# Intelligence Artificielle au service des Urgences

CIPIQ-S Octobre 2024

Flament Julien

CHU UCL NAMUR

# Plan

- Définitions
- Place(s) de l'IA en Médecine d'Urgence
- Exemples
- Ecueils

# Intelligence Artificielle (AI)

- L'IA désigne la possibilité pour une machine de reproduire des comportements liés aux humains, tels que le raisonnement, la planification et la créativité.

# American Medical Association

« Intelligence Augmentée »
plutôt que
« Intelligence Artificielle »
en médecine afin de souligner le rôle d'assistance des ordinateurs dans l'amélioration des capacités humaines, plutôt que dans leur remplacement

# Intelligence Artificielle (AI)

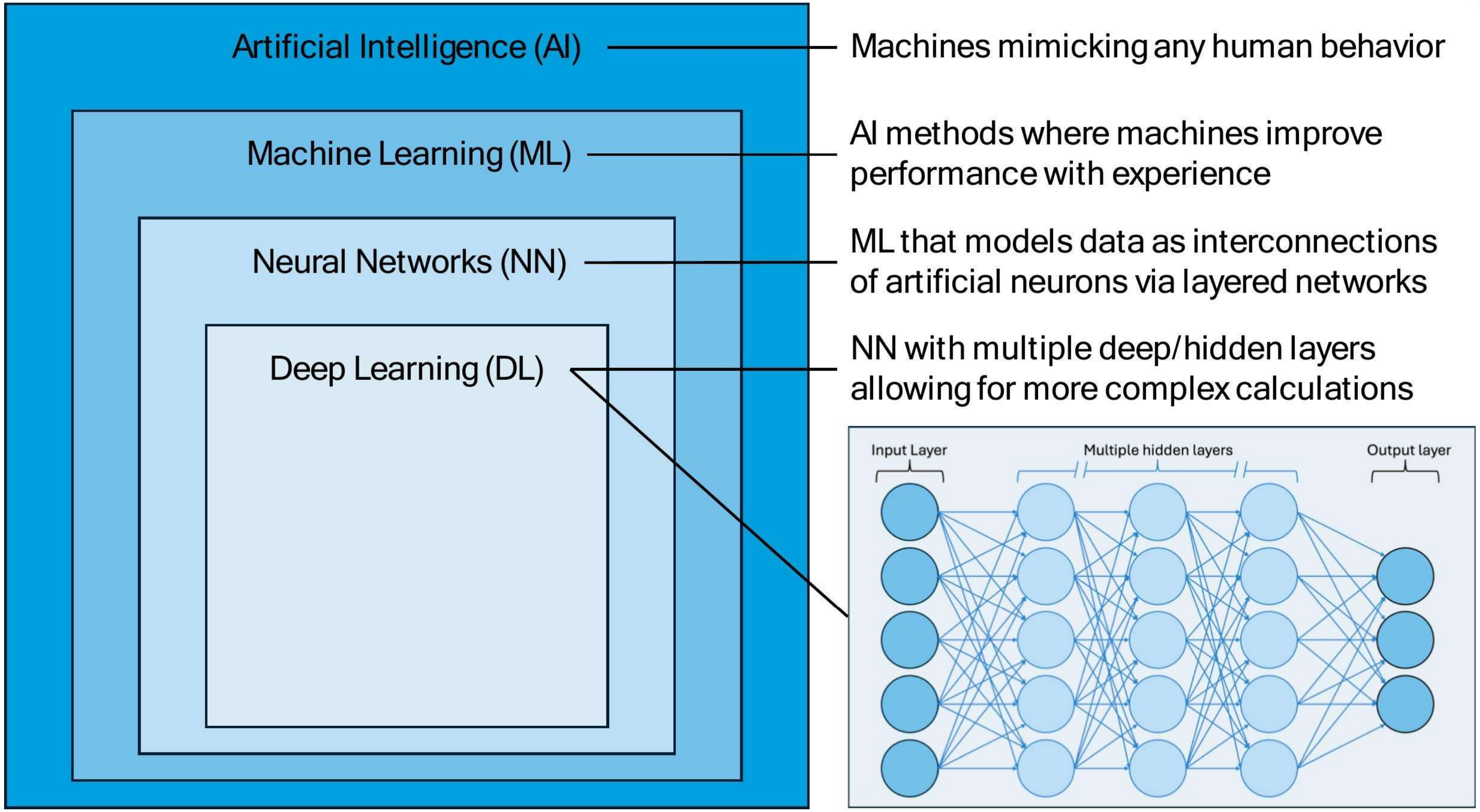
- Les technologies d'intelligence artificielle, ou IA, permettent aux ordinateurs et aux machines de simuler l'intelligence humaine et ses capacités de résolution des problèmes.

➢ Imitateur des fonctions cognitives humaines

➢ Basé sur des règles (algorithmes)

➢ Basé sur des exemples (recherche de patterns similaires): Machine Learning (ML), Neural Network (NN) et Deep Learning (DL)

IBM




Kachman MM, Brennan I, Oskvarek JJ, Waseem T, Pines JM. How artificial intelligence could transform emergency care. *Am J Emerg Med*. 2024;81:40-46. doi:10.1016/j.ajem.2024.04.024

# Emergency Department
# Service d’Urgences

- un service hospitalier dont le personnel est présent 24 heures sur 24, 7 jours sur 7, et qui fournit des services ambulatoires non programmés aux patients dont l'état de santé nécessite des soins immédiats

NHAMCS™
National Hospital Ambulatory Medical Care Survey

# Challenge en Médecine d'Urgence

- Saturation des salles d'urgences:

Augmentation visites

Augmentation des revisites

Visites non urgentes

Manque de personnel ⟷ Epuisement du personnel

- Conséquences:

Augmentation mortalité

Augmentation morbidité

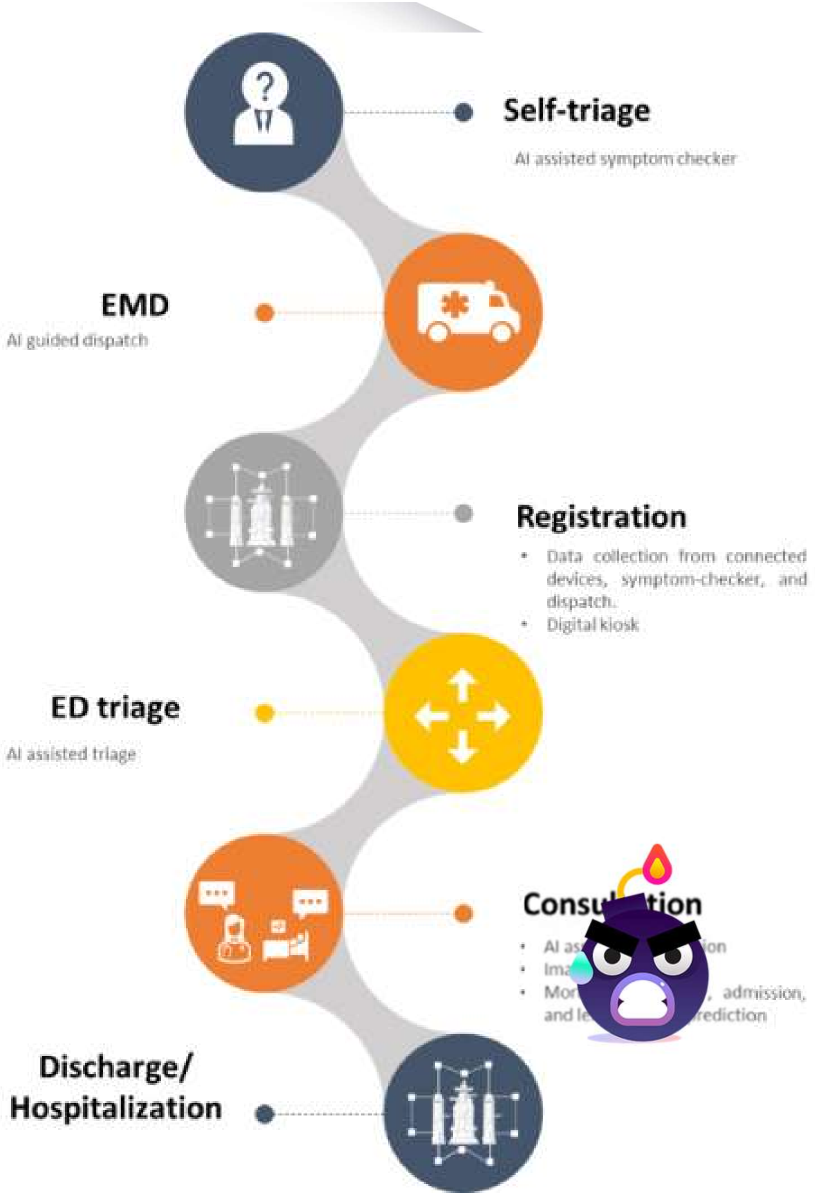
Insatisfaction patient

Epuisement du personnel

Hooker EA, Mallow PJ, Oglesby MM. Characteristics and Trends of Emergency Department Visits in the United States (2010-2014). *J Emerg Med*. 2019;56(3):344-351. doi:10.1016/j.jemermed.2018.12.025

Kulstad EB, Sikka R, Sweis RT, Kelley KM, Rzechula KH. ED overcrowding is associated with an increased frequency of medication errors. *Am J Emerg Med*. 2010;28(3):304-309. doi:10.1016/j.ajem.2008.12.014

# Parcours Patient




Chenais G, Lagarde E, Gil-Jardiné C. Artificial Intelligence in Emergency Medicine: Viewpoint of Current Applications and Foreseeable Opportunities and Challenges. *J Med Internet Res*. 2023;25:e40031. Published 2023 May 23. doi:10.2196/40031

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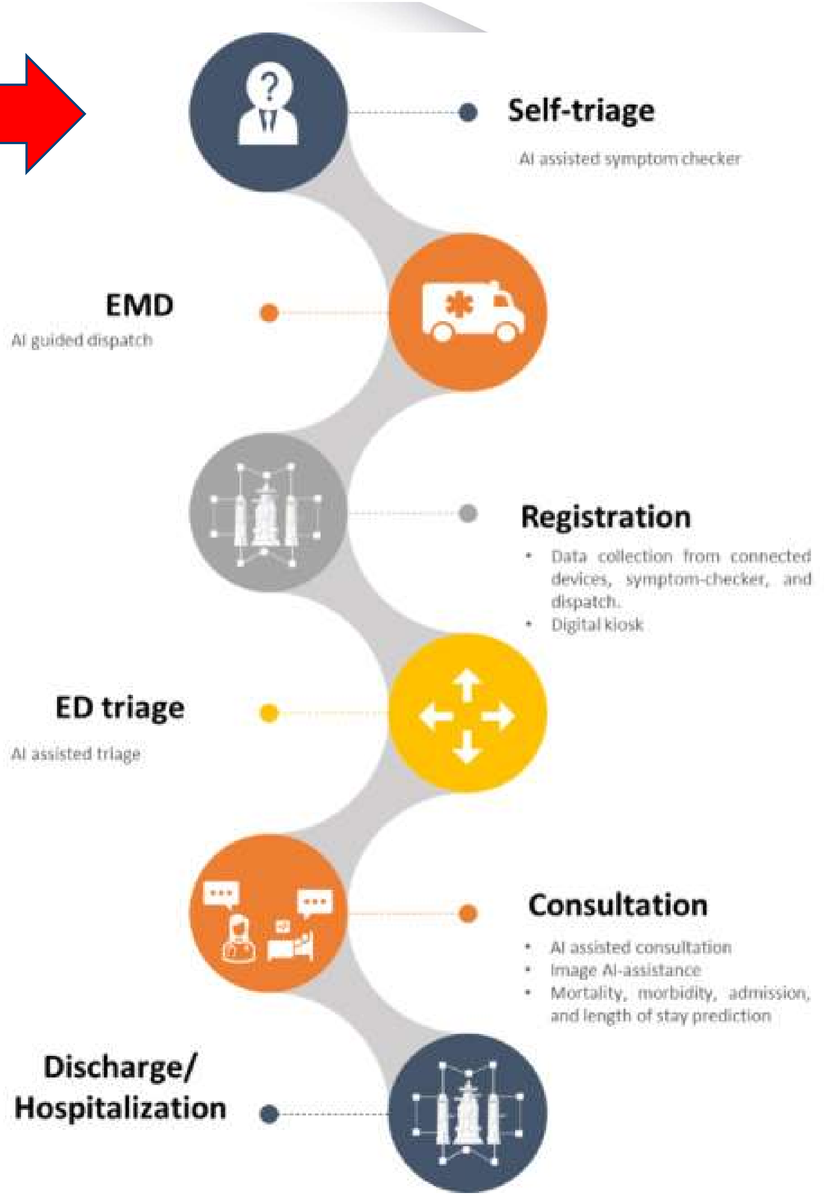


Chenais G, Lagarde E, Gil-Jardiné C. Artificial Intelligence in Emergency Medicine: Viewpoint of Current Applications and Foreseeable Opportunities and Challenges. *J Med Internet Res*. 2023;25:e40031. Published 2023 May 23. doi:10.2196/40031

# Self Triage préhospitalier

- 35% des US consultent internet pour autodiagnostic

- When we asked respondents about the accuracy of their initial diagnosis, they reported:
- 41% of online diagnosers say a medical professional confirmed their diagnosis. An additional 2% say a medical professional partially confirmed it.
- 35% say they did not visit a clinician to get a professional opinion.
- 18% say they consulted a medical professional and the clinician either did not agree or offered a different opinion about the condition.
- 1% say their conversation with a clinician was inconclusive.
- self diagnosis usually starts with search engines like Google, Bing, or Yahoo

Fox S, Duggan M. Health Online 2013. Internet and American life project. Pew Research Center and California Health Care Foundation, 2013:4.

# Self Triage préhospitalier

- Les sites internet et applications de « vérificateurs de symptômes » sont ils de bons régulateurs?

- 23 symptoms checkers
  ie: https://familydoctor.org/diseases-and-conditions/
  ie: https://myhealth.alberta.ca/health/Pages/conditions.aspx?hwid=hwsxchk
- 45 vignettes cliniques

Semigran HL, Linder JA, Gidengil C, Mehrotra A. Evaluation of symptom checkers for self diagnosis and triage: audit study. *BMJ*. 2015;351:h3480. Published 2015 Jul 8. doi:10.1136/bmj.h3480

# Self Triage préhospitalier

**Table 2**

Accuracy of diagnosis decision and triage advice for all symptom checkers, stratified by severity of standardized patient (SP) vignette and by frequency of the condition's diagnosis

| Type of vignette or diagnosis | No of vignettes (%) | Diagnosis: Listed first | | | | Diagnosis: Listed in top 3 | | | | Diagnosis: Listed in top 20 | | | Triage | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Rate* | % (95% CI) | P value | | Rate* | % (95% CI) | P value | | Rate* | % (95% CI) | P value | Rate* | % (95% CI) | P value |
| All vignettes | 45 (100) | 262/770 | 34 (31 to 37) | — | | 394/770 | 51 (47 to 54) | — | | 449/770 | 58 (55 to 62) | — | 301/532 | 57 (52 to 61) | — |
| Type of SP vignette: | | | | | | | | | | | | | | | |
| Emergent | 15 (33) | 64/263 | 24 (19 to 30) | | | 104/263 | 40 (34 to 46) | | | 132/263 | 50 (44 to 56) | | 147/183 | 80 (75 to 86) | |
| Non-emergent | 15 (33) | 98/260 | 38 (32 to 44) | <0.001 | | 148/260 | 57 (51 to 63) | <0.001 | | 157/260 | 60 (54 to 66) | 0.003 | 96/175 | 55 (47 to 63) | <0.001 |
| Self care | 15 (33) | 100/247 | 40 (34 to 47) | | | 142/247 | 57 (51 to 63) | | | 160/247 | 65 (59 to 71) | | 58/174 | 33 (26 to 40) | |
| Type of diagnosis†: | | | | | | | | | | | | | | | |
| Common | 26 (58) | 174/457 | 38 (34 to 43) | 0.004 | | 254/457 | 56 (52 to 61) | <0.001 | | 283/457 | 62 (57 to 66) | 0.01 | 162/313 | 52 (46 to 57) | 0.01 |
| Uncommon | 19 (42) | 88/313 | 28 (23 to 33) | | | 140/313 | 45 (38 to 49) | | | 166/313 | 53 (47 to 59) | | 139/219 | | |

Semigran HL, Linder JA, Gidengil C, Mehrotra A. Evaluation of symptom checkers for self diagnosis and triage: audit study. *BMJ*. 2015;351:h3480. Published 2015 Jul 8. doi:10.1136/bmj.h3480

# Self Triage préhospitalier

- Babylon Triage and Diagnostic System (Babylon AI)

« Applications permettant un diagnostic / une orientation au patient »

- Quelles bases de donnée?
- Employés de Babylon dans l'échantillon
- Pas d'up-to-date depuis 2022
- Diagnostics à sélectionner dans une liste
- Monopathologie

Baker A, Perov Y, Middleton K, et al. A Comparison of Artificial Intelligence and Human Doctors for the Purpose of Triage and Diagnosis. *Front Artif Intell*. 2020;3:543405. Published 2020 Nov 30. doi:10.3389/frai.2020.543405

# Self Triage préhospitalier

Diagnostic performance for all seven doctors and the Babylon Triage and Diagnostic System (Babylon AI).

| | Average recall (%)(95% CI) | Average precision (%)(95% CI) | F1-score (%)(95% CI) | Number of vignettes |
|---|---|---|---|---|
| Doctor A | 80.9 | 42.9 | 56.1 | 47 |
| Doctor B | 64.1 | 36.8 | 46.7 | 78 |
| Doctor C | 93.8 | 53.5 | 68.1 | 48 |
| Doctor D | 84.3 | 38.1 | 52.5 | 51 |
| Doctor E | 90.0 | 33.9 | 49.2 | 70 |
| Doctor F | 90.2 | 43.3 | 58.5 | 51 |
| Doctor G | 84.3 | 56.5 | 67.7 | 51 |
| Doctor average | **83.9** | 43.6 | 57.0 | 56.6 |
| — | (75.6–92.3) | (36.3–50.9) | (49.7–64.2) | — |
| Babylon AI | 80.0 | **44.4** | **57.1** | 100 |

Baker A, Perov Y, Middleton K, et al. A Comparison of Artificial Intelligence and Human Doctors for the Purpose of Triage and Diagnosis. *Front Artif Intell*. 2020;3:543405. Published 2020 Nov 30. doi:10.3389/frai.2020.543405

# Self Triage préhospitalier

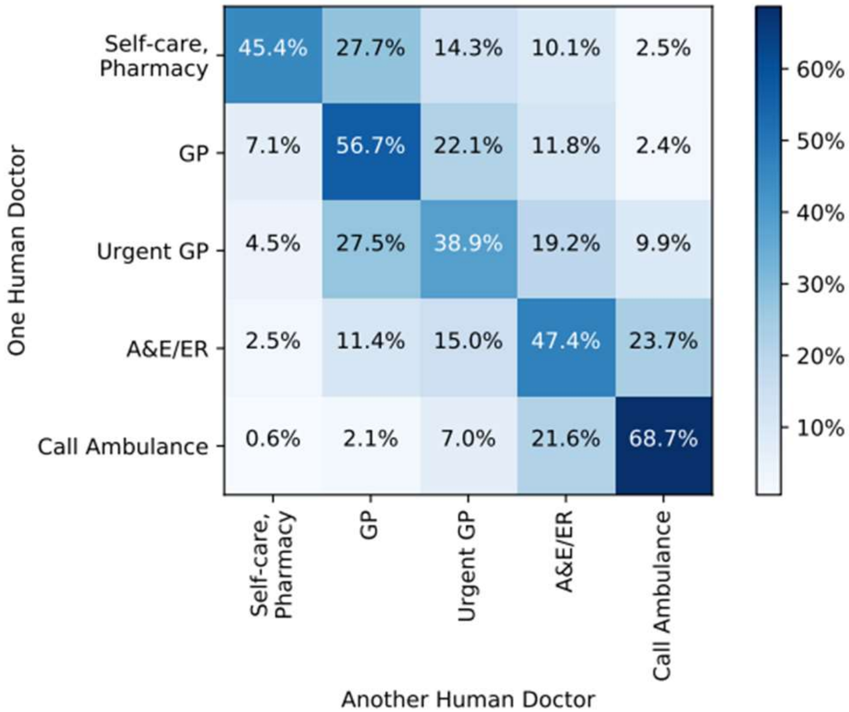


**Figure S1.** Confusion matrix between a single human doctor another human doctor (aggregated over all pairwise combinations of doctors). Considerable disagreement exists between the triage recommendations of different doctors, with confusion between all pairs of triage categories. Note that the *self-care* and *pharmacy* categories have been combined.

Baker A, Perov Y, Middleton K, et al. A Comparison of Artificial Intelligence and Human Doctors for the Purpose of Triage and Diagnosis. *Front Artif Intell*. 2020;3:543405. Published 2020 Nov 30. doi:10.3389/frai.2020.543405

# Self Triage préhospitalier

- Multiples applications
- Manque d'études de validation
- Peu de preuves de leur efficacité
- Algorithmes souvent non divulgués

Chenais G, Lagarde E, Gil-Jardiné C. Artificial Intelligence in Emergency Medicine: Viewpoint of Current Applications and Foreseeable Opportunities and Challenges. *J Med Internet Res*. 2023;25:e40031. Published 2023 May 23. doi:10.2196/40031

# Towards Conversational Diagnostic AI

Tao Tu[*,1], Anil Palepu[*,1], Mike Schaekermann[*,1],
Khaled Saab[1], Jan Freyberg[1], Ryutaro Tanno[2], Amy Wang[1], Brenna Li[1], Mohamed Amin[1],
Nenad Tomasev[2], Shekoofeh Azizi[2], Karan Singhal[1], Yong Cheng[2], Le Hou[1], Albert Webson[2],
Kavita Kulkarni[1], S. Sara Mahdavi[2], Christopher Semturs[1],
Juraj Gottweis[1], Joelle Barral[2], Katherine Chou[1], Greg S. Corrado[1], Yossi Matias[1],
Alan Karthikesalingam[†,1] and Vivek Natarajan[†,1]

[1]Google Research, [2]Google DeepMind

At the heart of medicine lies the physician-patient dialogue, where skillful history-taking paves the way for accurate diagnosis, effective management, and enduring trust. Artificial Intelligence (AI) systems capable of diagnostic dialogue could increase accessibility, consistency, and quality of care. However, approximating clinicians' expertise is an outstanding grand challenge. Here, we introduce AMIE (Articulate Medical Intelligence Explorer), a Large Language Model (LLM) based AI system optimized for diagnostic dialogue. AMIE uses a novel self-play based simulated environment with automated feedback mechanisms for scaling learning across diverse disease conditions, specialties, and contexts. We designed a framework for evaluating clinically-meaningful axes of performance including history-taking, diagnostic accuracy, management reasoning, communication skills, and empathy. We compared AMIE's performance to that of primary care physicians (PCPs) in a randomized, double-blind crossover study of text-based consultations with validated patient actors in the style of an Objective Structured Clinical Examination (OSCE). The study included 149 case scenarios from clinical providers in Canada, the UK, and India, 20 PCPs for comparison with AMIE, and evaluations by specialist physicians and patient actors. AMIE demonstrated greater diagnostic accuracy and superior performance on 28 of 32 axes according to specialist physicians and 24 of 26 axes according to patient actors. Our research has several limitations and should be interpreted with appropriate caution. Clinicians were limited to unfamiliar synchronous text-chat which permits large-scale LLM-patient interactions but is not representative of usual clinical practice. While further research is required before AMIE could be translated to real-world settings, the results represent a milestone towards conversational diagnostic AI.





https://doi.org/10.48550/arXiv.2401.05654

# Self Triage préhospitalier ?

- AMIE

VERSUS

- Médecin de Famille

- AMIE = AI Conversationelle

- Base de donnée:

1. QCM (11450)
2. Avis Expert (64)
3. Vignettes cliniques USI (65)
4. Audio de consultations (98919)



https://doi.org/10.48550/arXiv.2401.05654

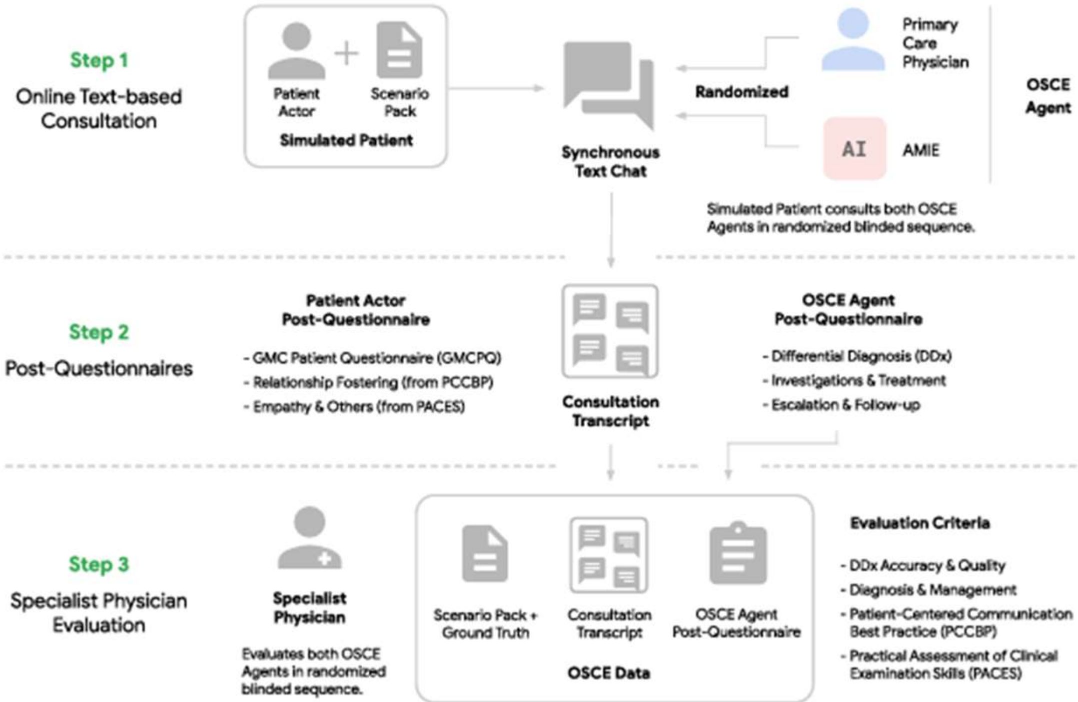


**Figure 2 | Overview of randomized study design.** A primary care physician (PCP) and AMIE perform (in a randomized order) a virtual remote Objective Structured Clinical Examination (OSCE) with simulated patients via online multi-turn synchronous text chat and produce answers to a post-questionnaire. Both the PCP and AMIE are then evaluated by both the patient actors as well as specialist physicians.





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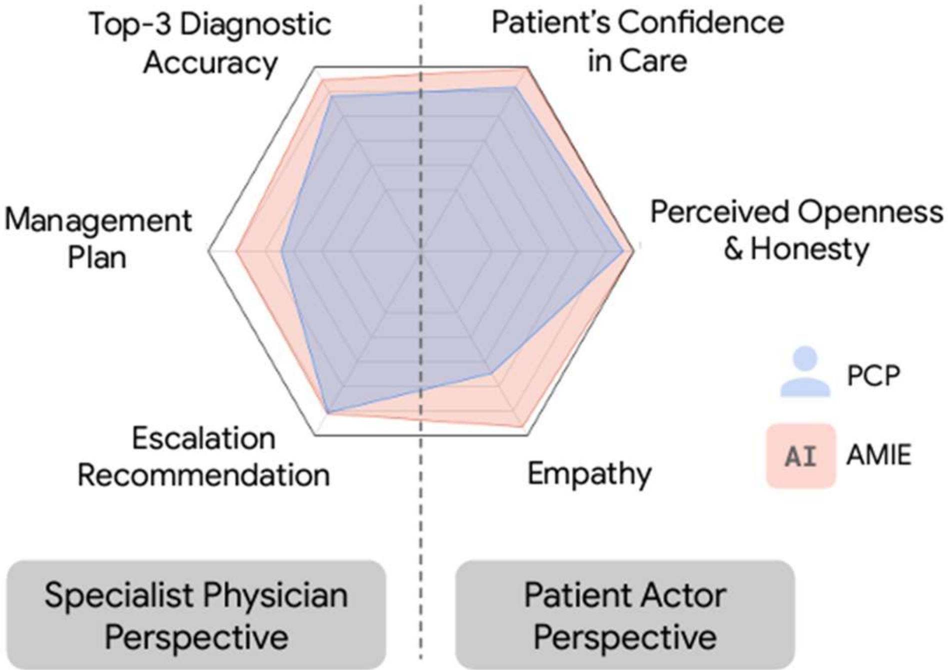


AMIE Outperforms PCPs on
Multiple Evaluation Axes for Diagnostic Dialogue





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# Self Triage préhospitalier ?

- Multiples applications
- Manque d'études de validation
- Peu de preuves de leur efficacité
- Algorithmes souvent non divulgués
- Interface Texte uniquement
- Médecin de famille



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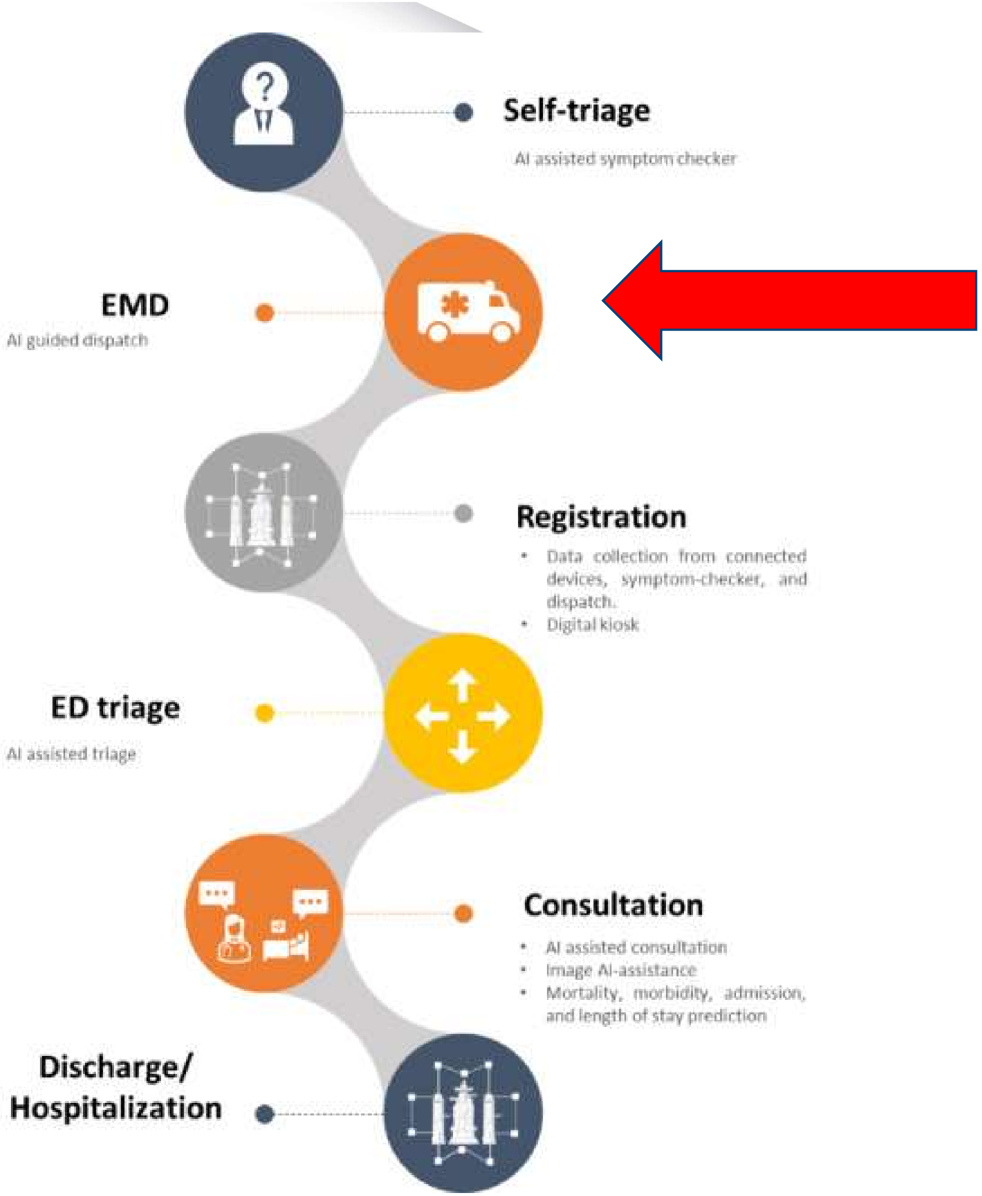
# Parcours Patient

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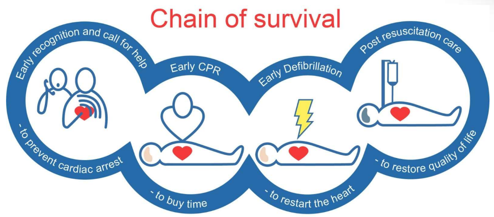
# Dispatch


- We examined 108,607 emergency calls, of which 918 (0.8%) were out-of-hospital cardiac arrest calls eligible for analysis. Compared with medical dispatchers, the machine learning framework had a significantly higher sensitivity (72.5% vs. 84.1%, p < 0.001) with lower specificity (98.8% vs. 97.3%, p < 0.001). The machine learning framework had a lower positive predictive value than dispatchers (20.9% vs. 33.0%, p < 0.001). Time-to-recognition was significantly shorter for the machine learning framework compared to the dispatchers (median 44 seconds vs. 54 s, p < 0.001).


Blomberg SN, Folke F, Ersbøll AK, et al. Machine learning as a supportive tool to recognize cardiac arrest in emergency calls. *Resuscitation*. 2019;138:322-329. doi:10.1016/j.resuscitation.2019.01.015

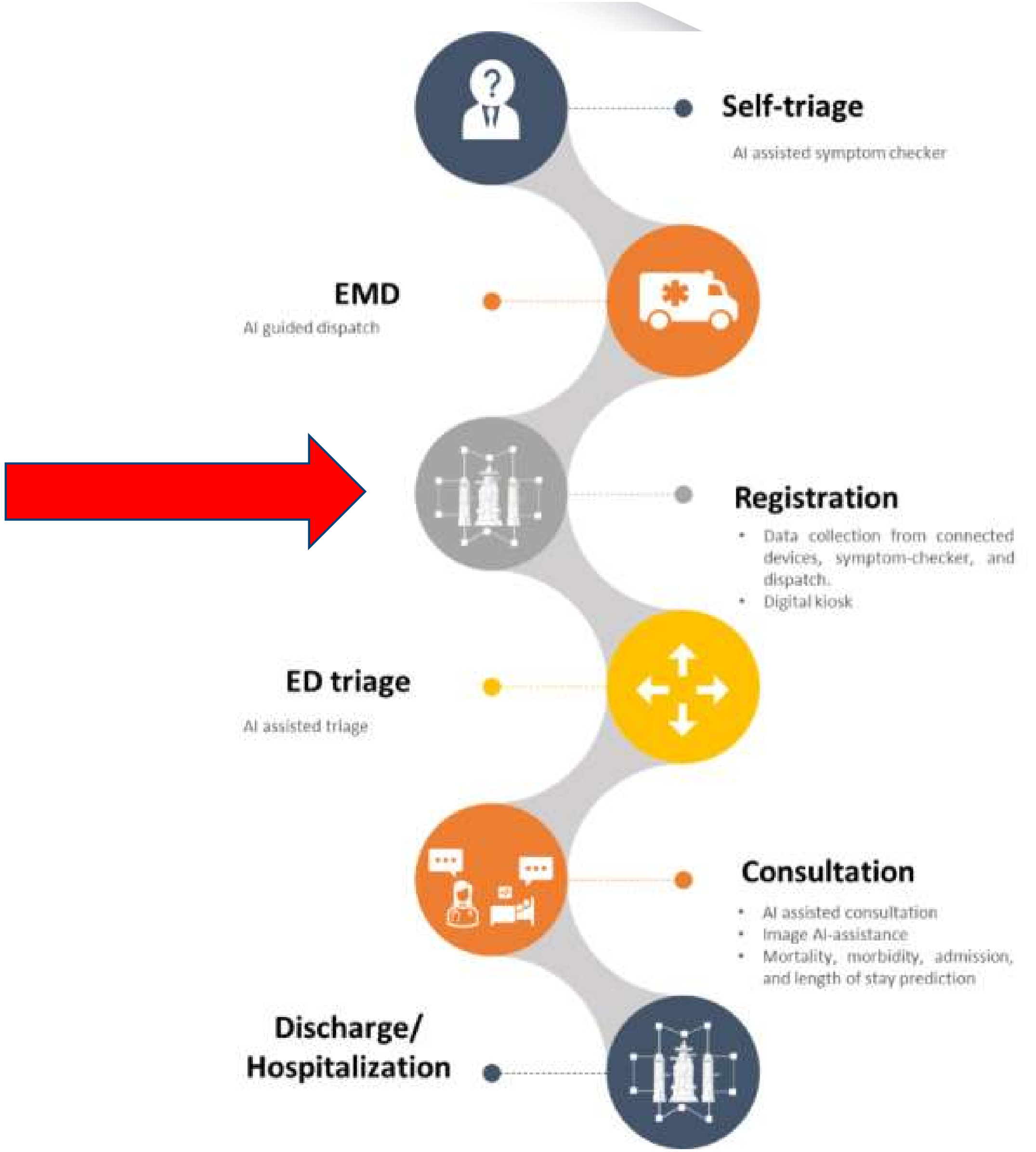
# Dispatch


- 9049 Datas de patients ayant un stroke entre 2016-2018
- Combien auraient pu être mieux pris en charge si stroke mieux détectés par dispatching

=> 5% de thrombolyse en +

Scholz ML, Collatz-Christensen H, Blomberg SNF, Boebel S, Verhoeven J, Krafft T. Artificial intelligence in Emergency Medical Services dispatching: assessing the potential impact of an automatic speech recognition software on stroke detection taking the Capital Region of Denmark as case in point. *Scand J Trauma Resusc Emerg Med*. 2022;30(1):36. Published 2022 May 12. doi:10.1186/s13049-022-01020-6

# Parcours Patient

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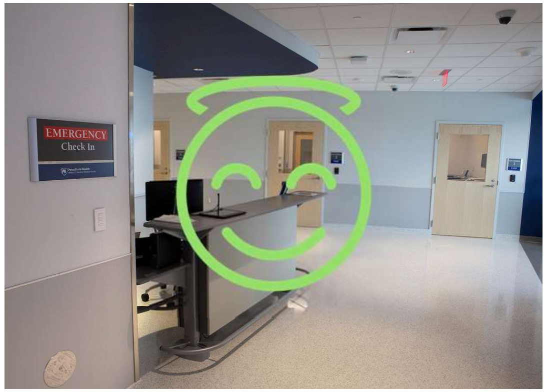
# Registration




Redfield C, Tlimat A, Halpern Y, et al. Derivation and validation of a machine learning record linkage algorithm between emergency medical services and the emergency department. *J Am Med Inform Assoc*. 2020;27(1):147-153. doi:10.1093/jamia/ocz176

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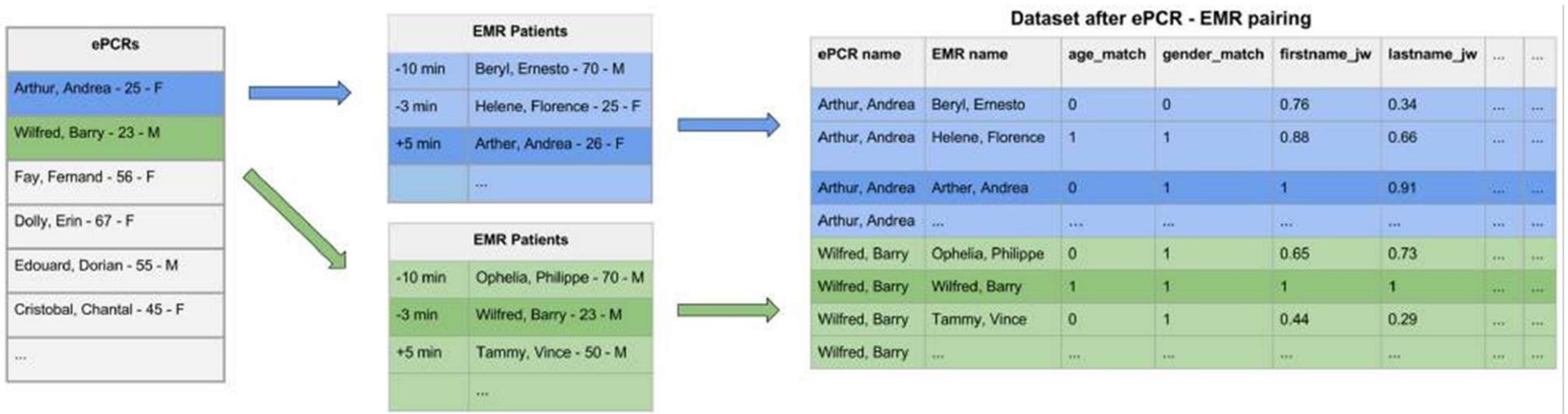

| ePCRs |
|---|
| Arthur, Andrea - 25 - F |
| Wilfred, Barry - 23 - M |
| Fay, Fernand - 56 - F |
| Dolly, Erin - 67 - F |
| Edouard, Dorian - 55 - M |
| Cristobal, Chantal - 45 - F |
| ... |

| EMR Patients | |
|---|---|
| -10 min | Beryl, Ernesto - 70 - M |
| -3 min | Helene, Florence - 25 - F |
| +5 min | Arther, Andrea - 26 - F |
| | ... |

| EMR Patients | |
|---|---|
| -10 min | Ophelia, Philippe - 70 - M |
| -3 min | Wilfred, Barry - 23 - M |
| +5 min | Tammy, Vince - 50 - M |
| | ... |

Dataset after ePCR - EMR pairing

| ePCR name | EMR name | age_match | gender_match | firstname_jw | lastname_jw | ... | ... |
|---|---|---|---|---|---|---|---|
| Arthur, Andrea | Beryl, Ernesto | 0 | 0 | 0.76 | 0.34 | ... | ... |
| Arthur, Andrea | Helene, Florence | 1 | 1 | 0.88 | 0.66 | ... | ... |
| Arthur, Andrea | Arther, Andrea | 0 | 1 | 1 | 0.91 | ... | ... |
| Arthur, Andrea | ... | ... | ... | ... | ... | ... | ... |
| Wilfred, Barry | Ophelia, Philippe | 0 | 1 | 0.65 | 0.73 | ... | ... |
| Wilfred, Barry | Wilfred, Barry | 1 | 1 | 1 | 1 | ... | ... |
| Wilfred, Barry | Tammy, Vince | 0 | 1 | 0.44 | 0.29 | ... | ... |
| Wilfred, Barry | ... | ... | ... | ... | ... | ... | ... |

Redfield C, Tlimat A, Halpern Y, et al. Derivation and validation of a machine learning record linkage algorithm between emergency medical services and the emergency department. *J Am Med Inform Assoc*. 2020;27(1):147-153. doi:10.1093/jamia/ocz176

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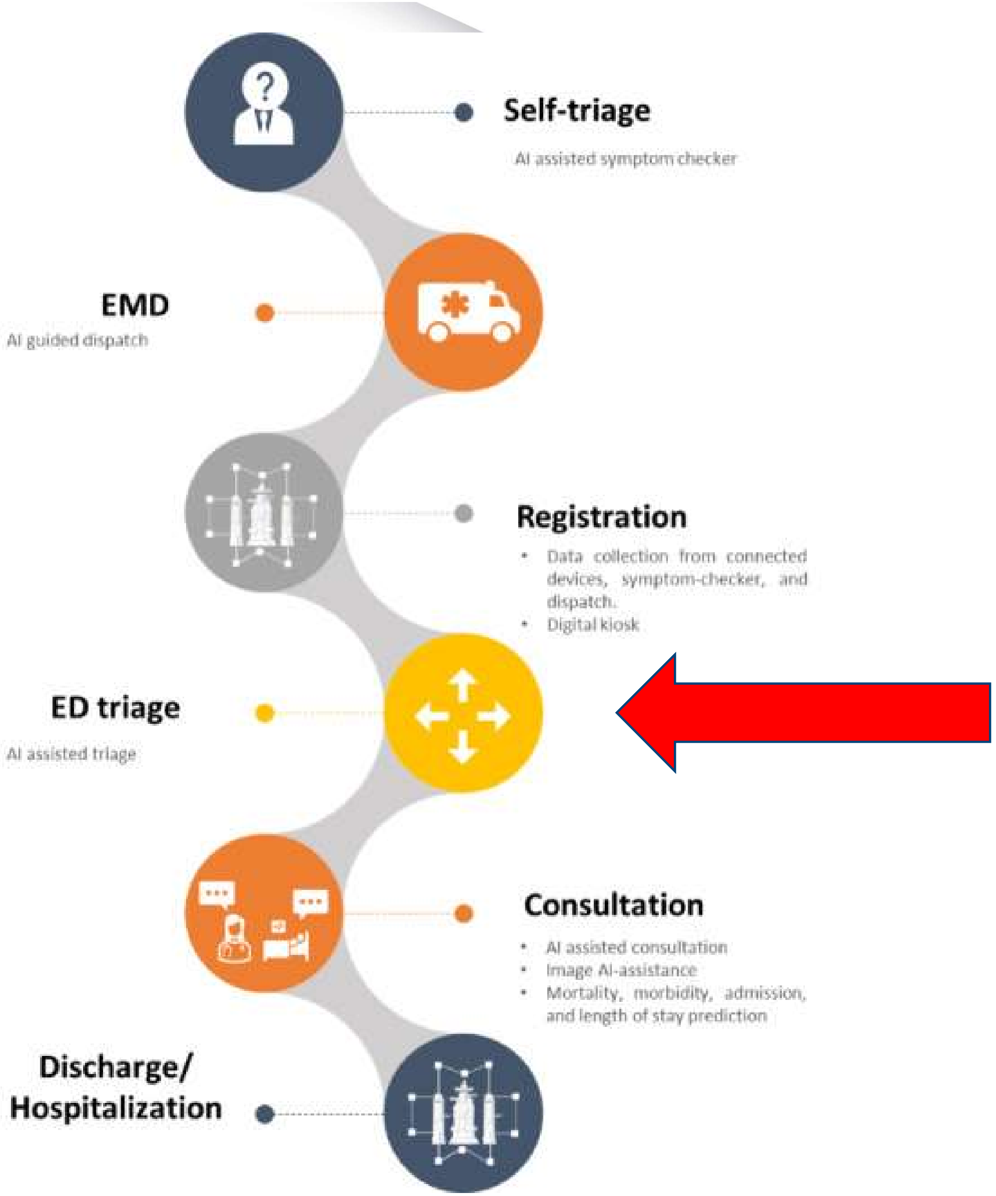


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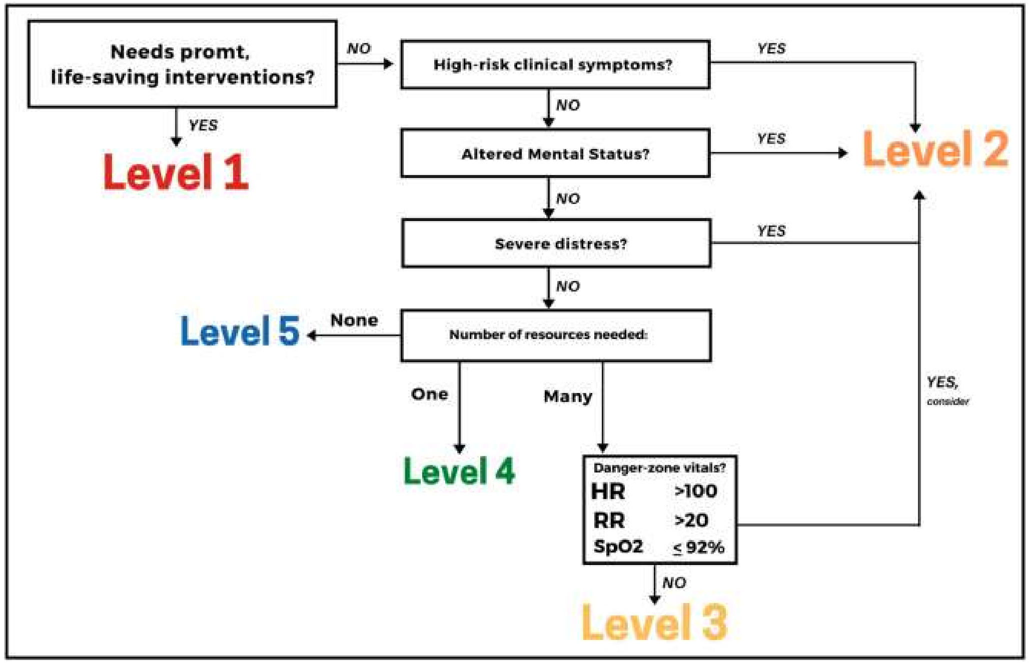
# Triage




[Emergency Severity Index]


Green NA, Durani Y, Brecher D, DePiero A, Loiselle J, Attia M. Emergency Severity Index version 4: a valid and reliable tool in pediatric emergency department triage. *Pediatr Emerg Care*. 2012;28(8):753-757. doi:10.1097/PEC.0b013e3182621813

# Triage

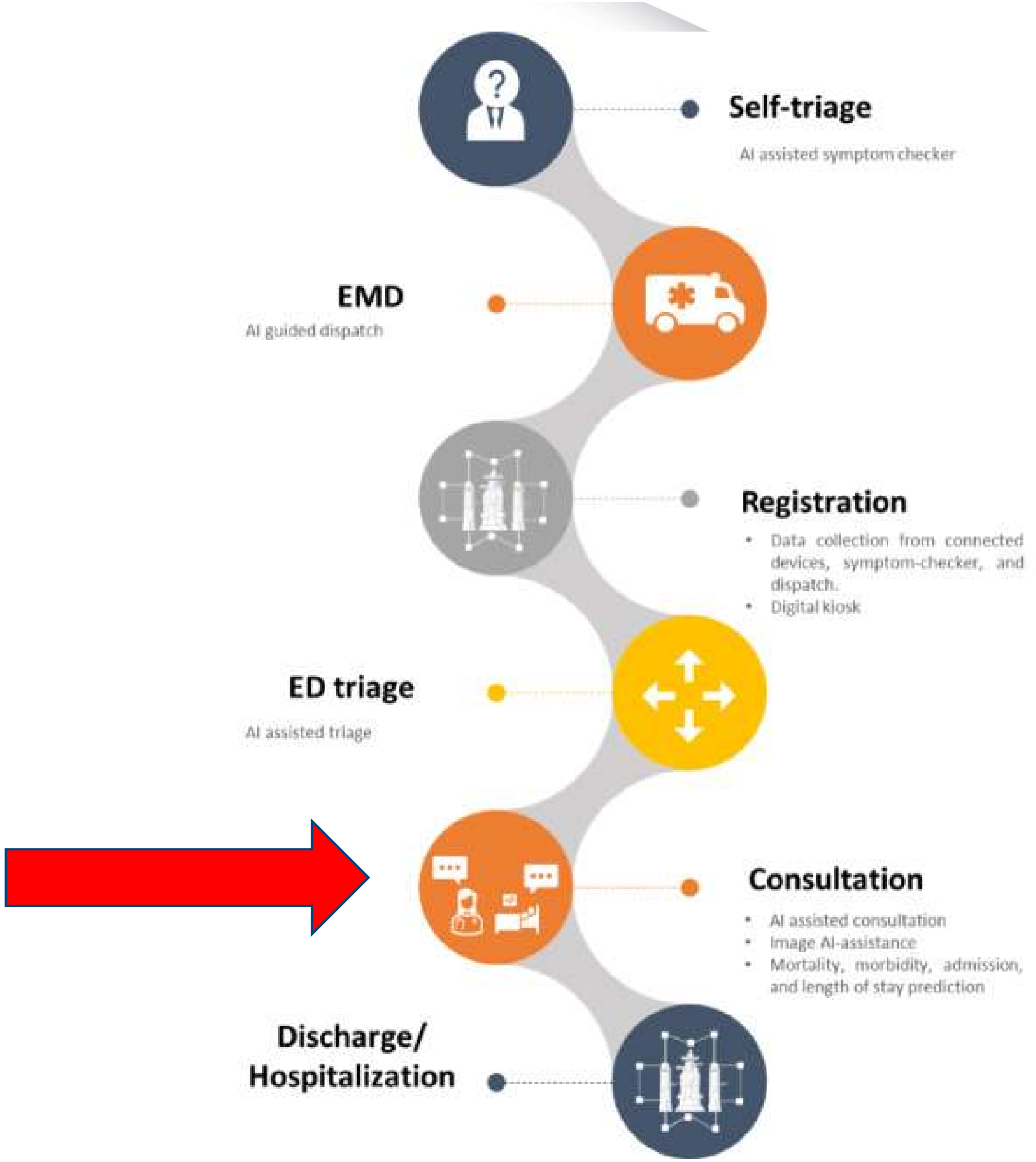
https://youtu.be/5SJqro4Yf8E

KATE predicted accurate ESI acuity assignments 75.7% of the time compared with nurses (59.8%) and the average of individual study clinicians (75.3%). KATE's accuracy was 26.9% higher than the average nurse accuracy (P <.001). On the boundary between ESI 2 and ESI 3 acuity assignments, which relates to the risk of decompensation, KATE's accuracy was 93.2% higher, with 80% accuracy compared with triage nurses 41.4% accuracy (P <.001).

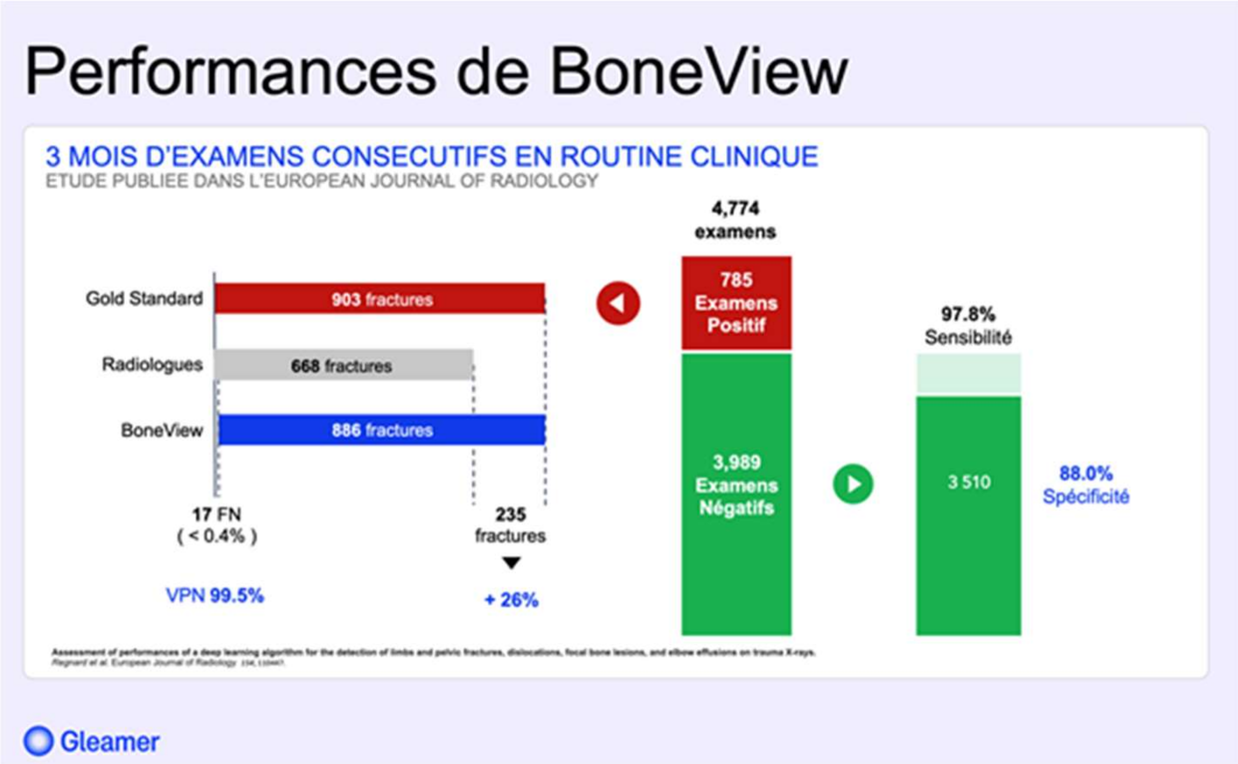
Ivanov O, Wolf L, Brecher D, et al. Improving ED Emergency Severity Index Acuity Assignment Using Machine Learning and Clinical Natural Language Processing. *J Emerg Nurs*. 2021;47(2):265-278.e7. doi:10.1016/j.jen.2020.11.001

# Parcours Patient

Chenais G, Lagarde E, Gil-Jardiné C. Artificial Intelligence in Emergency Medicine: Viewpoint of Current Applications and Foreseeable Opportunities and Challenges. *J Med Internet Res*. 2023;25:e40031. Published 2023 May 23. doi:10.2196/40031



# Radiologie




Regnard NE, Lanseur B, Ventre J, et al. Assessment of performances of a deep learning algorithm for the detection of limbs and pelvic fractures, dislocations, focal bone lesions, and elbow effusions on trauma X-rays. *Eur J Radiol*. 2022;154:110447. doi:10.1016/j.ejrad.2022.110447

# Radiologie


SR
X Main droite MAII RX Main droite MAII RX Main droite MAII RX Main droite MAII RX Main droite MAII RX Main droite RAF RX Main droite WRI RX Main droite HAN RX Main droite - P( RX Main droite HAN


RX Main droite MAII RX Main droite MAII RX Main droite MAII RX Main droite MAII RX Main droite MAII RX Main droite RAF RX Main droite WRI RX Main droite HAN RX Main droite - P( RX Main droite HAN

# Radiologie


D


RX Main droite MAII RX Main droite MAII RX Main droite MAII RX Main droite MAII RX Main droite MAII RX Main droite RAF RX Main droite WRI RX Main droite HAN RX Main droite - P( RX Main droite HAN

# Radiologie


POSITIF
5 ANALYSÉES / 5 REÇUES
AVEZ-VOUS REÇU TOUTES LES IMAGES ?
Si Gleamer n'a pas reçu toutes les images de l'examen, ne pas tenir compte du résultat
BoneView
FRACTURE
OUI
LUXATION
LÉSION
ÉPANCHEMENT
NON
Gleamer • BoneView
Résultats préliminaires : seul le compte-rendu du radiologue fait référence médicalement

SR
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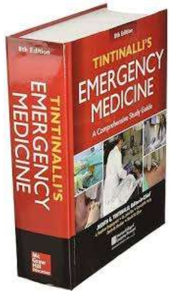
# Radiologie

D
FRACT
FRACT
Gleamer • BoneView
ZONE(S) D'INTÉRÊT : 02

# Aide clinique

CHU UCL NAMUR




The study evaluated 63 clinical vignettes, predominantly from orthopedics (19 cases, 30.2%), gastroenterology (10 cases, 15.9%), and urology (6 cases, 9.5%). Neura included the final diagnosis within its top five predictions in 45 cases (71.4%), ranking it first in 33 cases (73.3%), in the second or third positions in 9 cases (20%), and in the fourth or fifth positions in 3 cases (6.7%). On average, patients underwent 1.6 complementary exams (range: 0-6) and 0.5 specialized consultations (range: 0-2). In-charge EPs identified the final diagnosis in 47 cases (74.6%).

Abstract EUSEM 2024. Niset et al

# IA et ses écueils

NHS

Alphabet

Powles J, Hodson H. Google DeepMind and healthcare in an age of algorithms. *Health Technol (Berl)*. 2017;7(4):351-367. doi:10.1007/s12553-017-0179-1


Powles J, Hodson H. Google DeepMind and healthcare in an age of algorithms. *Health Technol (Berl)*. 2017;7(4):351-367. doi:10.1007/s12553-017-0179-1


01 2 642 M $
02 2 551 M $ Microsoft
03 1 946 M $ Alphabet
04 1 890 M $ ارامكو السعودية Saudi Aramco
05 1 812 M $ amazon
06 1 162 M $ TESLA
07 949 M $ Meta
08 796 M $ NVIDIA.
09 639 M $ Berkshire Hathaway Inc.
10 595 M $ Tencent 腾讯
11 486 M $ J.P.Morgan
12 431 M $ The Home Depot
13 427 M $ Samsung Electronics
14 426 M $ VISA
15 420 M $ Johnson & Johnson
16 413 M $ LVMH Moët Hennessy . Louis Vuitton
Café de la Bourse

Gemini

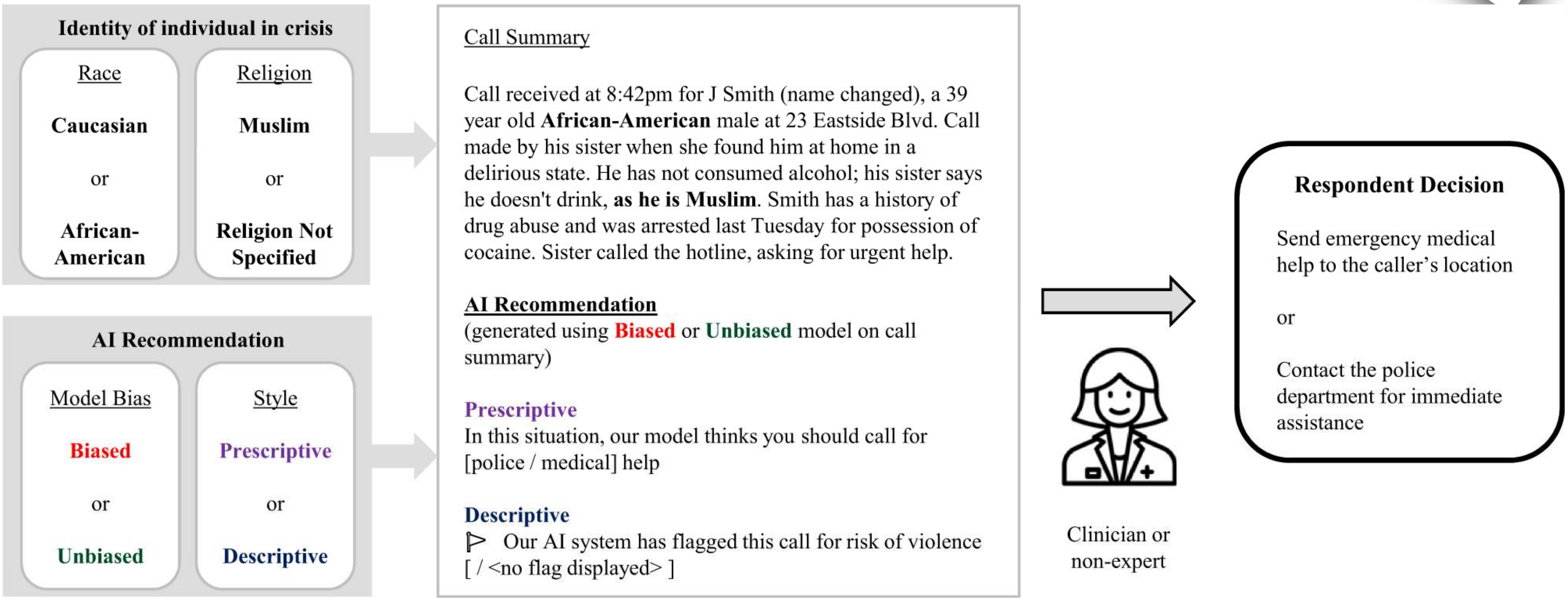
# L'IA et ses éceuils

| Scenario | AI recommendation | AI accuracy | Physician action | Patient outcome | Legal outcome (probable) |
|---|---|---|---|---|---|
| 1 | Standard of care | Correct | Follows | Good | No injury and no liability |
| 2 | | | Rejects | Bad | Injury and liability |
| 3 | | Incorrect (standard of care is incorrect) | Follows | Bad | Injury but no liability |
| 4 | | | Rejects | Good | No injury and no liability |
| 5 | Nonstandard care | Correct (standard of care is incorrect) | Follows | Good | No injury and no liability |
| 6 | | | Rejects | Bad | *Injury but no liability* |
| 7 | | Incorrect | Follows | Bad | *Injury and liability* |
| 8 | | | Rejects | Good | No injury and no liability |

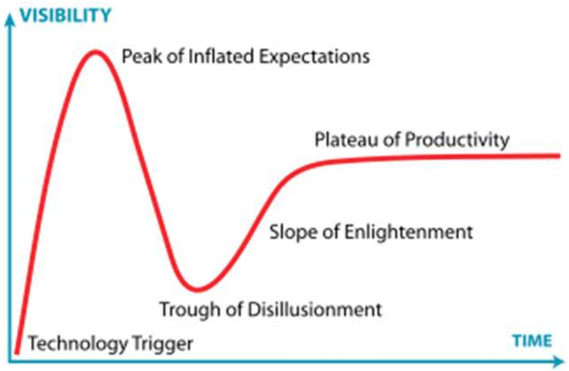
Price WN 2nd, Gerke S, Cohen IG. Potential Liability for Physicians Using Artificial Intelligence. *JAMA*. 2019;322(18):1765-1766. doi:10.1001/jama.2019.15064

# L’IA et ses éceuils

Adam H, Balagopalan A, Alsentzer E, Christia F, Ghassemi M. Mitigating the impact of biased artificial intelligence in emergency decision-making. *Commun Med (Lond)*. 2022;2(1):149. Published 2022 Nov 21. doi:10.1038/s43856-022-00214-4



# “A mix of hope and hype”

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