



Plan Nacional
Resistencia
Antibióticos



II Jornada del Comité Español del Antibiograma (CoEsAnt)



Madrid, 12 de febrero de 2026



Papel de la IA en la predicción de la sensibilidad a los antimicrobianos

Javier Fernández Domínguez
Cofundador Pragmatech AI Solutions

II Jornada del Comité Español del Antibiograma (CoEsAnt)



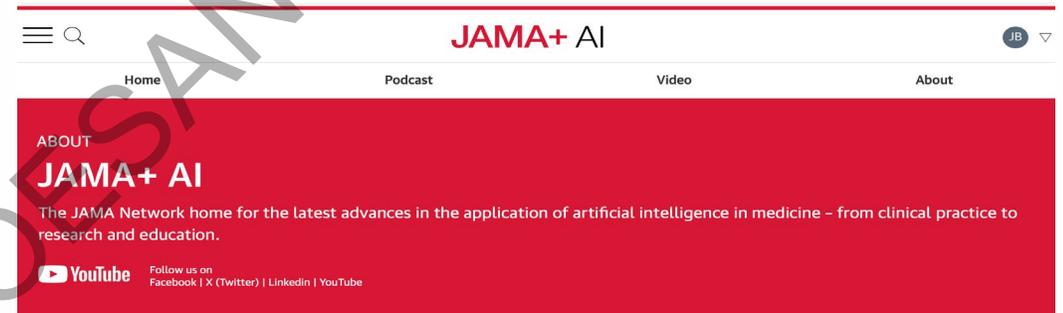
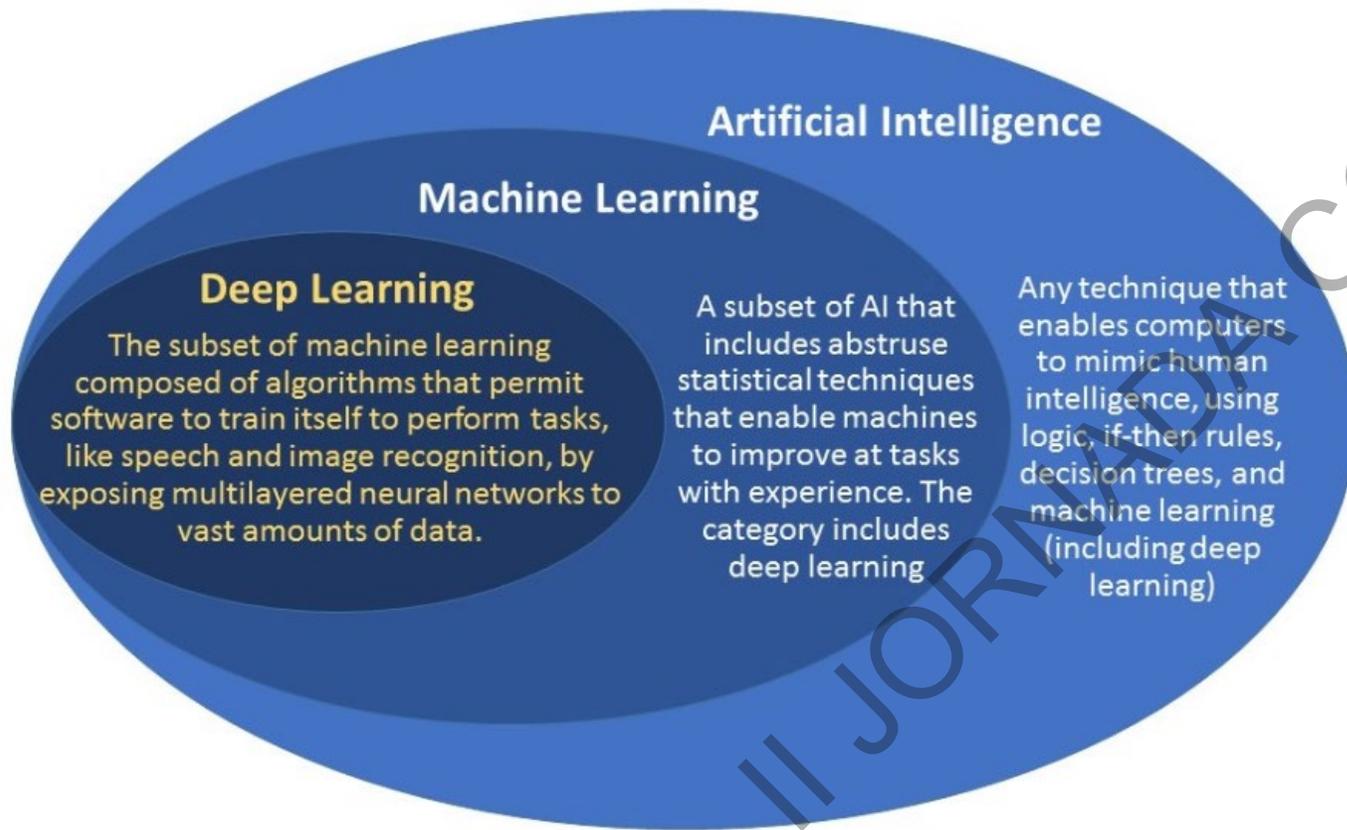
Conflicto de interés

Cofundador y CoCEO de Pragmatech AI Solutions

II JORNADA COESANT

II Jornada del Comité Español del Antibiograma (CoEsAnt)

La IA en Salud y en Microbiología y Enfermedades Infecciosas



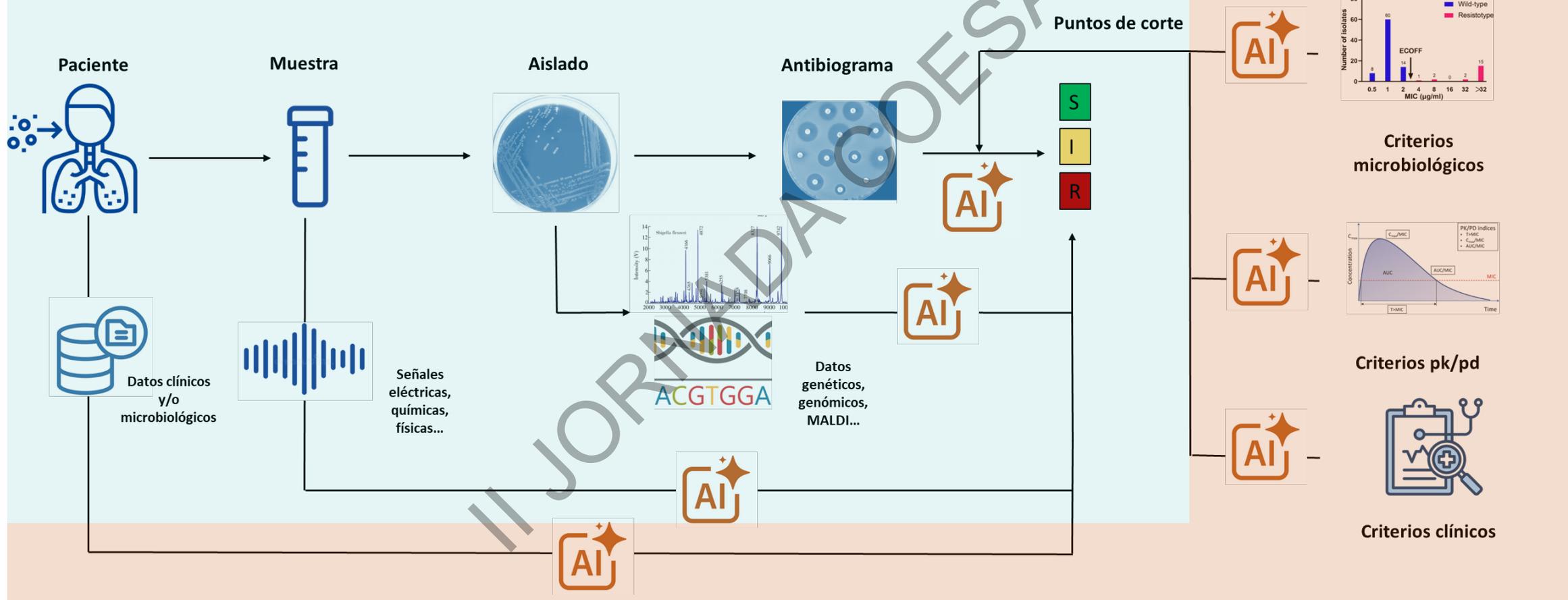
The Lancet Infectious Diseases Series on Artificial Intelligence and Infectious Diseases

Artificial intelligence (AI) offers promising opportunities to help tackle infectious disease threats by improving clinical management, outbreak detection, and infection control.

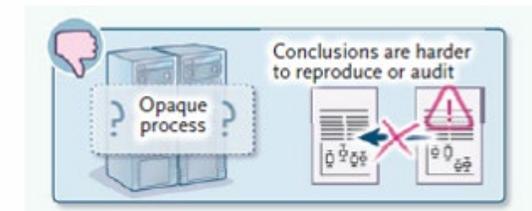
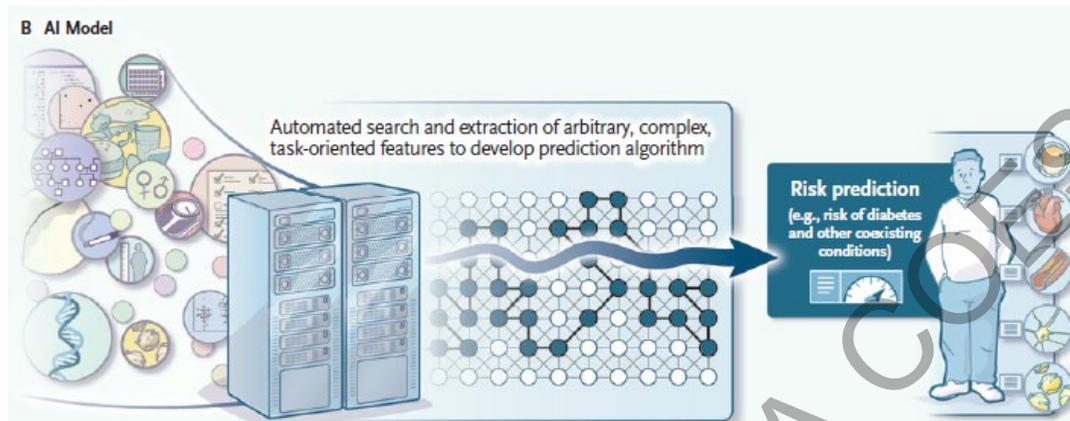
Potencial de la IA en la predicción de la resistencia

PREDICCIÓN SENSIBILIDAD IN VITRO

CORRELACIÓN CLÍNICA

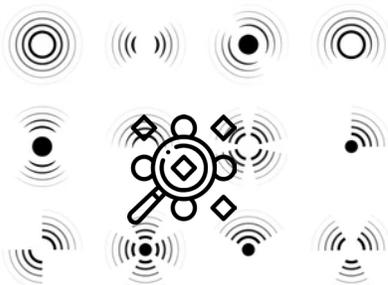


Antibiogramas rápidos y/o a partir de muestra directa

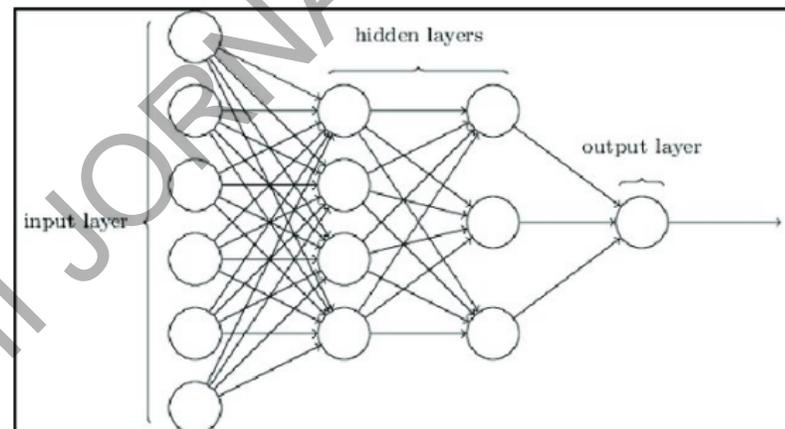


Hunter, D. J., & Holmes, C. (2023). Where Medical Statistics Meets Artificial Intelligence. *The New England journal of medicine*, 389(13), 1211–1219.

SEÑALES FENOTÍPICAS



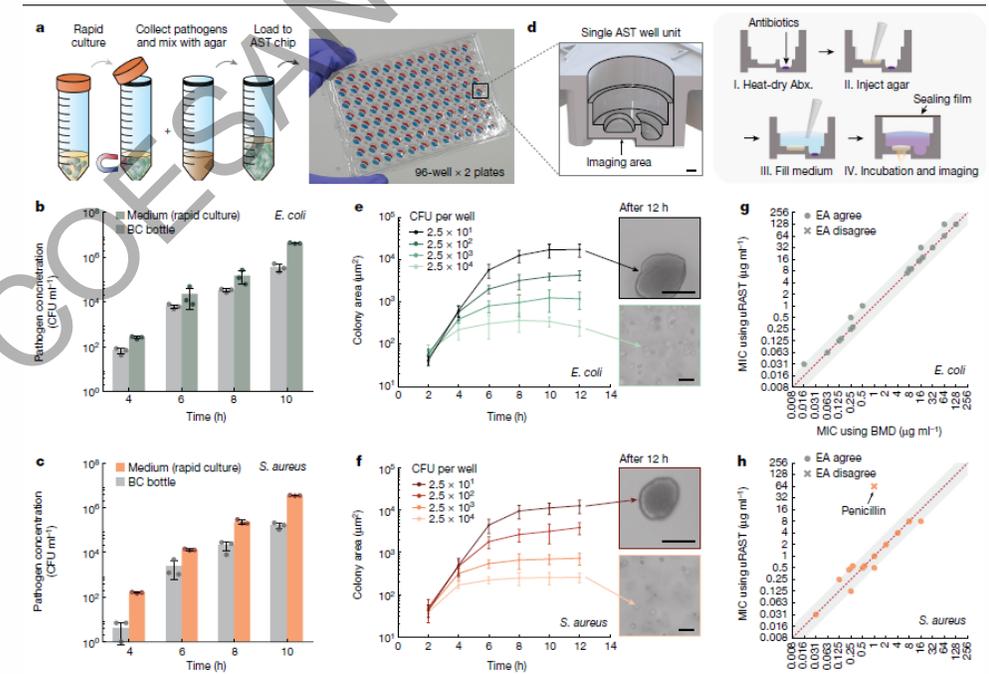
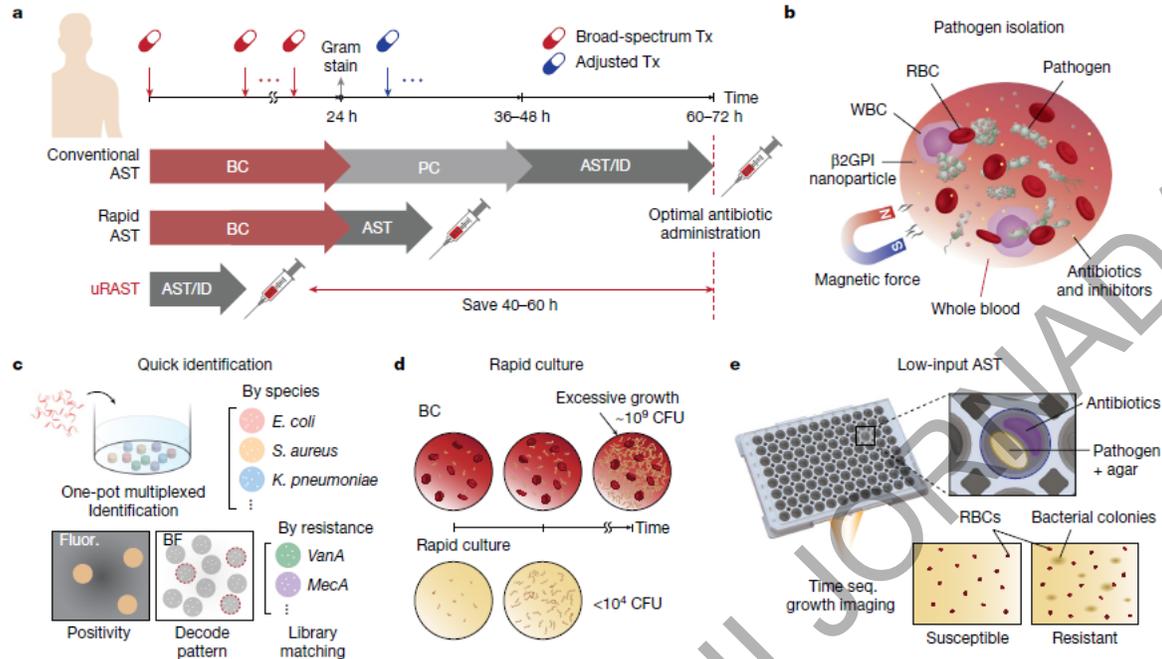
SEÑALES GENOTÍPICAS



Amoxicilina	R
Amoxicilina/Ácido clavulánico	R
Piperacilina/Tazobactam	R
Cefazolina	S
Cefuroxima	S
Cefotaxima/Ceftazidima	S
Cefepima	I

Antibiogramas rápidos y a partir de muestra directa

nature



- Captura mediante beta-2-glycoprotein I peptide
- Detección de microcolonias en ausencia/presencia de antibiótico
- Categorical agreement de 94.90% en 13h

Antibiogramas rápidos y a partir de muestra directa

nature communications



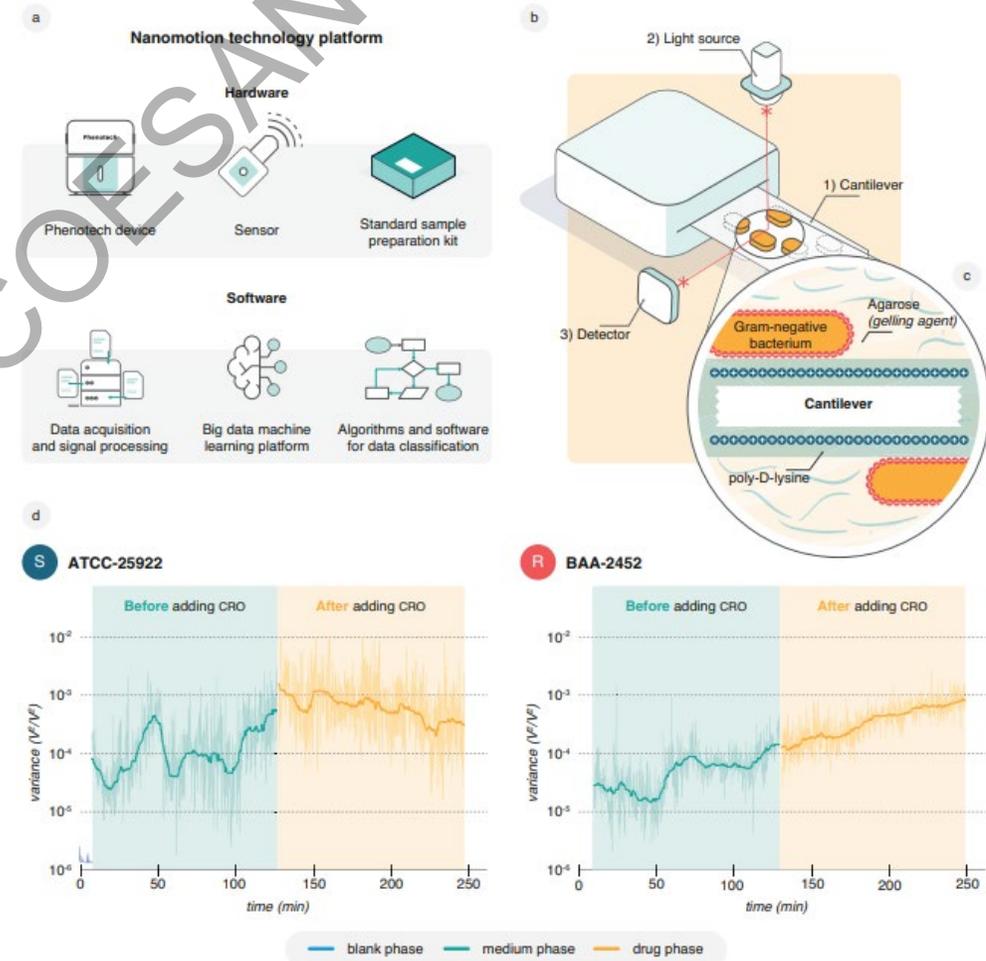
Article

<https://doi.org/10.1038/s41467-024-46213-y>

Accurate and rapid antibiotic susceptibility testing using a machine learning-assisted nanomotion technology platform

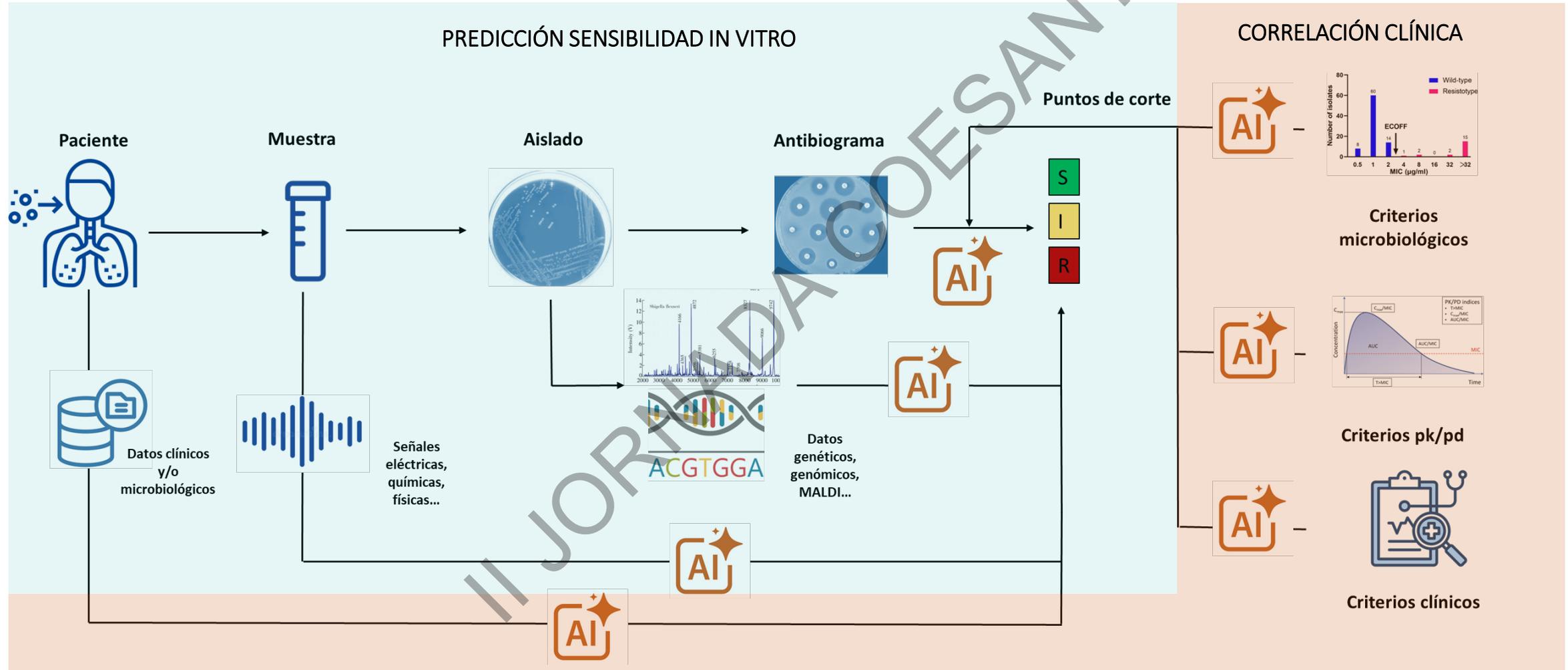
- Detección fenotípica independiente del crecimiento
- Basado en medición de vibración de células bacterianas
- Buenos valores de precisión diagnóstica

Metric	Model no. 1	Model no. 2	Model no. 3	Model no. 4
no. of samples	233	233	233	233
True positive	97	99	101	102
True negative	103	110	112	115
False positive	21	14	12	9
False negative	12	10	8	7
accuracy (%)	85.8	89.7	91.4	93.1
sensitivity (%)	89.0	90.8	92.7	93.6
specificity (%)	83.1	88.7	90.3	92.7
no. of SPs	1	2	3	4



Potencial de la IA en la predicción de la resistencia

PREDICCIÓN SENSIBILIDAD IN VITRO



Predicción de sensibilidad a partir de MALDI TOF/MS



BACTERIOLOGY
June 2023 Volume 61 Issue 6 e01751-22
<https://doi.org/10.1128/jcm.01751-22>

Direct Detection of Carbapenemase-Producing *Klebsiella pneumoniae* by MALDI-TOF Analysis of Full Spectra Applying Machine Learning

Eva Gato^a, Manuel J. Arroyo^b, Gema Méndez^b, Ana Candela^a, Bruno Kotska Rodiño-Janeiro^a, Javier Fernández ^c, Belén Rodríguez-Sánchez^d, Luis Mancera^b, Jorge Arca-Suárez^{a,e}, Alejandro Beceiro ^{a,e}, Germán Bou^{a,e}, Marina Oviaño ^{a,e}

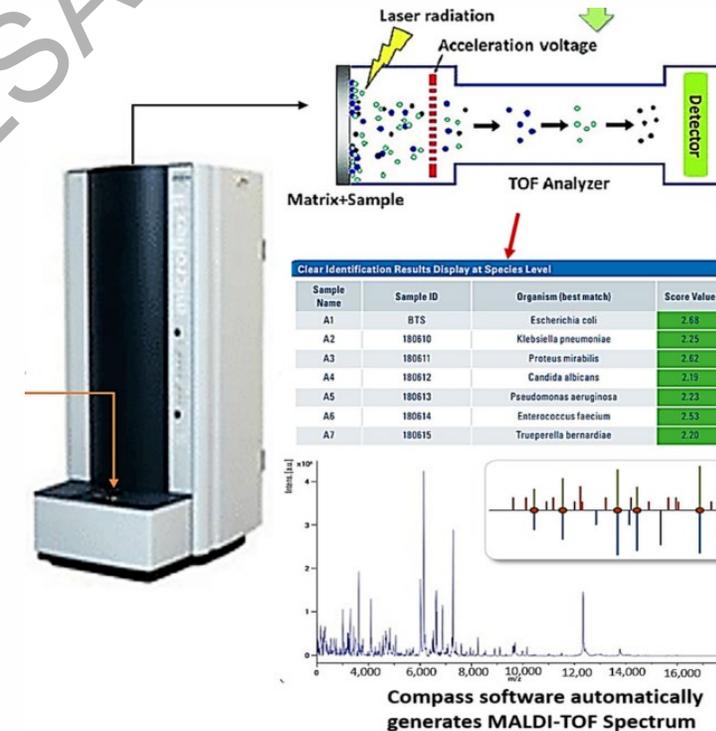
^aServicio de Microbiología, Complejo Hospitalario Universitario A Coruña, A Coruña, Spain

^bClover Bioanalytical Software S.L., Granada, Spain

^cServicio de Microbiología, Hospital Central de Asturias, Oviedo, Spain

^dServicio de Microbiología, Hospital General Gregorio Marañón, Madrid, Spain

^eCentro de Investigación Biomedica en Red Enfermedades Infecciosas (CIBERINFEC). Instituto de Salud Carlos III (ISCIII), Madrid, Spain



- 97,83 % precisión para detección de carbapenemasas

Predicción de sensibilidad a partir de genomas

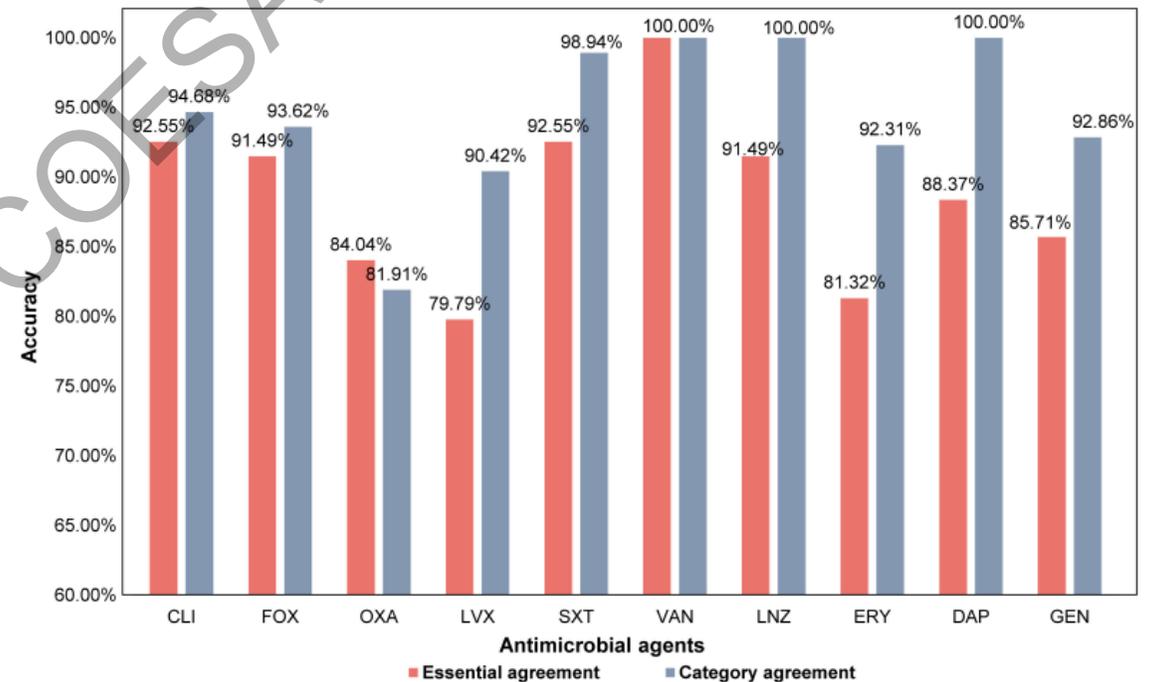
A Practical Approach for Predicting Antimicrobial Phenotype Resistance in *Staphylococcus aureus* Through Machine Learning Analysis of Genome Data

Shuyi Wang^{1,2†}, Chunjiang Zhao^{2†}, Yuyao Yin², Fengning Chen^{1,2}, Hongbin Chen² and Hui Wang^{1,2*}

TABLE 2 | Number of genomes with different minimum inhibitory concentration (MIC) to the 10 antimicrobial agents for the 466 *Staphylococcus aureus* isolates used in this study.

MICs (μg/mL) Antimicrobial agents	0.032	0.064	0.125	0.25	0.5	1	2	4	8	16	32	64	128	256	512	Total
Clindamycin	46	163	32	3	5	1			3	1	2	2	208			466
Cefoxitin							46	171	31	54	63	7	94			466
Oxacillin					217	40	39	39	15	13	5	5	93			466
Levofloxacin			51	207	45	26	5	9	33	90						466
Trimethoprim-Sulfamethoxazole	102	257	43	21	8	10	9	2	2	12						466
Vancocmycin					61	396	9									466
Linezolid					22	278	166									466
Erythromycin		4	33	112	6			4	9	6	9	12	12	10	237	454
Daptomycin			13	175	221	22										431
Gentamicin			8	34	3	5	1		1	4	2	1	5	3	2	69

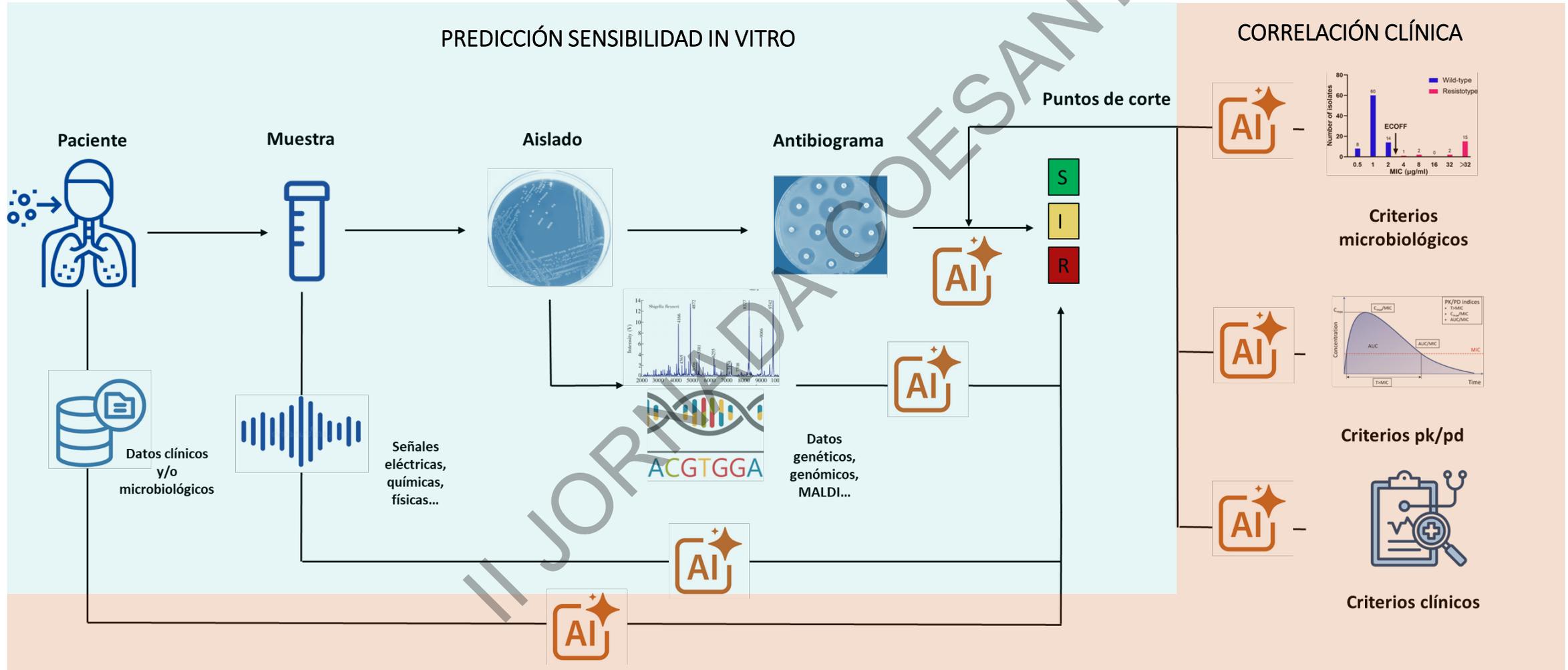
In this table, light green refers to susceptible isolates defined according to clinical breakpoints, light orange refers to intermediate isolates, and colorless refers to resistant isolates.



- Resultados de colonia en 18h

Potencial de la IA en la predicción de la resistencia

PREDICCIÓN SENSIBILIDAD IN VITRO



IA como asistente en la interpretación del antibiograma



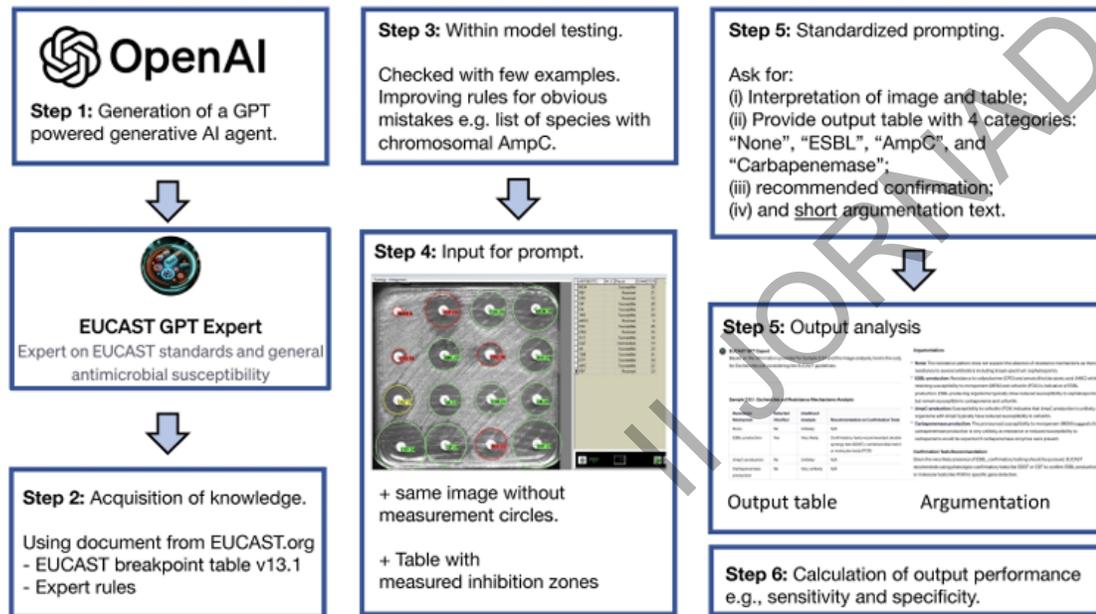
Journal of
Clinical Microbiology



Editor's Pick | Bacteriology | Full-Length Text

GPT-4-based AI agents—the new expert system for detection of antimicrobial resistance mechanisms?

Christian G. Giske,^{1,2} Michelle Bressan,³ Farah Fiechter,³ Vladimira Hinic,³ Stefano Mancini,³ Oliver Nolte,³ Adrian Egli³



- Analizados 225 aislados de enterobacterias
- GPT-4 sin personalizar: bajo rendimiento (sólo interpretó el 19.6% de los casos)
- GPT personalizado puede apoyar el diagnóstico, pero requiere validación a día de hoy

TABLE 1 Sensitivity and specificity of human experts and the customized EUCAST-GPT-expert

	Human experts ^a	EUCAST-GPT-expert ^b
ESBL		
Sensitivity	98.0% (91.8–100)	95.4% (94.5–96.3)
Specificity	99.1% (97.1–100)	69.2% (63.8–85.7)
AmpC		
Sensitivity	96.8% (93.3–100)	96.9% (87.5–96.9)
Specificity	97.1% (95.9–97.7)	86.3% (84.1–91.8)
Carbapenemases		
Sensitivity	95.5% (90.9–100)	100% (90.9–100)
Specificity	98.5% (98.5–98.5)	98.8% (98.8–98.8)

^aThree human experts (median).

^bThree independent prompting outputs from the customized GPT-4 agent "EUCAST-GPT-expert." As reference standard, we used the results reported according to our ISO-accredited laboratory information system. ESBL, extended spectrum beta-lactamase; None, no specific molecular resistance mechanism.

Potencial de la IA para la aplicación de puntos de corte dinámicos

EUCAST Clinical Breakpoint Table v. 1.3 2011-01-05

Other streptococci

Benzylpenicillin	0.25	2
Ampicillin	0.5	2
Ampicillin-sulbactam	Note ¹	Note ¹
Amoxicillin	0.5	2
Amoxicillin-clavulanate	Note ¹	Note ¹

Enterobacterales *

Benzylpenicillin	-	-
Ampicillin	Note ¹	8
Ampicillin-sulbactam ²	Note ¹	8
Amoxicillin	Note ¹	8
Amoxicillin-clavulanate ³	Note ¹	8

EUCAST Clinical Breakpoint Tables v. 16.0, valid from 2026-01-01

Viridans group streptococci

Benzylpenicillin (screen only)	0.25 ¹	0.25 ¹
Benzylpenicillin (indications other than endocarditis)	0.25	1
Benzylpenicillin (endocarditis)	0.25	0.25
Benzylpenicillin (endocarditis, in combination with other antimicrobial treatment)	(1) ²	(1) ²
Ampicillin (indications other than endocarditis)	0.5	2
Ampicillin iv (endocarditis)	0.5	0.5
Ampicillin-sulbactam ³	Note ^{1,4}	Note ^{1,4}
Amoxicillin (indications other than endocarditis)	0.5	2
Amoxicillin iv (endocarditis)	0.5	0.5
Amoxicillin-clavulanic acid ³	Note ^{1,4}	Note ^{1,4}

Enterobacterales *

Amoxicillin iv ¹	8	8	-	Note ^B	Note ^B
Amoxicillin oral (infections originating from the urinary tract) ¹	0.001	8	-	Note ^C	Note ^C
Amoxicillin oral (uncomplicated UTI only) ¹	8	8	-	Note ^B	Note ^B
Amoxicillin oral (other indications) ¹	(0.001) ³	(8) ³	-	Note ^{D,E}	Note ^{D,E}
Amoxicillin-clavulanic acid iv ¹	8 ⁴	8 ⁴	20-10	19 ^A	19 ^A 19-20
Amoxicillin-clavulanic acid oral (infections originating from the urinary tract) ¹	0.001 ⁴	8 ⁴	20-10	50 ^A	19 ^A 19-20
Amoxicillin-clavulanic acid oral (uncomplicated UTI only) ¹	32 ⁴	32 ⁴	20-10	16 ^A	16 ^A
Amoxicillin-clavulanic acid oral (other indications) ¹	(0.001) ^{3,4}	(8) ^{3,4}	20-10	(50) ^{A,D}	(19) ^{A,D} 19-20



Mito del Laberinto de Dédalo

Potencial de la IA para la aplicación de puntos de corte dinámicos

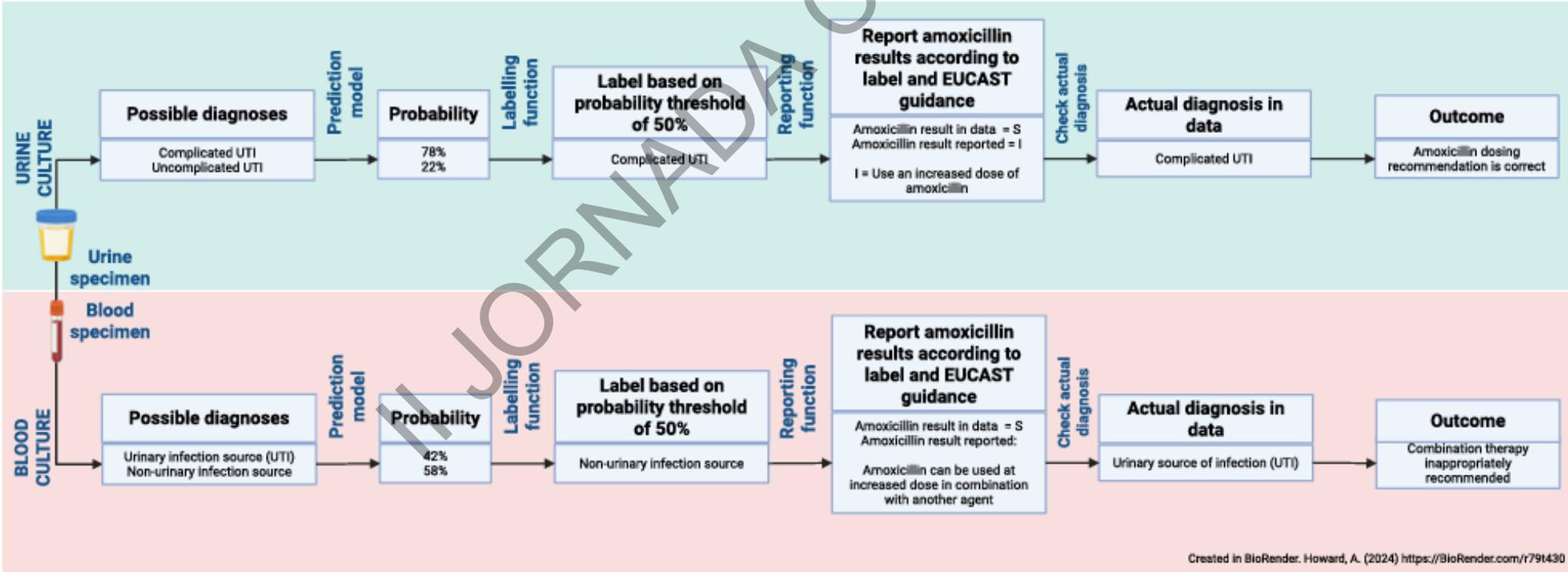
JOURNAL ARTICLE

Machine learning for personalized antimicrobial susceptibility breakpoints: (*Adaptive clinical breakpoint interpretation*)

Yinzheng Zhong, William Hope, Iain Buchan, Anoop Velluva, Alessandro Gerada, Conor Rosato, Peter L Green, Alex Howard

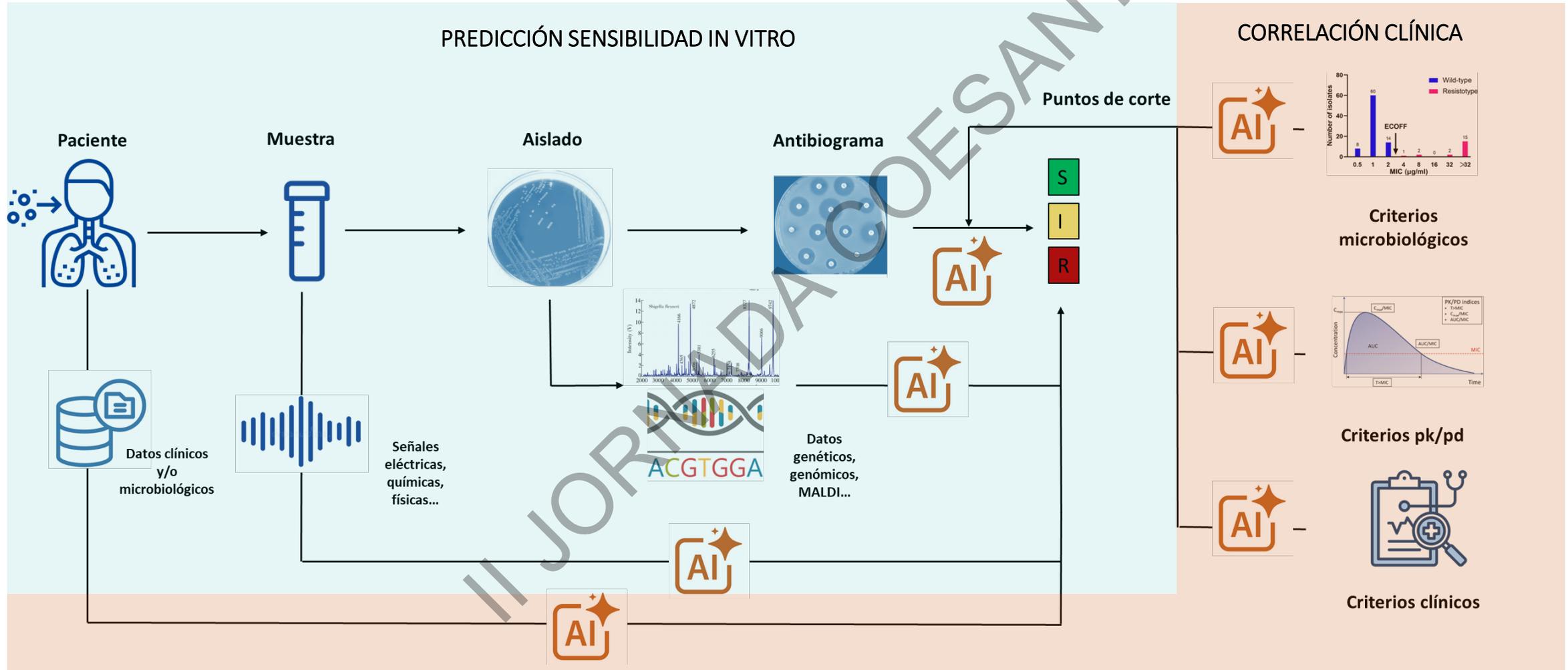
Journal of Antimicrobial Chemotherapy, Volume 81, Issue 1, January 2026, dkaf419,

Amoxicillin iv ¹	8	8	-	Note ^B	Note ^B	
Amoxicillin oral (infections originating from the urinary tract) ¹	0.001	8	-	Note ^C	Note ^C	
Amoxicillin oral (uncomplicated UTI only) ¹	8	8	-	Note ^B	Note ^B	
Amoxicillin oral (other indications) ¹	(0.001) ³	(8) ³	-	Note ^{D,E}	Note ^{D,E}	
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Amoxicillin-clavulanic acid oral (other indications) ¹	(0.001) ^{3,4}	(8) ^{3,4}	20-10	(50) ^{A,D}	(19) ^{A,D}	19-20

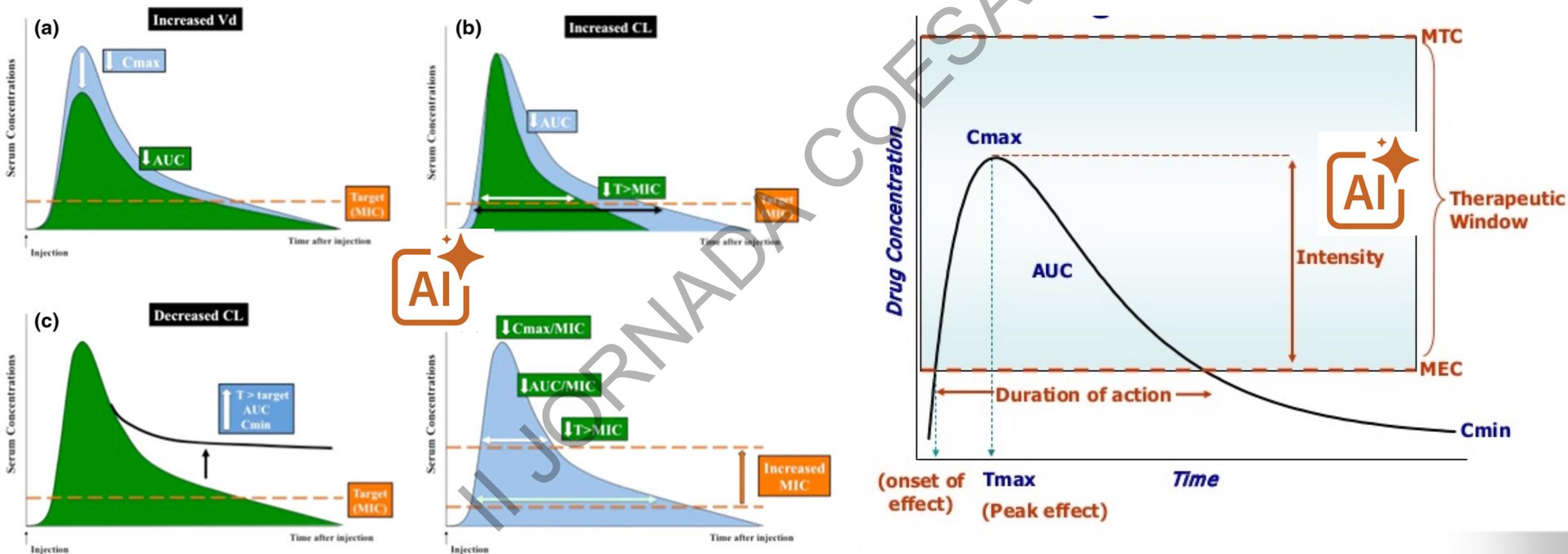


Potencial de la IA en la predicción de la resistencia

PREDICCIÓN SENSIBILIDAD IN VITRO



Potencial de la IA en PK-PD



- Importantes variaciones intra e interindividuales
- Imposibilidad de monitorización en todas las situaciones

Potencial de la IA en PK-PD

Clinical Pharmacokinetics (2024) 63:1137–1146
<https://doi.org/10.1007/s40262-024-01405-z>

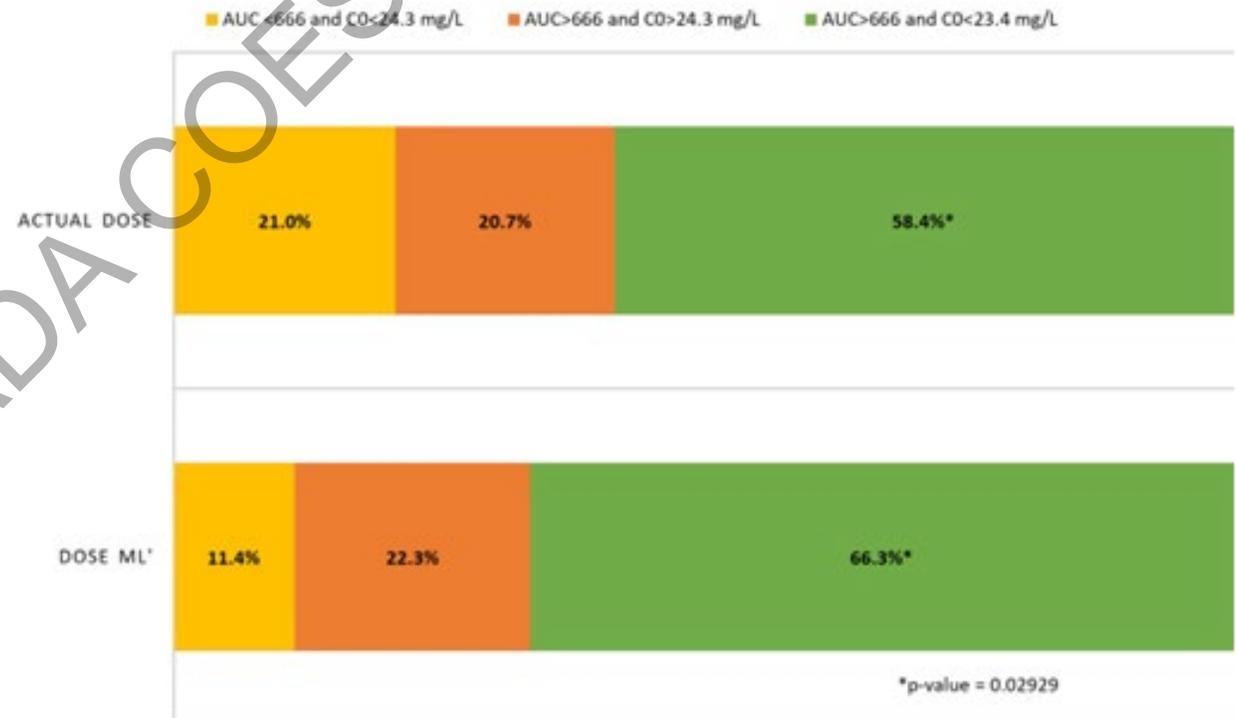
ORIGINAL RESEARCH ARTICLE



A Machine Learning Algorithm to Predict the Starting Dose of Daptomycin

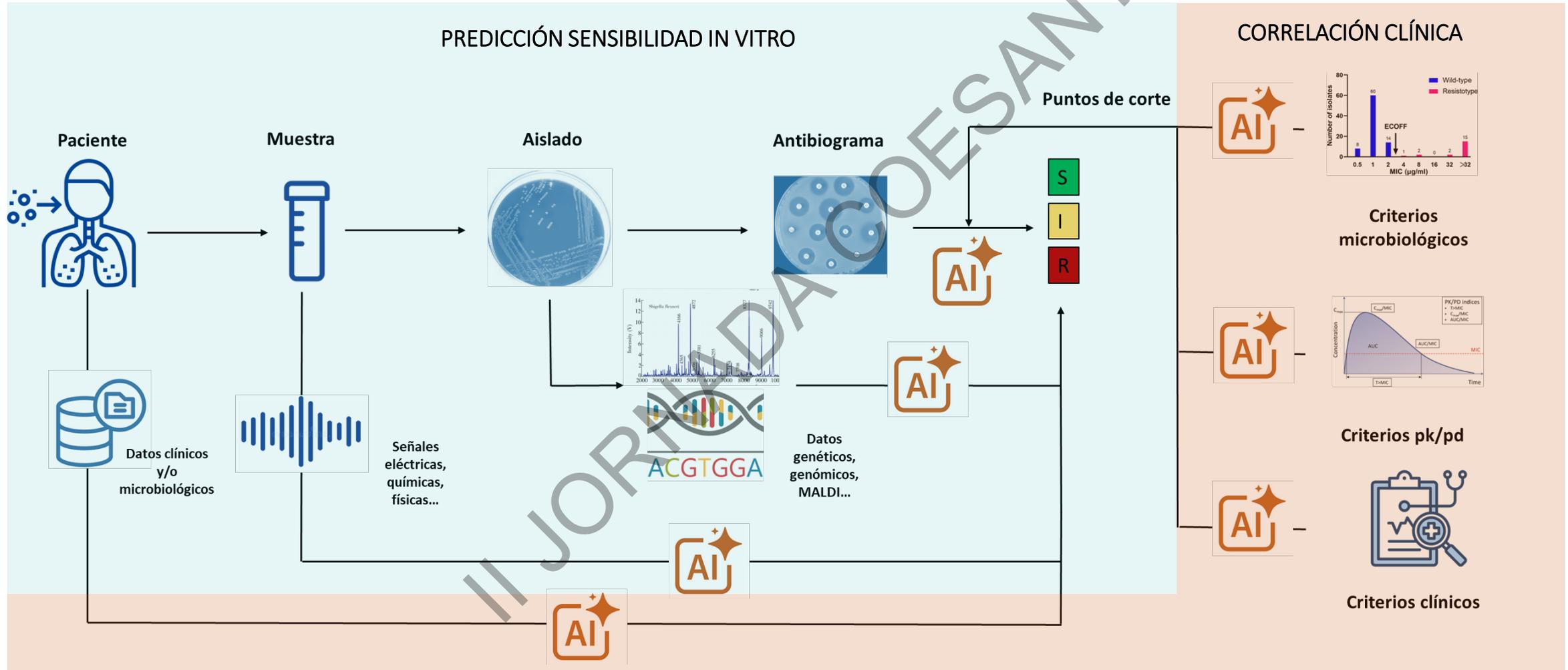
Florence Rivals¹ · Sylvain Goutelle^{2,3,4} · Cyrielle Codde^{5,6} · Romain Garreau^{2,3,4} · Laure Ponthier⁶ · Pierre Marquet^{1,6} · Tristan Ferry^{4,7,8} · Marc Labriffe^{1,6} · Alexandre Destere⁹ · Jean-Baptiste Woillard^{1,6}

- ML y pk/pd son claramente mejores que la práctica habitual sin diferencias significativas entre ambas (66.3% vs 68.3%, $p = 0.59$)
- ML sólo usa covariables clínicas y no ecuaciones complejas pk/pd
- El ML no sustituye al pk/pd clásico, pero puede ser una alternativa práctica, rápida y clínica, especialmente integrada en una app.



Potencial de la IA en la predicción de la resistencia

PREDICCIÓN SENSIBILIDAD IN VITRO



Potencial de la IA para la correlación clínica



JAMA Network

This Issue Views **20,356** | Citations **70** | Altmetric **191**

Viewpoint | ONLINE FIRST

June 26, 2013

Personalized Medicine vs Guideline-Based Medicine

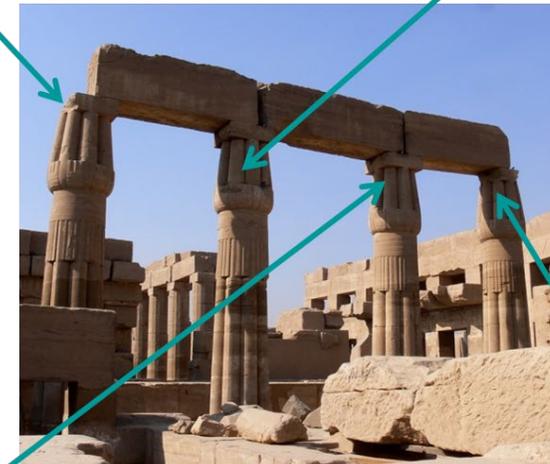
Jeffrey J. Goldberger, MD, MBA; Alfred E. Buxton, MD

- Criterios de inclusión y exclusión dejan fuera cierta población
- Resultados aplicables a poblaciones no a individuos
- Miles de variables a tener en cuenta: microorganismo, virulencia, resistencia...

Goldberger, J. J., & Buxton, A. E. (2013). Personalized medicine vs guideline-based medicine. *JAMA*, 309(24), 2559–2560.

Características del paciente
(gravedad, comorbilidades...)

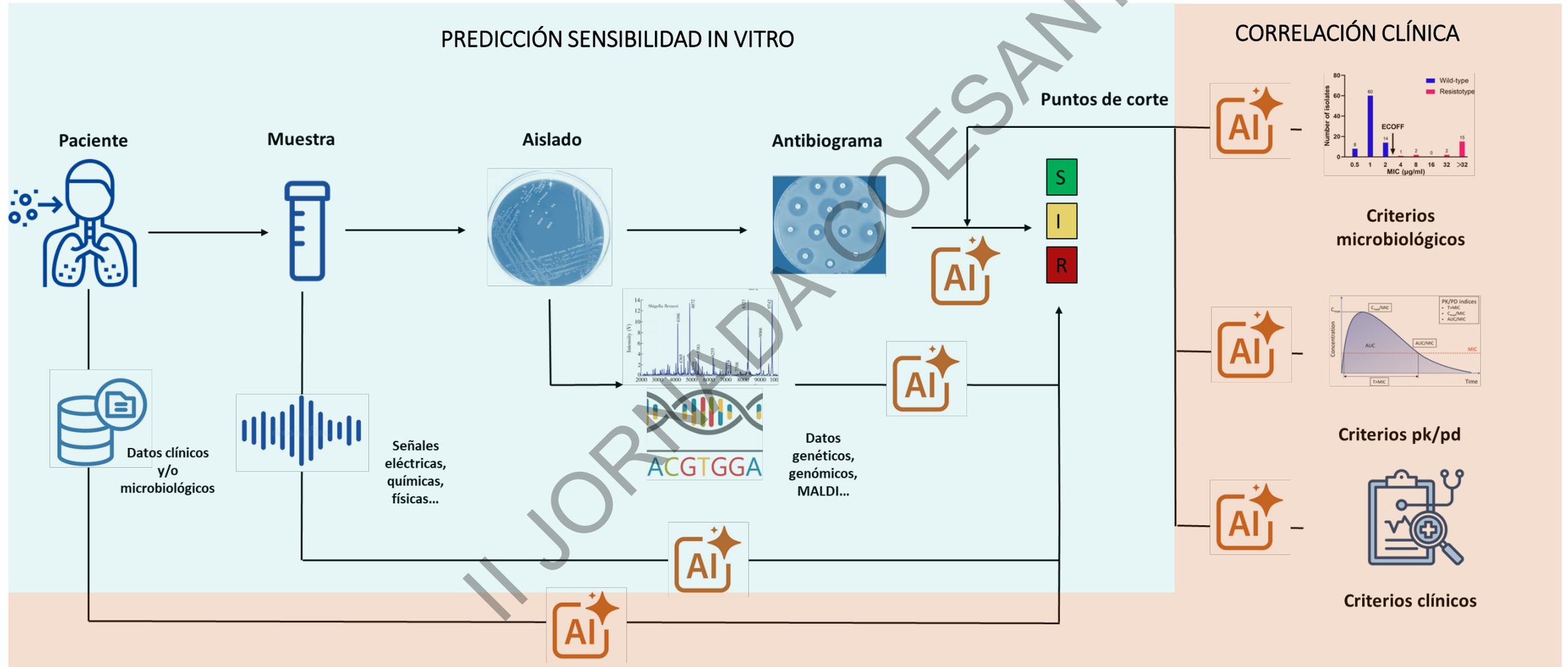
Origen de la infección



Propiedades del fármaco

Características de la bacteria
(mecanismos de resistencia)

Potencial de la IA en la predicción de la resistencia



Herramientas actuales para guiar la antibioterapia empírica

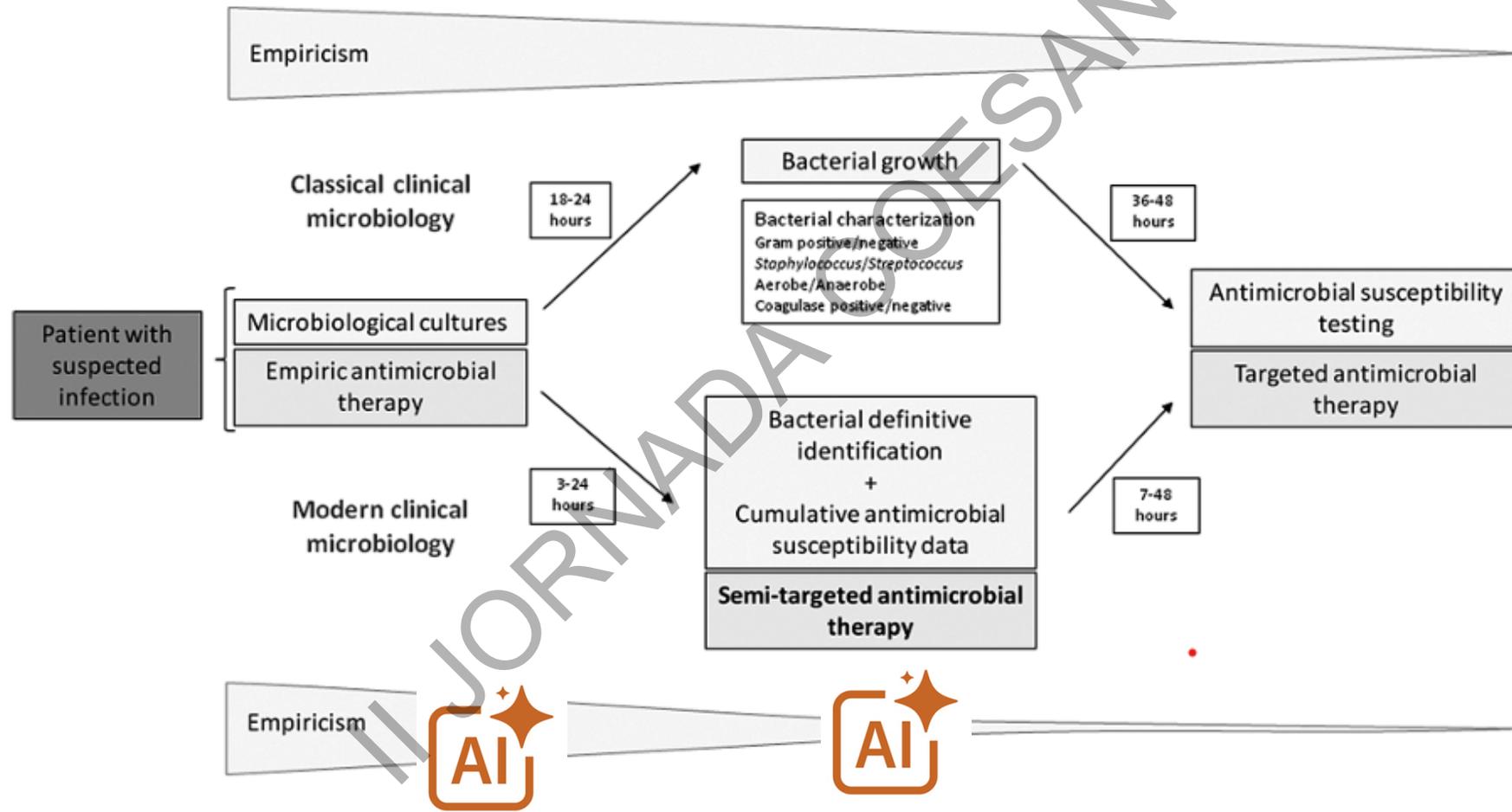


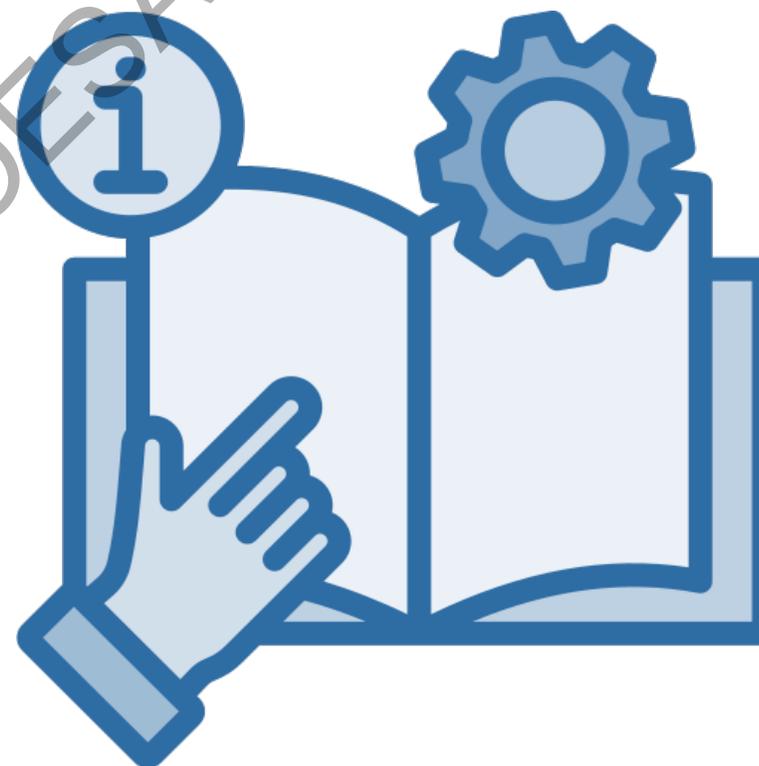
Figure 1. Integration of cumulative antimicrobial susceptibility data in the diagnostic stewardship.

Herramientas actuales para guiar la antibioterapia empírica

Informes de sensibilidad acumulada

	n	AMP	AMC	CRM	CTX	CIP	SXT	GM	TOB	FOS	NTF
<i>Escherichia coli</i>	3044	51,3	90,0	87,1	88,5	72,1	71,9	90,0	86,6	95,8	94,3
<i>Escherichia coli</i> BLEE	335	0,0	74,0	0,0	0,0	14,0	33,1	69,9	48,4	82,7	99,4
<i>Klebsiella pneumoniae</i>	578	R	85,1	83,1	86,2	79,9	85,6	94,6	91,4	NT	87,5
<i>Klebsiella pneumoniae</i> BLEE	75	R	42,7	0,0	0,0	12,0	21,3	62,7	41,3	NT	62,7
<i>Proteus mirabilis</i>	342	61,4	89,8	94,1	97,4	64,3	64,0	74,6	67,0	NT	R
<i>Pseudomonas aeruginosa</i>	161	R	R	R	R	87,6	R	NT	92,6	NT	R
<i>Morganella morganii</i>	94	R	R	R	76,2	62,8	64,9	78,7	85,1	NT	R
<i>Enterobacter cloacae</i> complex	77	R	R	R	71,1	85,7	75,3	93,5	93,5	NT	69,8
<i>Klebsiella oxytoca</i>	68	R	89,7	92,2	97,1	92,6	89,7	97,1	97,1	NT	100,0
<i>Citrobacter freundii</i> complex	53	R	R	R	75,5	79,3	79,3	90,6	90,6	NT	100,0
<i>Citrobacter koseri</i>	68	R	97,1	88,0	100,0	100,0	100,0	100,0	100,0	NT	98,5
<i>Klebsiella varillocola</i>	50	R	94,0	98,0	100,0	92,0	98,0	100,0	100,0	NT	98,0
<i>Klebsiella aerogenes</i>	45	R	R	R	88,9	93,3	100,0	97,8	95,6	NT	84,4
<i>Providencia stuartii</i>	35	R	R	R	77,1	8,6	80,0	R	R	NT	R

Guías de tratamiento empírico



- Información limitada
- No bien difundido entre médicos prescriptores

Potencial de la IA para guiar la antibioterapia empírica

Table 1. Performance of machine learning across different studies in predicting antibiotic susceptibility patterns.

Authors	Year of Publication	Medical Setting	Geographical Setting	Input Data	ML Algorithms	Performance Evaluation	Bacterial Species
Goodman et al. [27]	2016	Hospital admissions	USA	Blood cultures/AST	Recursive partitioning, DT	PPV 0.908-NPV 0.919	<i>Escherichia coli</i> , <i>Klebsiella pneumoniae</i> , <i>Klebsiella oxytoca</i>
Vazquez-Guillamet et al. [29]	2017	Hospital admissions	USA	EHR data/Blood cultures/AST	Recursive partitioning, DT	AUC 0.61–0.80	GNB
Sousa et al. [28]	2019	Hospital admissions	Spain	Clinical/demographic data/Blood cultures/AST	DT	AUC 0.76	BL-GNB
Moran et al. [20]	2020	Hospital admissions and primary care	UK	Blood/urine cultures	XGBoost	AUC 0.70	<i>Escherichia coli</i> , <i>Klebsiella pneumoniae</i> and <i>Pseudomonas aeruginosa</i>
Feretzakis et al. [33]	2020	Medical wards	Greece	Demographics/Cultures/AST/Bacterial Gram stain/Type of sample	MLR	AUC 0.758	All isolated bacterial species
Feretzakis et al. [34]	2020	Intensive Care Unit	Greece	Demographics/Cultures/AST/Bacterial Gram stain/Type of sample	LR, RF, k-NN, J48, MLP	AUC 0.726	All isolated bacterial species
Feretzakis et al. [35]	2021	Intensive Care Unit	Greece	Demographics/Cultures/AST/Bacterial Gram stain/Type of sample	JRip, RF, MLP, Class. Repr, REPTree	F-measure 0.884, AUC 0.933	<i>Pseudomonas aeruginosa</i> , <i>Acinetobacter baumannii</i> , <i>Klebsiella pneumoniae</i>
Martínez-Agüero et al. [36]	2019	Intensive Care Unit	Spain	Demographics/Clinical data/Type of sample/Cultures/AST	LR, k-NN, DT, RF, MLP	Accuracy for quinolone resistance 88.1 ± 1.6	<i>Pseudomonas</i> , <i>Stenotrophomonas</i> , <i>Enterococcus</i>
McGuire et al. [5]	2021	Hospital admissions	USA	Demographic, medication, vital sign, laboratory, billing code, procedure, culture, and sensitivity data (67 features)	XGBoost	AUC 0.846	Bacterial isolates with CR
Pascual-Sánchez et al. [32]	2021	Intensive Care Unit	Spain	EHR data	LR, DT, RF, XGBoost, MLP	AUC 0.76	MDR bacteria
García-Vidal et al. [31]	2021	FN Hematological Patients	Spain	EHR data	RF, GBM, XGBoost, GLM	AUC 0.79	MDR- <i>Pseudomonas aeruginosa</i> / ESBL-E
Henderson et al. [30]	2022	HIV patients	USA	EHR data	PLR, naïve Bayes, gradient boosting, SVM, RF	AUC 0.70	MDR-E

Potencial de la IA para guiar la antibioterapia empírica



ANTIMICROBIAL STEWARDSHIP
October 2024 Volume 68 Issue 10 e00777-24
<https://doi.org/10.1128/aac.00777-24>

Retrospective validation study of a machine learning-based software for empirical and organism-targeted antibiotic therapy selection

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Potencial de la IA para guiar la antibioterapia empírica

El paciente ha tenido una multiresistencia de tipo ECBLEE causada por Escherichia coli 30 días atrás.

✓	ANTIBIÓTICO	COBERTURA (%)
<input type="checkbox"/>	↑ MEROPENEM	96,95
<input type="checkbox"/>	↑ AMIKACINA	96,39
<input type="checkbox"/>	↑ ERTAPENEM	94,87
<input type="checkbox"/>	↑ NITROFURANTOINA	90,3
<input type="checkbox"/>	↑ IMIPENEM	87,43
<input type="checkbox"/>	↑ PIPERACILINA_TAZOBACTAM	85,96
<input type="checkbox"/>	⇒ FOSFOMICINA	83,3
<input type="checkbox"/>	⇒ GENTAMICINA	74,19
<input type="checkbox"/>	⇒ TOBRAMICINA	56,16
<input type="checkbox"/>	⇒ CEFEPIMA	55,67
<input type="checkbox"/>	⇒ CEFTAZIDIMA	53,82
<input type="checkbox"/>	⇒ AMOXICILINA_CLAVULANICO	50,47
<input type="checkbox"/>	↓ CEFUROXIMA	45,28
<input type="checkbox"/>	↓ TRIMETOPRIM_SULFAMETOXAZOL	41,13
<input type="checkbox"/>	↓ CEFOTAXIMA	38,96
<input type="checkbox"/>	↓ CIPROFLOXACINA	29,94

Procedencia: Hospital Modelo × Tipo de Atención: HOSPITAL × Servicio:

Tipo de Infección: Otras infecciones de tracto respiratorio inferior ×

Subtipo de infección: Neumonía comunitaria en pacientes con EPOC/bro... ×

PREDICCIÓN IAST

Los resultados mostrados para estas infecciones se basan exclusivamente en guías locales del hospital. No se utiliza Inteligencia Artificial para proveer de estas recomendaciones

Opción ×

- Antibiótico
- Tratamiento alternativo en neumonía leve (CURB-65: 0-1). Elección en pacientes alérgicos a betalactámicos o sospecha de Legionella.
 - LEVOFLOXACINA
- Tratamiento de elección en neumonía leve (CURB-65: 0-1).
 - AMOXICILINA_CLAVULANICO
- Tratamiento de elección en neumonía moderada/grave (CURB-65: >2) en pacientes alérgicos a betalactámicos.
 - MEROPENEM+LEVOFLOXACINA
 - AZTREONAM+LEVOFLOXACINA
- Tratamiento de elección en neumonía moderada/grave (CURB-65: >2).
 - CEFEPIMA
 - CEFEPIMA+LEVOFLOXACINA

Conclusiones: Potencial de la IA en la predicción de la sensibilidad a los antimicrobianos

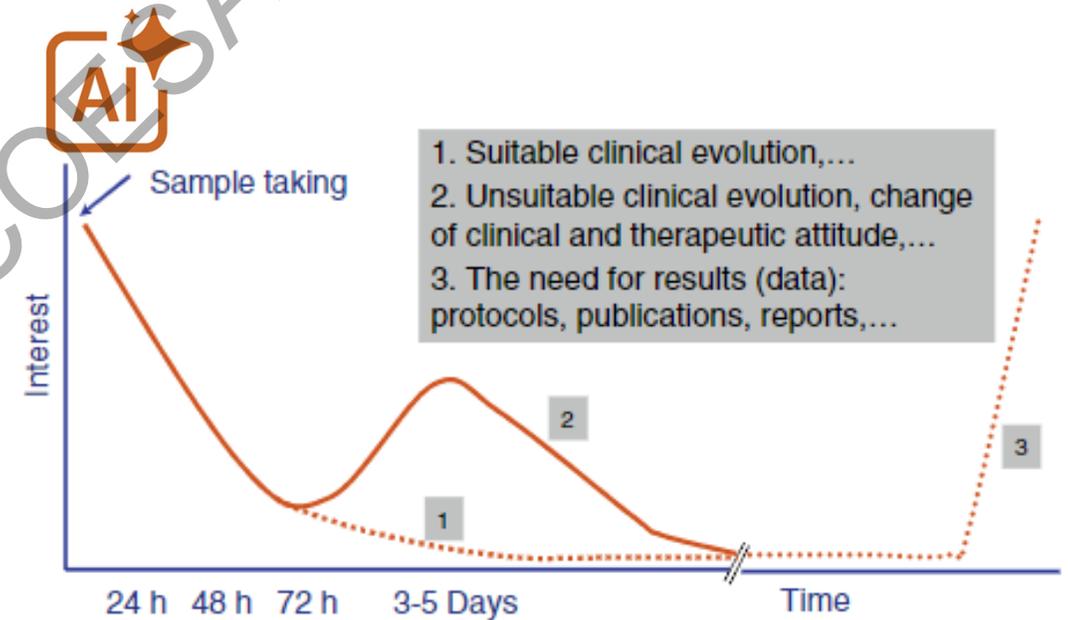
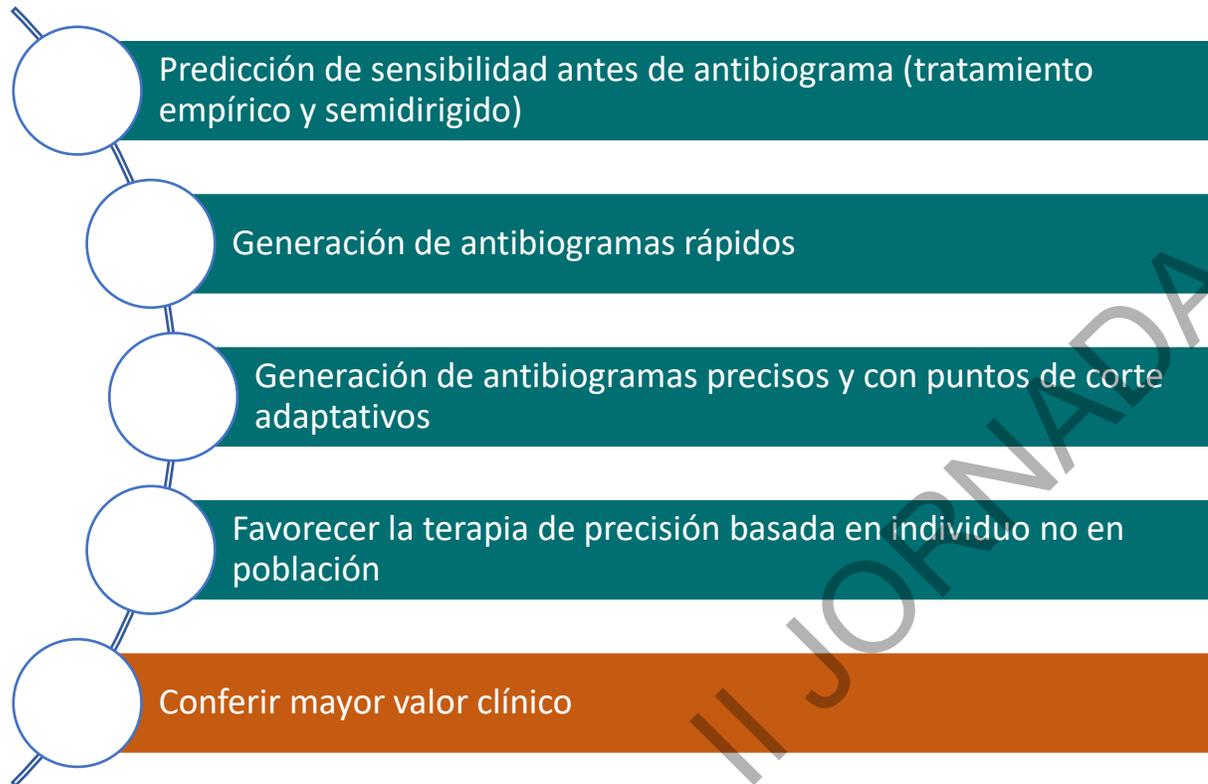


Figure 1. Evolution of the interest in the results of microbiological studies by the doctor who requested them.

Cantón R, et al. Economic impact of rapid diagnostic methods in Clinical Microbiology: Price of the test or overall clinical impact. *Enferm Infecc Microbiol Clin.* 2017 Dec;35(10):659-666.



¡MUCHAS GRACIAS!

Javier Fernández Domínguez

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