

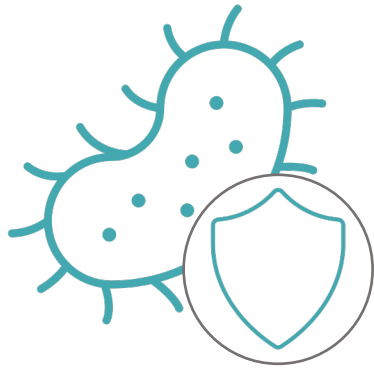
Machine learning based white blood count estimation for individualised antimicrobial cessation

William Bolton

ECCMID 2023

15th April 2023

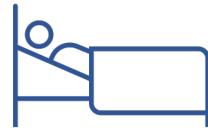
Machine learning can support optimised antibiotic decision making.



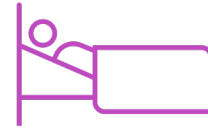
Antimicrobial resistance (AMR) is a global threat and one key strategy to tackle this is to optimise antimicrobial use



A



B



C

Clinical decision support systems (CDSSs) utilising machine learning (ML) have been developed to assist with managing infections

STAGES OF ANTIBIOTIC DECISION MAKING

1 Infection or not

2 Empiric treatment

3 Narrow therapy

IV to oral
switch

4 Duration

Cessation
Side effects

Antibiotic cessation decision making is complex and under-researched.



Shortened Courses of Antibiotics for Bacterial Infections: A Systematic Review of Randomized Controlled Trials
 Alexandra M. Hamriety,¹ and Jason C. Gallagher^{2*}
¹St. Christopher's Hospital for Children, Philadelphia, Pennsylvania, ²Department of Pharmacy Practice, Temple University, Philadelphia, Pennsylvania
 Published: 4 August 2019

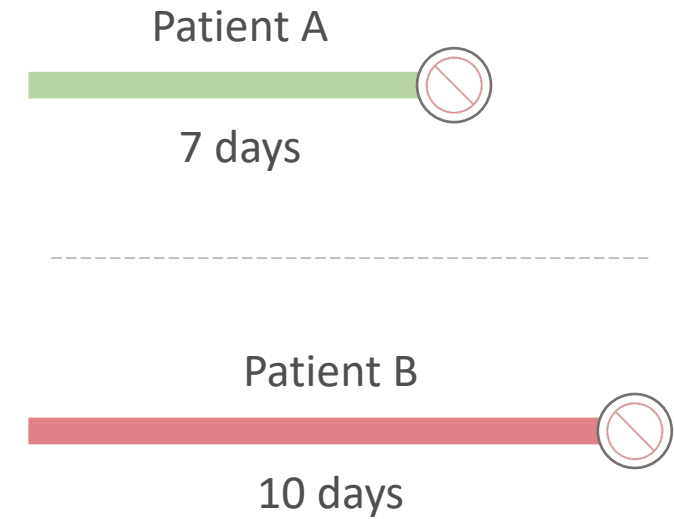
Duration of Antibiotic Therapy: Shorter Is Better
 Brad Spellberg, MD, and Roni Bitterman, MD
 Author, Article, and Discussion
<https://doi.org/10.7326/M19-0328>

Seven Versus Uncomplicated Noninferiority
 Dafna Yahav, Roni Bitterman, Noa Eliakim-Raz, and Dafna Yahav
 Author Notes
 Clinical Infectious Diseases, Volume 69, Issue 9, 1 November 2019, Pages 1476-1479, <https://doi.org/10.1093/cid/ciy1134>
 Published: 11 December 2019

Shorter Versus Longer Courses of Antibiotics for Infection in Hospitalized Patients: A Systematic Review and Meta-Analysis
 Stephanie Royer, MD, Kimberly M. DeMerle, MD, Robert P. Dickson, MD, Halle C. Prescott, MD, MS, et al.
 Department of Internal Medicine, University of Michigan, Ann Arbor, Michigan; Division of Hospital Medicine, Cincinnati Children's Hospital Medical Center, Cincinnati, Ohio; Department of Internal Medicine, University of Cincinnati, Cincinnati, Ohio; Veterans Affairs Center for Clinical Management Research, Veterans Affairs Ann Arbor Healthcare System, Ann Arbor, Michigan

Short-course Antibiotic Therapy—Replacing Constantine Units With “Shorter Is Better”
 Noah Wald-Dickler, Brad Spellberg
 Clinical Infectious Diseases, Volume 69, Issue 9, 1 November 2019, Pages 1476-1479, <https://doi.org/10.1093/cid/ciy1134>
 Published: 07 January 2019 Article history

Keywords: antibiotic stewardship, short-course therapy, durations of therapy, antibiotic resistance
Issue Section: Articles and Commentaries



One key challenge when treating a patient who has a bacterial infection is determining when it is appropriate to stop antibiotic treatment

Numerous studies have shown that on a population level, shorter treatment durations are often non-inferior to longer ones

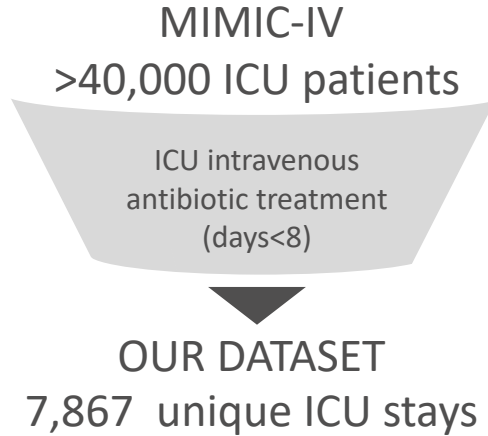
There is a poor understanding of the factors that facilitate or inhibit an individual from receiving a short duration of therapy

Aim

Utilise a machine learning and synthetic control-based approach to estimate patients total white blood cell count for any given day, if they were to stop vs. continue antibiotic treatment

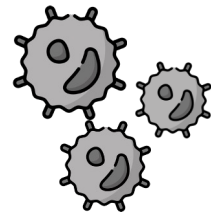
Routinely collected electronic health record data and an autoencoder were used for white blood cell count prediction.

DATASET



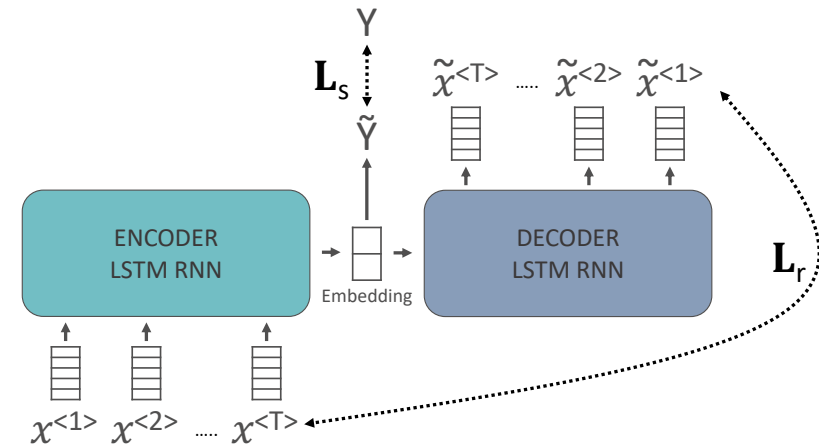
77 features

Total white blood cell count (WBC)



MODEL

Autoencoder



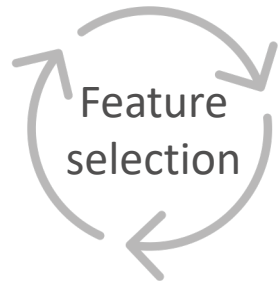
The encoder is trained using both a supervised loss (L_s) and reconstruction loss (L_r)

The autoencoder achieves reasonable WBC prediction performance and can be used for synthetic scenario estimation.

AUTOENCODER PREDICTIONS

77 features

Evaluation metric	Value
RMSE	3.28
MAE	2.68
MAPE	0.31

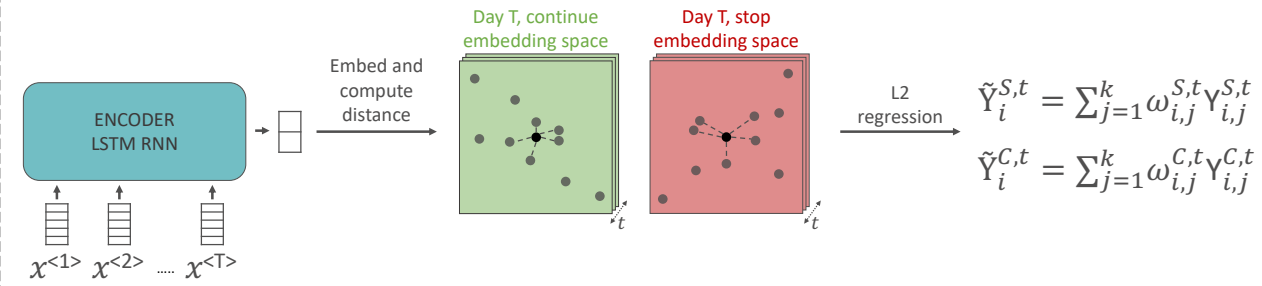


22 features

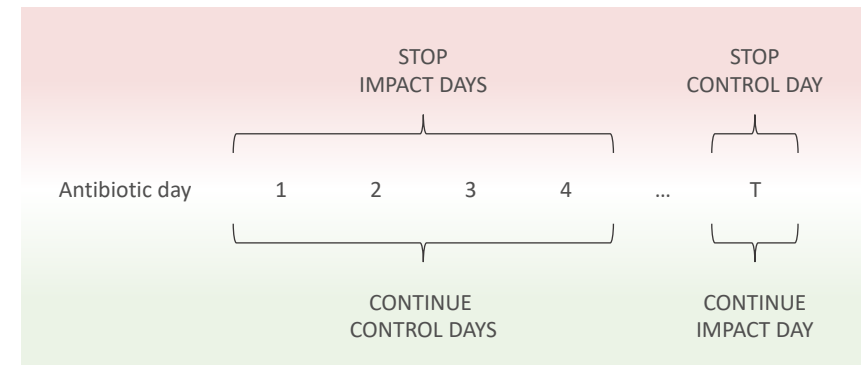
Evaluation metric	Value
RMSE	3.33
MAE	2.66
MAPE	0.36

SYNTHETIC ESTIMATION

Methodology



Evaluation



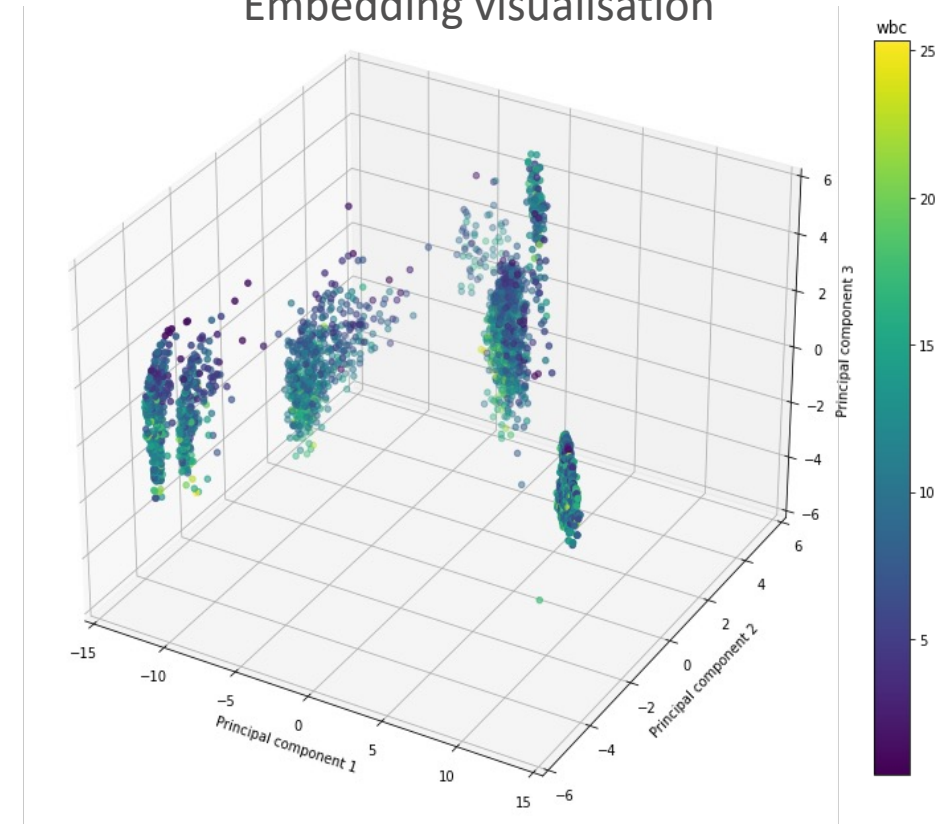
Our model can estimate patients white blood cell count under alternative antibiotic treatment.

SYNTHETIC WBC ESTIMATION RESULTS

Evaluation table

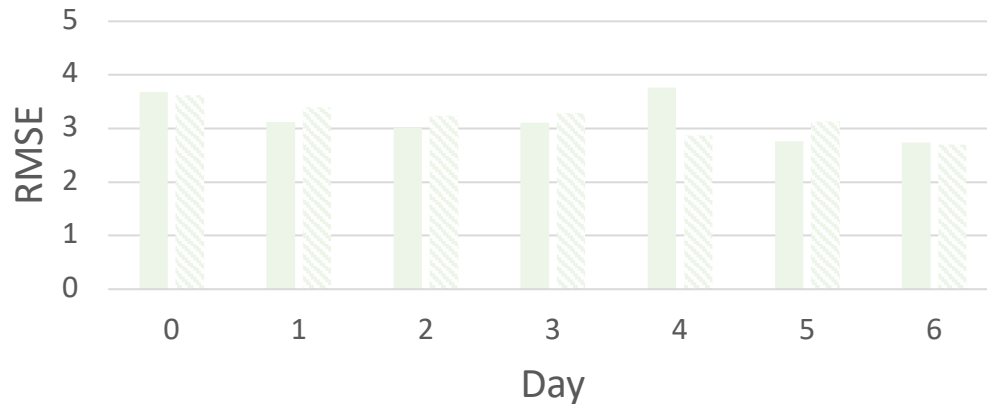
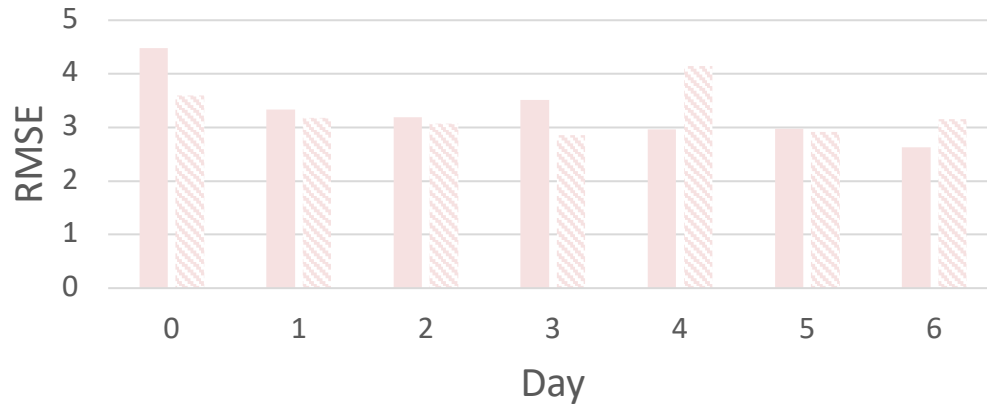
Scenario	Day(s)	WBC			
		Mean delta (days, p-value)	MAPE	MAE	RMSE
Stop	Impact	0.71*, <0.01	0.34	2.99	3.89
	Control	0.00, 0.06	0.32	2.50	3.24
Continue	Impact	-0.31*, <0.01	0.33	2.53	3.18
	Control	0.02*, 0.01	0.32	2.70	3.44

Embedding visualisation



Machine learning and synthetic outcome estimation for individualised antimicrobial cessation.

CONSISTENT ESTIMATION RESULTS



SYNTHETIC OUTCOME ESTIMATION

43 features

Mortality



Length of stay



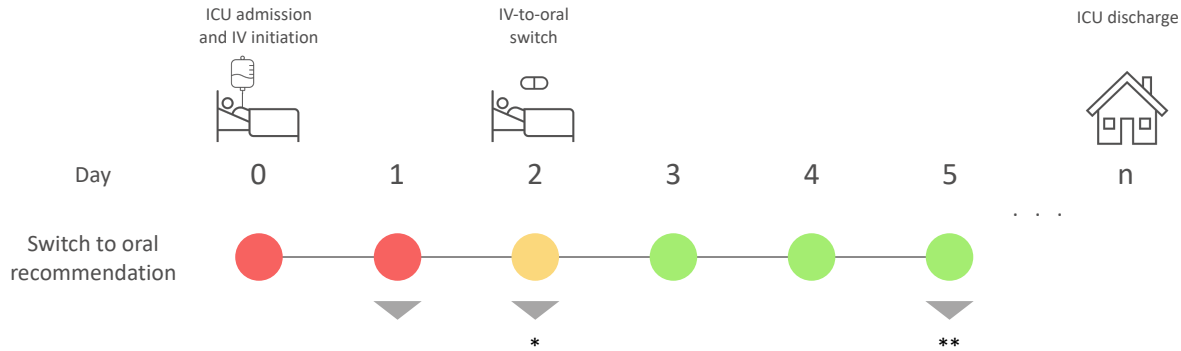
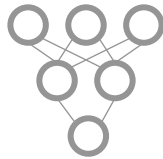
SCENARIO	DAY(S)	LOS				Mortality		
		Mean delta (days, p-value)	MAPE	MAE	RMSE	Mean delta	MAE	AUROC
STOP	IMPACT	2.71*, <0.01	0.36	3.30	4.80	0.06	0.25	0.66
	CONTROL	0.24, 0.60	0.26	1.32	1.93	0.05	0.15	0.72
CONTINUE	IMPACT	-2.09*, <0.01	0.77	2.85	3.16	0.05	0.18	0.67
	CONTROL	0.42*, 0.01	0.48	2.72	3.76	0.07	0.24	0.64

Other work includes machine learning to support IV to oral switching and understanding the impact of co-morbidities.



P3491

UKHSA **IVOS** criteria

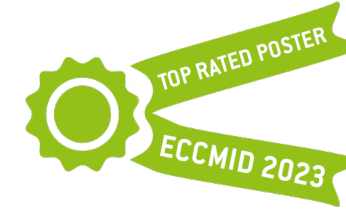


Day 1

Highlights

- Both thresholds predict switching is **not appropriate** at this time
- Predictions were correct for **100%** of similar examples
- O2 saturation pulseoximetry (feature 4) was of particular interest for these predictions

Patient	Importance	Feature					Switch to oral label	Switch to oral prediction	
		1	2	3	4	5		1 st threshold	2 nd threshold
	-	0.32	0.51	0.37	0.50	0.41	0	0	0
Example	1	0.28	0.38	0.54	0.29	0.48	0	0	0
	2	0.25	0.31	0.55	0.28	0.51	0	0	0
	3	0.21	0.29	0.52	0.45	0.52	0	0	0
	4	0.13	0.32	0.55	0.36	0.51	0	0	0



P3492

AMR-UTI: Antimicrobial Resistance in Urinary Tract Infections

Days preceding	Arthritis	HTN	Hypothyroid	Pulmonary	Fluids/Lytes	Lymphoma	CHF	Obesity	PVD	Rheumatic	Blood/Loss	DM	Renal	Depression	NeuroOther	Paralysis	Valvular	Coagulopathy	Anemia	Alcohol	HTNcx	Tumor	Weight/Loss	Liver	Psychoses	DMcx	Drugs	Mets	PUD	PHTN	HIV	
7	<0.01	<0.01	0.11	<0.01	<0.01	0.63	<0.01	0.02	<0.01	0.21	0.01	<0.01	<0.01	<0.01	0.01	<0.01	<0.01	0.01	<0.01	<0.01	<0.01	<0.01	0.12	<0.01	0.2	<0.01	0.03	<0.01	0.93	<0.01	0.05	
14	<0.01	<0.01	0.04	<0.01	<0.01	0.54	<0.01	0.02	<0.01	0.05	0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	0.23	<0.01	0.04	<0.01	0.93	<0.01	0.05	
30	<0.01	<0.01	0.01	<0.01	<0.01	0.57	<0.01	0.03	<0.01	0.02	0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	0.56	<0.01	0.03	<0.01	0.78	<0.01	<0.01	
90	<0.01	<0.01	<0.01	<0.01	<0.01	0.63	<0.01	0.61	<0.01	0.1	0.05	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	0.02	<0.01	0.01	<0.01	<0.01	<0.01	0.06	<0.01	0.01	<0.01	0.87	<0.01	<0.01	
180	<0.01	<0.01	<0.01	<0.01	<0.01	0.78	<0.01	0.88	<0.01	0.19	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	0.13	0.03	0.02	<0.01	<0.01	0.02	<0.01	0.4	<0.01	0.04	<0.01	0.7	<0.01	<0.01

Figure 1: Co-morbidities and empiric UTI treatment chi-square test of independence p-value results for differing diagnoses time windows preceding treatment. Green indicates statistical significance while red signifies no statistical significance. UTI, Urinary Tract Infection; HTN, Hypertension; CHF, Congestive Heart Failure; PVD, Peripheral Vascular Disease; DM, Diabetes Mellitus; PUD, Peptic Ulcer Disease; PHTN, Pulmonary Hypertension; HIV, Human Immunodeficiency Virus

Nitrofurantoin																												Trimethoprim-sulfamethoxazole																											
Days preceding	Arthritis	HTN	Hypothyroid	Pulmonary	Fluids/Lytes	Lymphoma	CHF	Obesity	PVD	Rheumatic	Blood/Loss	DM	Renal	Depression	NeuroOther	Paralysis	Valvular	Coagulopathy	Anemia	Alcohol	HTNcx	Tumor	Weight/Loss	Liver	Psychoses	DMcx	Drugs	Mets	PUD	PHTN	HIV																								
7	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01																							
14	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01																						
30	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01																						
90	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01																						
180	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01																						

Figure 2: Co-morbidities and antimicrobial resistance chi-square test of independence p-value results for differing diagnoses time windows preceding resistance testing. Results are shown for four of the most common antibiotics used to treat UTI infections. Green indicates statistical significance while red signifies no statistical significance. UTI, Urinary Tract Infection; HTN, Hypertension; CHF, Congestive Heart Failure; PVD, Peripheral Vascular Disease; DM, Diabetes Mellitus; PUD, Peptic Ulcer Disease; PHTN, Pulmonary Hypertension; HIV, Human Immunodeficiency Virus

Patient, public and stakeholder views as well as ethical theories have been considered to ensure solutions are fair.

ETHICAL VIEWPOINT

Comment

<https://doi.org/10.1038/s42256-022-00558-5>

Developing moral AI to support decision-making about antimicrobial use

William J. Bolton, Cosmin Badea, Pantelis Georgiou, Alison Holmes and Timothy M. Rawson

The use of decision-support systems based on artificial intelligence approaches in antimicrobial prescribing raises important moral questions. Adopting ethical

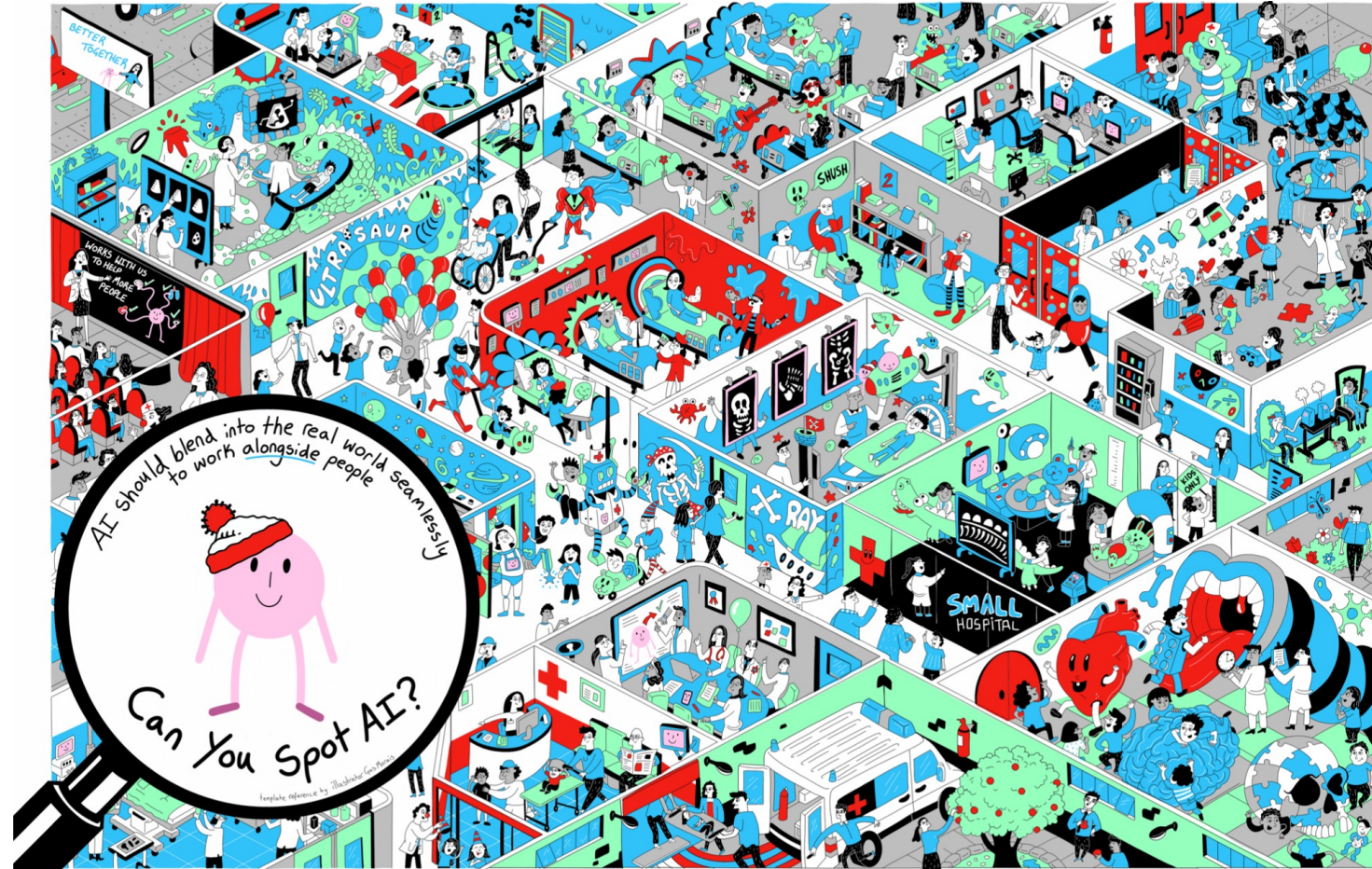
decision is morally right is often unclear. Incorporating such concepts into AI systems is complex but may be supported by the development of a consensus on the optimal approach to decision-making in this context. In this article, we aim to explore potential ethical frameworks and nuances that may be applied to define what is ethical or not during the development of AI-based clinical decision-support systems (CDSSs)

Check for updates

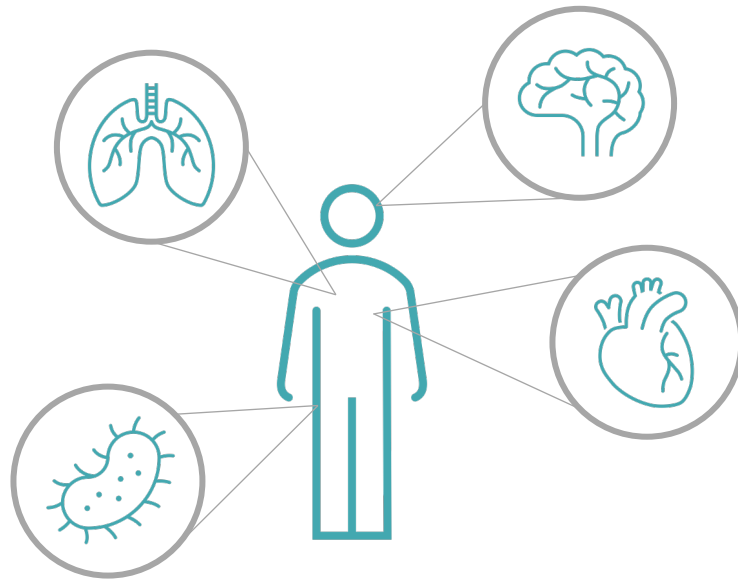
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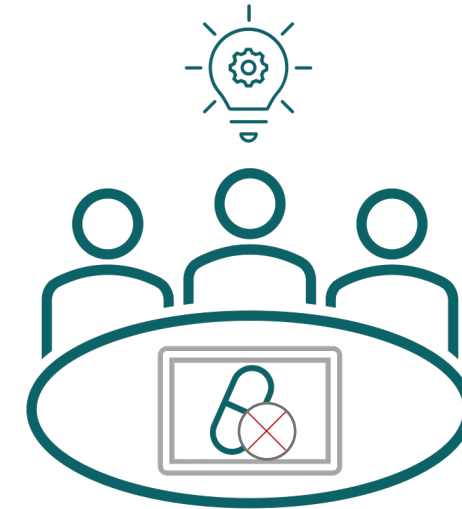
PRIMARY RESEARCH



Future research includes modeling patients' co-morbidities and addressing AI biases.



Model infection patients' co-morbidities through graphical methods



Investigate other aspects of antibiotic optimization and explore testing algorithms in real-world clinical settings

I would like to acknowledge the contribution of the following individuals.

Dr Tim Rawson

Professor Pantelis Georgiou

Professor Alison Holmes

Mr Richard Wilson

Dr David Antcliffe

Dr Bernard Hernandez Perez

Dr Esmita Charani

Thank you!

Linked 



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15th April 2023

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London**



Developing Moral AI to Support Antimicrobial Decision Making.

Regarding antimicrobial decision making, we believe a **utilitarian approach** is most suitable for developing AI-based CDSSs, and that technology should focus on the **likelihood of drug effectiveness and that of resistance** in order to have the biggest impact on supporting moral antimicrobial prescribing (Table. 1). Furthermore, for antimicrobials, **spatial and temporal considerations are critical** to optimise treatment outcomes and minimise the development of side effects or AMR. Decision making in antimicrobial prescribing is frequent, pressing, and both morally and technically complex. But by applying ethical theories to specific scenarios and incorporating moral paradigms, we can **ensure that AI-based CDSSs tackle global problems, such as the emerging AMR crisis, in a moral way.**

Variables	Description	Exemplar of starting antimicrobial treatment	Corresponding ad-hoc utility value
Intensity	How strong is the pleasure?	Treating a relevant infection with antimicrobials has the potential to save that person's life	Highly positive utility
Duration	How long will the pleasure last?	Any extension of life is immeasurable while it is reasonable AMR will continue in the near-term future	Positive utility
Certainty or uncertainty	How likely or unlikely is it that the pleasure will occur?	Limited information often means treatment may or may not be helpful and there is always an inherent risk of developing AMR	Neutral utility, without more information
Propinquity	How soon will the pleasure occur?	Treatment can be effective immediately however the same is true for the evolution of AMR	Neutral utility, without more information
Fecundity	The likelihood of further sensations of the same kind	-	Unable to assign
Purity	The likelihood of not being followed by opposite sensations	-	Unable to assign
Extent	How many people will be affected?	Prescribing antimicrobials effects the patient and those close to them, while the development of AMR is a certainty and may affect everyone, causing significant suffering and mortality	Immense negative utility

Co-morbid obesity leads to significantly worse infection outcomes.

MEAN	BODY MASS INDEX (BMI)	LENGTH OF ICU STAY	ANTIBIOTIC TREATMENT LENGTH
HEALTHY (HE)	22.40	5.86	5.18
OVERWEIGHT (OW)	27.38	7.98	5.86
OBESE (OB)	33.34	7.14	5.60
MORBIDLY OBESE (MB)	46.28	8.14	6.39

