Umetna inteligenca in diagnostični algoritmi pri sumu na sepso

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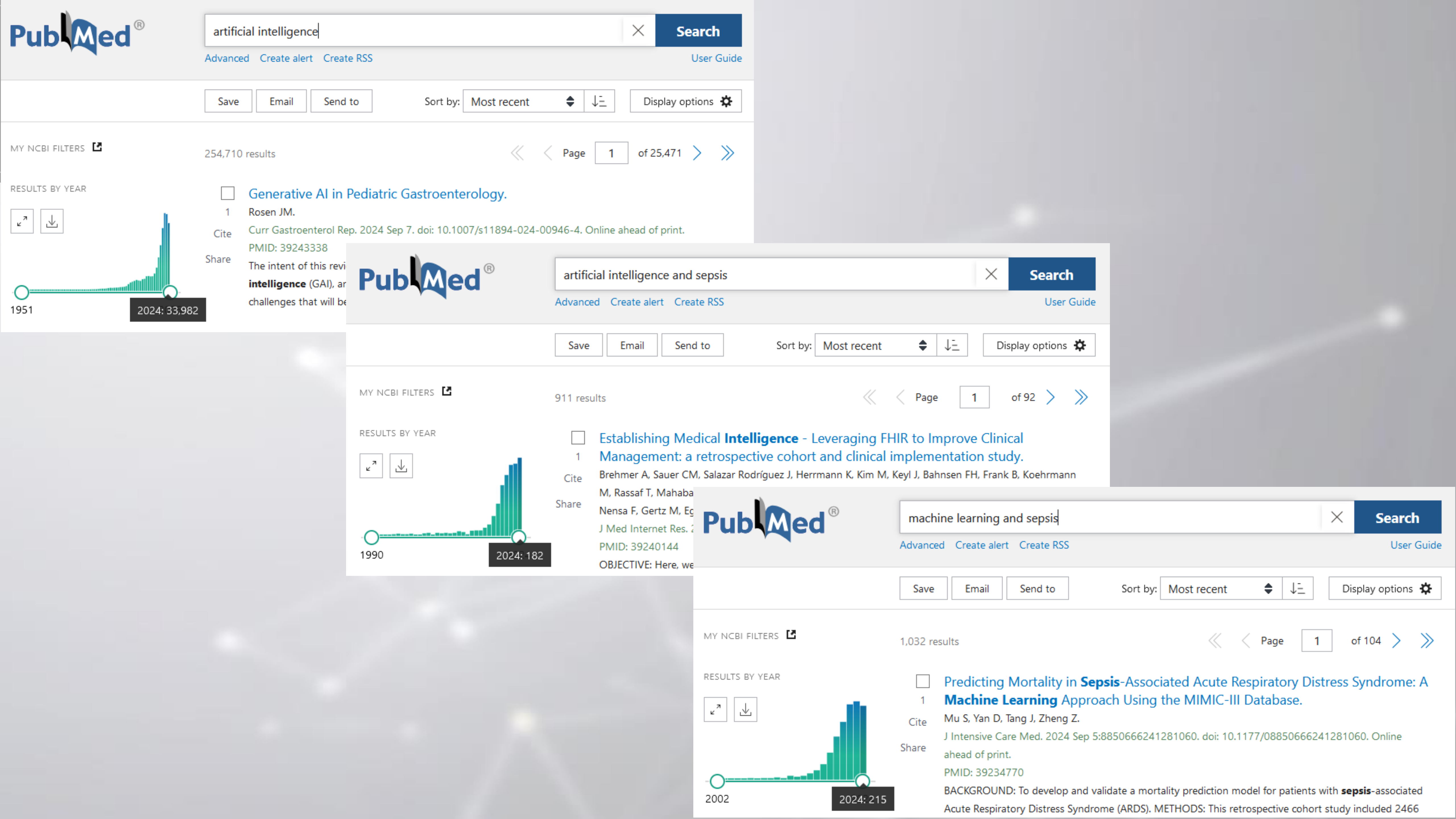
Klinika za infekcijske bolezni in vročinska stanja
UKC Ljubljana
Strokovno srečanje ob svetovnem dnevu sepse
12. september, 2024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RESULTS BY YEAR
Generative AI in Pediatric Gastroenterology.
1
Rosen JM.
Cite
Curr Gastroenterol Rep. 2024 Sep 7. doi: 10.1007/s11894-024-00946-4. Online ahead of print.
PMID: 39243338
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RESULTS BY YEAR
Establishing Medical Intelligence - Leveraging FHIR to Improve Clinical Management: a retrospective cohort and clinical implementation study.
1
Brehmer A, Sauer CM, Salazar Rodríguez J, Herrmann K, Kim M, Keyl J, Bahnsen FH, Frank B, Koehrmann
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M, Rassaf T, Mahaba
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Nensa F, Gertz M, Eg
J Med Internet Res. 2
PMID: 39240144
OBJECTIVE: Here, we
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2024: 182
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machine learning and sepsis
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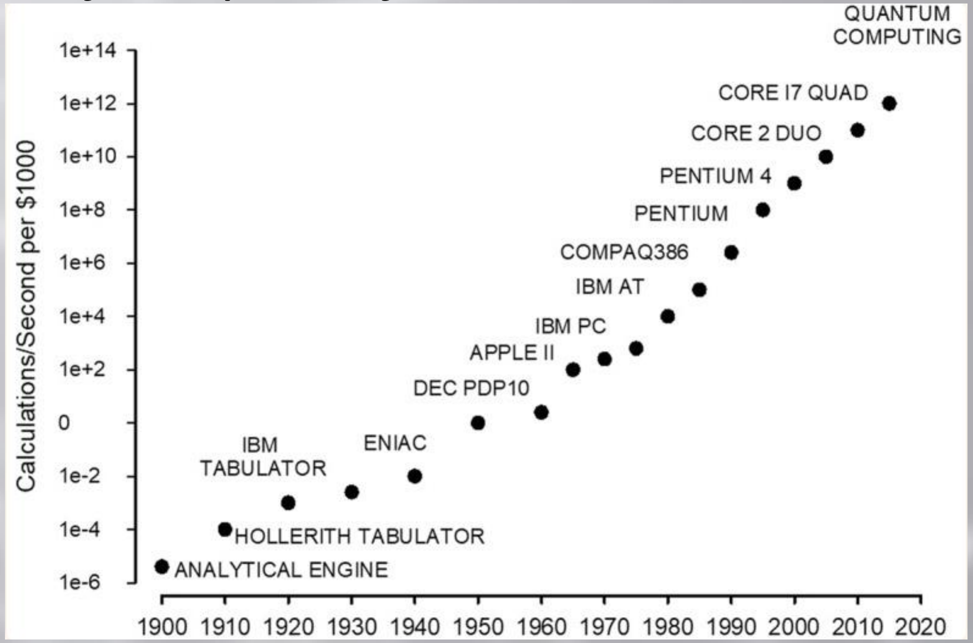
1,032 results
Page 1 of 104
RESULTS BY YEAR
Predicting Mortality in Sepsis-Associated Acute Respiratory Distress Syndrome: A Machine Learning Approach Using the MIMIC-III Database.
1
Mu S, Yan D, Tang J, Zheng Z.
Cite
J Intensive Care Med. 2024 Sep 5:8850666241281060. doi: 10.1177/08850666241281060. Online ahead of print.
Share
PMID: 39234770
BACKGROUND: To develop and validate a mortality prediction model for patients with sepsis-associated Acute Respiratory Distress Syndrome (ARDS). METHODS: This retrospective cohort study included 2466
2002
2024: 215

Kaj je umetna inteligenca?

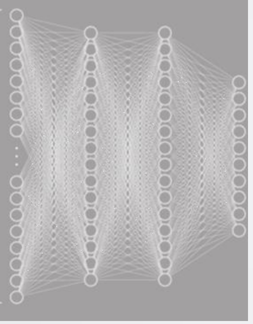
- inteligenca?
  - sposobnost razumevanja, načrtovanja, reševanja problemov, abstraktnega razmišljanja, učenja iz izkušenj (Mainstream Science on Intelligence, Wall Street journal, 1994)
  - ‚vrsta sposobnosti, ki posamezniku omogoča reševati probleme, ki so pomembni v danem kulturnem okolju' (dr. Howard Gardner)
- umetna inteligenca (UI)
  - veda, ki preučuje inteligentne agente, ki zaznavajo svoje okolje in izvajajo akcije, ki maksimizirajo možnost za doseganje njihovih ciljev
  - računalniški programi / modeli s sposobnostmi in zmožnostmi, ki jih smatramo za inteligentne
  - sistem, ki ima sposobnost intelektulnega procesiranja, ki je sicer značilen za ljudi – sposobnost razumevanja, ugotavljanja pomena, generaliziranja in učenja iz izkušenj (Encyclopedia Britannica)

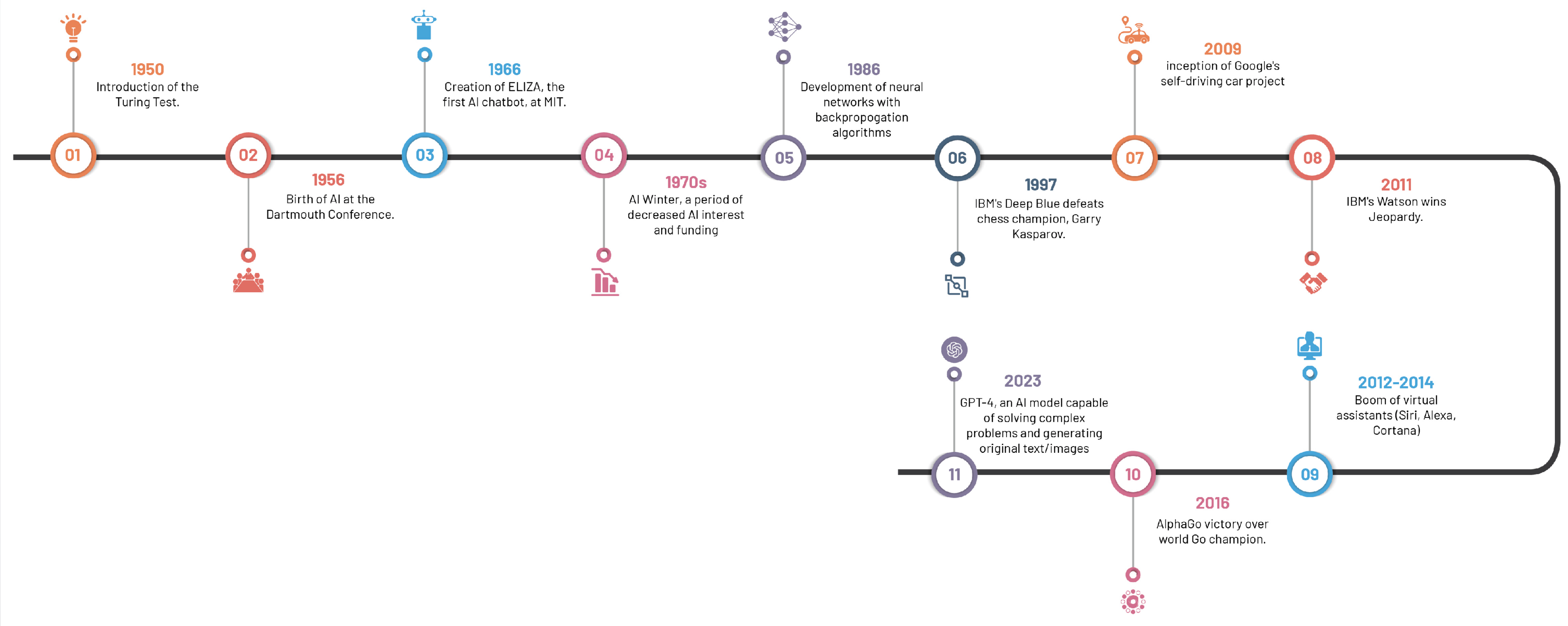
Zakaj računalniški sistemi?

- Človek ima sposobnost abstraktnega razmišljanja in domišljije
- Omejeno kapaciteto za delovni spomin – hkrati le ~ 4 kratkotrajne spomine
- Računalnik ima lahko obsežne kapacitete za delovni spomin, rešuje večdimenzionalne probleme, vidi nejasne rešitve
- Moorov zakon – št. tranzistorjev v integriranem vezju se podvoji na 2 leti
  - Od začetka 20. stoletja računska moč za 10^{18} večja

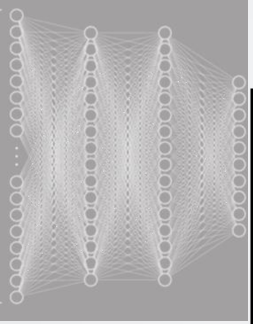


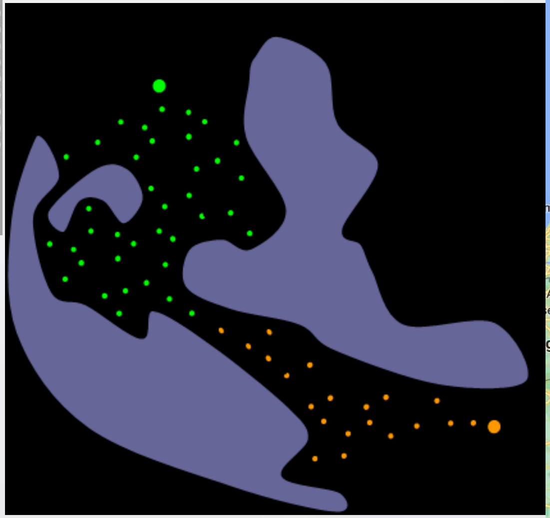
Gutierrez G. Crit Care. 2020
Gobet F, Clarkson G. Memory. 2004

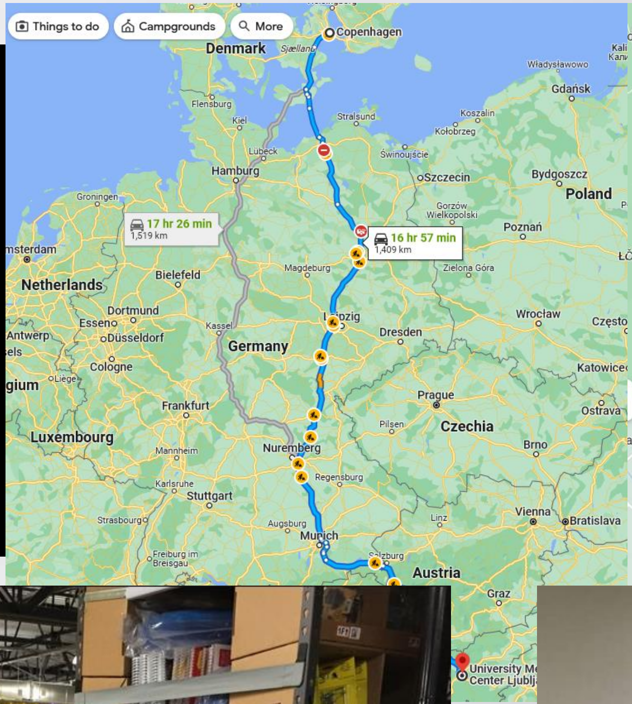




01
1950
Introduction of the Turing Test.
02
1956
Birth of AI at the Dartmouth Conference.
03
1966
Creation of ELIZA, the first AI chatbot, at MIT.
04
1970s
AI Winter, a period of decreased AI interest and funding
05
1986
Development of neural networks with backpropogation algorithms
06
1997
IBM's Deep Blue defeats chess champion, Garry Kasparov.
07
2009
inception of Google's self-driving car project
08
2011
IBM's Watson wins Jeopardy.
09
2012-2014
Boom of virtual assistants (Siri, Alexa, Cortana)
10
2016
AlphaGo victory over world Go champion.
11
2023
GPT-4, an AI model capable of solving complex problems and generating original text/images






Things to do
Campgrounds
More
Copenhagen
Denmark
Hamburg
Poland
Gdańsk
Bydgoszcz
Szczecin
Poznań
17 hr 26 min
1,519 km
16 hr 57 min
1,409 km
Netherlands
Bielefeld
Dortmund
Düsseldorf
Cologne
Germany
Leipzig
Dresden
Wrocław
Katowice
Frankfurt
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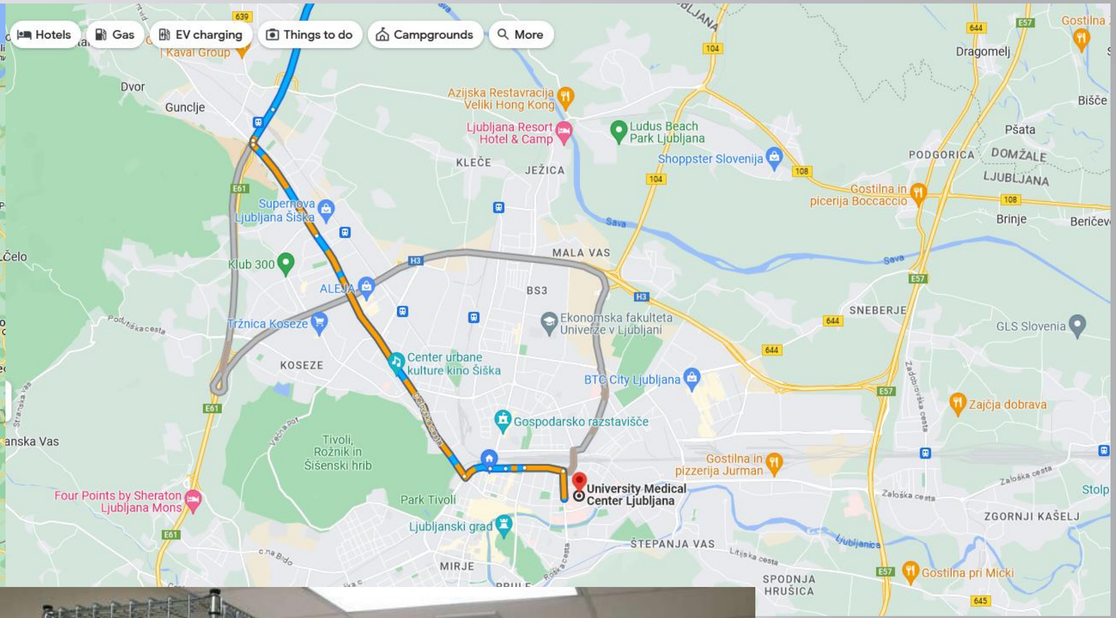
Graz
Brno
Ostrava


Hotels
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Things to do
Campgrounds
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Dragomelj
Dvor
Gunclje
Azijska Restavracija Veliki Hong Kong
Ljubljana Resort Hotel & Camp
Ludus Beach Park Ljubljana
Shoppster Slovenija
KLEČE
JEŽICA
PODGORICA
DOMŽALE
LJUBLJANA
Supernova Ljubljana Šiška
Klub 300
MALA VAS
BS3
ALEJA
Tržnica Koseze
Ekonomska fakulteta Univerze v Ljubljani
KOSEZE
Center urbane kulture kino Šiška
BTC City Ljubljana
SNEBERJE
GLS Slovenia
Zajčja dobrava
Gospodarsko razstavišče
Tivoli, Rožnik in Šišenski hrib
Gostilna in pizzerija Jurman
University Medical Center Ljubljana
Four Points by Sheraton Ljubljana Mons
Park Tivoli
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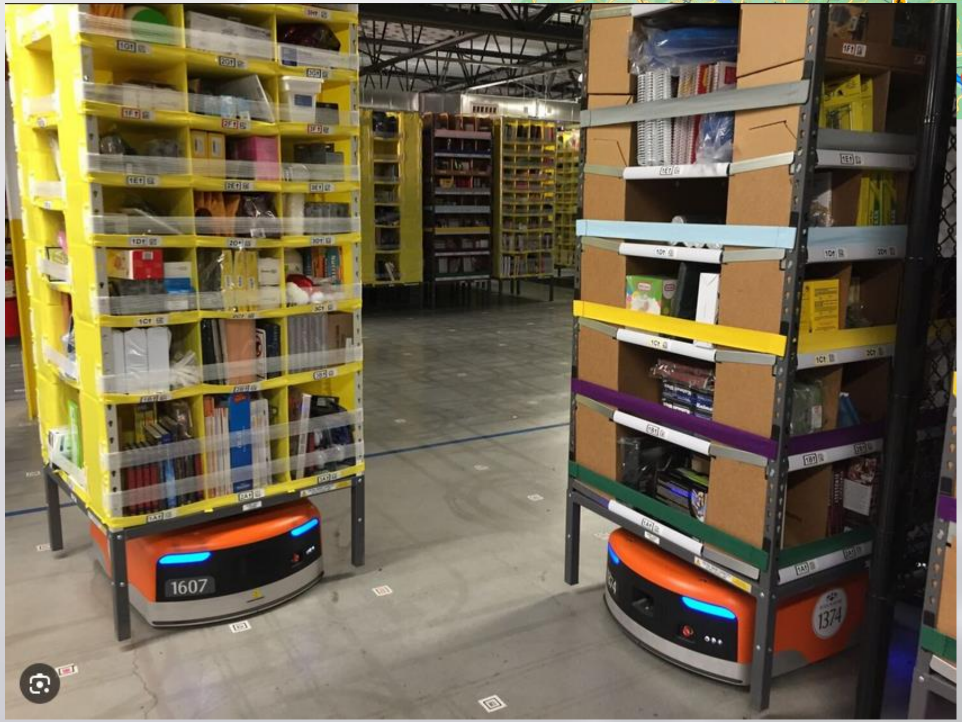
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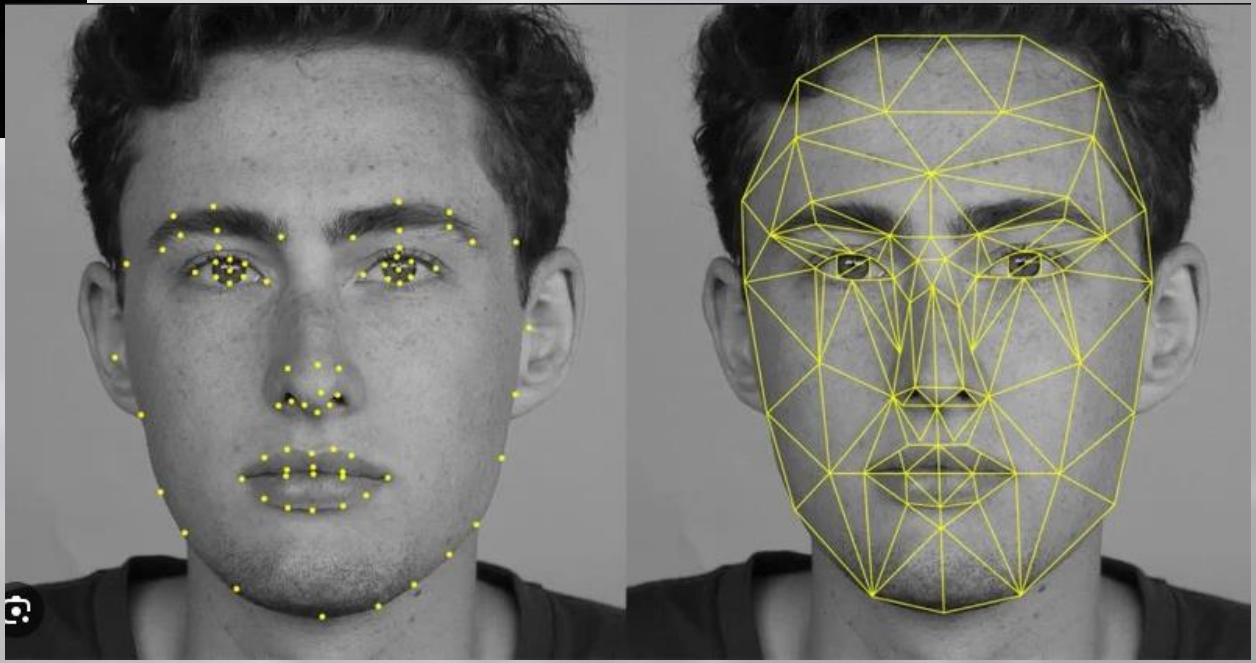


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Circle it

diagnose it

Umetna inteligenca v medicini

- Medicina: odkrivanje novih terapevtskih učinkovin, personalizirana diagnostika in zdravljenje, molekularna biologija, bioinformatika, slikovna diagnostika
- Digitalizacija in uporaba elektronskih zdravstvenih sistemov → velika količina podatkov
- Razvoj modelov UI (strojno učenje, nevronske mreže) za spremljanje in obdelavo podatkov
- Računalniški sistemi že dalj časa v uporabi za obravnavo kritično bolnih
  - Monitoriziranje, vodenje mehanske ventilacije, vodenje oksigenacije, obravnava ARDS
- Sistemi na osnovi zelo dovršenih logističnih izrazov IF/THEN/ELSE

ČE (if) neko določeno stanje drži, POTEM (then) program izvede navodilo 1, SICER (else) izvede navodilo 2

- Umetna inteligenca se namesto natančnih navodil ‚uči' in nadgrajuje preko izpostavitve številnim primerom

Gutierrez G. Crit Care. 2020

UI v medicini

- Radiologija
  - Presejanje, zgodnje odkrivanje in zdravljenje raka pljuč (CT)
  - Segmentacija možganskih tumorjev (MRI)
  - Ločevanje benignih in malignih tumorjev na mamografiji
  - Izboljšanje ločljivosti slik

- Mikrobiologija
- Epidemiologija
- Kirurgija
- Interna medicina

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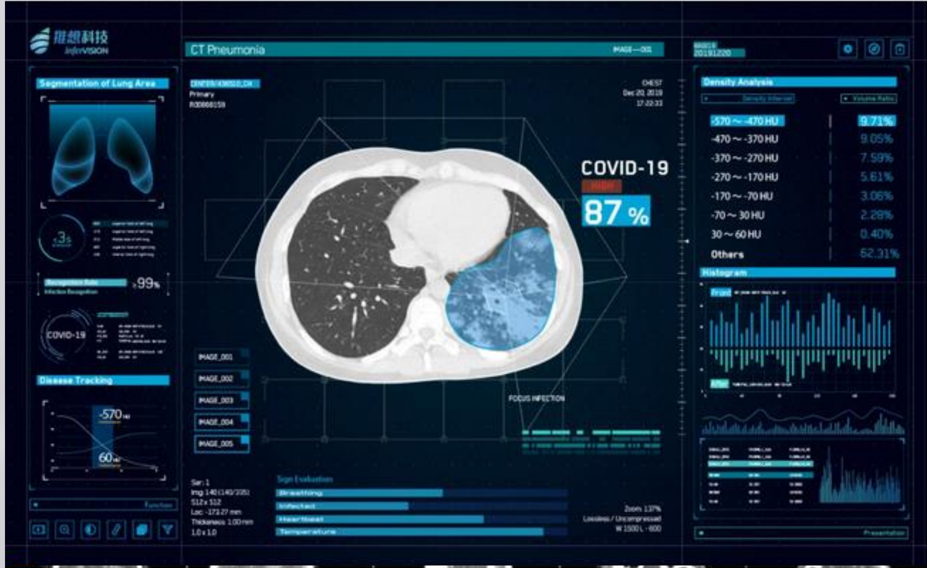
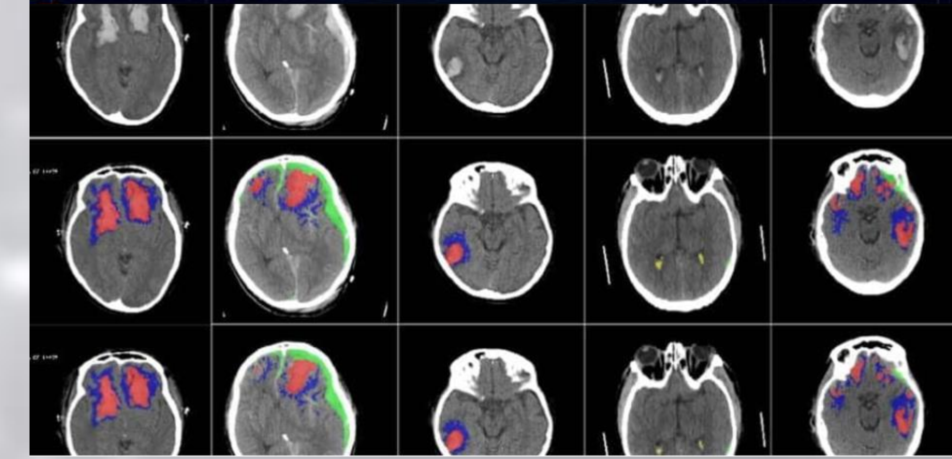




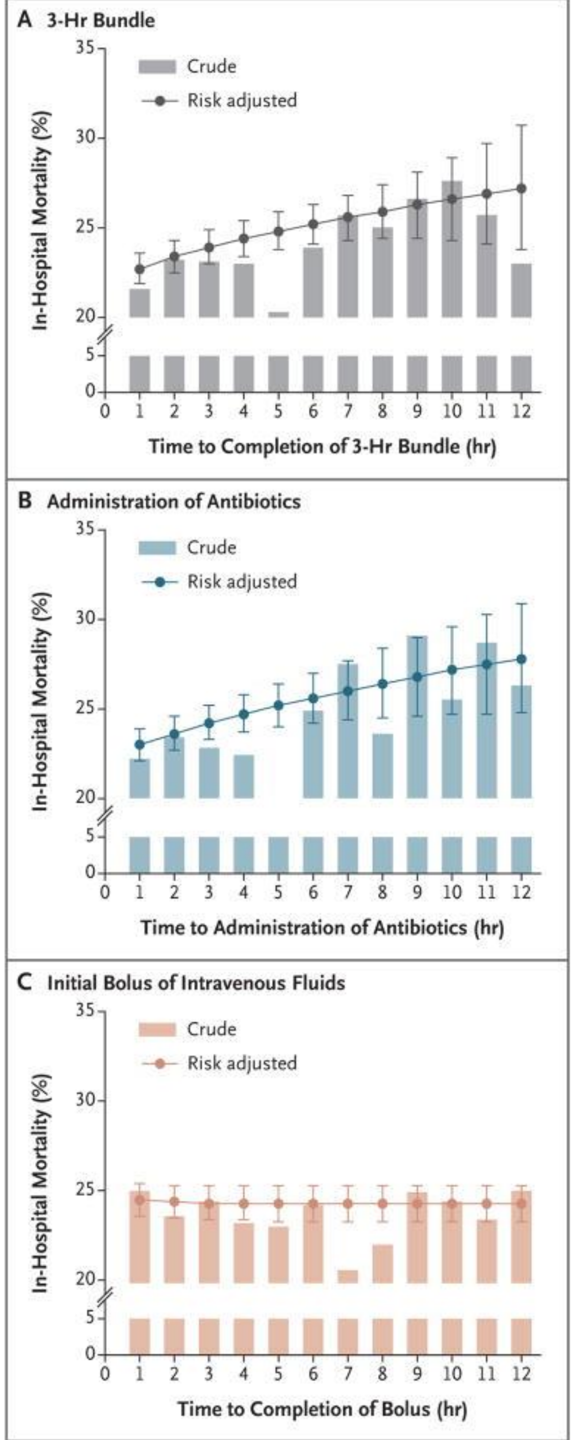
UI in zgodnja prepoznava sepse

Published in final edited form as:
N Engl J Med. 2017 June 08; 376(23): 2235–2244. doi:10.1056/NEJMoa1703058.

Time to Treatment and Mortality during Mandated Emergency Care for Sepsis

Christopher W. Seymour, M.D., **Foster Gesten, M.D.**, **Hallie C. Prescott, M.D.**, **Marcus E. Friedrich, M.D.**, **Theodore J. Iwashyna, M.D., Ph.D.**, **Gary S. Phillips, M.A.S.**, **Stanley Lemeshow, Ph.D.**, **Tiffany Osborn, M.D., M.P.H.**, **Kathleen M. Terry, Ph.D.**, and **Mitchell M. Levy, M.D.**

- 49331 bolnikov (2014 – 2016)
- Sveženj ukrepov v prvih 3 urah
- Višja umrljivost (OR 1.04/h, 95% CI 1.02-1.05)



UI in zgodnja prepoznava sepse

Surviving Sepsis Campaign: International Guidelines for Management of Sepsis and Septic Shock 2021

Recommendations 2021	Recommendation Strength and Quality of Evidence
1. For hospitals and health systems, we recommend using a performance improvement program for sepsis, including sepsis screening for acutely ill, high-risk patients and standard operating procedures for treatment.	**Strong** , *moderate-quality evidence (for screening)* **Strong** , *very low-quality evidence (for standard operating procedures)*

- Orodja/računala za presejanje različne občutljivosti
- SIRS, qSOFA, SOFA, NEWS, MEWS...
- Strojno učenje?

signs, signs of infection, quick Sequential Organ Failure Score (qSOFA) or Sequential Organ Failure Assessment (SOFA) criteria, National Early Warning Score (NEWS), or Modified Early Warning Score (MEWS) [26, 32]. Machine learning may improve performance of screening tools, and in a meta-analysis of 42,623 patients from seven studies for predicting hospital-acquired sepsis the pooled area under the receiving-operating curve (SAUROC) (0.89; 95% CI 0.86–0.92); sensitivity (81%; 95% CI 80–81), and specificity (72%; 95% CI 72–72) was higher

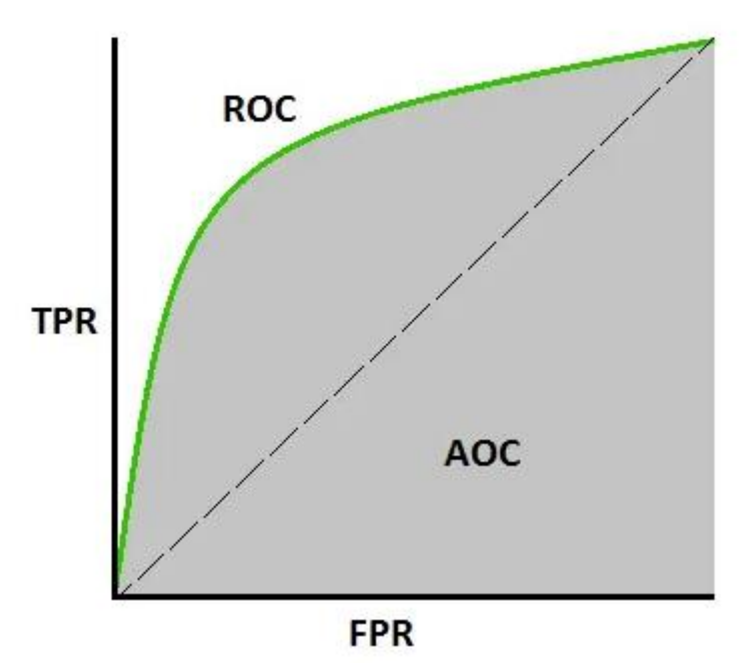
Meta-Analysis > Comput Methods Programs Biomed. 2019 Mar:170:1-9.
doi: 10.1016/j.cmpb.2018.12.027. Epub 2018 Dec 26.

Prediction of sepsis patients using machine learning approach: A meta-analysis

Md Mohaimenul Islam [1], Tahmina Nasrin [1], Bruno Andreas Walther [2], Chieh-Chen Wu [1], Hsuan-Chia Yang [3], Yu-Chuan Li [4]

- SAUROC 0.89 (sens 81%, spec 72%)
  - SIRS 0.7
  - MEWS 0.5
  - SOFA 0.78

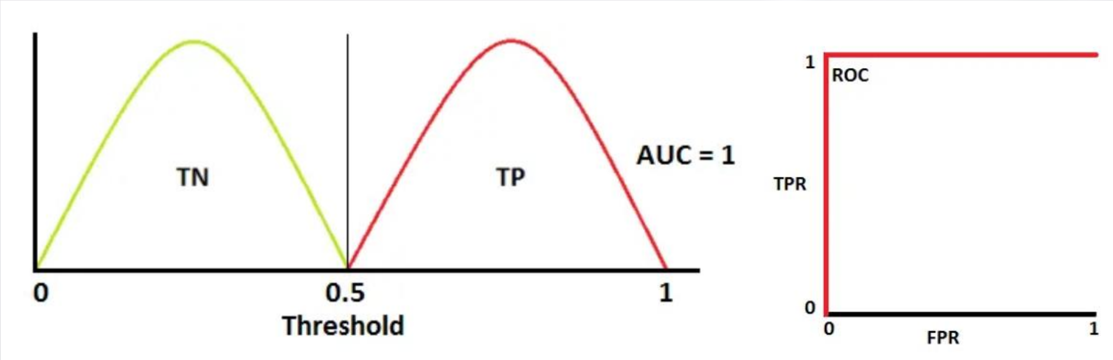
AUROC

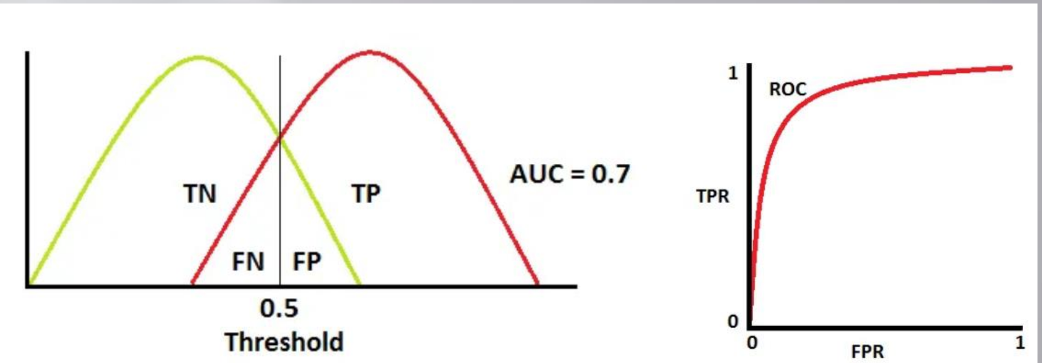


- površina pod krivuljo ‚receiver operating characteristic‘

  Area Under the Receiver Operating Characteristics – AUROC

- Najpomembnejša oblika ocene učinkovitosti klasifikacijskega modela
- ROC je verjetnostna krivulja, površina pod njo pa delež ločljivosti med skupinami



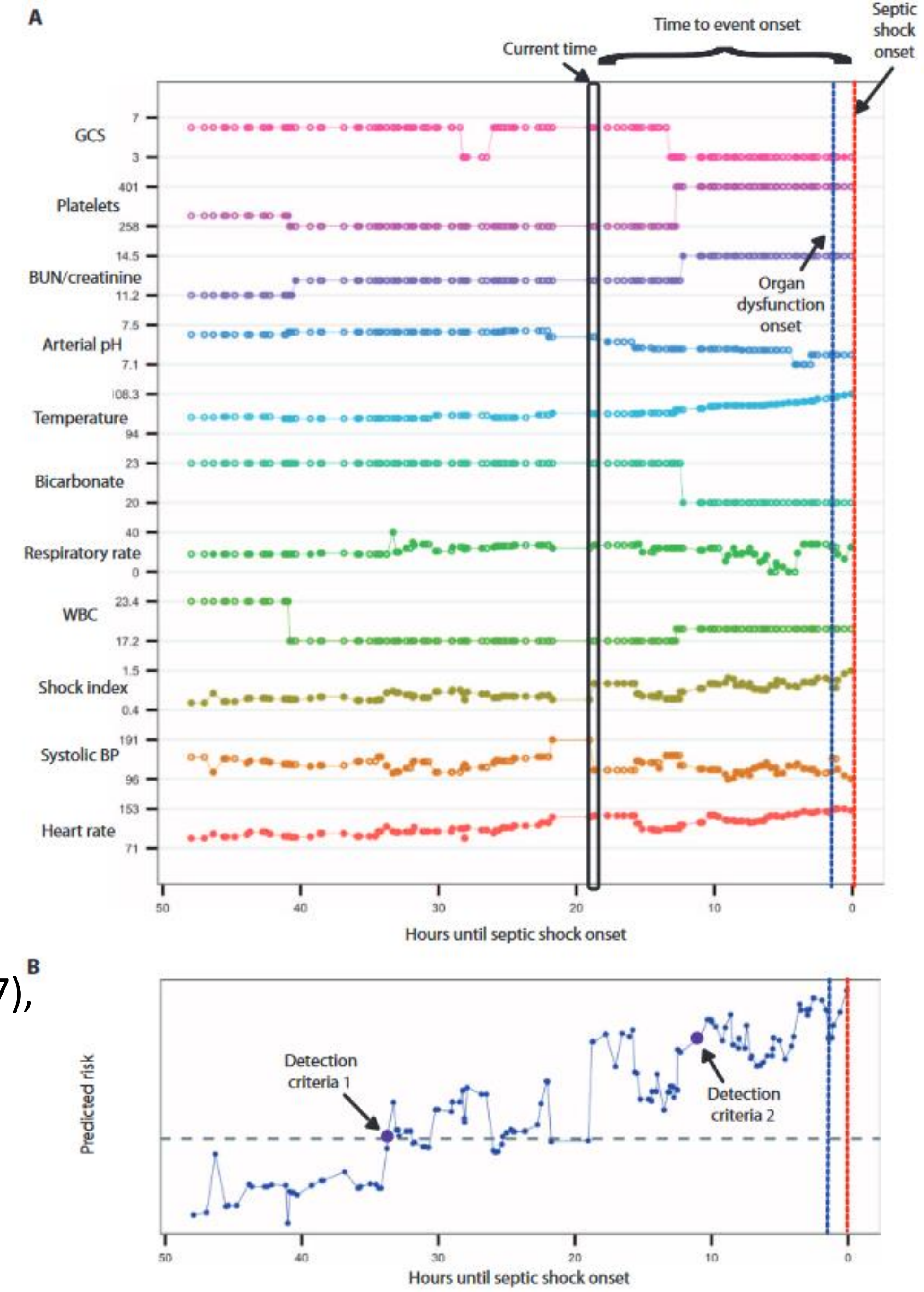


Modeli za zg... se
Targeted Real-ti... TREWS

- 13014 bolnikov za učenje (M
- 54 spremenljivk; rutinsko bel

- AUC 0.83 (95% CI 0.81-0.85),
- Zaznan razvoj sepse 28.2 ur (
- 67% zaznanih primerov pred

- Stara baza podatkov (2001-2007), stare definicije in protokoli obravnave
- Le podatki in bolniki na OIZ



re coefficients learned by TREWScore for a single imputation of the development

ıre name	Feature description	Weight

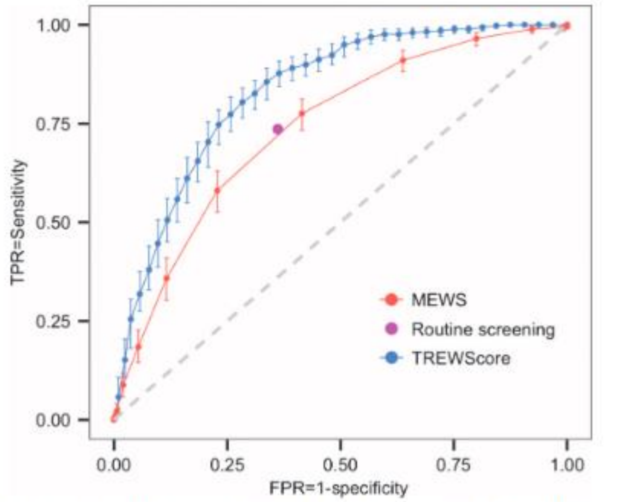
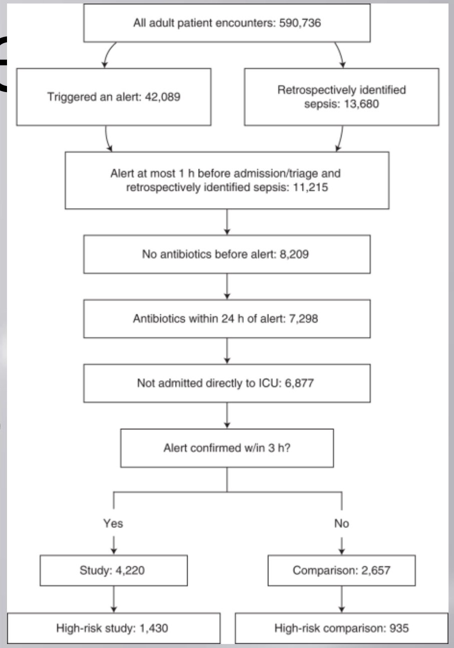


Fig. 2. ROC for detection of septic shock before onset in the validation set. The ROC curve for TREWScore is shown in blue, with the ROC curve for MEWS in red. The sensitivity and specificity performance of the routine screening criteria is indicated by the purple dot. Normal 95% CIs are shown for TREWScore and MEWS. TPR, true-positive rate; FPR, false-positive rate.

Henry KE et al. Sci Transl Med. 2015

Modeli za zgodnjo prepoznavo se

TREWS



- Prospektivna, multicentrična raziskava
- 590736 bolnikov v 5 bolnišnicah (urgentni centri ali sprejeti na oddelek)
- Dve roki: odziv na alarm znotraj 3 ur / brez odziva oz. kasneje
- 42089 alarmov (7.1%); 59% pred sprejemom, 41% po sprejemu

- Nižja umrljivost (14.6% vs. 19.2%)
- Hitrejše ‚izboljšanje' SOFA
- Krajši LOS (6.6 d vs. 8.1 d)

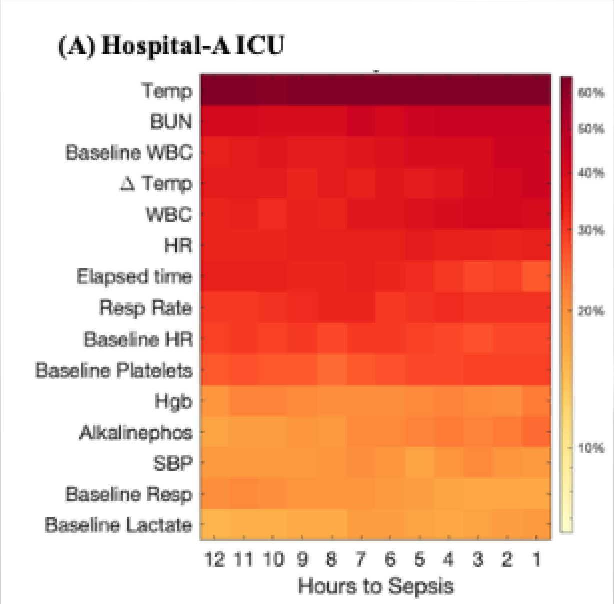
- Boljši vsi izvidi pri zgodnji administraciji atb
  - Prilagojeno razmerje obetov za hospitalno umrljivost 1.08/h (95% CI 1.02, 1.15)

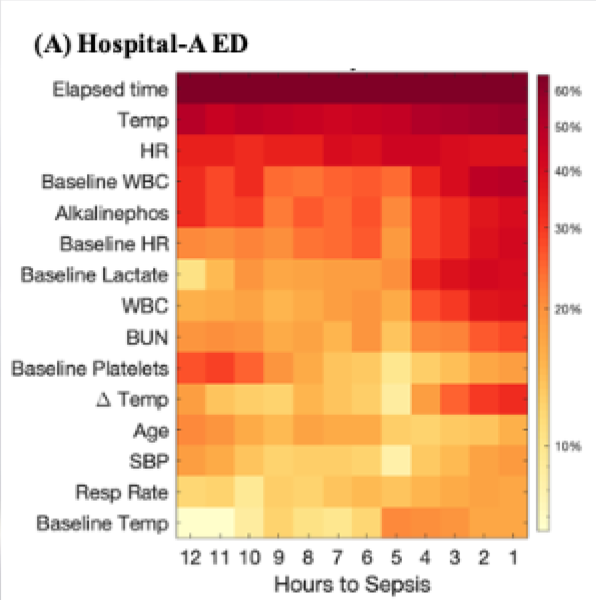
	Treatment	Comparison	ARD or ARR	P value[a]
All included	n = 4,220	n = 2,657		
In-hospital mortality, no. (rate)	617 (14.6%)	509 (19.2%)	ARD −3.34% (−5.10, −1.67%)	<0.001
			ARR −18.18% (−26.31, −9.65%)	<0.001
SOFA progression at 72 h[b]	−0.8 ± 2.7	−0.4 ± 2.9	ARD −0.26 (−0.42, −0.11)	0.001
Median length of stay (h)[c]	156 (99–260)	190 (118–323)	ARD −11.58 (−18.13, −5.03)	0.001
High-risk cohort	n = 1,430	n = 935		
In-hospital mortality, no. (rate)	422 (29.5%)	320 (34.2%)	ARD −4.50% (−8.31, −0.78%)	0.012
			ARR −13.19% (−22.81, −2.45%)	0.012
SOFA progression at 72 h[b]	−1.5 ± 3.5	−1.2 ± 3.6	ARD −0.38 (−0.71, −0.05)	0.025
Median length of stay (h)[c]	210 (129–351)	246 (155–434)	ARD −14.21 (−32.47, −4.04)	0.127

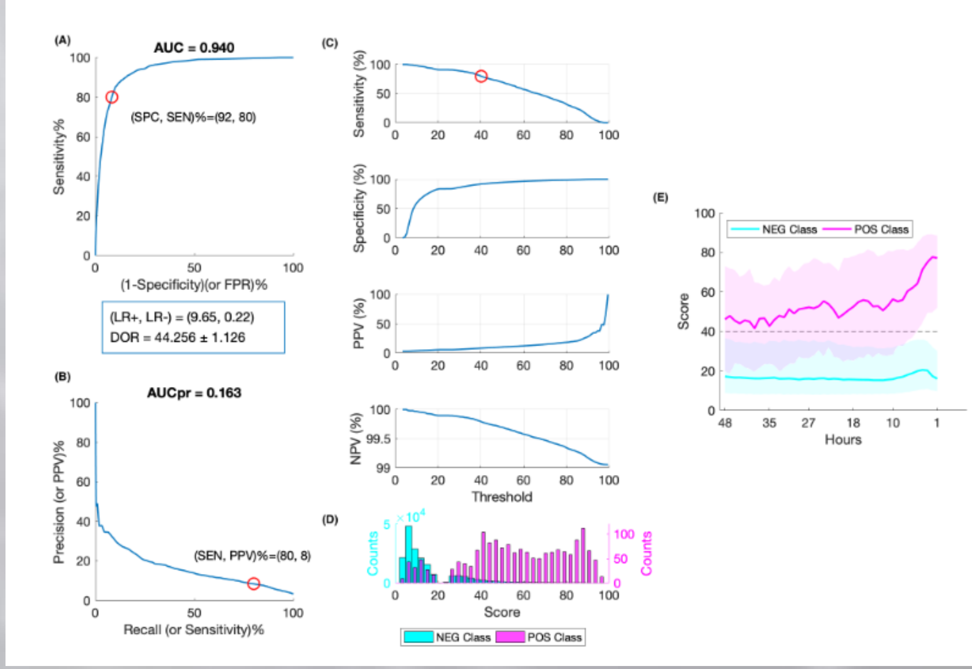
Henry KE et al. Sci Transl Med. 2015
Adams R et al. Nat Med. 2022

Modeli za zgodnjo prepoznavo sepse COMPOSER

- Podatki iz 6 kohort bolnikov v OIZ in UC; 515.720 bolnikov
- 40 spremenljivk (demografske značilnosti, vitalni znaki, laboratorijski izvidi)
- AUC/PNV 0.95/38% (OIZ) oz. 0.945/20% (UC)
- Prepoznava sepse 4 – 48 ur pred klinično prepoznavo



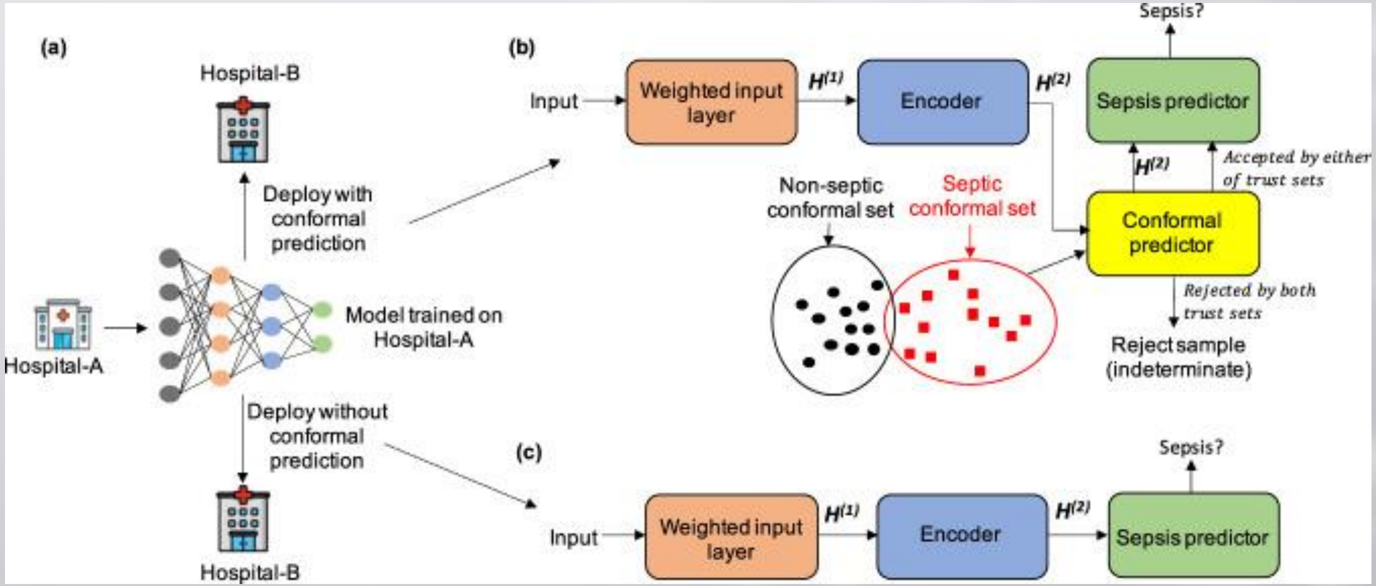


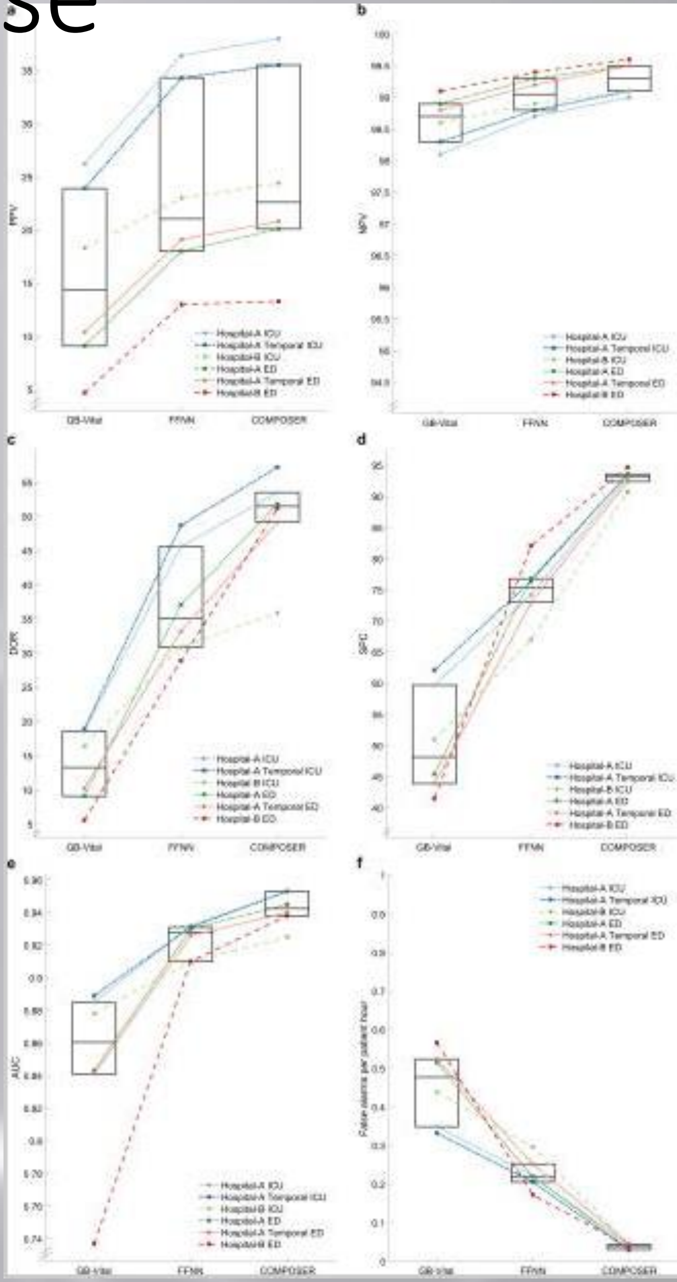


Shashikumar SP et al. NPJ Digit Med. 2021

Modeli za zgodnjo prepoznavo sepse
COMPOSER

- Konformalni model za detekcijo nepoznanih primerov / outlierjev
- 85% zmanjšanje lažno pozitivnih alarmov - alarm fatigue!
- <u>Št. lažnih alarmov na bolnika/ur:</u> 0.031 (OIZ) oz. 0.042(UC); specifičnost ~ 93%
- <u>Delež ‚nedoločljivih primerov' (nesep./sep.):</u> 26%/13% (OIZ) in 13%/6% (UC)
- V ‚nedoločljivi' skupini bolnikov s sepso dejansko septičnih: 1.1%





Shashikumar SP et al. NPJ Digit Med. 2021

Modeli za zgodnjo prepoznavo sepse COMPOSER

- Implementacija modela COMPOSER v dveh urgentnih centrih, 1.1.2011 – 30.4.2023;
- 6217 bolnikov (5065 pred in 1152 po (5m))

- Po uporabi modela 1,9 % absolutno zmanjšanje umrljivosti (17 % relativno zmanjšanje)
- Manjša sprememba v SOFA (nižje) znotraj 72 ur
- 5% absolutno oz. 10% relativno višja komplianca svežnja ukrepov za sepso
- Hitrejša obravnava in administracija antibiotika

Outcome	Pre-intervention value	Expected post-intervention value (95% CI)	Actual post-intervention value
In-hospital mortality %	10.3%	11.4% (9.8%–13.0%)	**9.5%**
Average 72-h Change in SOFA	3.71	3.71 (3.6–3.8)	**3.56**
Sepsis bundle compliance rate	48.3%	48.4% (45.5%–51.0%)	**53.4%**
Blood cultures prior to antibiotics compliance rate	71.1%	72.0% (69.9%–73.9%)	73.9%
Rate of antibiotics administered within 24 h prior and 3 h after severe sepsis onset.	82.8%	82.8% (81.3%–84.4%)	**84.6%**
Rate of lactate measured within 6 h prior and 3 h after severe sepsis onset	83.5%	83.4% (81.3%–85.8%)	85.6%
Rate of repeat lactate measured within 6 h after severe sepsis onset if initial lactate is elevated	97.8%	97.3% (96.2%–98.4%)	**98.6%**
Rate of administration of vasoactive medications within 6 h of septic shock	58.0%	57.5% (46.7%–68.2%)	55.5%
Rate of administration of 30cc/kg of fluids within 3 h of presentation of septic shock or hypotension	54.2%	53.9% (48.9%–58.8%)	**59.3%**
ICU transfer rate	32.6%	32.5% (30.7%–34.2%)	31.8%
Average ICU-free days	25.4	25.1 (24.6–25.6)	25.6

Boussina A et al. NPJ Digit Med. 2024. Erratum in: NPJ Digit Med. 2024.

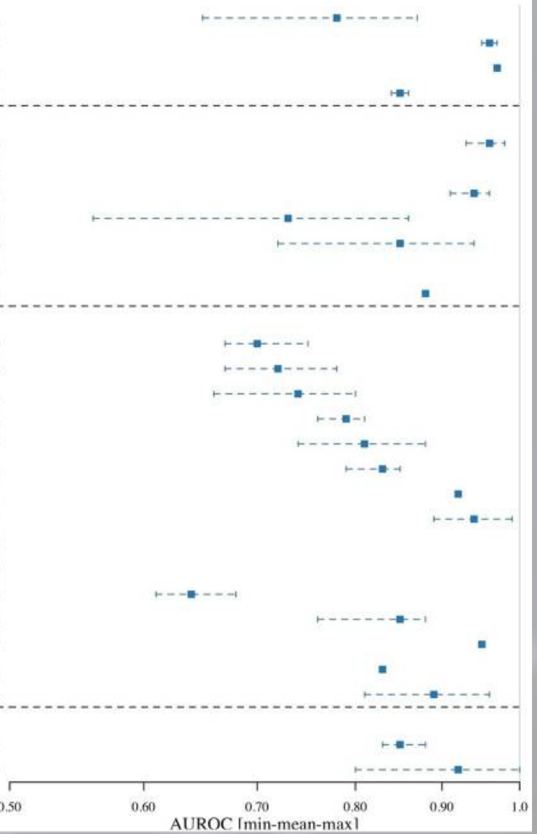
Modeli za zgodnjo prepoznavo sepse

Primerjava in ocena uporabljenih modelov

- Meta analiza 28 raziskav o uporabi UI za prepoznavo in napoved sepse in septičnega šoka v realnem času
- Večina raziskav v OIZ (15), manj na bolnišničnih oddelkih (7), UC (4) in najmanj v vseh (2)
- 36% raziskav uporabila dostopne podatke iz baze MIMIC-III

- AUROC
  - 0.68-0.99 (OIZ),
  - 0.96-0.98 (bolnišnični odd.) in
  - 0.87-0.97 (UC)

Paper	Target Condition	No. Models	Models	No. Patients	No. Features	Hrs bef. Onset
Emergency Department						
Horng, 2017	Sepsis	13	SVM, GLM, NB, EM	230936	10-12	-
Haug, 2016	Sepsis	6	NB	280143	24	-
Delahanty, 2019	Sepsis	1	EM	2759529	12	-
Brown, 2016	Severe sepsis and Septic shock	2	NB	93773-132748	5	-
In-Hospital						
Khojandi, 2018	Sepsis	3	EM	261258	9	0
Futoma, 2017	Sepsis	6	NNM, GLM	49312	32	0-12
McCoy, 2017	Severe sepsis, Sepsis	2	GLM	1665	6	0
Lin, 2018	Septic shock	16	More than 4*	25770	7	3-6
Khoshnevisan, 2018	Septic shock	9	More than 4*	25770	19	4
Thiel, 2010	Septic shock	6	DT	13785	24	Unavailable
Giannini, 2019	Severe sepsis and Septic shock	1	EM	162212	49	Unavailable
Intensive Care Unit						
Wang, 2018	Sepsis	3	GLM, SVM, EM	19358	12	0
Shashikumar II, 2017	Sepsis	3	GLM	1100	4-21	4
Shashikumar I, 2017	Sepsis	7	SVM	682	2-22	4
Scherpf, 2019	Sepsis	3	NNM	31238-31575	10	3-12
Desautels, 2016	Sepsis	2	GLM	22853	8	0-4
Nemati, 2018	Sepsis	8	PHM	27527-42411	48	4-12
Calvert II, 2016	Sepsis	1	GLM	1394	9	3
Kam, 2017	Sepsis	7	NNM, LSTM	5789	9	0-3
Van Wyk, 2018	Sepsis	2	EM	904	8	0
Van Wyk, 2019	Sepsis	1	EM	1388	7	0
Moss, 2016	Severe sepsis	2	GLM	3059	7	0
Guillen, 2015	Severe sepsis	9	GLM, SVM, EM	3446	7-19	2
Shimabukuro, 2017	Severe sepsis	1	GLM	142	17	0
Henry, 2015	Septic shock	1	PHM	16234	30	28.2
Calvert I, 2016	Septic shock	2	GLM	Unavailable	9	0-4
ED/In-Hospital/ICU						
Barton, 2019	Sepsis	3	EM	112952	6	0-48
Mao, 2017	Sepsis, Severe sepsis, Septic shock	10	EM	1140-239767	3-6	0



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Modeli za zgodnjo prepoznavo sepse

Primerjava in ocena uporabljenih modelov

- Le dve prospektivni in tri validacijske raziskave
- Meta-analiza modelov (111) in spremenljivk:
  - Najpomembnejše + srčni utrip, temperatura, fr. dihanja, PAAK // nevronske mreže
  - Najpomembnejše − uporaba definicije sepse Seymour et al., SOFA // drugi modeli UI
- omejitve
  - Podobne/enake kohorte – generalizacija?
  - Različne definicije sepse
  - Slabo poročanje podatkov
- QUADAS-2 kriterijih
  - 32% nejasno tveganje za bias
  - 68% visoko tveganje za bias
- GRADE
  - Vse raziskave nizka kvaliteta dokazov

	Paper	Design	Target condition	Patient encounters	Machine learning group	Control group
Interventional						
In-hospital	Giannini et al.	Pre-post implementation	Severe sepsis and septic shock	54,464 (6 pre-months, 1 post-month)		
					EWS 2.0	Unclear
					Primary/secondary outcome	Primary/secondary outcome
					Hospital LOS: 9 days	Hospital LOS: 9 days
					Time to ICU transfer after alert: 8 h[e]	Time to ICU transfer after alert: 16 h[e]
					In-hospital mortality: 10.3%	In-hospital mortality: 10.6%
	McCoy et al.	Pre-post implementation[b]	Severe sepsis	611 (3 pre-months, 2 post-months)		
					Linear model (Insight)	Manual nurse scoring[c]
					Primary outcome	Primary outcome
					In-hospital mortality: 2.94%	In-hospital mortality: 7.37%
					Secondary outcome	Secondary outcome
					Hospital LOS: 2.92 days	Hospital LOS: 3.35 days
					Readmission rate: 7.84%	Readmission rate: 46.19%
ICU	Shimabukuro et al.	RCT	Severe sepsis	142 (3 months)		
					Elastic net reg.[d] (Insight)	SIRS detector
					Primary outcome	Primary outcome
					Hospital LOS: 10.3 days[e]	Hospital LOS: 13.0 days[e]
					Secondary outcome	Secondary outcome
					ICU LOS: 6.3 days[e]	ICU LOS: 8.4 days[e]
					In-hospital mortality: 8.96%[e]	In-hospital mortality: 21.3%[e]

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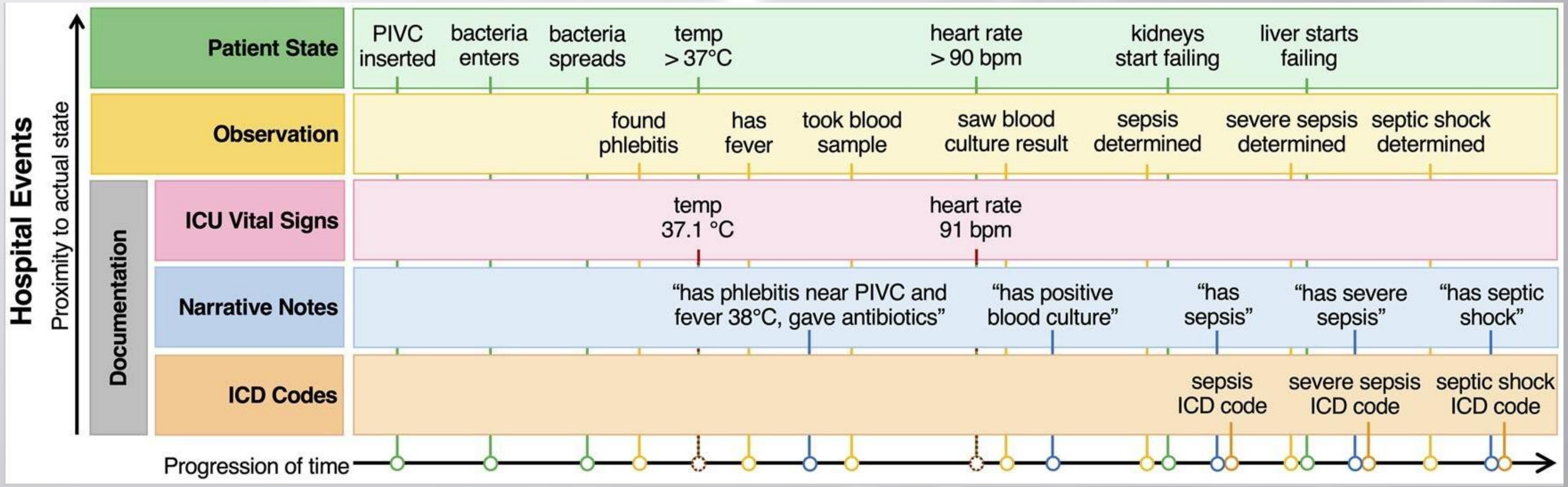
Modeli za zgodnjo prepoznavo sepse
Nestrukturirani podatki

- Pregledni članek – uporaba tudi nestrukturiranih podatkov iz zapisov osebja
- 9 raziskav; retrospektivne, različne kohorte (bolnišnična, MIMIC-II, MIMIC-III...), različni algoritmi
- Opisi simptomov, znakov, diagnoz, načrtov zdravljenja in navodil, vrste obravnave, lab. Izvidov
- Večina poročala AUC – glavni primerjalni parameter; zaradi različnih metod meta-analiza ni možna



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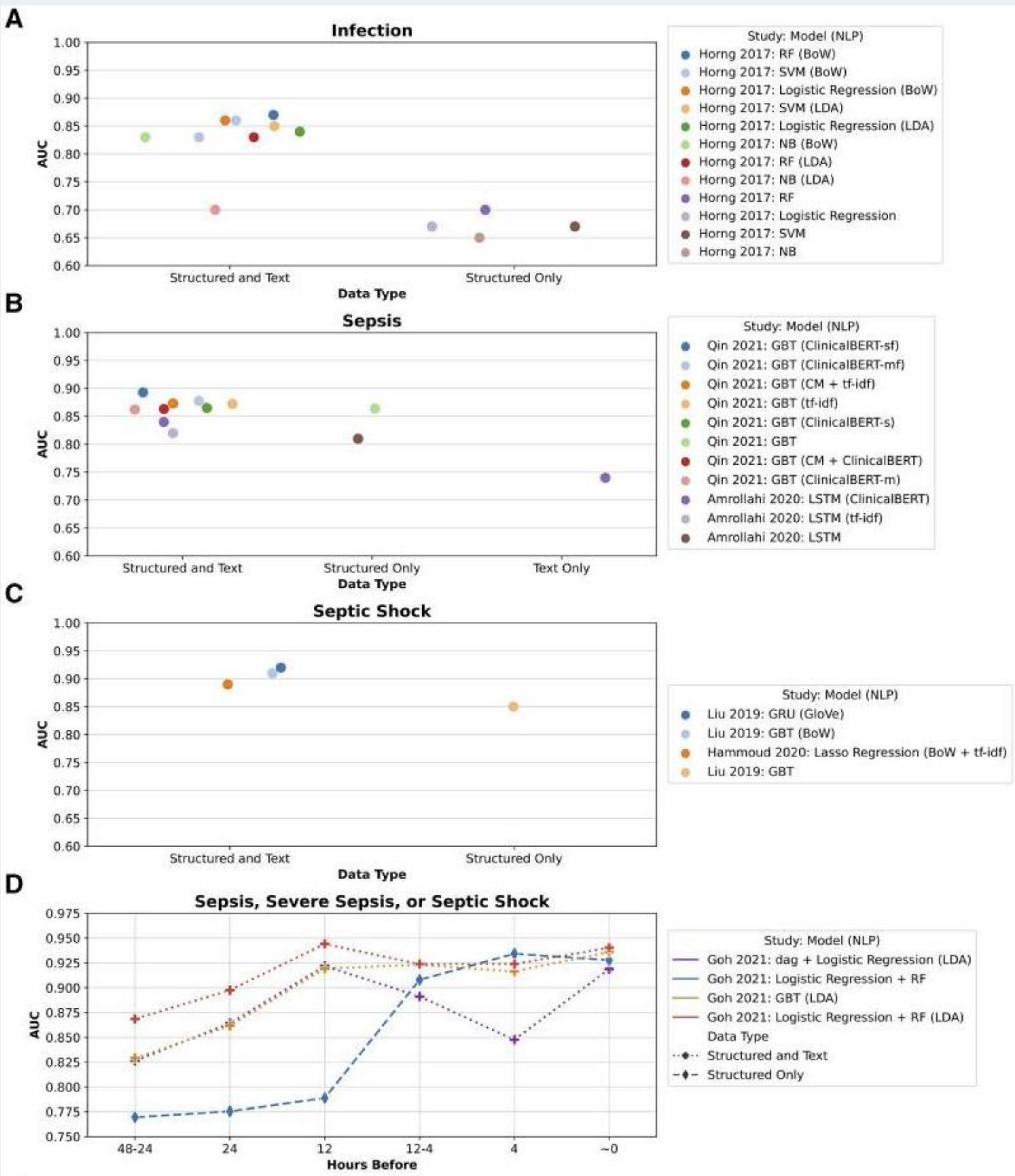
Study (year)	Hours[a]	Data types[b] DVLMC	T[c]	Models[d] (NLP)[e]	AUC[f]
Horng et al.[47] (2017)	Identify	DV- - -	CC + NN	RF (BoW)	0.87
		DV- - -	–	NB	0.65
Apostolova and Velez[48] (2017)	Identify	- - - - -	NN	SVM (BoW + tf-idf)	–
		- - - - -	NN	Logistic regression + KNN + SVM (PV)	–
Culliton et al.[49] (2017)	−4	- - - - -	CN	Ridge regression (GloVe)	0.64
	−8	- - - - -	CN	Ridge regression (GloVe)	0.66
	−24	- - - - -	CN	Ridge regression (GloVe)	0.73
	−24[g]	-V- -C	CN	Ridge regression (GloVe)	0.85
		-V- -C	–	Ridge regression (GloVe)	0.80
Delahanty et al.[51] (2019)	+1	-VL- -	–	GBT	0.93
	+3	-VL- -	–	GBT	0.95
	+6	-VL- -	–	GBT	0.96
	+12	-VL- -	–	GBT	0.97
	+24	-VL- -	–	GBT	0.97
Liu et al.[50] (2019)	−7	-VLM-	CN	GRU (GloVe)	0.92
	−7.3	-VLM-	CN	GBT (BoW)	0.91
	−6	-VLM-	–	GBT	0.85
Amrollahi et al.[53] (2020)	−4[h]	-VL- -	PN + NN	LSTM (ClinicalBERT)	0.84
		- - - - -	PN + NN	LSTM (ClinicalBERT)	0.74
Hammoud et al.[54] (2020)	−30.6	DVL- -	CN	Lasso regression (BoW + tf-idf)	0.89
Goh et al.[52] (2021)	Identify	DVLM-	PN	Logistic regression + RF (LDA)	0.94
		DVLM-	PN	dag + Logistic regression (LDA)	0.92
	−4	DVLM-	–	Logistic regression + RF	0.93
		DVLM-	PN	dag + Logistic regression (LDA)	0.85
	−6	DVLM-	PN	Logistic regression + RF (LDA)	0.92
		DVLM-	PN	dag + Logistic regression (LDA)	0.89
	−12	DVLM-	PN	Logistic regression + RF (LDA)	0.94
		DVLM-	–	Logistic regression + RF	0.79
	−24	DVLM-	PN	Logistic regression + RF (LDA)	0.90
		DVLM-	–	Logistic regression + RF	0.78
	−48	DVLM-	PN	Logistic regression + RF (LDA)	0.87
		DVLM-	–	Logistic regression + RF	0.77
Qin et al.[55] (2021)	−6 to 0[i]	-VL- -	CN	GBT (ClinicalBERT-sf)	0.89[j]
		-VL- -	–	GBT (ClinicalBERT-m)	0.86[j]



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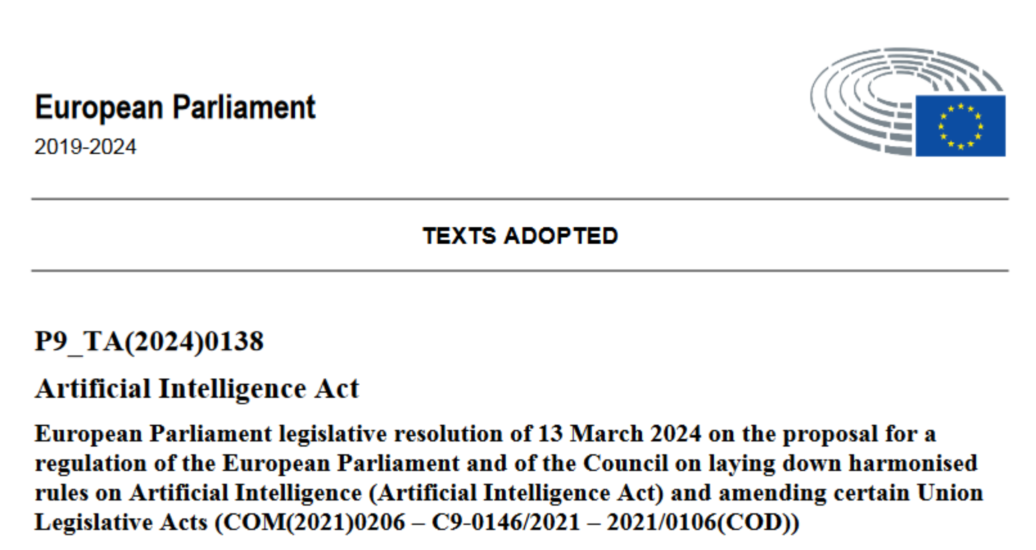
Problemi

- Beleženje velikega števila podatkov
  - Različni nivoji: urgentne amb., oddelek, OIZ
  - Kontinuirano merjenje
- Ustrezna tehnična podpora za obdelavo
  - Oprema za merjenje in beleženje
  - Zmogljivi procesorji za sprotno obdelavo
  - Cena
- Poenotenje zdravstvenih informacijskih sistemov (bolnišnica, regija, država...)
- Generalizacija modelov – ang. ‚*distribution shift*‘?
- Visoka stopnja lažno pozitivnih primerov
- Avtomatizacija - ang. ‚*automation bias*‘
- Nezaupanje (upravičeno?) v modele

Se moramo bati umetne inteligence?



European Parliament
2019-2024

TEXTS ADOPTED

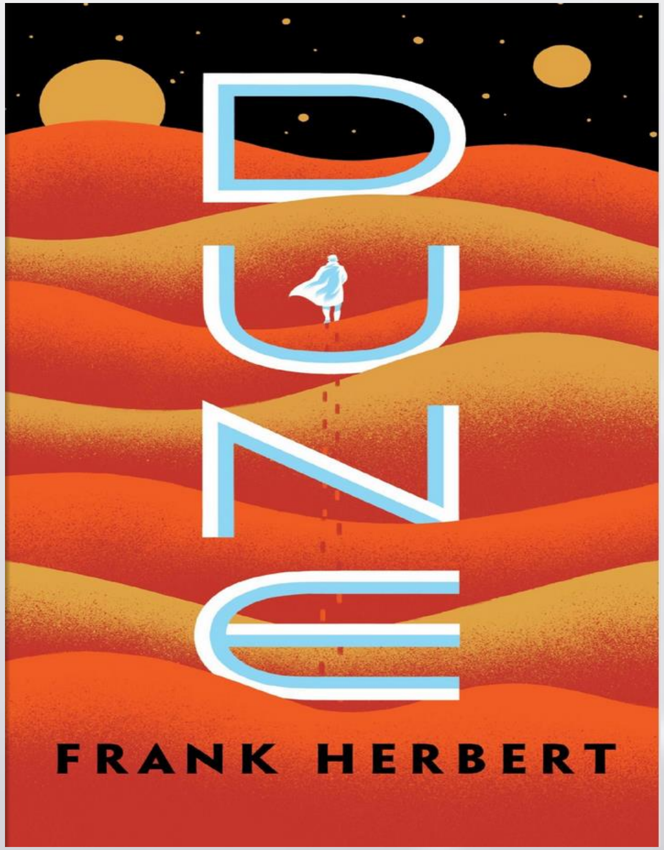
P9_TA(2024)0138

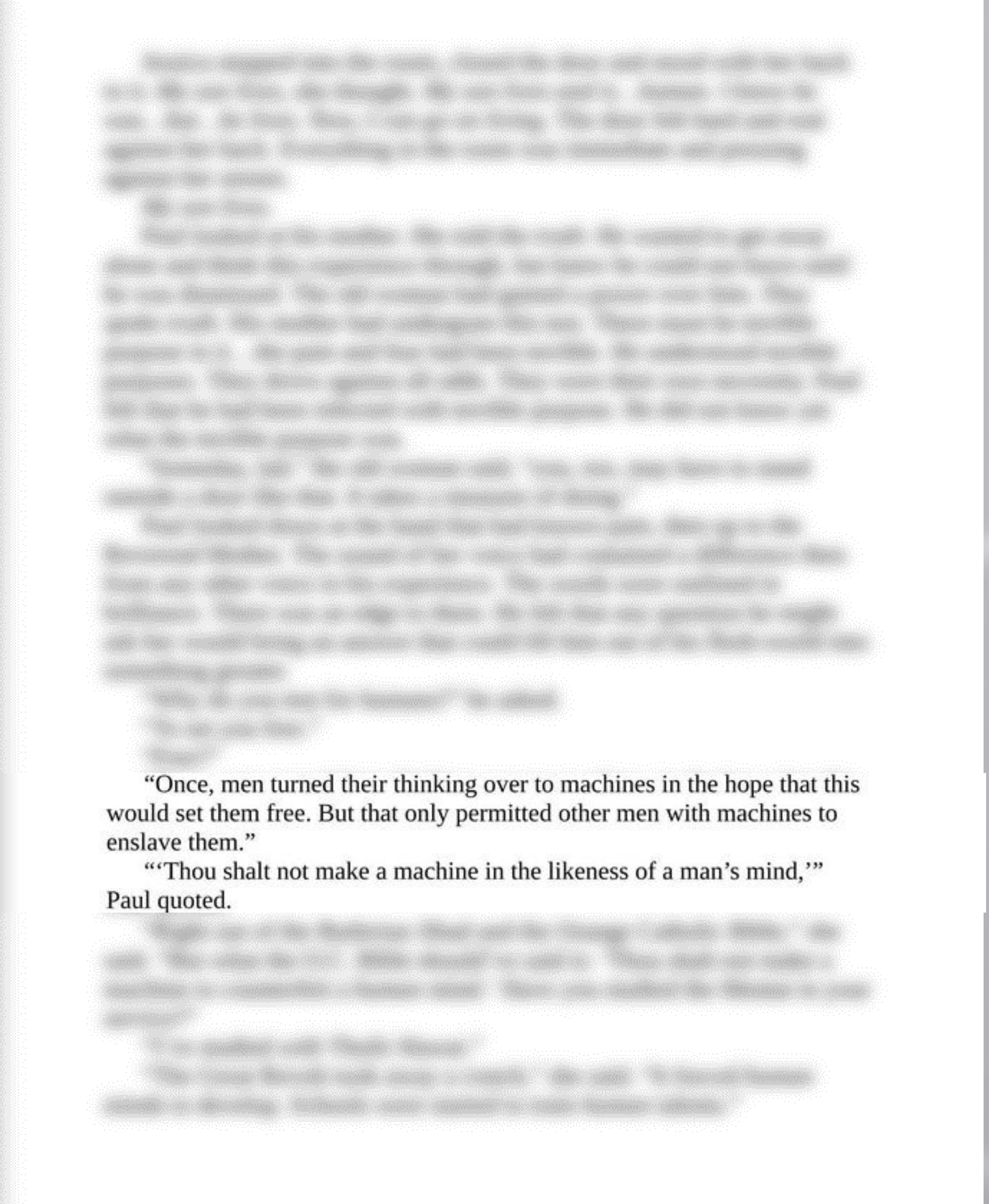
Artificial Intelligence Act

European Parliament legislative resolution of 13 March 2024 on the proposal for a regulation of the European Parliament and of the Council on laying down harmonised rules on Artificial Intelligence (Artificial Intelligence Act) and amending certain Union Legislative Acts (COM(2021)0206 – C9-0146/2021 – 2021/0106(COD))

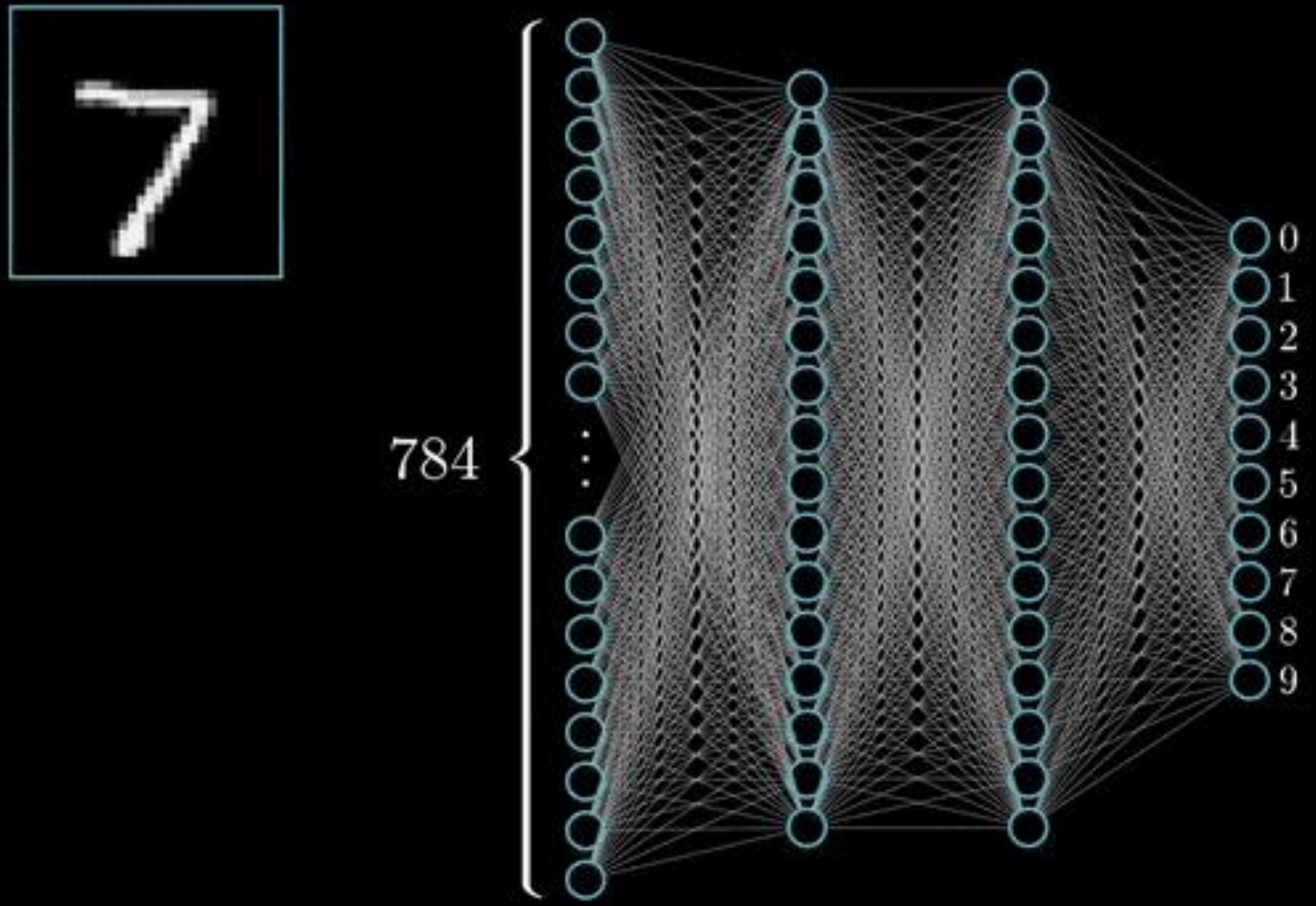
- Ureditev pravnih okvirjev za uporabo sistemov UI
- Prepovedi
  - Sklepanje o čustvenem stanju, družbeno točkovanje, biometrična identifikacija v živo
  - Usmerjanje vedenja, izkoriščanje ranljivosti
- Omejitve
  - Kritična infrastruktura – izobraževanje, zdravstvo, pravosodje in policija, dostop do bistvenih storitev

Se moramo ba




"Once, men turned their thinking over to machines in the hope that this would set them free. But that only permitted other men with machines to enslave them."

"'Thou shalt not make a machine in the likeness of a man's mind,'" Paul quoted.



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