of Unsupervised Learning in language via "books as training data to predict the 'next word in a sentence'"
- **GPT-2 (February 2019)**
  - ***1.5 billion parameters***
  - Text generation capabilities with coherent multi-paragraph text
  - Not released to the public due to potential for misuse

Reference: Marr, B. (2023). A short history of ChatGPT: How we got to where we are today. Forbes. https://www.forbes.com/sites/bernardmarr/2023/05/19/a-short-history-of-chatgpt-how-we-got-to-where-we-are-today/?sh=2da73a13674f

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Artificial Intelligence: Hype

- **GPT-3 (June 2020)**
  - ***175 billion parameters***
  - Advanced text-generation: draft e-mails, poetry, and programming code
  - Launch of ChatGPT to the public
- **GPT-4 (March 2023)**
  - ***1.76 trillion parameters***
  - Enhanced factual accuracy, steerability, and search internet real-time
- **ChatGPT Goals**
  - **Education**: create intelligent tutoring systems as personalized assists to students
  - **Healthcare**: chatbot for clinical decision support, medical record keeping, analyzing & interpreting medical literature, and disease surveillance

Reference: Marr, B. (2023). A short history of ChatGPT: How we got to where we are today. Forbes. https://www.forbes.com/sites/bernardmarr/2023/05/19/a-short-history-of-chatgpt-how-we-got-to-where-we-are-today/?sh=2da73a13674f

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GPT-5 Launch — August 2025

- **Official Launch**: On **August 7**, OpenAI released **GPT-5** as its flagship model, offering:
  - Major improvements in reasoning, instruction-following, health-related answers, and coding speed.
  - Multimodal enhancements, longer context windows (up to **1 million tokens**), **memory persistence**, and variants like Mini, Nano, and Chat.
  - Integrations included Gmail/Google Calendar connectors, voice options, personalities, and "Smart" mode in Copilot.
  - Released **free to all users**, though early feedback noted reduced emotional warmth.
- **Reception & Response**:
  - Mixed user reactions, with frustration over emotional tone changes and rollout missteps.
  - Altman acknowledged errors and pledged more model options, higher usage limits, and improved responsiveness.
  - Internally, OpenAI focused on positioning ChatGPT as a **“super assistant”** to rival Siri, Alexa, and Gemini—integrating deeply into daily life across contexts.
  - Hardware integration was also envisioned.
- Just Say **“Thank You”**

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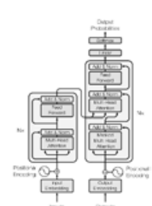
Artificial Intelligence: Hype

- **Transformer** Key Components:
  - Encoder & Decoder Stacks
  - Attention
  - Multi-Head Attention
  - Position-wise Feed-Forward NN
- OpenAI & ChatGPT
  - > 30,000 Nvidia A100 GPUs
    - GPU cost: $300 - $450 million
  - Cost to run ChatGPT
    - $100K/Day or $3M/Month
    - GPT-5 Model 6-month Training >$500M



The Transformer – model architecture

Reference: Vaswani et al. (2017). Attention is all you need. 31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA. Retrieved from: https://arxiv.org/pdf/1706.03762.pdf

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Artificial Intelligence: Hype

- **ChatGPT Concerns**
  1. **Data Privacy & Security:** Data breach and unauthorized access
  2. **Data Bias:** Model Training on less diverse & representative populations
  3. **Clinical Decision-Making:** meant to assist, NOT REPLACE, clinicians
  4. **Limited Interpretability:** due to complex NNs, difficult to identify & correct errors
  5. **Lack of Regulation:** rapidly evolving without "rules or laws"
     - **Data ownership**: once placed into the algorithm

Reference: Asch, D. (2023). An interview with ChatGPT about healthcare. NEJM Catalyst. Retrieved from: https://catalyst.nejm.org/doi/full/10.1056/CAT.23.0043

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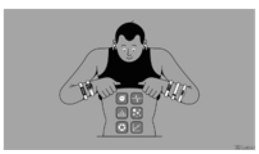
Artificial Intelligence: Hype

- Wearables a promise of "new solutions"



Wearable technology promises to revolutionize health care

Reference: Leaders. (2022). Wearable technology promises to revolutionise health care. The Economist. Retrieved from: https://www.economist.com/leaders/2022/05/05/wearable-technology-promises-to-revolutionise-health-care

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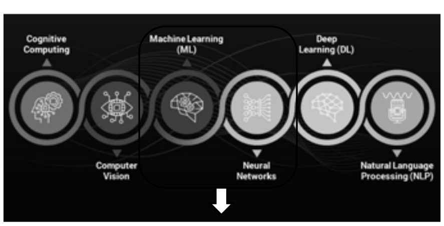
Artificial Intelligence: What is It?



Reference: Swiss Cognitive (2021). 6 major sub-fields of artificial intelligence. Retrieved from: https://swisscognitive.ch/2021/08/28/fields-of-artificial-intelligence/

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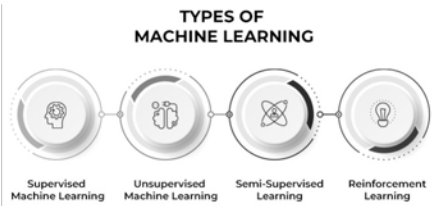
Artificial Intelligence: What is It?



Reference: Swiss Cognitive (2021). 6 major sub-fields of artificial intelligence. Retrieved from: https://swisscognitive.ch/2021/08/28/fields-of-artificial-intelligence/

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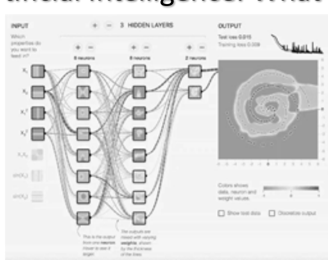

Reference: Swiss Cognitive (2021). 6 major sub-fields of artificial intelligence. Retrieved from: https://swisscognitive.ch/2021/08/28/fields-of-artificial-intelligence/

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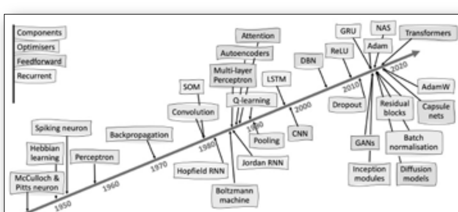
Artificial Intelligence: Growth



Reference: Lones, M. A. (2023). How to avoid machine learning pitfalls: a guide for academic researchers. arXiv.org.

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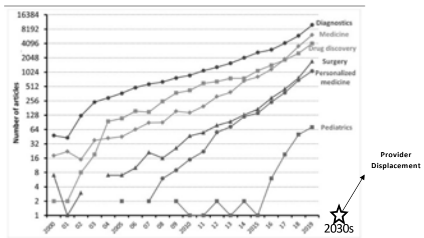
Artificial Intelligence: Promise



Rajula, Hema Sekhar Reddy et al. "Comparison of Conventional Statistical Methods with Machine Learning in Medicine: Diagnosis, Drug Development, and Treatment." Medicina (Kaunas, Lithuania) vol. 56,9 455. 8 Sep. 2020, doi:10.3390/medicina56090455

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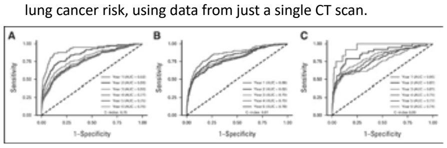
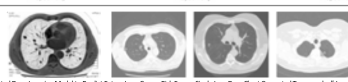
Artificial Intelligence: Promise

- a deep learning model named **"Sybil"** that can be used to predict lung cancer risk, using data from just a single CT scan.





Mikhael, Peter G., et al. "Sybil: A Validated Deep Learning Model to Predict Future Lung Cancer Risk From a Single Low-Dose Chest Computed Tomography." Journal of Clinical Oncology, vol. 41, no. 12, 2023, pp. 2191–200, https://doi.org/10.1200/JCO.22.01345.

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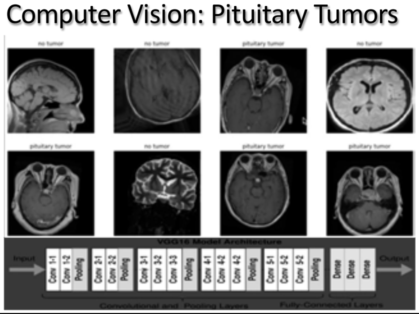
Computer Vision: Pituitary Tumors



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The Rise of AI in Ultrasound

- **Artificial intelligence (AI)**, including machine learning and deep learning, is increasingly being incorporated into Anesthesia research and applications.
- **Ultrasound (US) has inherent advantages**: non-invasive, less costly, and no radiation exposure, making it common for screening and diagnosis.
- AI, particularly **deep learning with convolutional neural networks (CNNs)**, can **learn non-programmatically from large amounts of data**.
- This offers the potential to perform tasks more **rapidly and accurately than humans in specific areas such as imaging and pattern recognition**.
- **Medical imaging analysis** is highly compatible with AI, with fundamental tasks including classification, detection, and segmentation.
- **The US Food and Drug Administration (FDA)** has **approved AI-driven medical devices for clinical use**.

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AI Techniques for Enhanced Ultrasound Imaging

- **Ultrasound imaging:**
- **Limitations:** Often suffers from **low spatial resolution and artifacts** (speckles, clutter, acoustic shadow, reverberation).
- These features can hinder both traditional and **AI-based image processing and recognition**.
- **AI is being used to improve ultrasound image quality** by enhancing **despeckle performance** and **overall image quality**.
- This **data-driven approach** can potentially avoid the need for creating a model for each specific domain.
- However, **improving ultrasound image quality with AI requires large amounts of targeted, high-quality training data**, which can be challenging to prepare.

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Key Trends in Ultrasound Systems

Adding AI to Ultrasound Systems Increases Diagnostic Capabilities

GE Voluson SWIFT & GE Vivid S70 Cardiac Ultrasound, AI enables:

- Acquire faster, more repeatable exams consistently.
- Reduced exam time with up to 80% fewer clicks,
- Increase to 99% accuracy
- AI automatically recognizes the anatomy on standard 2-D scan planes decreasing inter-operator variability.
- Anatomical identification: automate measurements making them more reproducible.


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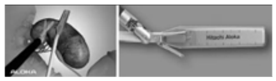
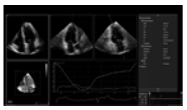
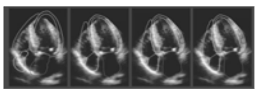
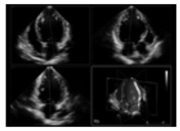
Key Trends in Ultrasound Systems

Adding AI to Ultrasound Systems Increases Diagnostic Capabilities

Philips 3D Ultrasound



- Automating Cardiac Evaluation Real-Time
- **Can we Automate POCUS intraoperative for better Cardiac Evaluation**?

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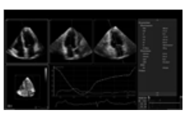
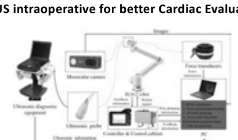
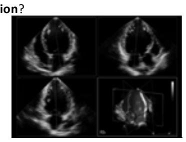
Key Trends in Ultrasound Systems

Adding AI to Ultrasound Systems Increases Diagnostic Capabilities

Philips 3D Ultrasound

- Automating Cardiac Evaluation Real-Time
- **Can we Automate POCUS intraoperative for better Cardiac Evaluation**?

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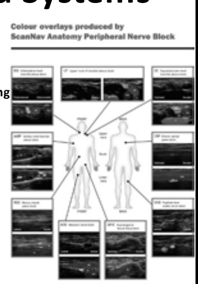
Key Trends in Ultrasound Systems

Adding AI to Ultrasound Systems Increases Diagnostic Capabilities

Intelligent Ultrasound with AnatomyGuide – Simulators for Teaching

Reference: https://www.intelligentultrasound.com/2019/06/13/intelligent-ultrasound-commences-clinical-trial-for-anatomyguide/

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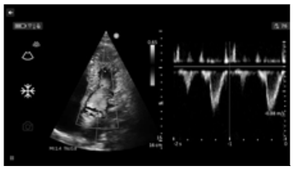
Key Trends in Ultrasound Systems

Adding AI to Ultrasound Systems Increases Diagnostic Capabilities

GE Handheld Vscan Air Ultrasound



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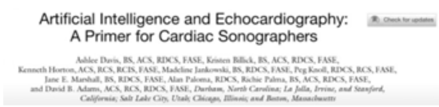

Artificial Intelligence and Echocardiography: A Primer for Cardiac Sonographers

Check for updates

Ashlee Davis, BS, ACS, RDCS, FASE, Kristen Billick, BS, ACS, RDCS, FASE, Kenneth Horton, ACS, RCS, RCIS, FASE, Madeline Jankowski, BS, RDCS, FASE, Peg Knoll, RDCS, RCS, FASE, Jane E. Marshall, BS, RDCS, FASE, Alan Paloma, RDCS, Richie Palma, BS, ACS, RDCS, FASE, and David B. Adams, ACS, RCS, RDCS, FASE, *Durham, North Carolina; La Jolla, Irvine, and Stanford, California; Salt Lake City, Utah; Chicago, Illinois; and Boston, Massachusetts*

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Automatic Computing VTI (Auto VTI)

- Neural network algorithm trained with thousands of cardiac images
- **Automatically detects** the **apical 5-chamber view** and **LV outflow tract (LVOT)**

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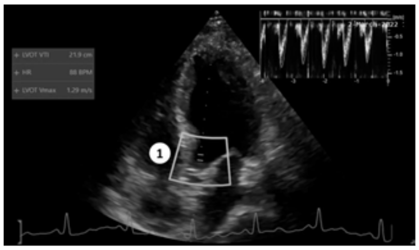
Automatic Computing VTI



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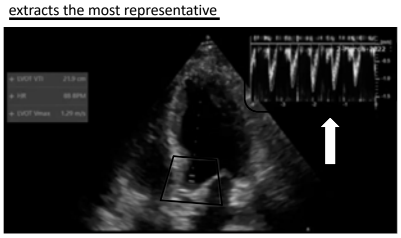
Automatic Computing VTI (Auto VTI)

- Automatically records hundreds of **Doppler Signals** and extracts the most representative



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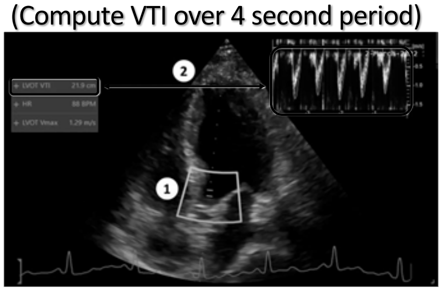
Automatic Computing VTI (Compute VTI over 4 second period)



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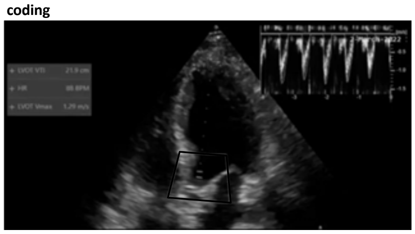
Automatic Computing VTI

- User feedback regarding image and signal quality using **color-coding**



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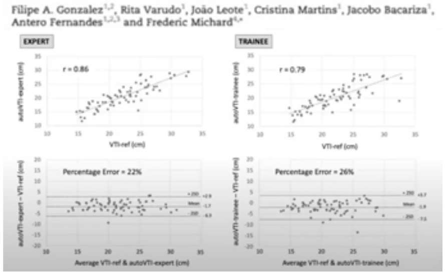
The automation of sub-aortic velocity time integral measurements by transthoracic echocardiography: clinical evaluation of an artificial intelligence-enabled tool in critically ill patients

Filipe A. Gonzalez[1,2], Rita Varudo[1], João Leote[1], Cristina Martins[1], Jacobo Bacariza[1], Antero Fernandes[1,2,3] and Frederic Michard[4,*]



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RealTime LVEF

- Neural Network Algorithm trained with thousands of cardiac images
- Automatically detects the apical 4-chamber view, endocardial borders and end-diastolic and end-systolic times for the mitral valve motion (no need for ECG)

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RealTime LVEF

- Neural Network Algorithm trained with **Millions of cardiac images**
- **Automatically detects** the **apical 4-chamber view**, endocardial borders and end-diastolic and end-systolic times for the mitral valve motion (no need for ECG)
- Automatically estimates LV volumes and LVEF
- **User feedback** regarding image quality using **color coding**

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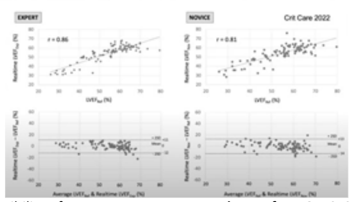
Machine learning for the real-time assessment of left ventricular ejection fraction in critically ill patients: A bedside evaluation by novices and experts in echocardiography

Rita Varudo[1], Filipe A Gonzalez[1,2], João Leote[1], Cristina Martins[1], Jacobo Bacariza[1], Antero Fernandes[1,2,3], Frederic Michard[4]



- Reproducibility of LVEF measurements was **better for NOVICES with the machine learning algorithm** than for manual measurements done by the EXPERTS.
  - 6 +/- 5% vs 9 +/- 6%, p < 0.001

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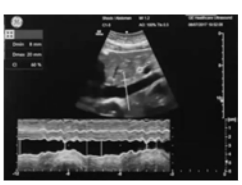
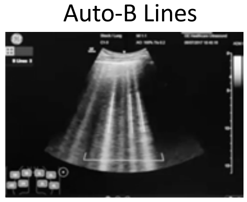
Other AI Automations

Auto-IVC



Automatic quantification of IVC-Respiratory Variation

Auto-B Lines



Estimate Pulmonary Edema

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Clinical Applications of AI in Ultrasound Procedures

- **Vessel Detection**: AI techniques, especially neural networks, are used for ultrasound image classification to identify structures like the femoral artery and vein with high accuracy.
- AI can assist in **vessel segmentation** for applications like deep vein thrombosis detection, anesthesia guidance, and catheter placement by determining the location and size of vessels.
- **Guidance for Spinal Injections**: Neural networks can assist in identifying vertebral levels and anatomical landmarks for epidural placement with accuracy up to 95%.
- AI is being developed to automatically identify and locate needle targets in spinal US images before or during needle insertion
- Potentially increasing analgesic effectiveness and reducing complications.
- Guidance for Regional Injections:

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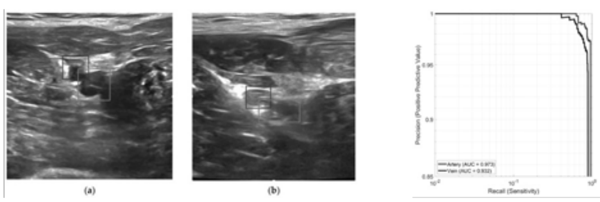
Vessel Detection



Brattain, L. J., Pierce, T. T., Gjesteby, L. A., Johnson, M. R., DeLosa, N. D., Werblin, J. S., Gupta, J. F., Ozturk, A., Wang, X., Li, Q., Telfer, B. A., & Samir, A. E. (2021). AI-Enabled, Ultrasound-Guided Handheld Robotic Device for Femoral Vascular Access. Biosensors, 11(12), 522. https://doi.org/10.3390/bios11120522

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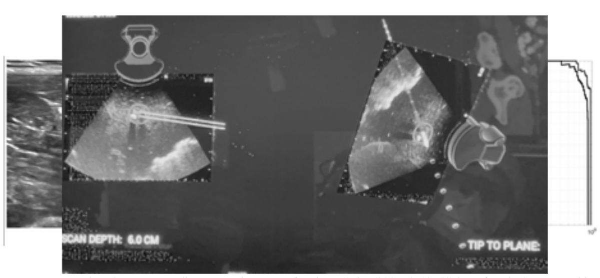
Guided Needle Detection



Brattain, L. J., Pierce, T. T., Gjesteby, L. A., Johnson, M. R., DeLosa, N. D., Werblin, J. S., Gupta, J. F., Ozturk, A., Wang, X., Li, Q., Telfer, B. A., & Samir, A. E. (2021). AI-Enabled, Ultrasound-Guided Handheld Robotic Device for Femoral Vascular Access. Biosensors, 11(12), 522. https://doi.org/10.3390/bios11120522

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AI for Enhanced Anesthesia Monitoring - Depth of Anesthesia (DOA)

- Maintaining the **appropriate depth of anesthesia (DOA) is crucial** for avoiding intraoperative awareness and postoperative complications.
- Traditional monitoring with **Bispectral Index (BIS) has limitations** such as time lag and susceptibility to interference.
- AI algorithms can extract multiple effective features from electroencephalography (EEG) to assess DOA more accurately in real-time.
- **Deep learning models** have been developed to predict the depth of anesthesia based on EEG data with high accuracy.

Reference: Li, R., Wu, Q., Liu, J., et al. (2020). Monitoring depth of anesthesia based on hybrid features and recurrent neural network. Frontiers in Neuroscience, 14, 26.

Reference: Ortolani, O., Conti, A., Di Filippo, A., et al. (2002). EEG signal processing in anaesthesia: use of a neural network technique for monitoring depth of anaesthesia. British Journal of Anaesthesia, 88(5), 644–648.

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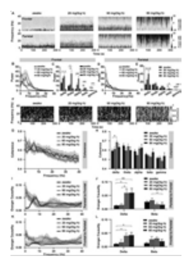
Density Spectral Array



Tu, Z., Zhang, Y., Lv, X. et al. Accurate Machine Learning-based Monitoring of Anesthesia Depth with EEG Recording. Neurosci. Bull. 41, 449–460 (2025). https://doi.org/10.1007/s12264-024-01297-w

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Closed-Loop Anesthesia Systems - AI in Control

- **Closed-loop target-controlled infusion (TCI) systems**, driven by AI, are being developed to automate anesthetic drug administration.
- These systems aim to **compensate for individual patient differences in pharmacokinetics and pharmacodynamics**.
- Components include: sensors (e.g., BIS), controllers (AI algorithms), and actuators (infusion pumps).
- Examples include systems for automated propofol and remifentanil infusion guided by BIS and other parameters.
- The McSleepy system represents an early attempt at a fully automated closed-loop anesthesia delivery system.

Reference: Hemmerling, TM., Arbeid, E., Wehbe, M., et al. (2013a). Evaluation of a novel closed-loop total intravenous anaesthesia drug delivery system: a randomized controlled trial. British Journal of Anaesthesia, 110(6), 1031–1039.

Reference: Liu, Q., Cai, J., Fan, S-Z., et al. (2012). Spectrum analysis of EEG signals using CNN to model patient's consciousness level based on anesthesiologists' experience, vol. 7. IEEE Access; 53731–42. (Note: While the provided text mentions Liu et al. (2012) in the context of BIS control, the full citation provided is from a later year. Please verify the year if needed).

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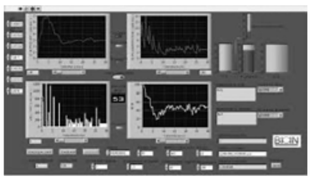
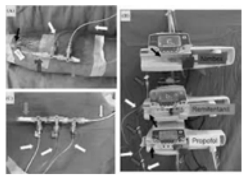
Closed-Loop Anesthesia Systems - AI in Control (1st Case Report)

Total intravenous anesthesia in a closed loop system: Report of the first case in Colombia | Colombian...





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AI in Anesthesia and Hypotension Prediction

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Intraoperative Hypotension Prediction

- **Improved patient safety with early hypotension prediction:** Predicting intraoperative hypotension allows prompt intervention, reducing risks of kidney and heart injuries.
- **Enhanced monitoring accuracy with ML-generated HPI:** Hypotension Prediction Index (HPI) from biosignal data enhances monitoring precision for immediate corrective actions.
- **Diverse population validation shows ML algorithm robustness:** Validation across varied patient groups ensures reliability and applicability in real-world clinical settings.

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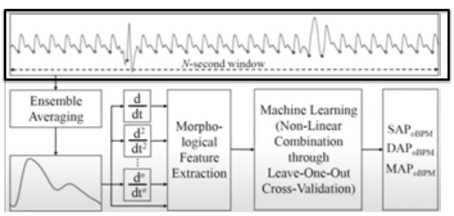

- So you give the ML algorithm the corresponding pulse oximetry waveforms and give the algorithm the corresponding blood pressure values.

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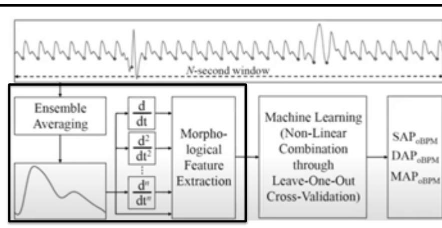

- So you give the ML algorithm the corresponding pulse oximetry waveforms and give the algorithm the corresponding blood pressure values.
- Then the ML will be able to learn to recognizing specific patterns of phenotypes characteristic of changes in blood pressure.
- Then be able to predict a rise or drop in blood pressure.

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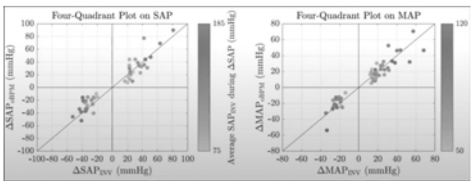
Technology, Computing, and Simulation

ORIGINAL CLINICAL RESEARCH REPORT

Automated Pulse Oximeter Waveform Analysis to Track Changes in Blood Pressure During Anesthesia Induction: A Proof-of-Concept Study

Yassine Ghamri, MSc,* Martin Proença, PhD,† Gregory Hofmann, MSc,* Philippe Renevey, PhD,† Guillaume Bonnier, PhD,† Fabian Braun, PhD,† Alexandre Axis, MD,* Mathieu Lemay, PhD,† and Patrick Schoettker, MD*



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ORIGINAL ARTICLES

Evaluation of the ability of a commercially available cuffless wearable device to track blood pressure changes

Tan, Isabella; Gnanenthiran, Sonali R.; Chan, Justine; Kyriakoulis, Konstantinos G.; Schlaich, Markus P.; Rodgers, Anthony; Stergiou, George S.; Schutte, Aletta E.

Author Information

Journal of Hypertension 41(6):p 1003-1010, June 2023. | DOI: 10.1097/HJH.0000000000003428

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Unable to track night-time BP decline

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ORIGINAL ARTICLES

Evaluation of the ability of a commercially available cuffless wearable device to track blood pressure changes

Journal of Hypertension

Unable to track medication-induced BP changes

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AI in Difficult Airway Management

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AI in Difficult Airway Management

- Prediction and Management of Difficult Airway
- AI Tools for Intraoperative Assistance

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Prediction and Management of Difficult Airway

- **Automated difficult airway prediction model:** Utilizing AI for accurate and timely identification of high-risk patients.
- **Machine learning for personalized airway management:** Tailoring interventions based on individual patient characteristics and risk factors.

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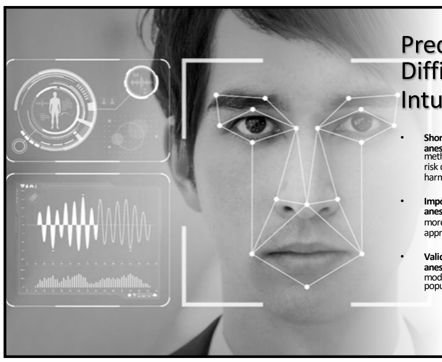

Predicting Difficult Intubation

- **Shortcomings of traditional methods in anesthesia risk assessment:** Traditional methods fail to detect majority of high-risk cases, leading to potential patient harm.
- **Importance of ML models in improving anesthesia safety:** ML models offer a more accurate and comprehensive approach for identifying at-risk patients.
- **Validation challenges for ML models in anesthesia prediction:** Crucial to validate model performance in larger and diverse populations for reliable use.

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Robotic Assistance in Anesthesia Administration

- **Enhancing anesthesia precision:** Robotic assistance with AI ensures exact dosage delivery for improved patient outcomes.
- **Minimizing medication errors:** AI technology in anesthesia administration reduces the risk of human dosing mistakes.
- **Increasing procedural efficiency:** Integration of AI in anesthesia improves workflow speed and accuracy during surgeries.

RESEARCH LETTER

Evaluation of a Novel, Image-Guided Robotic Intubation Platform for Difficult Airways: A Prospective Observational Study

Nekhendzy, Vladimir MD, FASA[1]; Karbonskienė, Aurika MD[2]; Bilskienė, Diana MD[2]; Borodičienė, Jurgita MD[2]; Kalibatienė, Lina MD[2]

Author Information

Anesthesia & Analgesia ()10.1213/ANE.0000000000007658, August 01, 2025. | DOI:

ANESTHESIA & ANALGESIA

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The Solution: SPIRO's Handheld, AI Guided Intubation Robot

- Predictable, Reproducible and Safe
- Near 100% first pass success
- Expected 90% reduction in complications

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GE Healthcare Aisys CS^2: Automated End-tidal Control (EtC)

- Et Control is an optional gas delivery mode, on GE Healthcare's Aisys CS^2 anesthesia machine, driven by novel software
- The anesthesia provider sets the target end tidal oxygen (EtO_2) and end tidal anesthetic agent (EtAA) values
- The minimum FGF is set by default
- The system monitors the EtO_2 and EtAA values and adjusts the **gas/agent delivery** and **total flow** to maintain values at target levels

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MASTER Trial: 4 Institutions

- The **M**ulti-Site Anesthesia randomized controlled **ST**udy of **E**nd tidal control (Et control) compared to conventional anesthesia **R**esults (master anesthesia trial*)
- Conducted at four institutions (**Duke, Emory, Iowa, Loma Linda**) from June 2017 to July 2018 after initial feasibility trial at Iowa in February through September 2014.
- 248 patients (final 220 after some removals based on inclusion and exclusion criteria) randomize to Manual or EtC

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Primary Outcomes

- Demonstrate *the End tidal Control (Et Control)* ***achieves and maintains*** *the concentration of end-tidal anesthesia agent (EtAA), and the concentration of end-tidal oxygen* ***(EtO_2)***, in a matter that is non-inferior to conventional anesthesia practice, via margin of 5%, in an **adult general surgical** population
- no children below the age of 18 were used in the trial.

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Secondary Goal

- Gather additional **functional and safety data** in clinical use of the investigational Et Control option
- Gather data on the **amount of inhaled anesthetic agent and gas used** in the Et Control versus the Control (standard practice) arms
- Obtained the data on the **number and frequency of user interactions** with the Aisys CS2 to user interface in the Et Control versus the Control arms
- Collect **time to discharge from the operating room,** which is a measure from the time of end of surgery (often defined as procedure in time) last ditch, or placement of last dressing) to time of last breath, as measured on the Aisys CS2.

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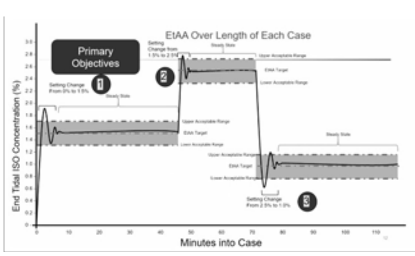

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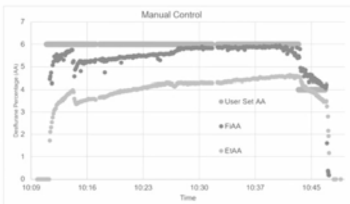
Desflurane: Manual Control

Manual Control for Desflurane Example

- Manual Control method matches inspired eventually
- But End Tidal not close



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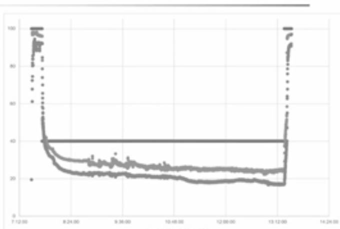
Oxygen: Manual Control

Manual Control – Oxygen, Drifting Low

- Low FGF was used for most of this case
- Green shows O_2 setting
- EtO_2 was close to 20% as oxygen was being consumed
- Purple shows FiO_2



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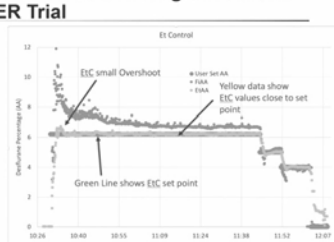
Desflurane: AI Control

Example of One EtC Case Using Desflurane – From MASTER Trial

- Data derived from internal machine logs
- Green shows EtC setting
- Yellow dots show measured EtAA
- Blue dots show machine FiAA
- Small Overshoot
- Matches each change closely



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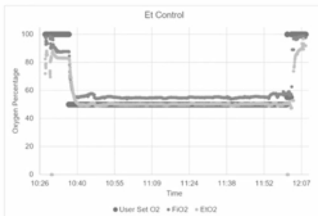
Oxygen: AI Control

Oxygen Concentrations from the Same EtC Case

- EtO_2 is a little slower than anesthetic agent to arrive at set points
- EtC Algorithm controls this rate of change
- Green shows EtC setting
- Yellow dots show measured EtO2
- Blue dots show machine FiO2



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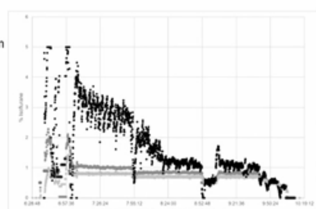
Vaporizer Adjustments: AI

Isoflurane EtC With Detail of Vaporizer Action

- Black dots show agent concentrations EtC algorithm was commanding from vaporizer
- Rapid changes due to confounding factors
  - Weight, Cardiac Output
  - Circuit volume



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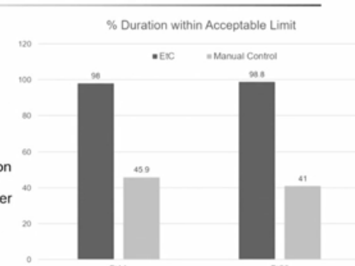
Percentage of Time within acceptable Limits

- Shows % duration of EtAA concentration during steady state maintained within the acceptable limit; P<0.001
- EtC // Manual
- Definition: The difference between the measured end tidal concentration and the steady state concentration (target concentration) is < the greater of 5% of the steady state concentration or 0.1% for Iso, 0.2% for Sev, 0.6% for Des.



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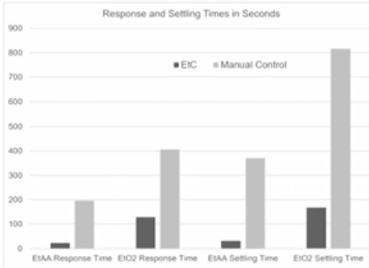
Response and Settling Times

– Response and Settling times are very fast with EtC; all highly significant $p<0.001$

– EtC // Manual



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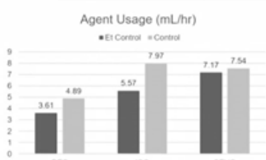
Agent Usage: From Induction to Patient Disconnect (MAC Corrected mL/hr)

Agent	Et Control	Control	P-value	% Savings
DES	3.61 ± 1.437 (27)	4.89 ± 2.585 (19)	0.062	26.2%
ISO	5.57 ± 2.158 (17)	7.97 ± 2.072 (15)	0.003	30.1%
SEVO	7.17 ± 2.124 (56)	7.54 ± 2.092 (82)	0.320	4.9%
Oxygen	1.66 ± 0.594 (100)	1.89 ± 0.792 (116)	0.016	12.2%



Agent savings align with European data for DES and ISO

Agent savings are minimal for SEVO because Minimum Flow kept at 2 L/min

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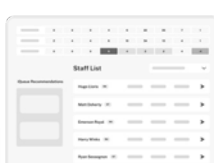
AI – Driven Scheduling & Staffing

Perfect Serve - AnesthesiaGo

UKG - Dimensions



LeanTaaS - iQueue

CAUTION

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Autonomous Medical Coding

CodaMetrix | Epic Research

60-70% reduction IN MANUAL CODING	5X faster TURNAROUND TIME	70% reduction IN CODING DENIALS	30%+ savings ON CODING COSTS

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AI-Powered Financial Analytics & Decision Support

Claims Denial Prevention:

- Machine learning models flag claims likely to be denied (e.g., missing documentation or certain diagnosis-procedure mismatches) so they can be corrected before submission.
- This proactive approach **increases the clean-claim rate and improves overall reimbursement**.

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AI-Powered Financial Analytics & Decision Support

Regulatory Compliance:

- AI tools stay updated on coding changes and payer rules, automatically checking each claim for compliance.
- By catching issues (like new modifier requirements) early, practices avoid costly denials or penalties.

HealthStream®

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Anesthesia Opportunities

- Workflow Optimization
- Training & Simulation
- Clinical Decision Support
- Preoperative Risk Assessment
- Personalized Care Pathways
- Real-Time Monitoring
- Predictive Analytics & Patient Outcomes
- Patient Education
- Quality Improvement: Data Analysis
- Research

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Questions

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