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Analysis

Integrating the latest technologies in critical care to make the most of available patient data

By Emma Green, Practical Patient Care 10 Jan 2020

FACILITIES | FACILITIES MANAGERS BEDS

Critical care - and the medical sector generally - is lagging behind other industries when it comes to implementing the latest technology into its practices

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Advanced Technology is Changing the Future of Critical Care

The practice of critical care medicine can be traced back to the 1850s when Florence Nightingale separated critically ill patients from other patients to monitor them closely. This model was later adopted during the Second World War during the treatment of military personnel. In parts of Europe and the US, there was greater use of mechanical ventilation outside the operating room during and after the polio epidemic (1950's). Over the years, advances in technology have made monitoring equipment affordable.To care for critically ill patients, intensive care units (ICUs)with the necessary equipment and specially trained staff have become an integral part of hospitals around the world.

nature portfolio

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How new digital technologies are transforming intensive care

A conversation with DOCTOR HO-YOUNG LEE, director of digital medicine at the Institute of Radiation Medicine in Seoul National University Bundang Hospital (SNUBH)

Produced by nature research custom media

FROST & SULLIVAN

Mar 26, 2018

Medical Device Interoperability Solutions to Address Intensivist Crisis in Critical Care

Overcoming the Shortfall of Intensive Care Workforce through Systematic Implementation of Centralized Patient Monitoring and Virtual ICU Solutions Growing Complexity in the High-acuity Care Environment The high-acuity care environment is dynamically changing globally, especially with regard to operating rooms, intensive care units, and their workforce. The growing shortfall of intensive care workforce is challenging the [...]


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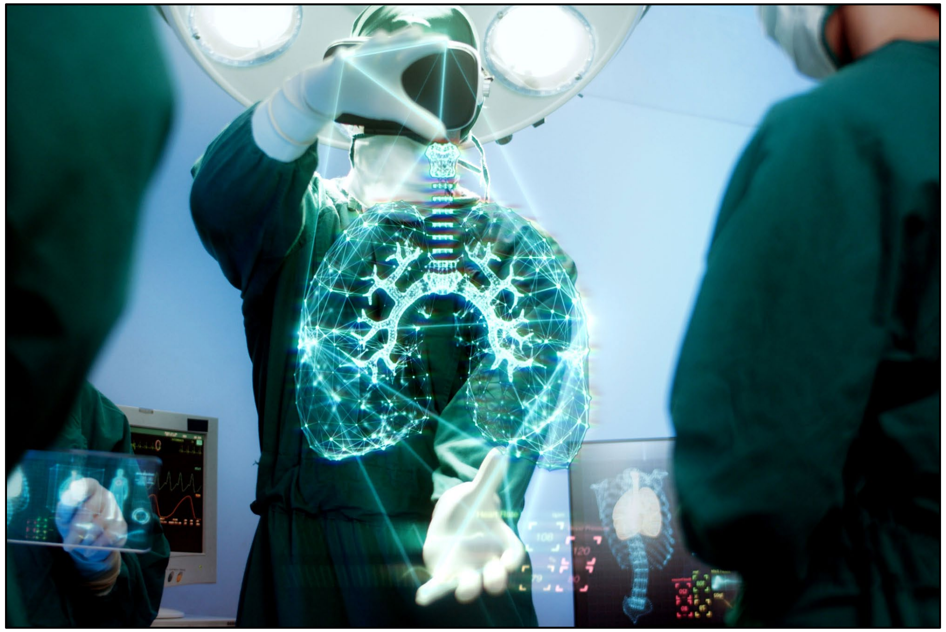
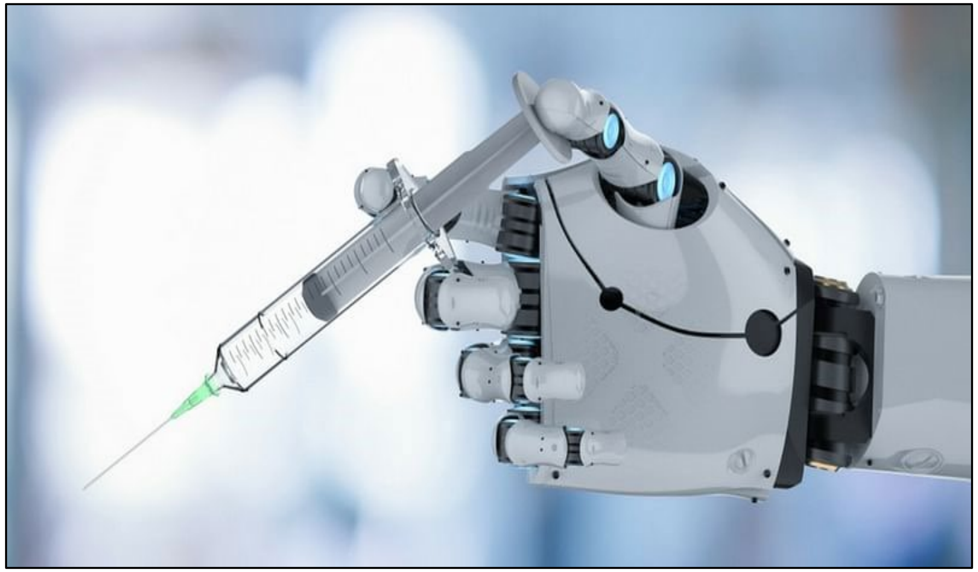


FUTURE BUSINESS TECH

Jan 09, 2022

The World in 2050: Top 20 Future Technologies

THE WORLD IN 2050

In 2050, the world will look dramatically different due to significant technological advancements. For example:

1. The World's First Artificial General Intelligence Is Close To Becoming A Reality

By 2050, major tech companies have already launched official projects to develop the world's first artificial general intelligence. Billions of dollars are invested in these projects and large full-time staff are dedicated to this effort. These highly complex projects are expected to take anywhere from 10 to 20 years to complete.

Fyzici chtějí experimentem vysvětlit, zda žijeme v realitě, nebo v matrixu

16. listopadu 2021

Skupina fyziků chce odpovědět na kontroverzní otázku, která odnepaměti rezonuje lidskou společností. Žijeme v nám patřící realitě, nebo v někým vytvořené simulaci? Pravda nás však může vyjít draho.

Matrix | foto: film Matrix

GEP INSIGHT DRIVES INNOVATION

BLOGS | STRATEGY | TECHNOLOGY | MIND

HOME › BLOG › TECHNOLOGY › VISION OR DELUSION HOW FUTURE TECHNOLOGY VARIES PRESENT DAY EXPECTATIONS

VISION OR DELUSION: HOW FUTURE TECHNOLOGY VARIES FROM PRESENT-DAY EXPECTATIONS

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Journal
Crime Psychology Review ›
Volume 2, 2016 - Issue 1

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Original Articles

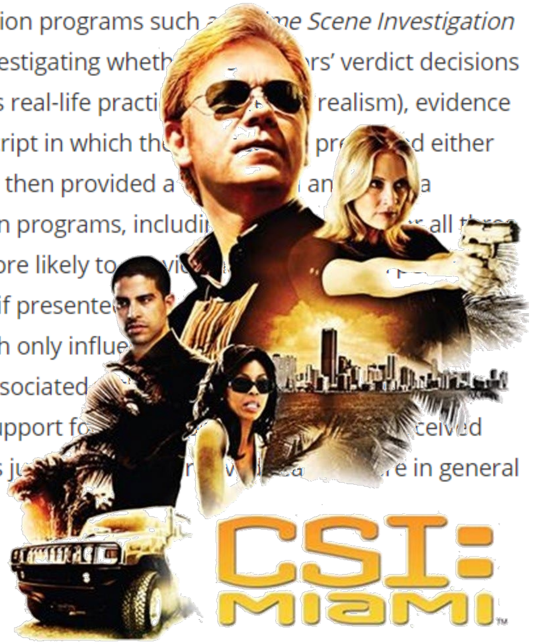
The CSI effect and its controversial existence and impact: a mixed methods review

Kimberley Schanz & C. Gabrielle Salfati

Pages 60-79 | Published online: 08 Dec 2016

Download citation https://doi.org/10.1080/23744006.2016.1260276 Check for updates

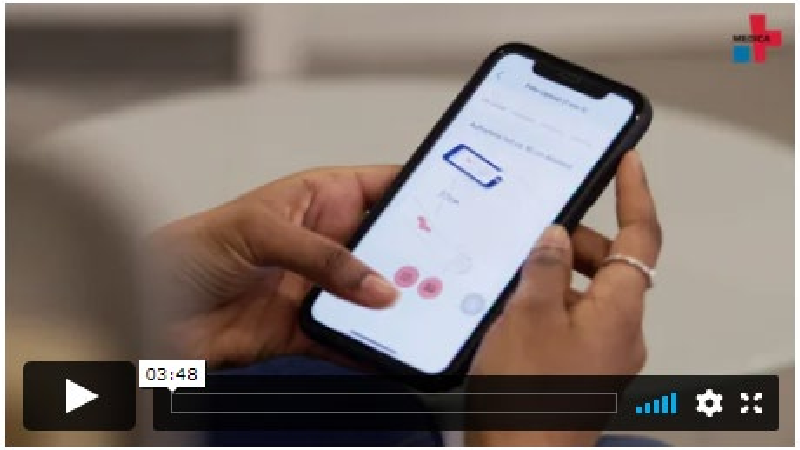
Anecdotal claims from legal professionals suggest that jurors are increasingly expecting DNA evidence in criminal trials, due to the popularity of crime-drama television programs such a ... me Scene Investigation (CSI). This study extends research on the "CSI-effect" by investigating wheth ... rs' verdict decisions differ as a function of the perception that television reflects real-life practi ... realism), evidence type, and evidence strength. Participants read a trial transcript in which th ... pr ... d either strong or weak DNA/fingerprint/eyewitness evidence. They then provided a ... an ... a questionnaire to assess their perceived realism of television programs, includi ... all types of evidence, jurors high in perceived realism were more likely to ... realism. Additionally, jurors were more likely to vote guilty if presente ... compared to eyewitness testimony, while evidence strength only influe ... conditions. Results suggest that perceived realism is not associated ... evidence be presented in court, and thus do not provide support fo ... ceived realism may actually be a desirable trait for prosecutors, as ju ... e in general more likely to convict.



Defining digital trends

Digitalization is growing rapidly, and new questions are arising. How do wearables, mHealth, apps and artificial intelligence make medicine smarter? How can they be used to combat pandemics? And above all, how do we use them safely?

What intensive care patients really need



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Where healthcare is going

Product categories

MEDICA 2022	MEDICA 2022	Imaging and diagnostics / medical equipment and devices
MEDICA 2022 3,596 exhibitors	01 Imaging and diagnostics / medical equipment and devices 1,520 exhibitors	01.01 Diagnostics 285 exhibitors
		01.02 Imaging supplies 147 exhibitors
		01.03 Surgery devices, endoscopy devices 354 exhibitors
		01.06 Intense medicine / anesthesiology / respiration 244 exhibitors
		01.07 Emergency medicine, rescue equipment 52 exhibitors

MEDICA START-UP PARK

Loaded with enthusiasm and start-up energy, the MEDICA START-UP PARK sees young companies present themselves and their ideas, find the right counterparts and make valuable contacts.

Intensive Care Med (2018) 44:922–924

WHAT'S NEW IN INTENSIVE CARE

Intensive care medicine in 2050: towards critical care without central lines

Jean-Louis Vincent[1*], Frederic Michard[2] and Bernd Saugel[3]

Central venous catheters (CVCs) are still widely used in critically ill patients to enable certain drugs to be administered safely, to facilitate blood sampling, and for the measurement of central venous pressure (CVP) and central venous oxygen saturation ($ScvO_2$). They are also used occasionally to perform transpulmonary thermodilution measurements and to calibrate devices that use pulse wave analysis. Although CVC-related infectious complications have decreased over time and CVC placement is safer with ultrasound guidance [1], CVC use is still associated with potential traumatic, hemorrhagic, thrombotic, and infectious complications. Recent and continuing technological innovation now makes it possible to imagine an intensive care world without central lines.

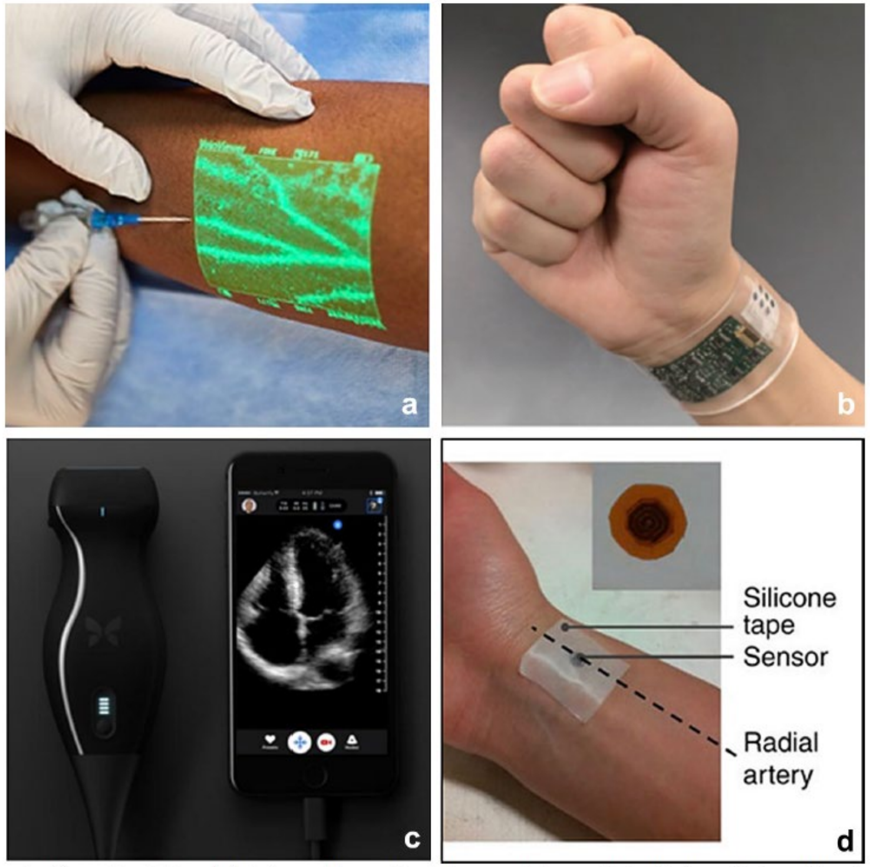


Fig. 1 Examples of innovations that may help to decrease the use of central venous catheters and their related complications. **a** New visualization technique to facilitate peripheral catheter insertion (VeinViewer®, with permission from christiemed.com); **b** wearable sensor enabling electrolyte monitoring from perspiration (from [7] with permission); **c** pocket echo probe for point-of-care ultrasound evaluations (iQ, with permission from butterflynetwork.com); **d** wearable sensor enabling continuous monitoring of arterial pressure (from [12] with permission)

NIS — nemocniční informační systém

PDMS — (patient data management systém) systém integrující monitoraci pacientů, NIS, administrativní funkce a klinické rozhodování v prostředí intenzivní péče

BIG DATA — souhrn velkého objemu dat z různých zdrojů, bez jednotné struktury, a jejich následná analýza

AI — umělá inteligence (artificial intelligence)

Neurocrit Care (2022) 37:S170–S172

Big Data and Artificial Intelligence in Intensive Care Unit: From "Bla, Bla, Bla" to the Incredible Five V's

Valentina Bellini[1], Marina Valente[2], Paolo Pelosi[3,4], Paolo Del Rio[2] and Elena Bignami[1*]

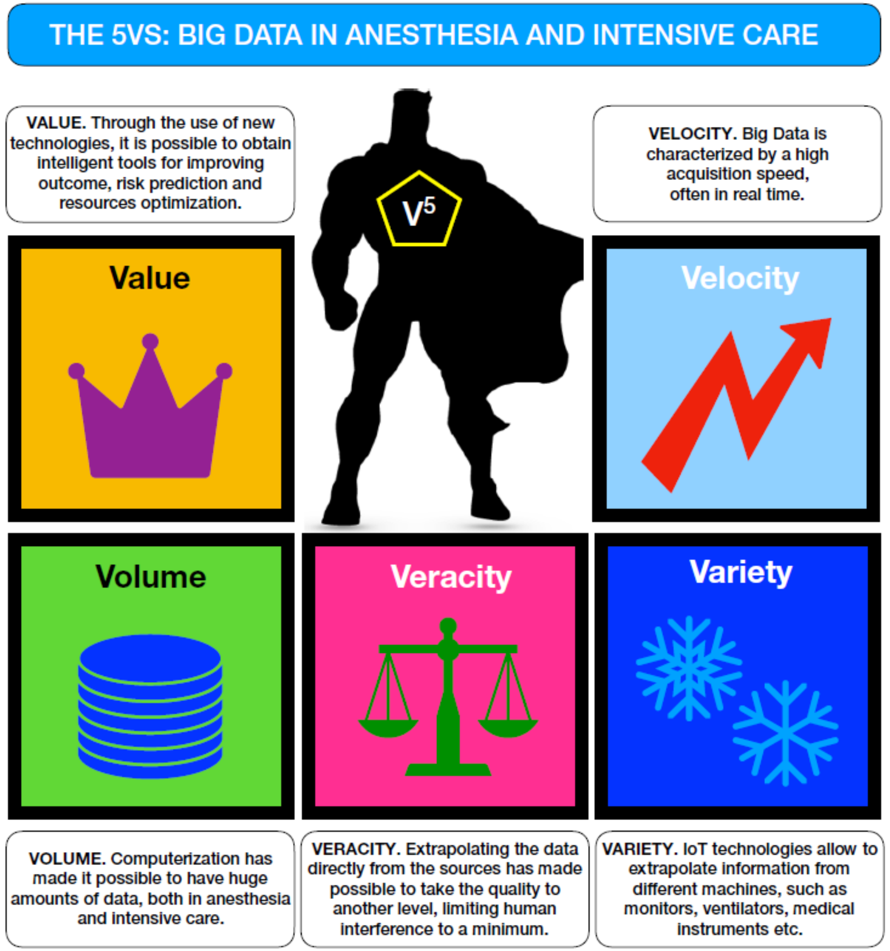
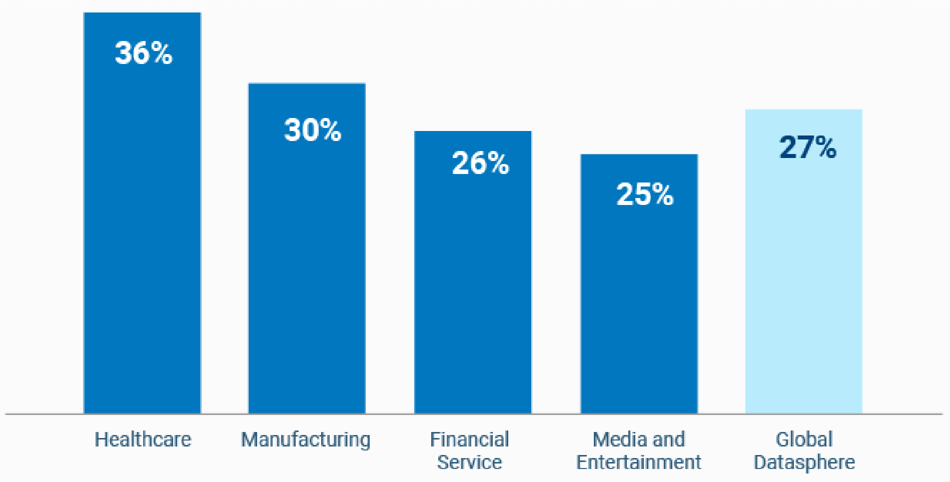


Fig. 1 Graphic representation of the five V's that define big data: variety, velocity, volume, veracity, and value. Each of them is reinterpreted in the anesthesia and critical care setting. Big data, through their intrinsic characteristics, are the superheroes of our story entitled, "AI in Intensive Care Unit"; thanks to the quality of the data they provide, they can create solid foundations for the application of new technologies. AI, artificial intelligence

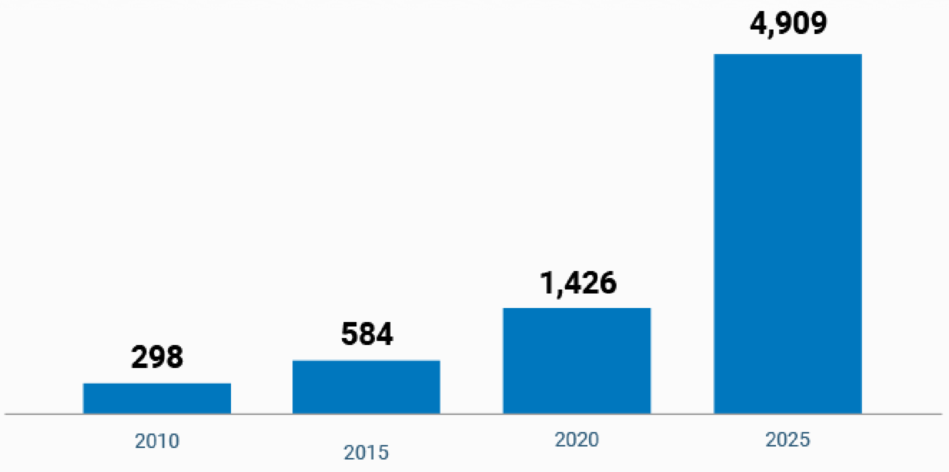
Today, approximately 30% of the world's data volume is being generated by the healthcare industry. By 2025, the compound annual growth rate of data for healthcare will reach 36%. That's 6% faster than manufacturing, 10% faster than financial services, and 11% faster than media & entertainment.

2018-2025 Data – Compound Annual Growth Rate (CAGR)

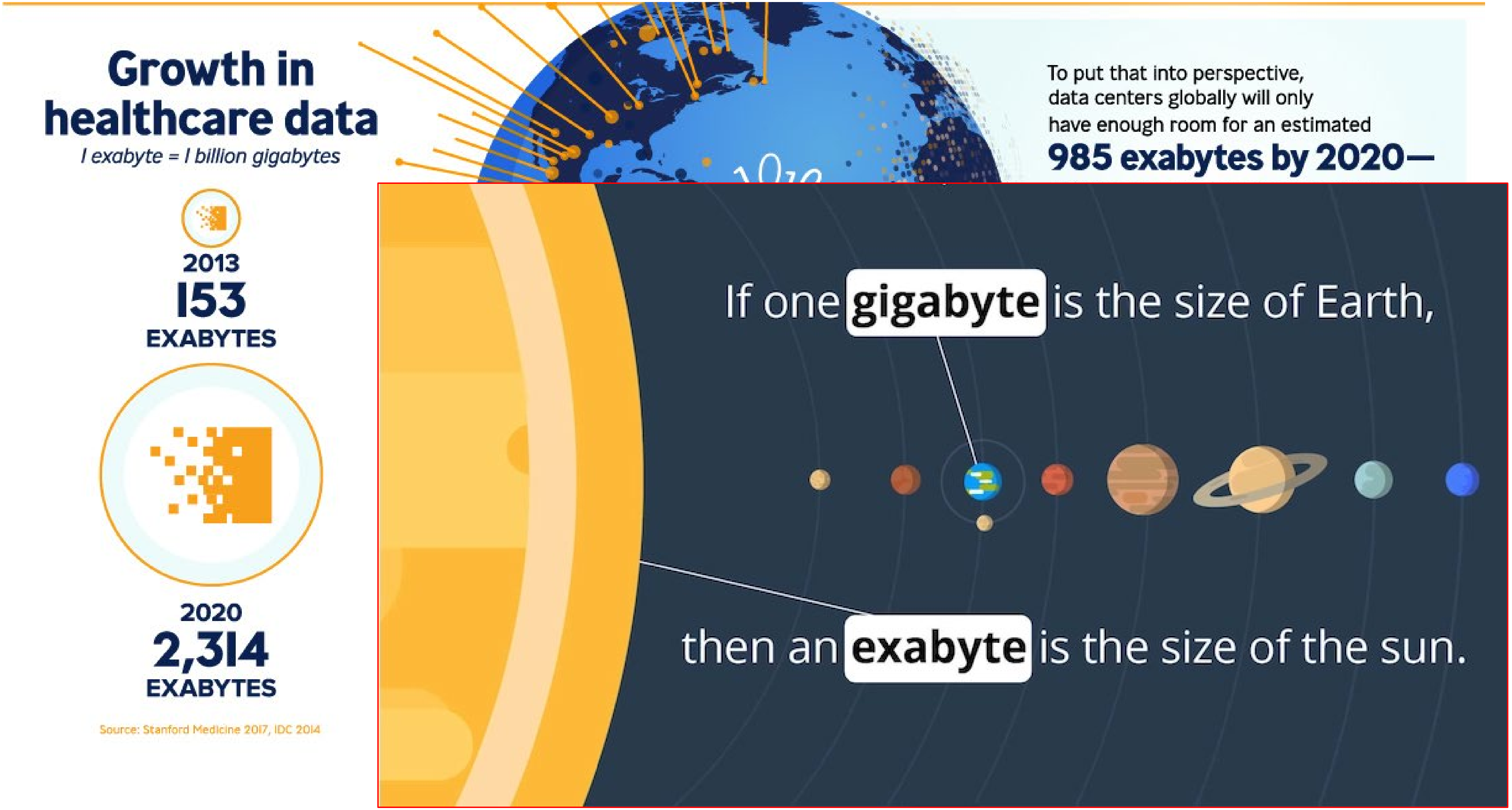


Source: Coughlin et al Internal Medicine Journal article "Looking to tomorrow's healthcare today: a participatory health perspective". IDC White Paper, Doc# US44413318, November 2018: The Digitization of the World – From Edge to Core".

The Number of Digital Device Interactions / Capita / Day



Source: Coughlin et al Internal Medicine Journal article "Looking to tomorrow's healthcare today: a participatory health perspective". IDC White Paper, Doc# US44413318, November 2018: The Digitization of the World – From Edge to Core".


Growth in healthcare data
I exabyte = I billion gigabytes
2013
153
EXABYTES
2020
2,314
EXABYTES
Source: Stanford Medicine 2017, IDC 2014
To put that into perspective, data centers globally will only have enough room for an estimated
985 exabytes by 2020—
If one gigabyte is the size of Earth,
then an exabyte is the size of the sun.

NIS

nemocniční informační systém

PDMS

(patient data management systém) systém integrující monitoraci pacientů, NIS, administrativní funkce a klinické rozhodování v prostředí intenzivní péče

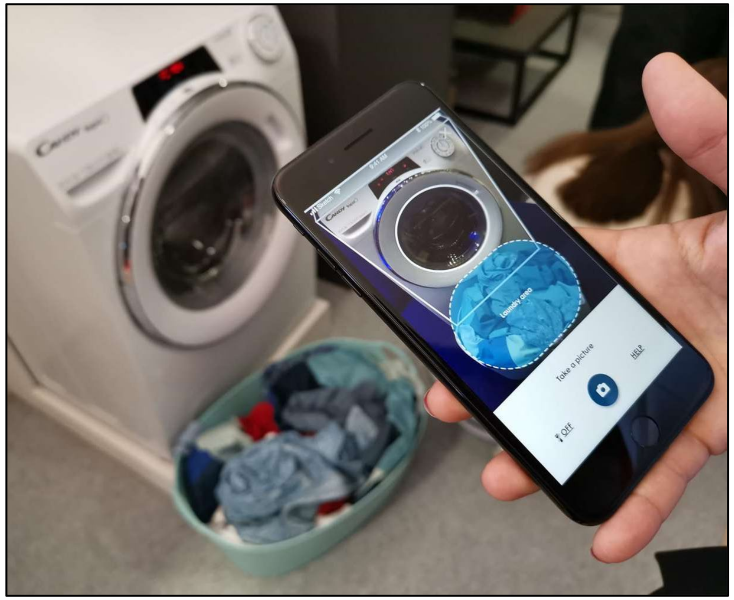
BIG DATA

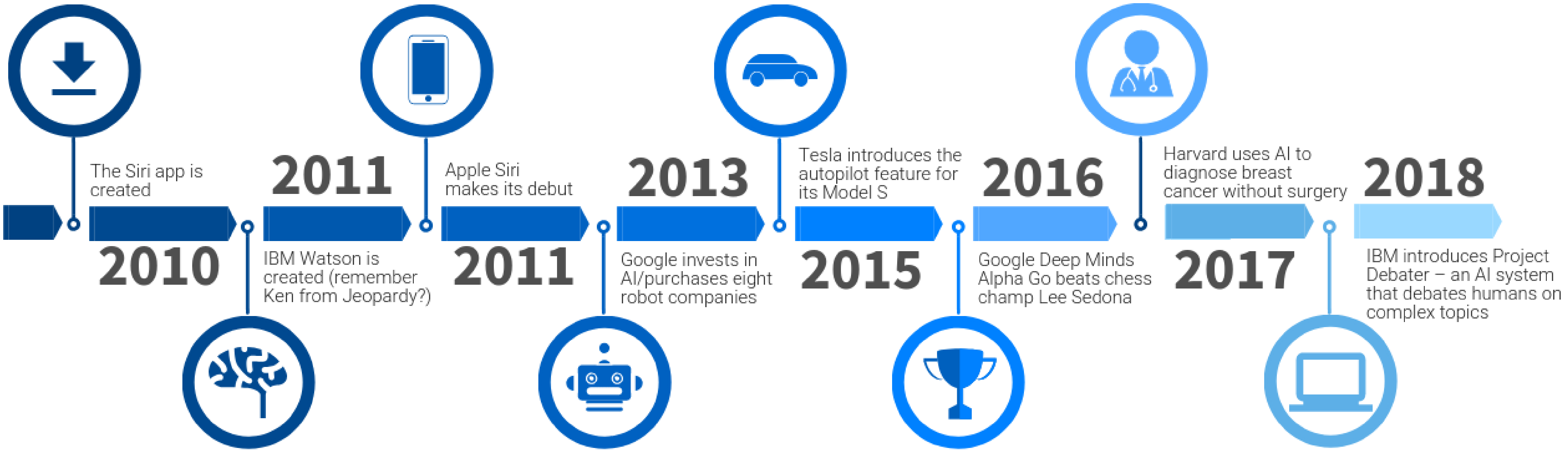
souhrn velkého objemu dat z různých zdrojů, bez jednotné struktury, a jejich následná analýza

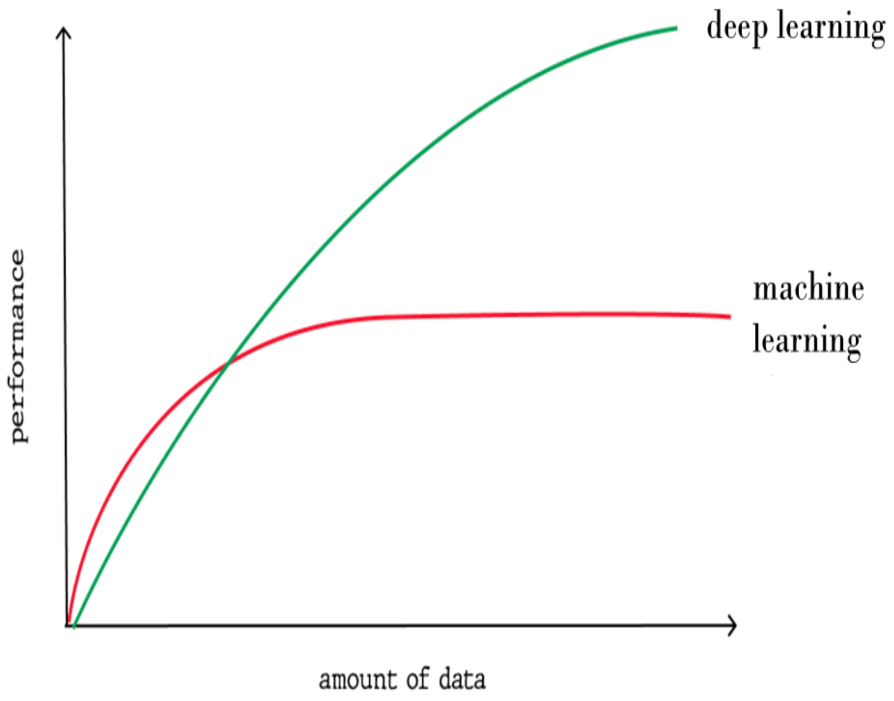
AI

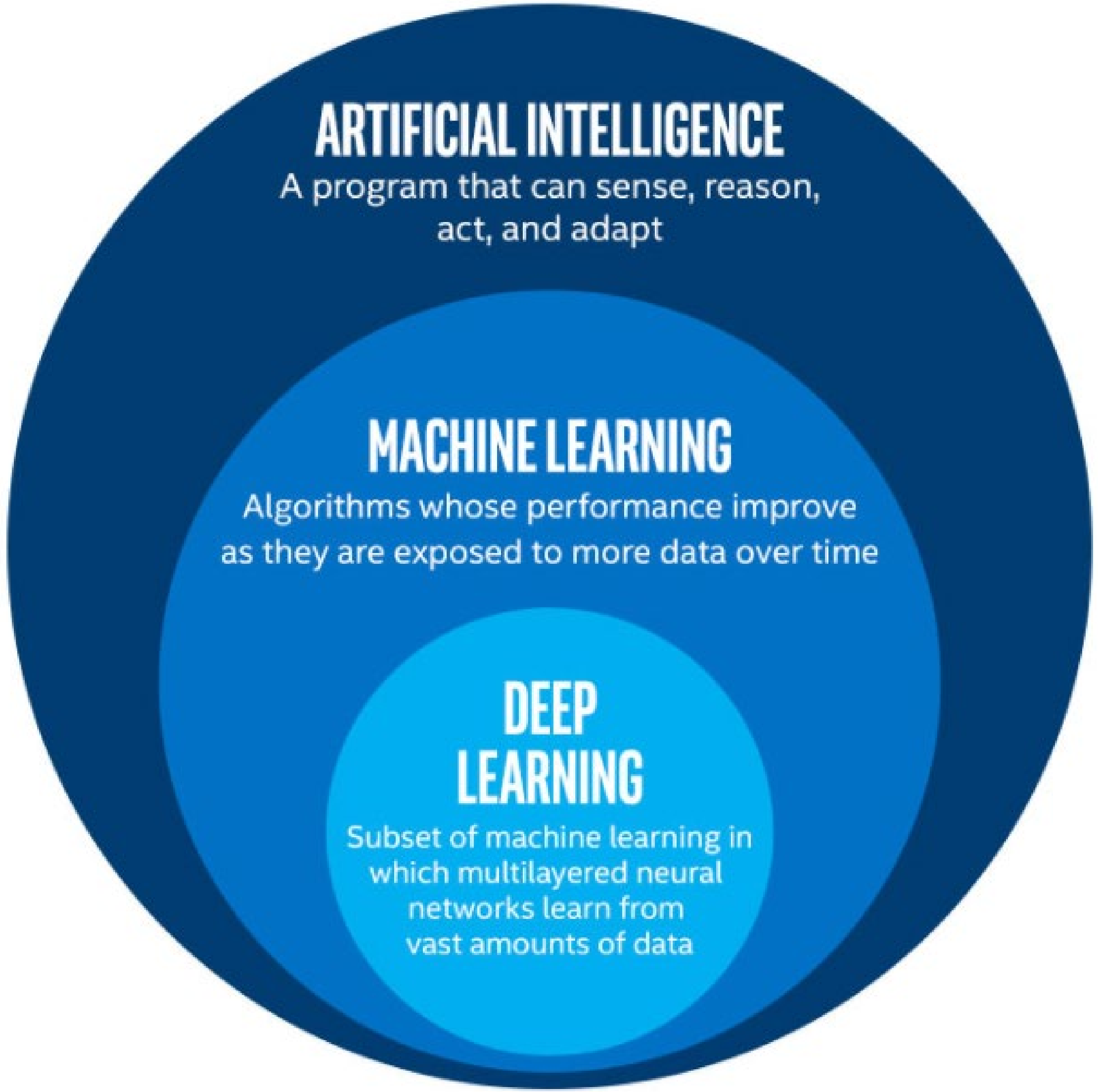
umělá inteligence (artificial intelligence)

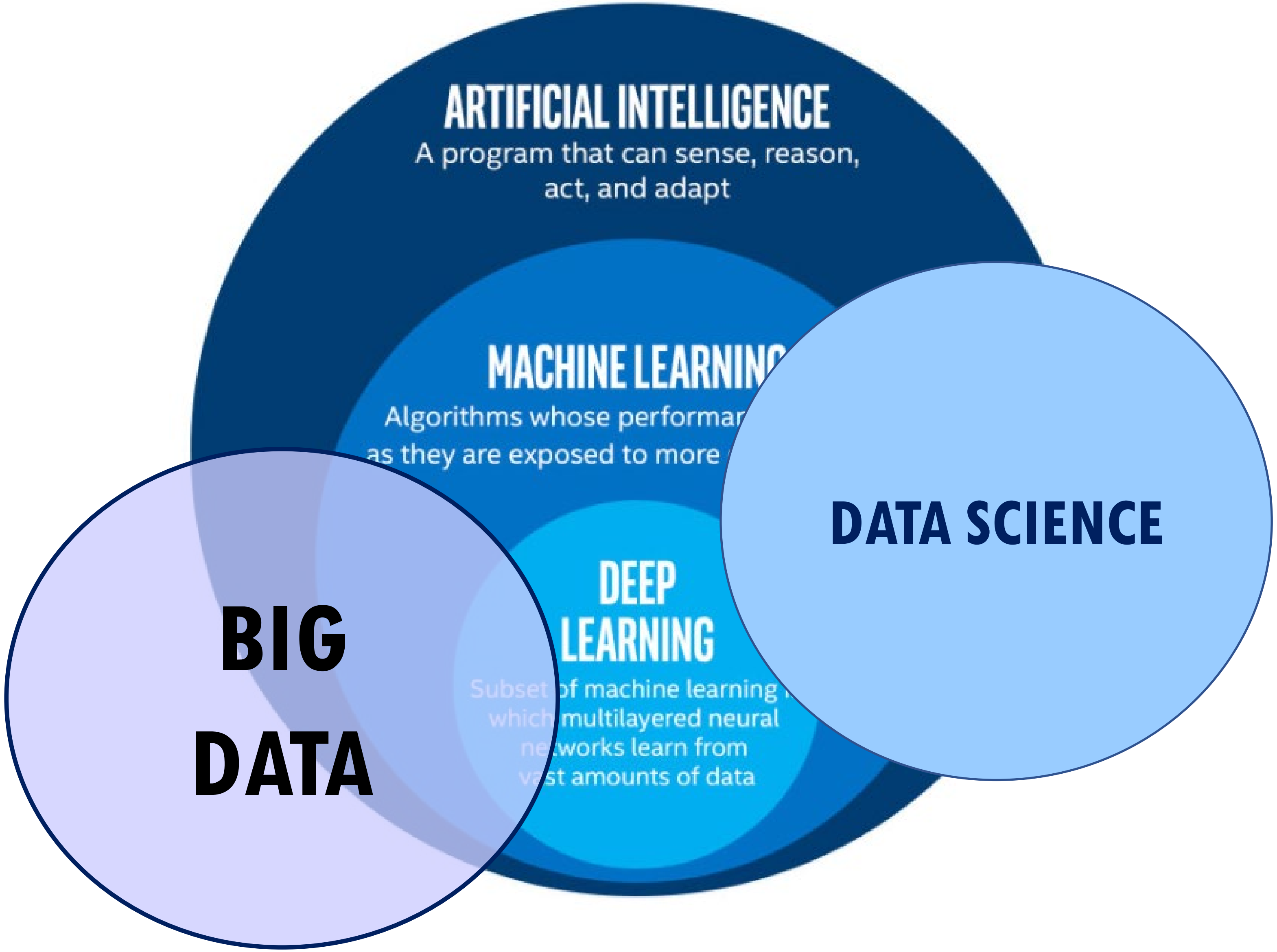
SMART HOME

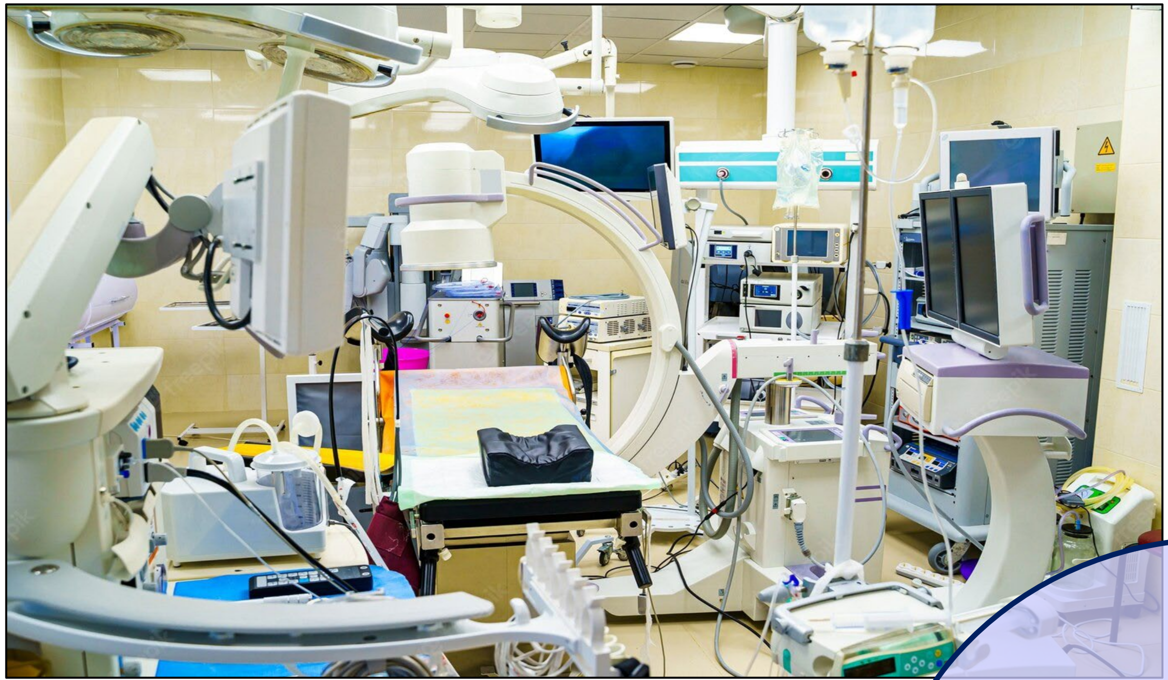


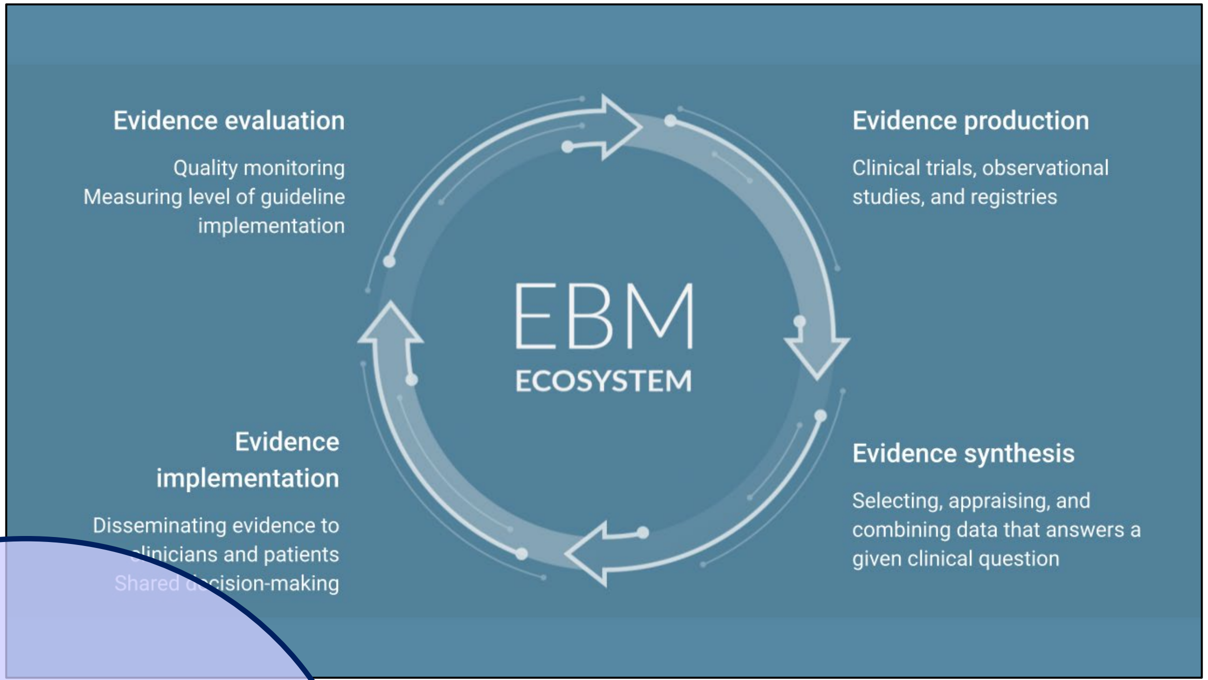

2010
The Siri app is created
2011
IBM Watson is created (remember Ken from Jeopardy?)
2011
Apple Siri makes its debut
2013
Google invests in AI/purchases eight robot companies
2015
Tesla introduces the autopilot feature for its Model S
2016
Google Deep Minds Alpha Go beats chess champ Lee Sedona
2017
Harvard uses AI to diagnose breast cancer without surgery
2018
IBM introduces Project Debater – an AI system that debates humans on complex topics


deep learning
machine learning
performance
amount of data


ARTIFICIAL INTELLIGENCE
A program that can sense, reason, act, and adapt
MACHINE LEARNING
Algorithms whose performance improve as they are exposed to more data over time
DEEP LEARNING
Subset of machine learning in which multilayered neural networks learn from vast amounts of data

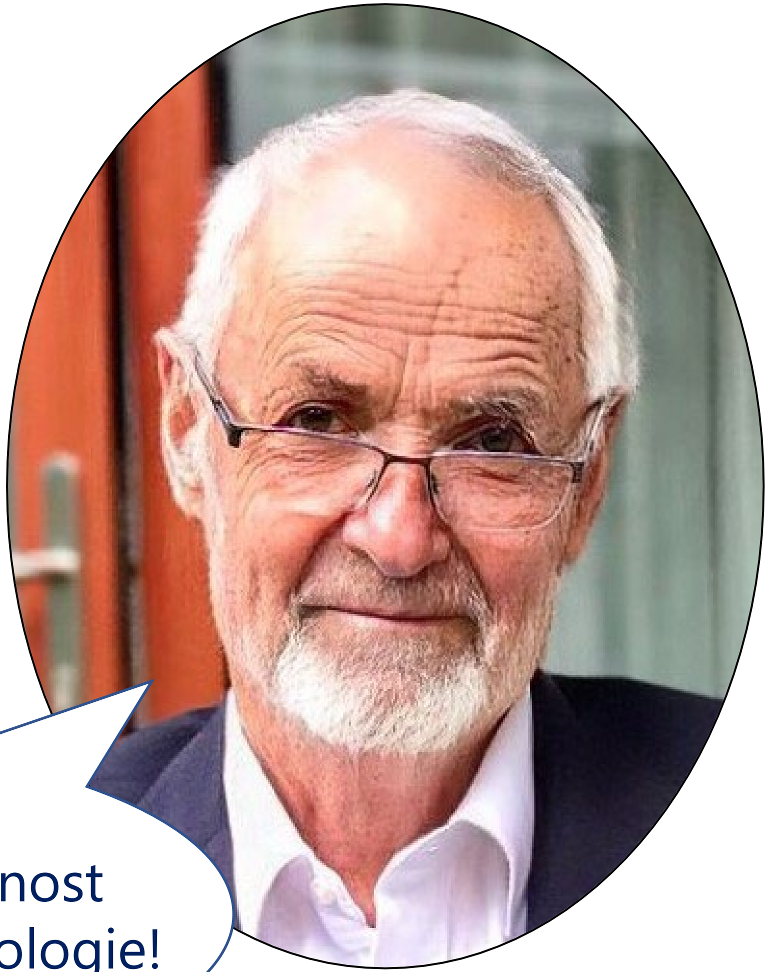

ARTIFICIAL INTELLIGENCE
A program that can sense, reason, act, and adapt
MACHINE LEARNIN
Algorithms whose performa
as they are exposed to more
DEEP LEARNING
Subset of machine learning
which multilayered neural
networks learn from
vast amounts of data
BIG DATA
DATA SCIENCE




Evidence evaluation
Quality monitoring
Measuring level of guideline implementation
Evidence production
Clinical trials, observational studies, and registries
EBM
ECOSYSTEM
Evidence implementation
Disseminating evidence to
linicians and patients
Shared
cision-making
Evidence synthesis
Selecting, appraising, and combining data that answers a given clinical question

BIG DATA

Zdravotnictví se bez
AI již neobejde, jen si to zatím
nechceme připustit…



Blbost.
Zdravý rozum a zkušenost
jsou nad všechny technologie!

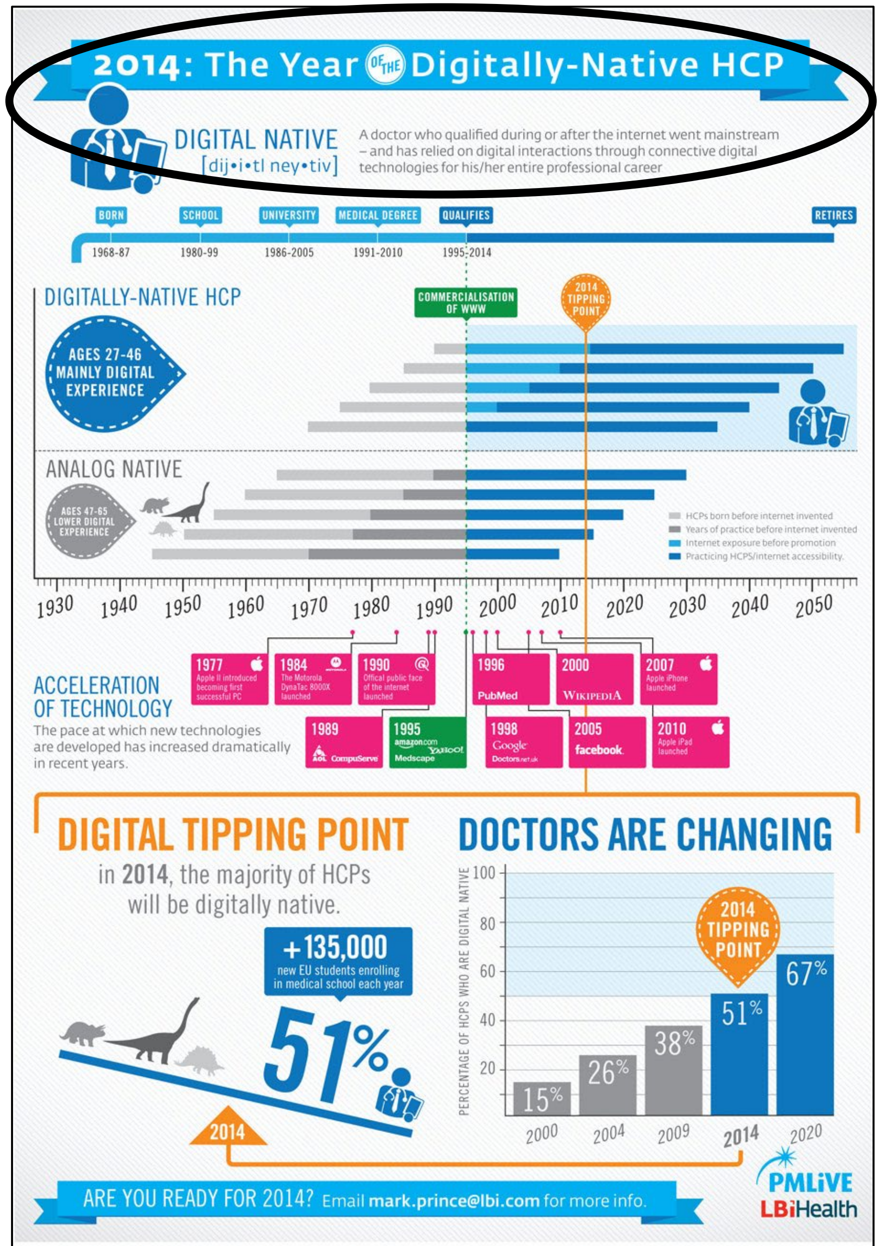
HCP = healthcare professional

Dnešní vydání HN

Hospodářské Noviny

Čeští lékaři jsou k telemedicíně zatím obezřetní. Modernější technologie přijímají jen ti mladší

Moderním technologiím jsou nakloněni mladší lékaři i pacienti, takže do budoucna má telemedicína snad otevřené dveře. Podporu jim vyjadřuje také ministr zdravotnictví Adam Vojtěch.

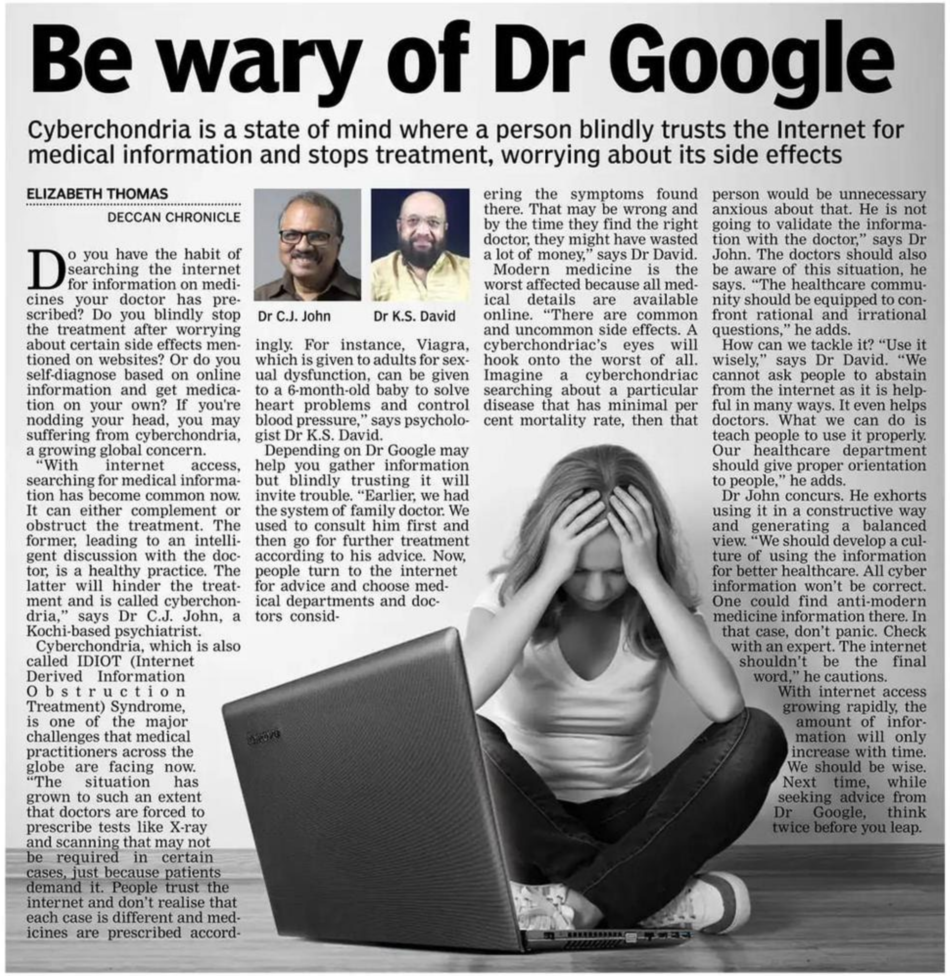


Infographic compiled by LBi Health and published by PMLiVE and The Directory

Kyberchondrie

WIKIPEDIE
Otevřená encyklopedie

Kyberchondrie (Cyberchondria) je hovorový pojem sloužící k popisu chování člověka, který užívá internet k nadměrnému získávání informací o zdraví a zdravotní péči. Informace o zdraví může člověk soustřeďovat pro sebe, ale také vzhledem k blízkému člověku. Je považován za specifickou formu hypochondrie.



Be wary of Dr Google

Cyberchondria is a state of mind where a person blindly trusts the Internet for medical information and stops treatment, worrying about its side effects

ELIZABETH THOMAS
DECCAN CHRONICLE

Dr C.J. John
Dr K.S. David

Do you have the habit of searching the internet for information on medicines your doctor has prescribed? Do you blindly stop the treatment after worrying about certain side effects mentioned on websites? Or do you self-diagnose based on online information and get medication on your own? If you're nodding your head, you may suffering from cyberchondria, a growing global concern.

"With internet access, searching for medical information has become common now. It can either complement or obstruct the treatment. The former, leading to an intelligent discussion with the doctor, is a healthy practice. The latter will hinder the treatment and is called cyberchondria," says Dr C.J. John, a Kochi-based psychiatrist.

Cyberchondria, which is also called IDIOT (Internet Derived Information Obstruction Treatment) Syndrome, is one of the major challenges that medical practitioners across the globe are facing now. "The situation has grown to such an extent that doctors are forced to prescribe tests like X-ray and scanning that may not be required in certain cases, just because patients demand it. People trust the internet and don't realise that each case is different and medicines are prescribed accordingly. For instance, Viagra, which is given to adults for sexual dysfunction, can be given to a 6-month-old baby to solve heart problems and control blood pressure," says psychologist Dr K.S. David.

Depending on Dr Google may help you gather information but blindly trusting it will invite trouble. "Earlier, we had the system of family doctor. We used to consult him first and then go for further treatment according to his advice. Now, people turn to the internet for advice and choose medical departments and doctors considering the symptoms found there. That may be wrong and by the time they find the right doctor, they might have wasted a lot of money," says Dr David.

Modern medicine is the worst affected because all medical details are available online. "There are common and uncommon side effects. A cyberchondriac's eyes will hook onto the worst of all. Imagine a cyberchondriac searching about a particular disease that has minimal per cent mortality rate, then that person would be unnecessary anxious about that. He is not going to validate the information with the doctor," says Dr John. The doctors should also be aware of this situation, he says. "The healthcare community should be equipped to confront rational and irrational questions," he adds.

How can we tackle it? "Use it wisely," says Dr David. "We cannot ask people to abstain from the internet as it is helpful in many ways. It even helps doctors. What we can do is teach people to use it properly. Our healthcare department should give proper orientation to people," he adds.

Dr John concurs. He exhorts using it in a constructive way and generating a balanced view. "We should develop a culture of using the information for better healthcare. All cyber information won't be correct. One could find anti-modern medicine information there. In that case, don't panic. Check with an expert. The internet shouldn't be the final word," he cautions.

With internet access growing rapidly, the amount of information will only increase with time. We should be wise. Next time, while seeking advice from Dr Google, think twice before you leap.

Symbiotic ⇔ Competitive Community Relationships

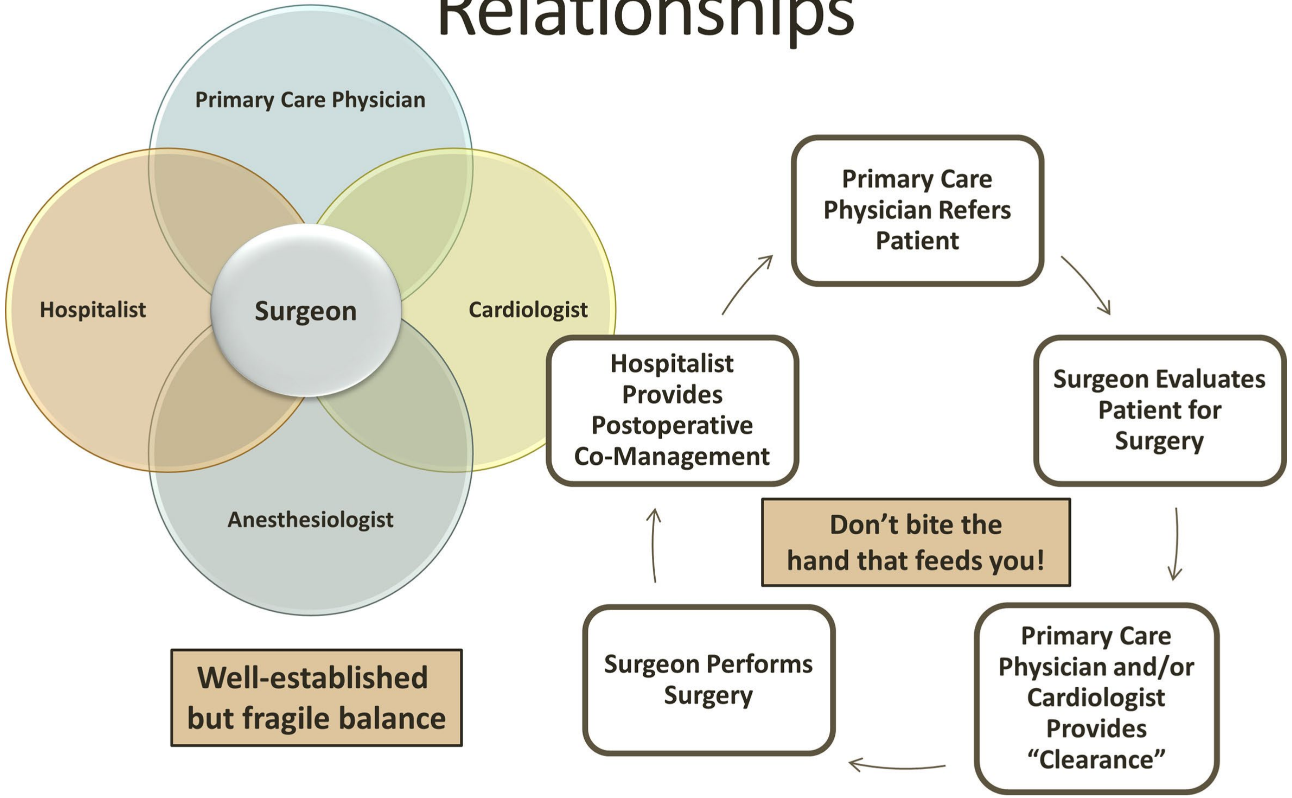


Figure 5. Frequently well-established, competitive versus symbiotic relationships among perioperative health care providers in the community (*Courtesy of* T.R. Vetter, MD, MPH, Austin, TX; Published with permission from Thomas R. Vetter MD, MPH).

Intensive Care Med (2019) 45:1298–1300

WHAT'S NEW IN INTENSIVE CARE

Artificial intelligence in intensive care: are we there yet?

Matthieu Komorowski*

Gutierrez *Critical Care* (2020) 24:101

Critical Care

REVIEW Open Access

Artificial Intelligence in the Intensive Care Unit

Guillermo Gutierrez

Mortality Prediction of ICU Patients Using Machine Learning Techniques

Babita Majhi[1]*, Aarti Kashyap[1] and Ritanjali Majhi[2]

[1]*Dept. of CSIT, Guru Ghasidas Vishwavidyalaya, Central University, Bilaspur, India*
[2]*School of Management, National Institute of Technology Karnataka, Surathkal, India*

First published: 06 August 2021 | https://doi.org/10.1002/9781119711278.ch1

Abstract

The intensive care unit (ICU) admits highly ill patients to facilitate them serious attention and treatment using ventilators and other sophisticated medical equipments. These equipments are very costly hence its optimized uses are necessary. ICUs have a number of staffs in comparison to the number of patients admitted for regular monitoring of the patients. In brief, ICUs involve large amount of budget in comparison to other sections of any hospital. Therefore to help the doctors to find out which patient is more at risk mortality prediction is an important area of research. In data mining mortality prediction is a binary classification problem i.e. die or survive. As a result it attracts the machine learning group to apply the algorithms to do the mortality prediction. In this chapter six different machine learning methods such as Functional Link Artificial Neural Network (FLANN), Support Vector Machine (SVM), Discriminate Analysis (DA), Decision Tree (DT), Naïve Bayesian Network and K-Nearest Neighbors (KNN) are used to develop model for mortality prediction collecting data from Physionet Challenge 2012 and did the performance analysis of them. There are three separate data set each with 4000 records in Physionet Challenge 2012. This chapter uses dataset A containing 4000 records of different patients. The simulation study reveals that the decision tree based model outperforms the rest five models with an accuracy of 97.95% during testing. It is followed by the FA-FLANN model in the second rank with an accuracy of 87.60%.

Table 1.1 Time series variables with description and physical units recorded in the ICU [6].

S. no.	Variables	Description	Physical units
1.	Albumin	Albumin	g/dL
2.	ALP	Alkaline Phosphate	IU/L
3.	ALT	Alanine transaminase	IU/L
4.	AST	Aspartate transaminase	IU/L
5.	Bilirubin	Bilirubin	mg/dL
6.	BUN	Blood urea nitrogen	mg/dL
7.	Cholesterol	Cholesterol	mg/dL
8.	Creatinine	Creatinine	mg/dL
9.	DiasABP	Invasive diastolic arterial blood pressure	mmHg
10.	FiO2	Fractional inspired oxygen	[0–1]
11.	GCS	Glasgow Coma Score	[3–15]
12.	Glucose	Serum Glucose	mg/dL
13.	HCO3	Serum Bicarbonate	mmol/L
14.	HCT	Hematocrit	%
15.	HR	Heart Rate	bpm
16.	K	Serum Potassium	mEq/L
17.	Lactate	Lactate	mmol/L
18.	Mg	Serum Magnesium	mmol/L
19.	MAP	Invasive mean arterial blood pressure	mmHg
20.	MechVent	Mechanical Respiration Ventilation	0/1(true/false)
21.	Na	Serum Sodium	mEq/L
22.	NIDiasABP	Non-invasive diastolic arterial blood pressure	mmHg
23.	NIMAP	Non-invasive mean arterial blood pressure	mmHg
24.	NISysABP	Non-invasive systolic arterial blood pressure	mmHg
25.	PaCO2	Partial pressure of arterial carbon dioxide	mmHg
26.	PaO2	Partial pressure of arterial oxygen	mmHg
27.	pH	Arterial pH	[0–14]
28.	Platelets	Platelets	cells/nL
29.	RespRate	Respiration Rate	bpm
30.	SaO2	O2 saturation in hemoglobin	%
31.	SysABP	Invasive systolic arterial blood pressure	mmHg
32.	Temp	Temperature	°C
33.	TropI	Troponin-I	µg/L
34.	TropT	Troponin-T	µg/L
35.	Urine	Urine Output	mL
36.	WBC	White Blood Cells Count	cells/nL

Table 1.2 Time series variables with physical units [30].

S. no.	Variables	Physical units
1.	Temperature	Celsius
2.	Heart Rate	bpm
3.	Urine Output	mL
4.	pH	[0–14]
5.	Respiration Rate	bpm
6.	GCS (Glassgow Coma Index)	[3–15]
7.	FiO2 (Fractional Inspired Oxygen)	[0–1]
8.	PaCo2 (Partial Pressure Carbon dioxide)	mmHg
9.	MAP (Invasive Mean arterial blood pressure)	mmHg
10.	SysABP (Invasive Systolic arterial blood pressure)	mmHg
11.	DiasABP (Invasive Diastolic arterial blood pressure)	mmHg
12.	NIMAP (Non-invasive mean arterial blood pressure)	mmHg
13.	NIDiasABP (blood pre	
14.	Mechanical	
15.	NISysABP (blood pre	

Predikace ICU mortality s přesností 98%

Table 1.3 Comparison of different models during testing.

S. no.	Model name	Error during testing		Accuracy	Rank
		Value	(%)		
1.	FA-FLANN	0.1240	12.40%	87.60%	2
2.	DA	0.1395	13.95%	86.05%	5
3.	DT	0.0205	2.05%	97.95%	1
4.	KNN	0.1340	13.4%	86.6%	4
5.	Naive Bayesian	0.4520	45.20%	54.80%	6
6.	SVM	0.1385	13.85%	86.15%	3

OPEN

Mortality prediction of patients in intensive care units using machine learning algorithms based on electronic health records

Min Hyuk Choi[1], Dokyun Kim[1], Eui Jun Choi[2], Yeo Jin Jung[2], Yong Jun Choi[3], Jae Hwa Cho[3] & Seok Hoon Jeong[1]✉

Improving predictive models for intensive care unit (ICU) inpatients requires a new strategy that periodically includes the latest clinical data and can be updated to reflect local characteristics. We extracted data from all adult patients admitted to the ICUs of two university hospitals with different characteristics from 2006 to 2020, and a total of 85,146 patients were included in this study. Machine learning algorithms were trained to predict in-hospital mortality. The predictive performance of conventional scoring models and machine learning algorithms was assessed by the area under the receiver operating characteristic curve (AUROC). The conventional scoring systems had various predictive powers, with the ... (AUROC 0.803 [0.795–0.810] for hospital G) showing the highest AUROC among them. The best performing machine learning models achieved an AUROC of 0.977 (0.973–0.980) in hospital S and 0.955 (0.950–0.961) in hospital G. The use of ML models in conjunction with conventional scoring systems can provide more useful information for predicting the prognosis of critically ill patients. In this study, we suggest that the predictive model can be made more robust by training with the individual data of each hospital.

AUROC of 0.977 (0.973–0.980)

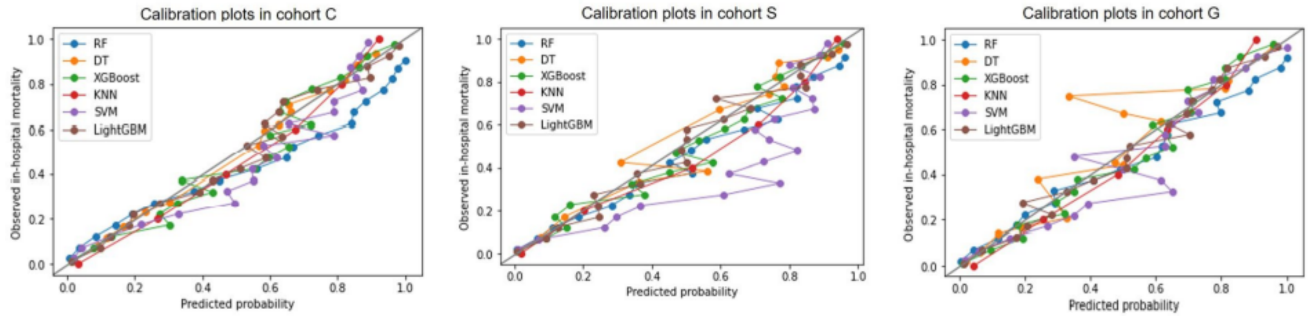


Figure 2. Comparison of machine learning-based in-hospital mortality prediction models.

The calibration plots show the agreement of between predicted probability and observed in-hospital mortality. The black line at 45 degrees indicates perfect calibration where the predicted and observed probabilities are equal.

Admission variables (obtained within 24 h of ICU admission)	Hospital S				Hospital G				
	Overall (N = 61,589)	No hospital mortality (N = 54,313)	Hospital mortality (N = 7276)	P*	Overall (N = 23,557)	No hospital mortality (N = 19,458)	Hospital mortality (N = 4099)	P*	P†
Age, years	67 [57–74]	66 [57–74]	67 [56–76]	< 0.001	65 [53–75]	64 [52–74]	70 [58–78]	< 0.001	< 0.001
Sex				0.004				0.174	< 0.001
Female	22,744 (36.9%)	19,944 (36.7%)	2800 (38.5%)		9034 (38.3%)	7501 (38.5%)	1533 (37.4%)		
Male	38,845 (63.1%)	34,369 (63.3%)	4476 (61.5%)		14,523 (61.7%)	11,957 (61.5%)	2566 (62.6%)		
Types of admission				< 0.001				< 0.001	< 0.001
Medical	39,560 (64.2%)	34,232 (63.0%)	5328 (73.2%)		11,365 (48.2%)	9073 (46.6%)	2292 (55.9%)		
Surgical	22,029 (35.8%)	20,081 (37.0%)	1948 (26.8%)		12,192 (51.8%)	10,385 (53.4%)	1807 (44.1%)		
Year of admission				< 0.001				< 0.001	0.033
2006–2010	16,531 (26.8%)	14,422 (26.6%)	2109 (29.0%)		6379 (27.1%)	5322 (27.4%)	1057 (25.8%)		
2011–2015	20,945 (34.0%)	18,371 (33.8%)	2574 (35.4%)		8179 (34.7%)	6637 (34.1%)	1542 (37.6%)		
2016–2020	24,113 (39.2%)	21,520 (39.6%)	2593 (35.6%)		8999 (38.2%)	7499 (38.5%)	1500 (36.6%)		
Conventional scoring systems									
APACHE II	13 [10–17]	13 [10–16]	19 [13–26]	< 0.001	16 [11–21]	15 [10–19]	22 [18–28]	< 0.001	< 0.001
APACHE III	55 [47–65]	54 [46–63]	74 [57–96]	< 0.001	60 [50–74]	57 [48–69]	79 [66–95]	< 0.001	< 0.001
SAPS II	34 [28–42]	33 [27–40]	48 [36–64]	< 0.001	37 [29–48]	35 [27–44]	52 [42–64]	< 0.001	< 0.001
SAPS III	47 [40–55]	46 [40–53]	59 [50–70]	< 0.001	51 [43–61]	49 [42–57]	65 [56–74]	< 0.001	< 0.001
MPM0 II	2 [2–2]	2 [2–2]	2 [1–3]	< 0.001	2 [1, 2]	1 [1, 2]	2 [1–3]	< 0.001	< 0.001
MPM0 III	2 [2–3]	2 [2, 3]	2 [1–3]	< 0.001	2 [1, 2]	2 [1, 2]	2 [2–4]	< 0.001	< 0.001
SOFA	4 [2–8]	4 [2–7]	7 [4–11]	< 0.001	6 [3–9]	6 [2–9]	10 [7–12]	< 0.001	< 0.001
Pitt bacteremia score	1 [0–4]	1 [0–4]	2 [0–5]	< 0.001	3 [1–5]	3 [1–4]	5 [3–7]	< 0.001	< 0.001
Underlying comorbidities									
Charlson comorbidity index	5 [4–6]	5 [4–6]	5 [4–7]	< 0.001	5 [3–6]	4 [3–6]	5 [4–7]	< 0.001	< 0.001
Cancer	5137 (8.3%)	3101 (5.7%)	2036 (28.0%)	< 0.001	4239 (18.0%)	3002 (15.4%)	1237 (30.2%)	< 0.001	< 0.001
Cerebrovascular diseases	14,373 (23.3%)	13,433 (24.7%)	940 (12.9%)	< 0.001	4533 (19.2%)	3716 (19.1%)	817 (19.9%)	0.226	< 0.001
Diabetes mellitus	16,696 (27.1%)	15,126 (27.8%)	1570 (21.6%)	< 0.001	4086 (17.3%)	3391 (17.4%)	695 (17.0%)	0.482	< 0.001
Hypertension	28,407 (46.1%)	26,538 (48.9%)	1869 (25.7%)	< 0.001	5406 (22.9%)	4677 (24.0%)	729 (17.8%)	< 0.001	< 0.001
Chronic pulmonary diseases	1832 (3.0%)	1364 (2.5%)	468 (6.4%)	< 0.001	541 (2.3%)	332 (1.7%)	209 (5.1%)	< 0.001	< 0.001
Hemiplegia	2041 (3.3%)	1900 (3.5%)	141 (1.9%)	< 0.001	1650 (7.0%)	1500 (7.7%)	150 (3.7%)	< 0.001	< 0.001
Liver diseases	2080 (3.4%)	1235 (2.3%)	845 (11.6%)	< 0.001	1248 (5.3%)	922 (4.7%)	326 (8.0%)	< 0.001	< 0.001
Myocardial infarction	11,682 (19.0%)	10,888 (20.0%)	794 (10.9%)	< 0.001	2886 (12.3%)	2482 (12.8%)	404 (9.9%)	< 0.001	< 0.001
Renal diseases	3462 (5.6%)	2798 (5.2%)	664 (9.1%)	< 0.001	1367 (5.8%)	981 (5.0%)	386 (9.4%)	< 0.001	0.313
Ulcer	1168 (1.9%)	926 (1.7%)	242 (3.3%)	< 0.001	485 (2.1%)	370 (1.9%)	115 (2.8%)	< 0.001	0.131
Transplantation	766 (1.2%)	265 (0.5%)	501 (6.9%)	< 0.001	203 (0.9%)	153 (0.8%)	50 (1.2%)	0.008	< 0.001
Ventilator use	10,537 (17.1%)	8895 (16.4%)	1642 (22.6%)	< 0.001	5957 (25.3%)	4745 (24.4%)	1212 (29.6%)	< 0.001	< 0.001
Vasopressor use	21,448 (34.8%)	18,089 (33.3%)	3359 (46.2%)	< 0.001	11,708 (49.7%)	8439 (43.4%)	3269 (79.8%)	< 0.001	< 0.001
Cardiac arrest	809 (1.3%)	694 (1.3%)	115 (1.6%)	0.038	1228 (5.2%)	414 (2.1%)	814 (19.9%)	< 0.001	< 0.001
Bacterial infection on ICU admission									
Site of infection				< 0.001				< 0.001	< 0.001
Multiple sites	843 (1.4%)	108 (0.2%)	735 (10.1%)		275 (1.2%)	906 (4.7%)	529 (12.9%)		
Lungs	428 (0.7%)	283 (0.5%)	145 (2.0%)		1435 (6.1%)	383 (2.0%)	238 (5.8%)		
Bloodstream	251 (0.4%)	119 (0.2%)	132 (1.8%)		183 (0.8%)	110 (0.6%)	73 (1.8%)		
Urinary tract	503 (0.8%)	363 (0.7%)	140 (1.9%)		621 (2.6%)	383 (2.0%)	238 (5.8%)		
CNS	3 (0.0%)	0 (0.0%)	3 (0.0%)		0 (0.0%)	165 (0.8%)	110 (2.7%)		
Abdomen	27 (0.0%)	19 (0.0%)	8 (0.1%)		156 (0.7%)	103 (0.5%)	53 (1.3%)		
None	59,521 (96.6%)	53,418 (98.4%)	6103 (83.9%)		20,887 (88.7%)	17,791 (91.4%)	3096 (75.5%)		
Antibiotic use at ICU admission (may be multiple)	28,255 (45.9%)	22,754 (41.9%)	5501 (75.6%)	< 0.001	16,867 (71.6%)	13,110 (67.4%)	3757 (91.7%)	< 0.001	< 0.001
3rd-generation cephalosporins	6788 (11.0%)	4947 (9.1%)	1841 (25.3%)	< 0.001	5649 (24.0%)	4490 (23.1%)	1159 (28.3%)	< 0.001	< 0.001
4th-generation cephalosporins	450 (0.7%)	30 (0.1%)	420 (5.8%)	< 0.001	591 (2.5%)	296 (1.5%)	295 (7.2%)	< 0.001	< 0.001
Beta lactam/beta lactamase inhibitors	8744 (14.2%)	5646 (10.4%)	3098 (42.6%)	< 0.001	6362 (27.0%)	4401 (22.6%)	1961 (47.8%)	< 0.001	< 0.001
Carbapenems	2300 (3.7%)	587 (1.1%)	1713 (23.5%)	< 0.001	2524 (10.7%)	1409 (7.2%)	1115 (27.2%)	< 0.001	< 0.001
Glycopeptides	7144 (11.6%)	4280 (7.9%)	2864 (39.4%)	< 0.001	3526 (15.0%)	2182 (11.2%)	1344 (32.8%)	< 0.001	< 0.001
Penicillins	3389 (5.5%)	3082 (5.7%)	307 (4.2%)	< 0.001	211 (0.9%)	150 (0.8%)	61 (1.5%)	< 0.001	< 0.001
Quinolones	3926 (6.4%)	1773 (3.3%)	2153 (29.6%)	< 0.001	4369 (18.5%)	2845 (14.6%)	1524 (37.2%)	< 0.001	< 0.001

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Superiority of Supervised Machine Learning on Reading Chest X-Rays in Intensive Care Units

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Purpose: Portable chest radiographs are diagnostically indispensable in intensive care units (ICU). This study aimed to determine if the proposed machine learning technique increased in accuracy as the number of radiograph readings increased and if it was accurate in a clinical setting.

Methods: Two independent data sets of portable chest radiographs ($n = 380$, a single Japanese hospital; $n = 1{,}720$, The National Institution of Health [NIH] ChestX-ray8 dataset) were analyzed. Each data set was divided training data and study data. Images were classified as atelectasis, pleural effusion, pneumonia, or no emergency. DenseNet-121, as a pre-trained deep convolutional neural network was used and ensemble learning was performed on the best-performing algorithms. Diagnostic accuracy and proce

machine learning was 70 times faster than the time taken by ICU physicians

Results: In the s
diagnostic accuracy
significantly improv
10 ... ories toward
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ma ... ns (9.66 s vs.
12 ... U physicians
in ... ural effusion,

diagnostic accuracy was higher by machine learning than by ICU physicians

0.856 vs. 0.706, $P < 0.01$; pneumonia, 0.720 vs. 0.744, $P = 0.88$; no emergency, 0.751 vs. 0.698, $P = 0.47$).

Conclusions: We developed an automatic detection system for portable chest radiographs in ICU setting; its performance was superior and quite faster than ICU physicians.

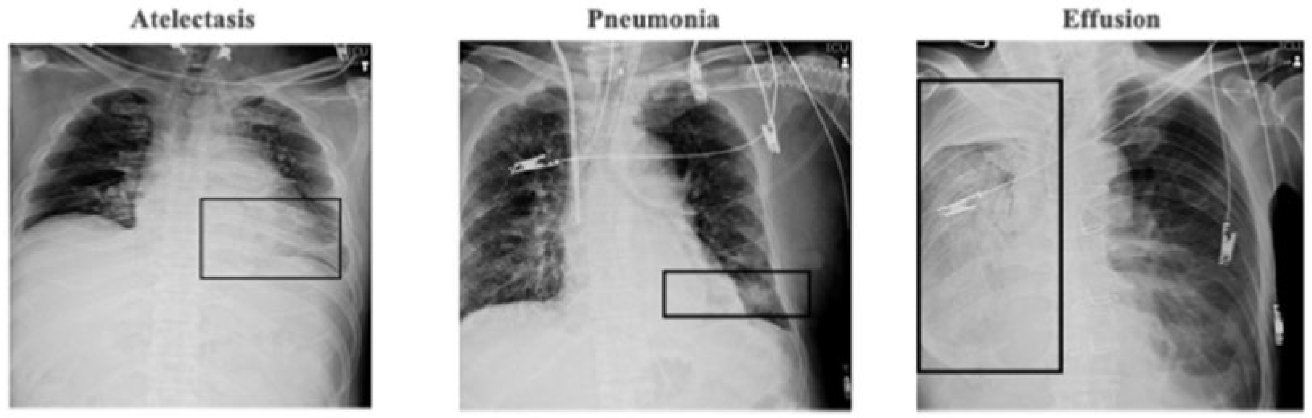

FIGURE 1 | NIH repository test image sample.

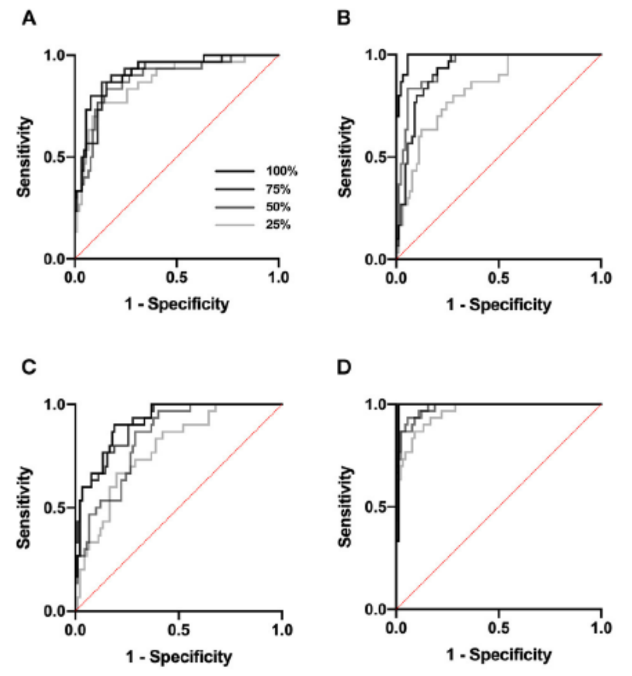

FIGURE 2 | ROC curve. ROC analysis was performed at a sample size of 25, 50, 75, and 100%. **(A)** ROC analysis for atelectasis. **(B)** for pleural effusion. **(C)** for pneumonia. **(D)** for no emergency.

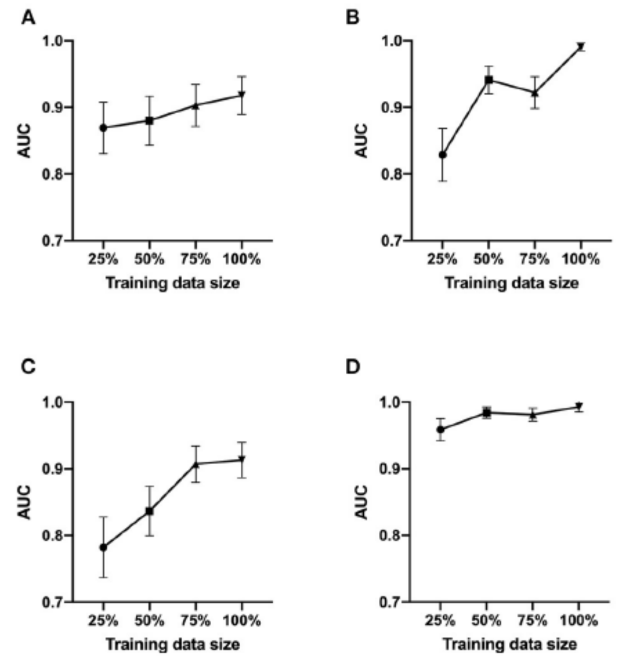

FIGURE 3 | AUC values as a function of the sample size. The AUC of ROC analysis was shown at a sample size of 25, 50, 75, and 100%. **(A)** for atelectasis. **(B)** for pleural effusion. **(C)** for pneumonia. **(D)** for no emergency.

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A Machine Learning decision-making tool for extubation in Intensive Care Unit patients

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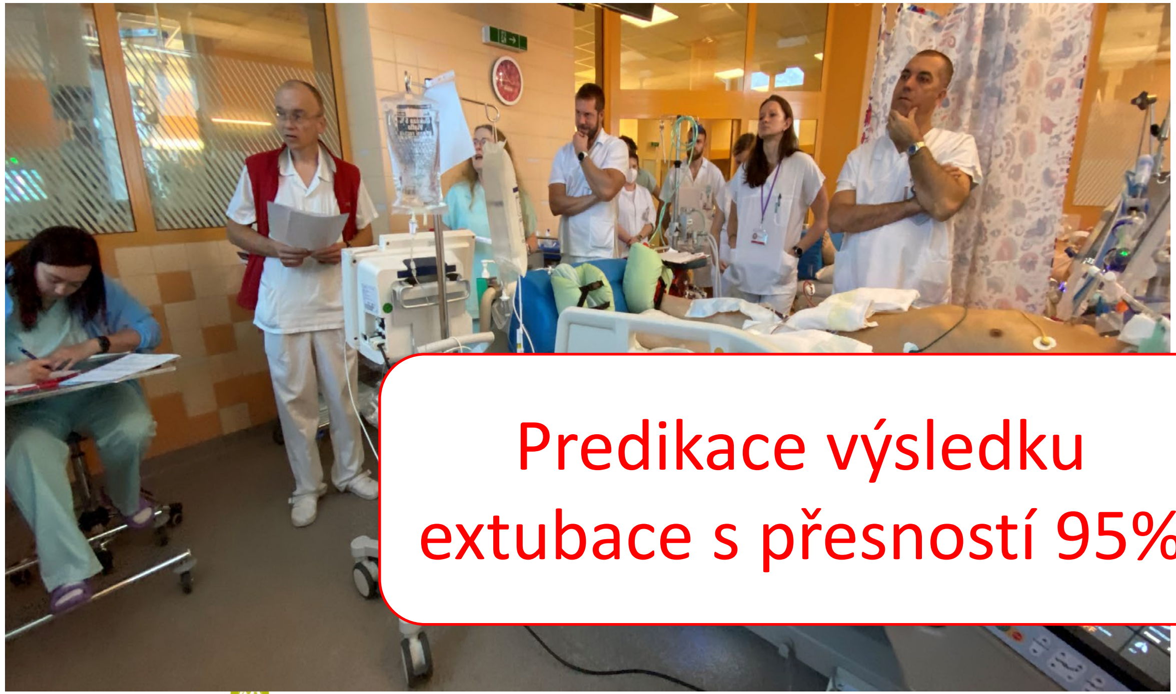
Conclusions: Machine Learning-based tools have been found to accurately predict the extubation outcome in critical patients with invasive mechanical ventilation. The use of this important predictive capability to assess the extubation decision could potentially reduce the rate of extubation failure, currently at 9%. With about 40% of critically ill patients eventually receiving invasive mechanical ventilation during their stay and given the serious potential complications associated to reintubation, the excellent predictive ability of the model presented here suggests that Machine Learning techniques could significantly improve the clinical outcomes of critical patients.



Predikace výsledku extubace s přesností 95%

Table 1 List and characteristics of the variables used as model predictors.

Variable	Units	Symbol	Type	Comments
Time under IMV	h	Δt	I	
Ventilation mode	-	V-Mode	I	
Tidal Volume	L	V_T	I	
Heart Rate	m^{-1}	HR	I	
Respiratory rate	m^{-1}	RR	I	
Peak inspiratory pressure	cmH_2O	P_{IP}	I	
Plateau Pressure	cmH_2O	P_{PLAT}	I	
O_2 saturation to inspired fraction ratio	-	SpFiO2	I	
Respiratory rate-oxygenation index	min	ROX	II	SpFiO2/RR
Rapid Shallow Breathing Index	L^{-1}	RSBI	II	RR/V_T
Number of previous MV events	-	NPE	III	
Total Cumulative Dose (sedatives and analgesics)	mg	TCD	III	
Total Given Dose (sedatives and analgesics)	mg	TGD	III	
Glasgow Coma Scale	-	GCS	III	
Richmond Agitation-Sedation Scale	-	RASS	III	
Age at admission to ICU	yr	AGE	IV	
APACHE II score	-	APACHEII	IV	
Body Mass Index at admission to ICU	kgm^{-2}	BMI	IV	
Gender	-	GENDER	IV	Categorical
SEMICYUC code	-	ICUAR	IV	Categorical

Table 4
Mean accuracy and AUROC for each classifier using a classification threshold of 0.5 and undersampling for class imbalance.

Classifier	% Accuracy	% AUROC
SVM	94.6	98.3
GBM	89.6	96.1
LDA	72.4	79.4

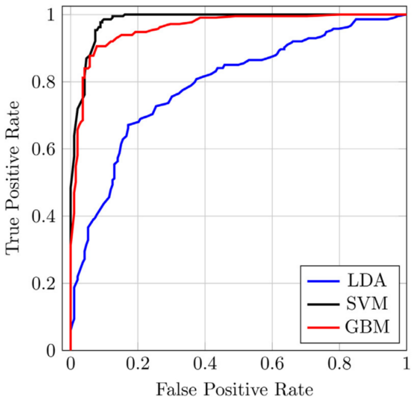


Fig. 2. Mean ROC curve for SVM, GBM and LDA classifiers.

Machine-learning Algorithm to Predict Hypotension Based on High-fidelity Arterial Pressure Waveform Analysis

Feras Hatib, Ph.D., Zhongping Jian, Ph.D., Sai Buddi, Ph.D., Christine Lee, M.S., Jos Settels, M.S., Karen Sibert, M.D., F.A.S.A., Joseph Rinehart, M.D., Maxime Cannesson, M.D., Ph.D.

ABSTRACT

Background: With appropriate algorithms, computers can learn to detect patterns and associations in large data sets. The authors' goal was to apply machine learning to arterial pressure waveforms and create an algorithm to predict hypotension. The algorithm detects early alteration in waveforms that can herald the weakening of cardiovascular compensatory mechanisms affecting preload, afterload, and contractility.

Methods: The algorithm was dev … sist-
ing of 1,334 patients' records wit … (2)
a prospective, local hospital coho … rial
waveform recording and 1,923 ep … gh-
fidelity arterial pressure wavefor … Hg).
Receiver-operating characteristic … ean
arterial pressure less than 65 mmHg.

Results: Using 3,022 individual features per cardiac cycle, the algorithm predicted arterial hypotension with a sensitivity and specificity of 88% (85 to 90%) and 87% (85 to 90%) 15 min before a hypotensive event (area under the curve, 0.95 [0.94 to 0.95]); 89% (87 to 91%) and 90% (87 to 92%) 10 min before (area under the curve, 0.95 [0.95 to 0.96]); 92% (90 to 94%) and 92% (90 to 94%) 5 min before (area under the curve, 0.97 [0.97 to 0.98]).

Conclusions: The results demonstrate that a machine-learning algorithm can be trained, with large data sets of high-fidelity arterial waveforms, to predict hypotension in surgical patients' records. (ANESTHESIOLOGY 2018; 129:663-74)

Sensitivita i specificita 88%
15 min před začátkem události

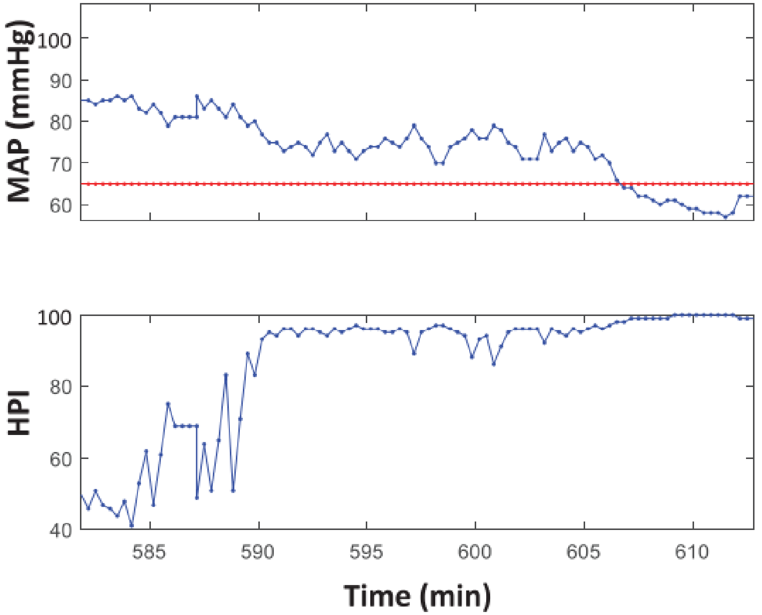


Fig. 5. One illustrative patient record showing the association between the algorithm output (Hypotension Prediction Index [HPI]) and the evolution of mean arterial pressure (MAP) over time.

Crystalloid *versus* Colloid for Intraoperative Goal-directed Fluid Therapy Using a Closed-loop System

A Randomized, Double-blinded, Controlled Trial in Major Abdominal Surgery

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ABSTRACT

Background: The type of fluid and volume regimen given intraoperatively both can impact patient outcome after major surgery. This two-arm, parallel, randomized controlled, double-blind, bi-center superiority study tested the hypothesis that when using closed-loop assisted goal-directed fluid therapy, balanced colloids are associated with fewer postoperative complications compared to balanced crystalloids in patients having major elective abdominal surgery.

Methods: One hundred and sixty patients were enrolled in the protocol. All patients had maintenance-balanced crystalloid administration of $3\,ml \cdot kg^{-1} \cdot h^{-1}$. A closed-loop system delivered additional 100-ml fluid boluses (patients were randomized to receive either a balanced-crystalloid or colloid solution) according to a predefined goal-directed strategy, using a stroke volume and stroke volume variation monitor. All patients were included in the analysis. The primary outcome was the Post-Operative Morbidity Survey score, a nine-domain scale, at day 2 postsurgery. Secondary outcomes included all postoperative complications.

Results: Patients randomized in the colloid group had a lower Post-Operative Morbidity Survey score (median [interquartile range] of 2 [1 to 3] *vs.* 3 [1 to 4], difference –1 [95% CI, –1 to 0]; $P < 0.001$) and a lower incidence of postoperative complications. Total volume of fluid administered intraoperatively and net fluid balance were significantly lower in the colloid group.

Conclusions: Under our study conditions, a colloid-based goal-directed fluid therapy was associated with fewer postoperative complications than a crystalloid one. This beneficial effect may be related to a lower intraoperative fluid balance when a balanced colloid was used. However, given the study design, the mechanism for the difference cannot be determined with certainty. (Anesthesiology 2018; 128:55-66)

Table 4. Postoperative Data and Outcome Variables

Variables	Crystalloid Group (N = 80)	Colloid Group (N = 80)	Difference (95% CI)	*P* Value
POMS score at POD2	3 [1 to 4]	2 [1 to 3]	1 (0 to 1)	**< 0.001**
Patients under vasopressors (%)	18	4	14 (4 to 23)	**0.009**
Fluid balance at POD1 (ml/kg)	22.1 [11.7 to 40.9]	15.8 [9.2 to 26.0]	5.5 (–0.2 to 12.0)	0.06
Weight gain at POD2 (kg)*	0.25 [0 to 1.00]	0.00 [–0.20 to 0.10]	0.30 (0.0 to 1.00)	**0.028**
Blood components transfusion (%)				
PRBC	20	11	9 (–2 to 20)	0.13
FFP	3	1	1 (–3 to 5)	1.0
Major complications (%)				
Patients with any major complications (%)	23	9	14 (3 to 25)	**0.015**
Anastomotic leakage†	8	0	8 (1 to 16)	**0.046**
Peritonitis	5	1	4 (–2 to 9)	0.37
Sepsis	6	4	3 (–4 to 9)	0.72
Wound dehiscence	5	1	4 (–2 to 9)	0.37
Pulmonary embolism	4	0	4 (0 to 8)	0.25
Pulmonary edema	6	1	5 (0 to 11)	0.21
Acute coronary syndrome	0	1	-1 (–4 to 1)	1.00
Stroke	0	1	-1 (–4 to 1)	1.00
Reoperation	8	4	4 (–3 to 11)	0.50
30-day mortality	4	0	4 (0 to 8)	0.25
Minor complications (%)				
Patients with any minor complications (%)	63	44	19 (4 to 34)	**0.016**
Urinary and other infection	26	16	10 (–3 to 23)	0.12
Paralytic ileus	14	9	5 (–5 to 15)	0.32
Need for loop diuretics	11	5	6 (–2 to 15)	0.25
Postoperative confusion	5	3	3 (–3 to 8)	0.68
Postoperative nausea and vomiting	33	28	5 (–9 to 19)	0.49
Acute kidney injury	23	19	4 (–9 to 16)	0.56
Length of stay				
ICU/PACU (h)	20 [18 to 22]	20 [18 to 22]	0 (–1 to 1)	0.96
Hospital (days)	10 [6 to 16]	10 [6 to 13]	1 (–1 to 3)	0.43
Fit for discharge criteria (days)	10 [6 to 15]	9 [6 to 12]	1 (–1 to 3)	0.22
30-day readmission	5	8	–3 (–10 to 5)	0.75

Outcome data are presented as value (%) and/or median [25th to 75th percentiles] and difference (95% CI). Bold indicates significant results with *P* value < 0.05.
*Data were available for 62 patients in the crystalloid group and 67 patients in the colloid group. †Determined among the 102 patients who underwent gastrointestinal anastomosis.
FFP = fresh-frozen plasma; ICU = intensive care unit; KDIGO = Kidney Disease: Improving Global Outcomes; PACU = postanesthesia care unit; POD = postoperative day; POMS = Post-Operative Morbidity Survey; PRBC = packed erythrocyte.

Improvements in Patient Monitoring in the Intensive Care Unit: Survey Study

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Textbox 1. The five most anticipated improvements for patient monitoring by intensive care unit staff.

- Reduction of false alarms
- Implementation of hospital alarm standard operating procedures
- Introduction of wireless sensors
- Introduction of a clinical decision support system based on artificial intelligence
- Enhancement of staff members' digital literacy

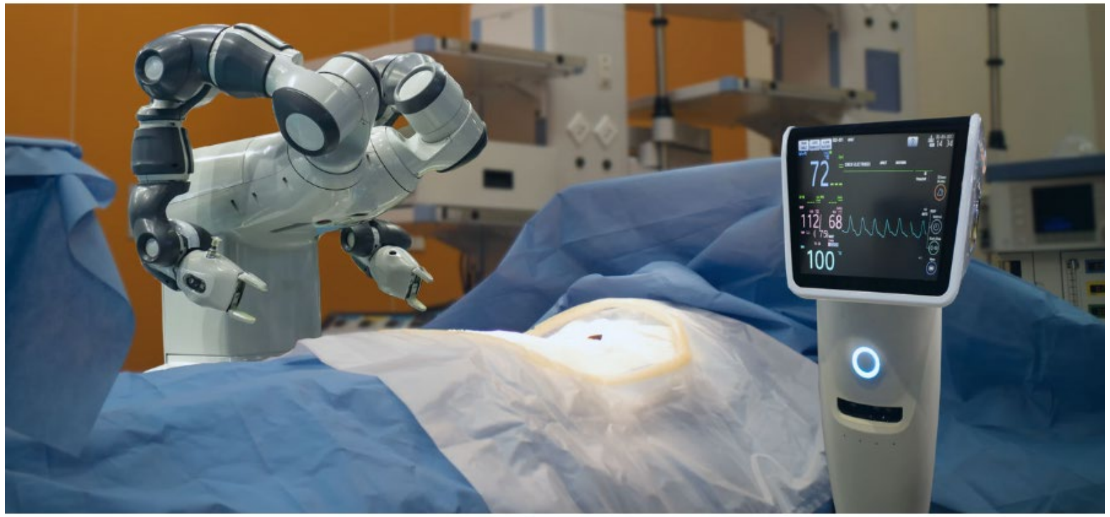
- Méně falešných alarmů
- Bezdrátové senzory
- Rozhodovací systémy

NEWS

Artificial Intelligence, Digital Health

06/08/2019

Germany: A survey shows widespread support for AI in medicine



65% of respondents support artificial intelligence use in medical diagnostics

Figure 8. Attitude of ICU staff towards novel digital technology. An asterisk indicates statistical significance.

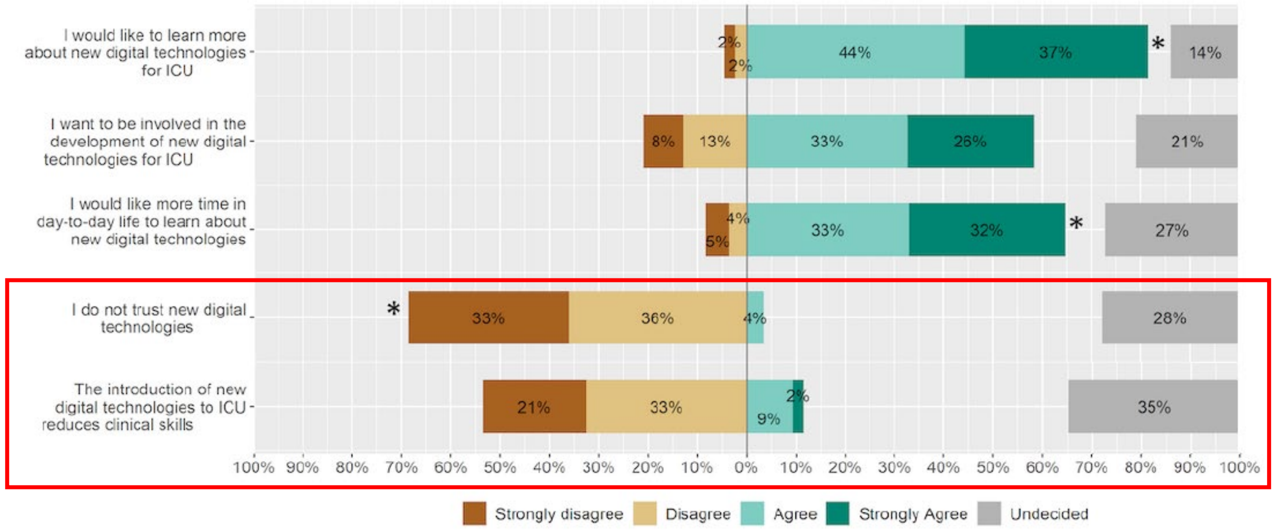
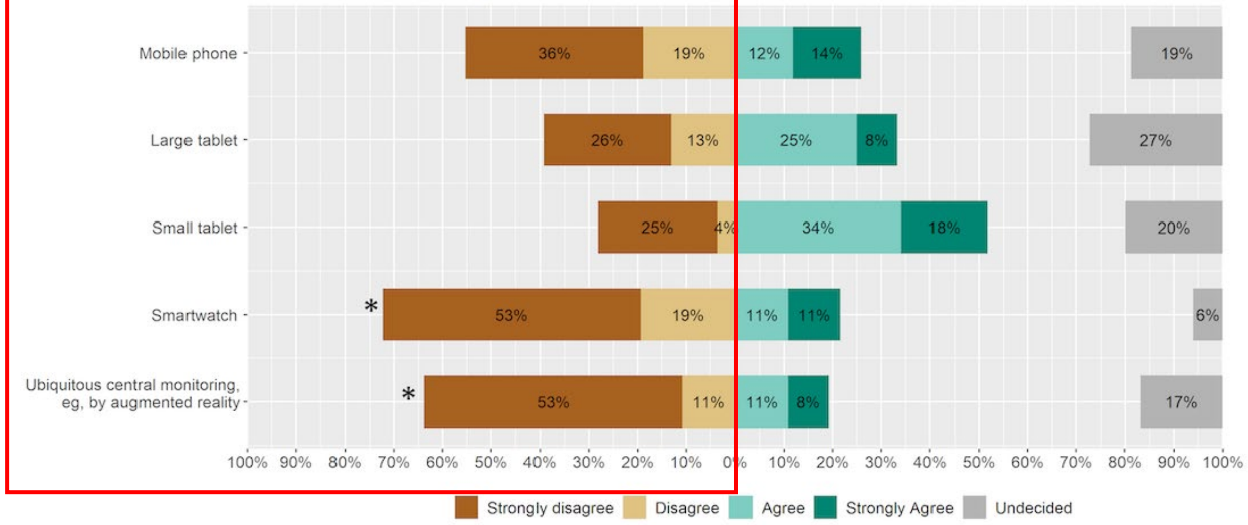
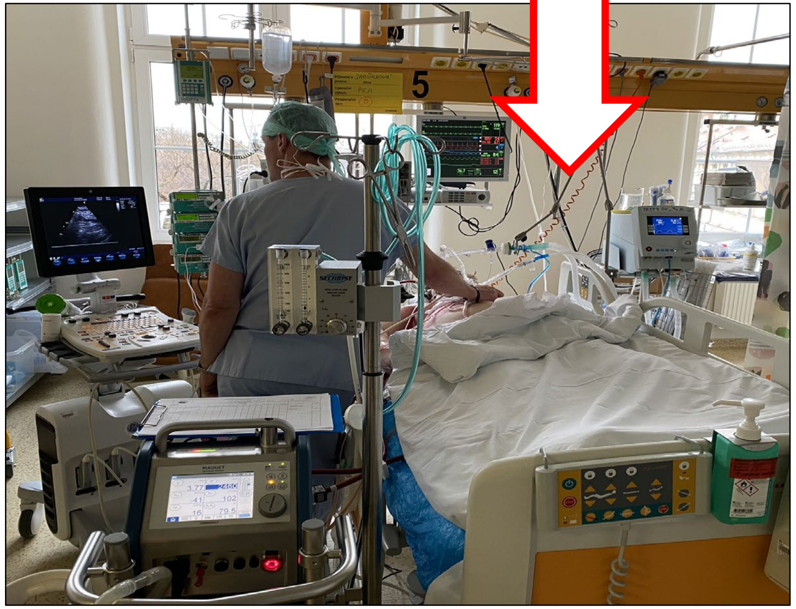
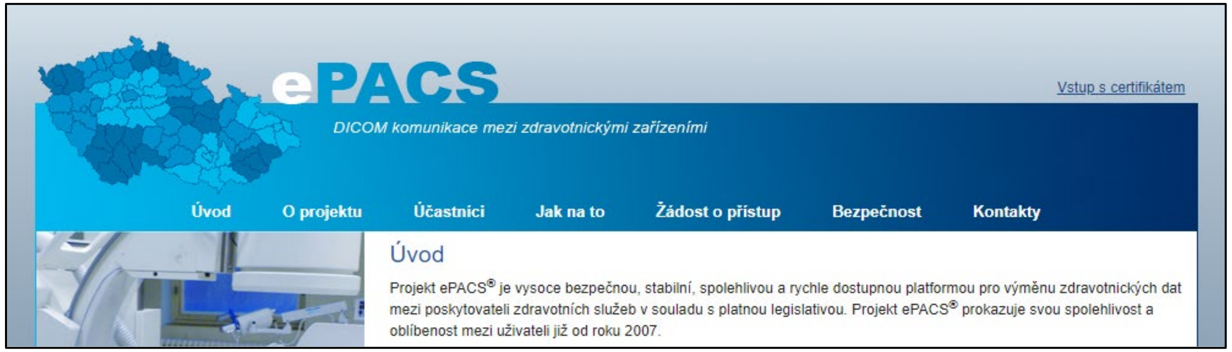


Figure 4. Suggestions for remote patient monitoring display devices in intensive care medicine for usage on hospital premises. An asterisk indicates statistical significance.







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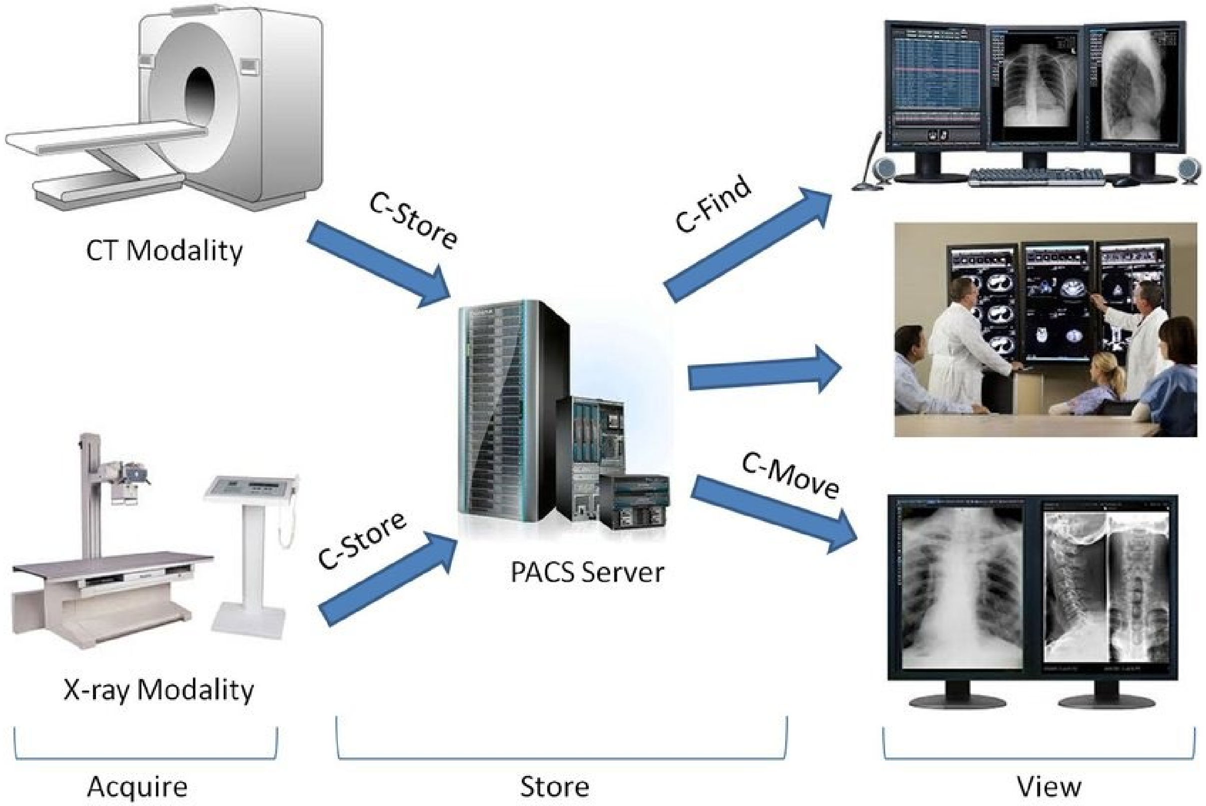
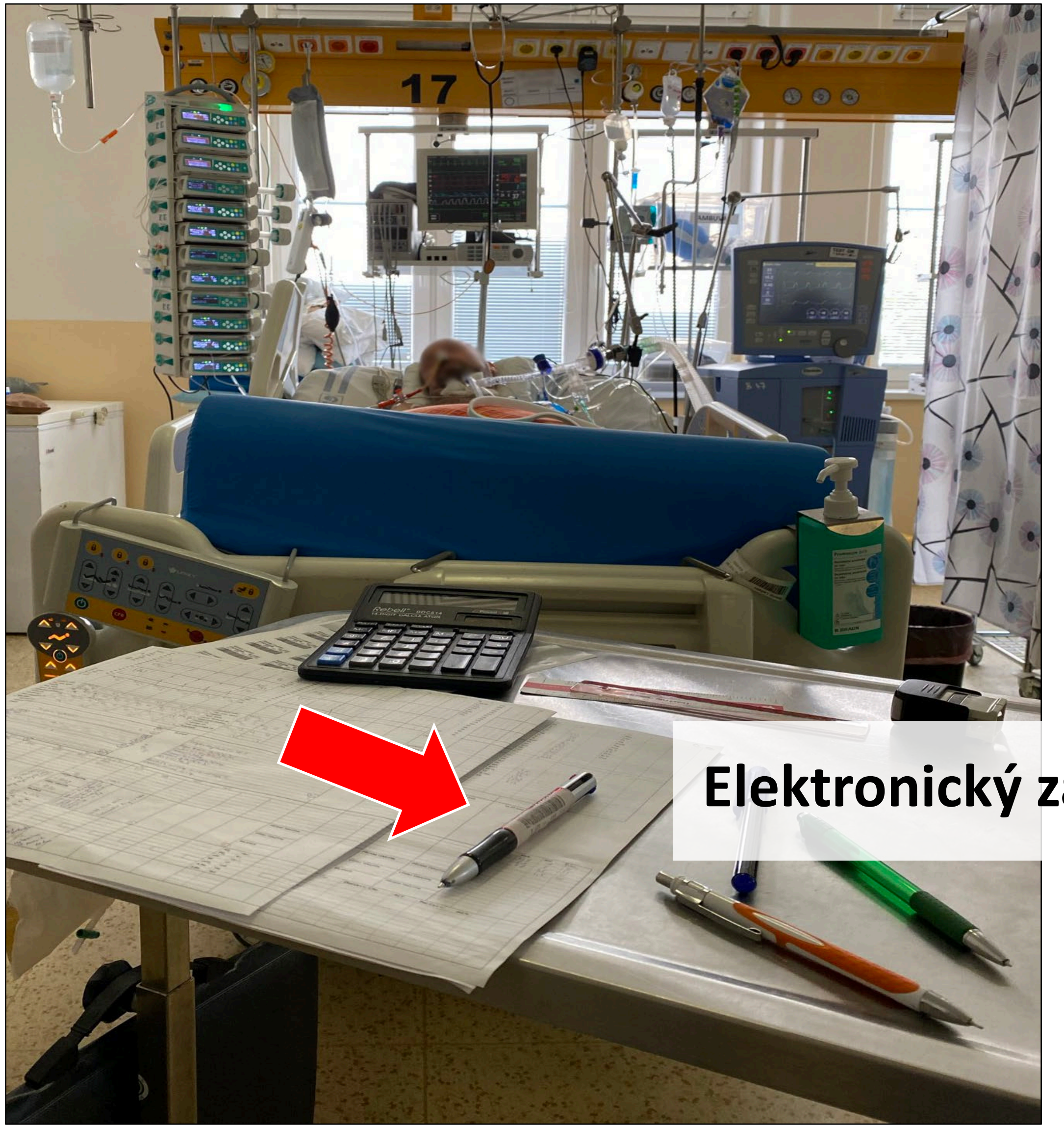
Projekt ePACS® je vysoce bezpečnou, stabilní, spolehlivou a rychle dostupnou platformou pro výměnu zdravotnických dat mezi poskytovateli zdravotních služeb v souladu s platnou legislativou. Projekt ePACS® prokazuje svou spolehlivost a oblíbenost mezi uživateli již od roku 2007.



CT Modality
C-Store
C-Find
PACS Server
C-Move
C-Store
X-ray Modality
Acquire
Store
View



Elektronický zápis do dokumentace…?

PERSPECTIVES in Health Information Management

Sajeesh Kumar, PhD; Shezana Merchant, MD; and Rebecca Reynolds, EdD, RHIA. "Tele-ICU: Efficacy and Cost-Effectiveness of Remotely Managing Critical Care." *Perspectives in Health Information Management* (Spring 2013): 1-13.

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Tele-ICU: Efficacy and Cost-Effectiveness of Remotely Managing Critical Care

Home > Tele-ICU: Efficacy and Cost-Effectivene...

2013 Spring

by Sajeesh Kumar, PhD; Shezana Merchant, MD; and Rebecca Reynolds, EdD, RHIA

Abstract

Tele-ICU is the use of an off-site command center in wh... ...ed critical care nurses) is connected with patients in di... audio, visual, and electronic means. T... the efficacy and cost-effectivene... adoption. While the available... actual costs were not repor... reporting, and adjustment f... path, especially in the Unite...

Keywords: cost-effectiveness, cri...

V USA existuje 6 000 ICU, ale na nich pracuje pouze 5 500 kvalifikovaných intenzivistů

Introduction

There is a shortage of intensivists in the United State... ...e demand for them is only going to increase with the aging population.[1] As of 2010, less than 15 p... ...cent of intensive care units (ICUs) are able to provide intensivist care.[2] There are 6,000 ICUs but only 5,500 board-certified intensivists.[3] Studies have shown that hospitals with a dedicated intensivist on staff had a significant reduction in ICU mortality and average length of stay (LOS).[4, 5] The complexity of today's ICU services entails the need for sharing health information through off-site ICU centers.[6] Tele-ICU is the use of health information exchanged from a hospital critical care unit to another site via electronic communications.[7] Tele-ICU intensivists provide real-time services to multiple care centers regardless of their locations. Tele-ICU uses an off-site command center in which a critical care team (intensivists and critical care nurses) is connected with patients in distant ICUs through real-time audio, visual, and electronic means. Similar to a bedside team, offsite tele-ICU intensivists require full access to patient data. Tele-ICU is capable of providing real-time monitoring of patient instability or any abnormality in laboratory results, ordering diagnostic tests, making diagnoses and ordering treatment, and implementing interventions through the control of life-support devices. As a result, tele-ICU holds great promise in improving the quality of critical care given to patients and increasing the productivity of intensivists. This article explores the available studies related to efficacy and cost-effectiveness of tele-ICU applications and outlines possible barriers to broader adoption.

Current Issue

Why Telemedicine, *Why Now?*

v odlehlých oblastech zlepšuje přístup ke kvalitní péči

Provide access to quality care

Rural patients can rece... medical experti... in their comm... and screenin... care and maint...

zvyšuje kapacitu nemocnic bez vysokých nákladů

Manage capac...

Virtual services can reduce unnecessary hospital and emergency room visits, while opening up capacity for patients who do need inpatient care. Hospitals can extend services beyond their walls through remote ICU and specialist consultations, rather than paying doctors to be on call without clinical need. Provider groups can also load balance patient coverage across several offices to decrease wait times.

Meet patient demand.

74% of Millennials prefer telemedicine visits to in-person ...ents.[10] Instead of driving 40 minutes to a hospital ...minutes for a 10-minute exam, these ...mand the immediacy and convenience ...heir healthcare experience.

telemedicínu preferuje 74% mileniálů

...ps for aging populations.

...Japan, more than one in four people are at least 65 years old. The United States will ha... ...people 65 and older by 2... half a million ce... patients often... difficult to atte... the most seamle... and consistent senior c...

zvýší dostupnost péče rostoucímu počtu starých lidí

Offer a 360-degree view into patient care.

By inserting telemedicine at the right touchpoints across the continuum of care, providers can improve care coordin... interventio... patients... gain deep... of health and a... challenges, family environment and personal behaviors.

zlepší koordinaci péče

SEPTEMBER 10, 2019
EBOOK
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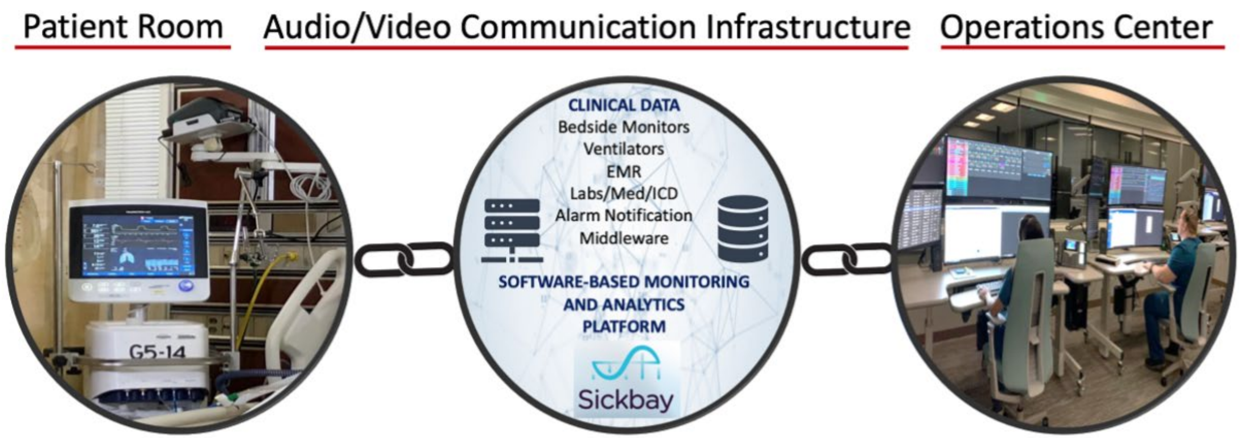

Figure 2. The three main components of the virtual intensive care unit system. AV: audiovisual; EMR: electronic medical record; ICD: Implantable Cardioverter-Defibrilators.

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Analytic Review

Journal of Intensive Care Medicine 1-6
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When Will Telemedicine Appear in the ICU?

Mark V. Avdalovic, MD, FCCP[1,2] and James P. Marcin, MD, MPH[3,4]

Abstract

As our population ages and the demand for high-level intensive care unit (ICU) services increase, the ICU physician supply continues to lag. In addition, hospitals, physician groups, and patients are demanding rapid access for the highest level of expertise in the care of critically ill patients. Telemedicine in the ICU combined with remote patient monitoring has been increasingly touted as a model of care to increase efficiencies and quality of care. Telemedicine in the ICU provides the potential to connect critically ill patients to sophisticated specialty care on a 24/7 basis, even for those hospitalized in rural locations where access to timely specialty consultations are uncommon. Research on the use of telemedicine in the ICU has suggested improved outcomes, such as reductions in mortality, reductions in length of stay, and greater adherence to evidence-based guidelines. Although the clinical footprint of telemedicine in ICU has grown over the past 20 years, there has been a relative slowing of implementation. This review examines the clinical evidence supporting the use of telemedicine in the ICU and discusses the impact on clinical efficacy and costs of care. Additionally, we review the current hurdles to more rapid adoption, including the significant financial investment, different models of care affecting the return on investment, and the varied cultural attitudes that impact the success and acceptance of care models using telemedicine in the ICU.

Keywords telemedicine, telehealth, tele-ICU

Over the past 10 years, critical care services provided by telemedicine have increased and currently represent approximately 13% of all ICU care.[5]

Tele-ICU představují dnes 13% všech amerických ICU pokles ICU i nemocniční mortality !

OPEN

Critical Care Explorations

Effects of Telemedicine ICU Intervention on Care Standardization and Patient Outcomes: An Observational Study

Christian D. Becker, MD, PhD[1–5]; Mario V. Fusaro, MD[1,3,5]; Zohair Al Aseri, MD[6]; Konstantin Millerman, MD, MBA[1,3]; Corey Scurlock, MD, MBA[1–5]

Objectives: Given the numerous recent changes in ICU practices and protocols, we sought to confirm whether favorable effects of telemedicine ICU interventions on ICU mortality and length of stay can be replicated by a more recent telemedicine ICU intervention.

Design, Setting and Patients: Observational before-after telemedicine ICU intervention study in seven adult ICUs in two hospitals. The study included 1,403 patients in the preintervention period (October 2014 to September 2015) and 14,874 patients in the postintervention period (January 2016 to December 2018).

Intervention: Telemedicine ICU implementation.

Measurements and Main Results: ICU and hospital mortality and length of stay, best practice adherence rates, and telemedicine ICU performance metrics. Unadjusted ICU and hospital mortality and lengths of stay were not statistically significantly different. Adjustment for Acute Physiology and Chronic Health Evaluation Version IVa score, ICU type, and ICU admission time via logistic regression yielded significantly lower ICU and hospital mortality odds ratios of 0.58 (95% CI, 0.45–0.74) and 0.66 (95% CI, 0.54–0.80), respectively. When adjusting for acuity by comparing observed-over-expected length of stay ratios through Acute Physiology and Chronic Health Evaluation IVa methodology, we found significantly lower ICU and hospital length of stay in the postintervention group. ICU mortality improvements were driven by nighttime ICU admissions (odds ratio 0.45 [95% CI, 0.33–0.61]) as compared to daytime ICU admissions (odds ratio 0.81 [95% CI, 0.55–1.20]), whereas hospital mortality improvements were seen in both subgroups but more prominently in nighttime ICU admissions (odds ratio 0.57 [95% CI, 0.44–0.74]) as compared to daytime ICU admissions (odds ratio 0.73 [95% CI, 0.55–0.97]), suggesting that telemedicine ICU intervention can effectively supplement low intensity bedside staffing hours (nighttime).

Conclusions: In this pre-post observational study, telemedicine ICU intervention was associated with improvements in care standardization and decreases in ICU and hospital mortality and length of stay. The mortality benefits were mediated in part through telemedicine ICU supplementation of low intensity bedside staffing hours.

Key Words: bed utilization; capacity; care standardization; electronic intensive care unit; telemedicine; telemedicine intensive care unit

TABLE 2. Mortality and Length of Stay Outcomes Before and After Intervention of Telemedicine ICU Service

Outcomes	Preintervention Group	Postintervention Group	Unadjusted *p*	OR (95% CI)	Adjusted *p*
ICU mortality rate, *n* (%)	111 (7.9)	1,025 (6.9)	0.15	0.58 (0.45–0.74)	< 0.001
Hospital mortality rate, *n* (%)	174 (12.4)	1,666 (11.2)	0.17	0.66 (0.54–0.80)	< 0.001
Mean ICU length of stay, d (SD)	4.73 (6.09)	4.78 (6.09)	0.77		
Mean hospital length of stay, d (SD)	13.66 (20.87)	14.02 (13.65)	0.356		
Observed/expected ICU length of stay ratio (SD)	1.35 (1.09)	1.22 (2.21)			0.04
Observed/expected hospital length of stay (SD)	1.22 (2.03)	1.09 (0.99)			< 0.001

OR = odds ratio.

Nonacuity-adjusted ICU and hospital mortality rates were not statistically significantly different (χ^2), whereas odds ratios for ICU and hospital mortality were significantly lower in the postintervention group when adjusted for Acute Physiology, Age and Chronic Health Evaluation Version IVa (APACHE IVa) scores, ICU type, and ICU admission time (daytime vs nighttime). Unadjusted ICU and hospital length of stay (LOS) were not statistically significantly different (Mann-Whitney), but when LOS was corrected for acuity through (indirect standardization) observed over expected ratios calculated by APACHE IVa, a significant reduction in ICU and hospital LOS in the postintervention period was observed.

TABLE 3. Unadjusted and Acuity-Adjusted ICU and Hospital Mortality Rates Pre- Versus Post Telemedicine ICU Intervention for the Subgroups of Daytime Versus Nighttime ICU Admissions

Outcome	Subgroup	Preintervention Group, *n* (%)	Postintervention Group, *n* (%)	Unadjusted p (χ^2)	OR (95% CI)	Adjusted *p*
ICU mortality	Daytime ICU admissions	39/762 (5.1)	458/7,052 (6.5)	0.139	0.81 (0.55–1.20)	0.292
	Nighttime ICU admissions	72/819 (8.8)	567/7,532 (7.5)	0.196	0.45 (0.33–0.61)	< 0.001
Hospital mortality	Daytime ICU admissions	72/762 (9.4)	741/7,052 (10.5)	0.363	0.73 (0.55–0.97)	0.033
	Nighttime ICU admissions	102/819 (12.5)	925/7,532 (12.3)	0.886	0.57 (0.44–0.74)	< 0.001

OR = odds ratio.

Memorial Hermann Health System. Preliminary data from this multi-hospital health system at the University of Texas in Houston, which has a Tele-ICU system monitoring 4 open ICUs with about 140 beds, indicate reductions in mortality in 5 of their ICUs that have been operating since October 2004 (see Figure 7-2).

Figure 7-2

Mortality Rates in Memorial Hermann Health System[38]

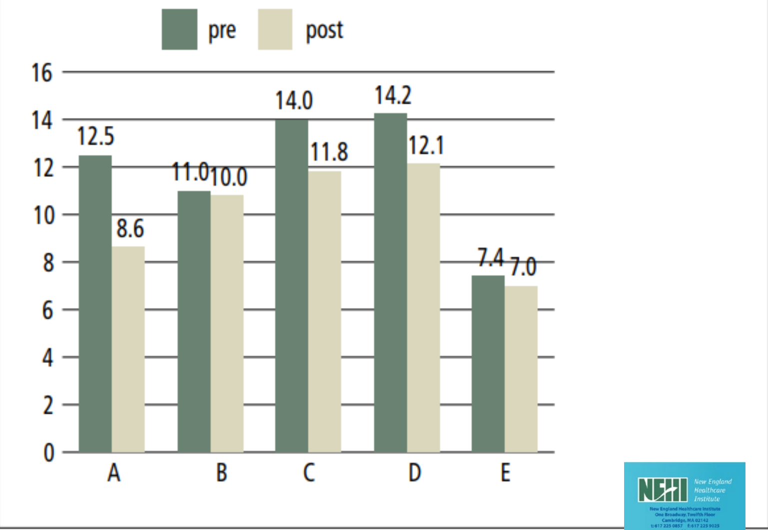


Figure 7-3

ICU LOS Rates in Memorial Hermann Health System[43]

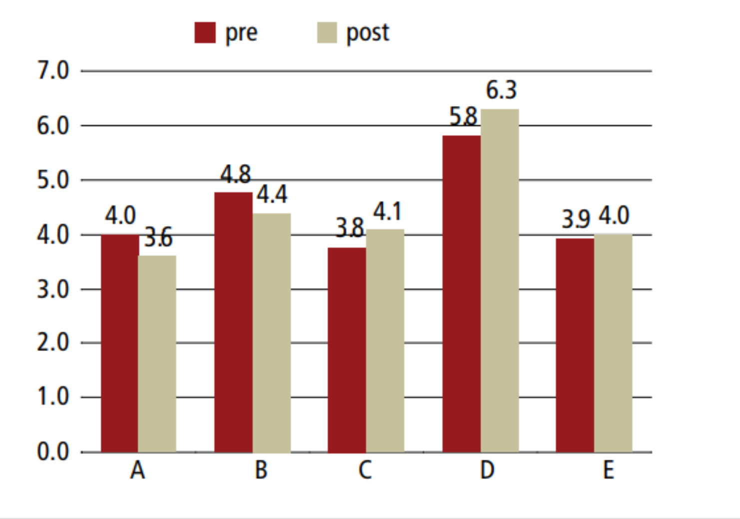
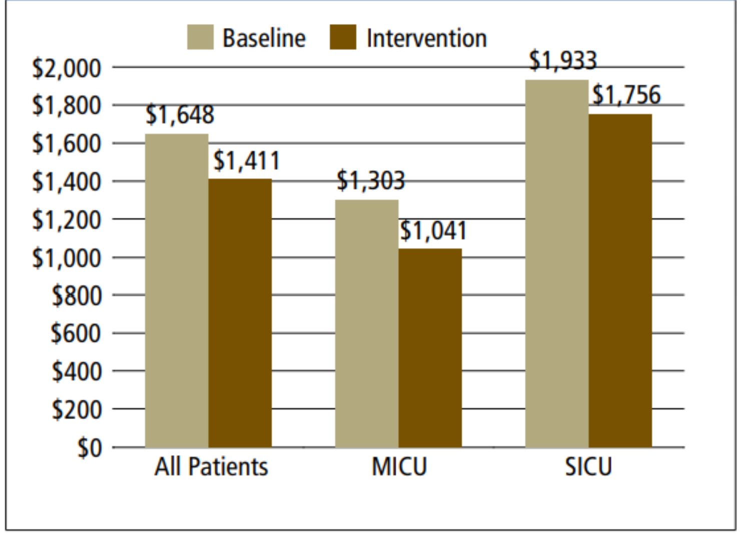


Figure 7-4

Change in Costs per Case[45]



CHEST Topics in Practice Management

Clinical and Financial Considerations for Implementing an ICU Telemedicine Program

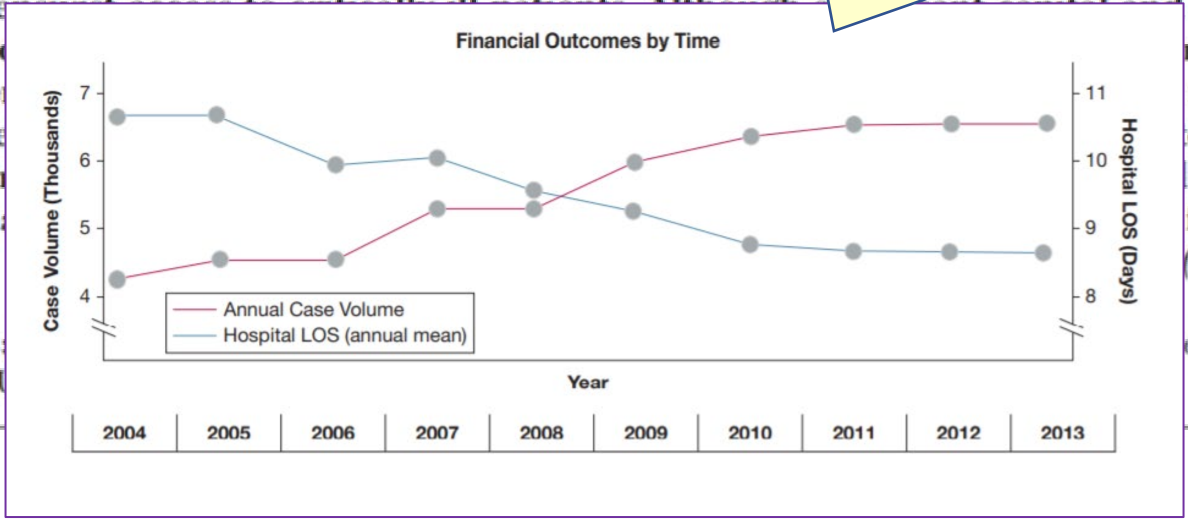
Robert J. Kruklitis, MD, PhD, FCCP; Joseph A. Tracy, MS; and Matthew M. McCambridge, MD

zlepšená dostupnost intenzivisty pro kritický nemocné pacienty

sice vyšší náklady,
ale vrátí se to v nepřímých ziscích (např. LOS)

…on in the United States increases and ag… …uality, safe, …ctive care to the most critically ill patien… …the pro… …d shortage of intensivists, innovative changes to i… …ductivity …ill be necessary. Telemedicine programs in the ICUs … …l strategy to improve inte… …maintenance costs are ass… …nefits, such as decreased le… …must be carefully designe… …ele-ICUs. We review the fi… …development and mainten… …for tele-ICUs. …*(6):1392–1396*

Abbreviations: … …elemedicine program in the ICU…



Critical Care

Enhanced Critical Care Program

What is Enhanced Critical Care?

Enhanced Critical Care is an electronic intensive care unit designed to improve care and shorten hospital stays. In addition to being cared for by local providers and nurses, patients benefit from telemedicine technology so that they can be monitored remotely by highly experienced intensivists, advanced care providers and critical care nurses who specialize in caring for patients with complex medical and surgical problems.

How it works

In-room computers, high-quality video cameras and audio monitors transmit vital signs, test results and imaging exams from the patients' bedsides to an operations center located in Rochester, Minnesota. There, a team of providers and nurses continuously watches for small trends that could mean potential problems for patients. When a change is detected, the team alerts local staff so they can address the situation. High-definition monitors and video cameras allow the Mayo Clinic Enhanced Critical Care staff to communicate with local staff, patients and their families.

Patients may experience one or more of the following program benefits:

- Shorter hospital stays
- Improved patient results
- Fewer transfers to other facilities
- High level of care close to home
- Improved patient and family satisfaction
- Reduced cost of care

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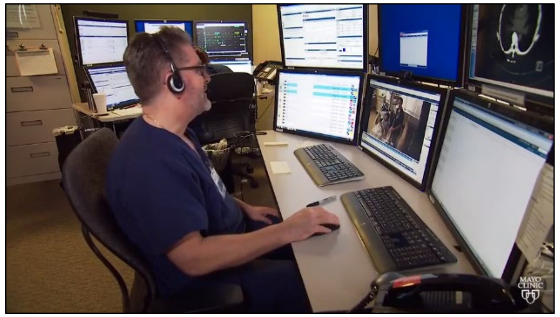

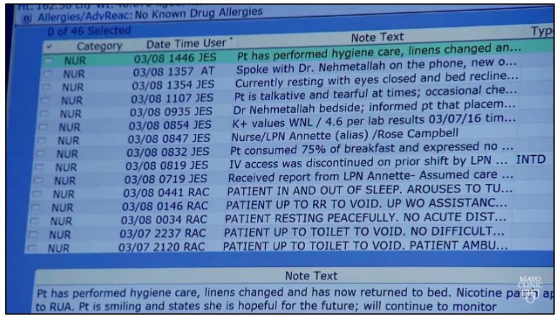

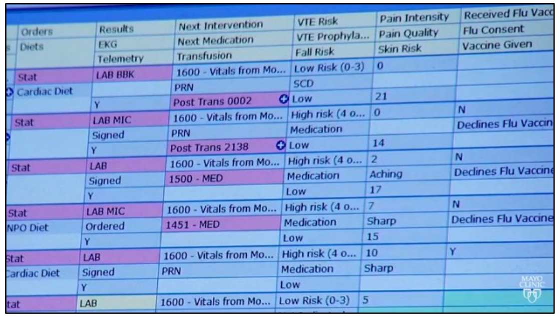

International Journal of Medical Informatics 105 (2017) 49–58

Technology meets tradition: The perceived impact of the introduction of information and communication technology on ward rounds in the intensive care unit

Jennifer J. Plumb[a,*], Isla Hains[a], Michael J. Parr[b], David Milliss[c], Robert Herkes[c] Johanna I. Westbrook[a]

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[c] Sydney Local Health District, Sydney, Australia

ABSTRACT

Background: Public policy in many health systems is currently dominated by the quest to find ways to 'do more with less'—to achieve better outcomes at a reduced cost. The success or failure of initiatives in support of this quest are often understood in terms of an adversarial dynamic or struggle between the professional logics of medicine and of management. Here, we use the case of the introduction of information and communication technology (ICT) to a well-established ritual of medical autonomy (the medical ward round) to articulate a more nuanced explanation of how and why new ways of working with technology are accepted and adopted (or not).
Methods: The study was conducted across four intensive care units (ICUs) in major teaching hospitals in Sydney, Australia. Using interviews, we examined 48 doctors' perceptions of the impact of ICT on ward round practice. We applied the concept of institutional logics to frame our analysis. Interview transcripts were analysed using a hybrid of deductive and inductive thematic analysis.
Results: The doctors displayed a complex engagement with the technology that belies simplistic characterisations of medical rejection of managerial encroachment. In fact, they selectively welcomed into the ward round aspects of the technology which reinforced the doctor's place in the healthcare hierarchy and which augmented their role as scientists. At the same time, they guarded against allowing managerial logic embedded in ICT to de-emphasise their embodied subjectivity in relation to the patient as a person rather than as a collection of parameters.
Conclusion: ICT can force the disruption of some aspects of existing routines, even where these are long-established rituals. Resistance arose when the new technology did not fit with the 'logic of care'. Incorporation of the logic of care into the design and customisation of clinical information systems is a challenge and potentially counterproductive, because it could attempt to apply a technological fix to what is essentially a social problem. However, there are significant opportunities to ensure that new technologies do not obstruct doctors' roles as carers nor disrupt the embodied relationship they need to have with patients.

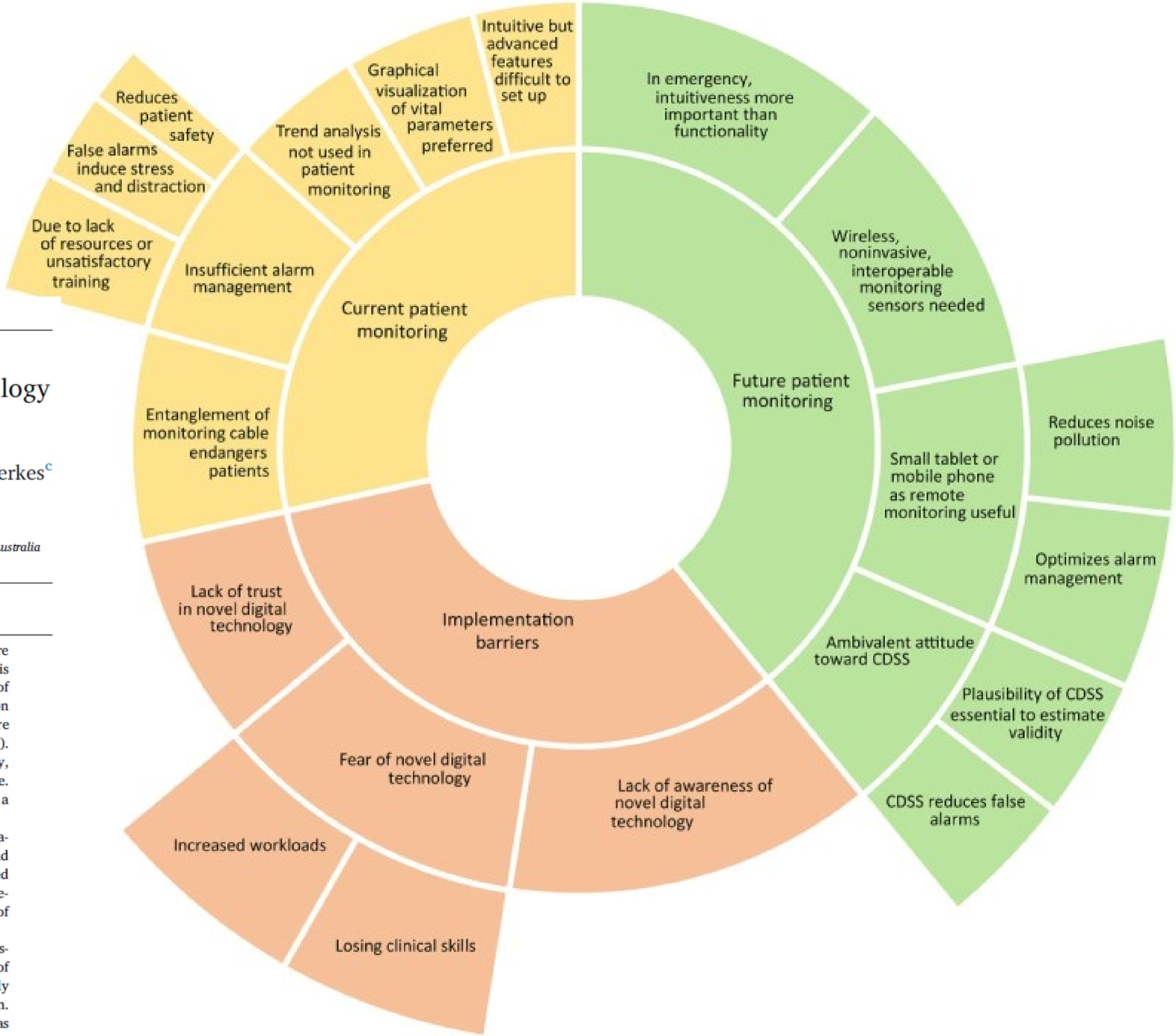

Figure 2. Within three categories (inner ring), 12 themes (middle ring) were identified and specified (outer ring) to reflect the requirements of a novel patient monitoring technology from the view of intensive care staff. CDSS: clinical decision support system.