Investigación sobre IA en Educación

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Imagen creada con IA Midjourney

Conflictos de interés y precisiones

No tengo ningún conflicto de interés.

No tengo relación con las marcas que serán mencionadas como ejemplo en esta presentación.

Actualización de la presentación.

Uso de IA: 1 imagen

IA en educación (IAEd) es un área interdisciplinar

Xu, W., & Ouyang, F. (2022). A systematic review of AI role in the educational system based on a proposed conceptual framework. Education and Information Technologies, 27(3), 4195–4223. https://doi.org/10.1007/s10639-021-10774-y

Investigación en IAEd en los últimos años

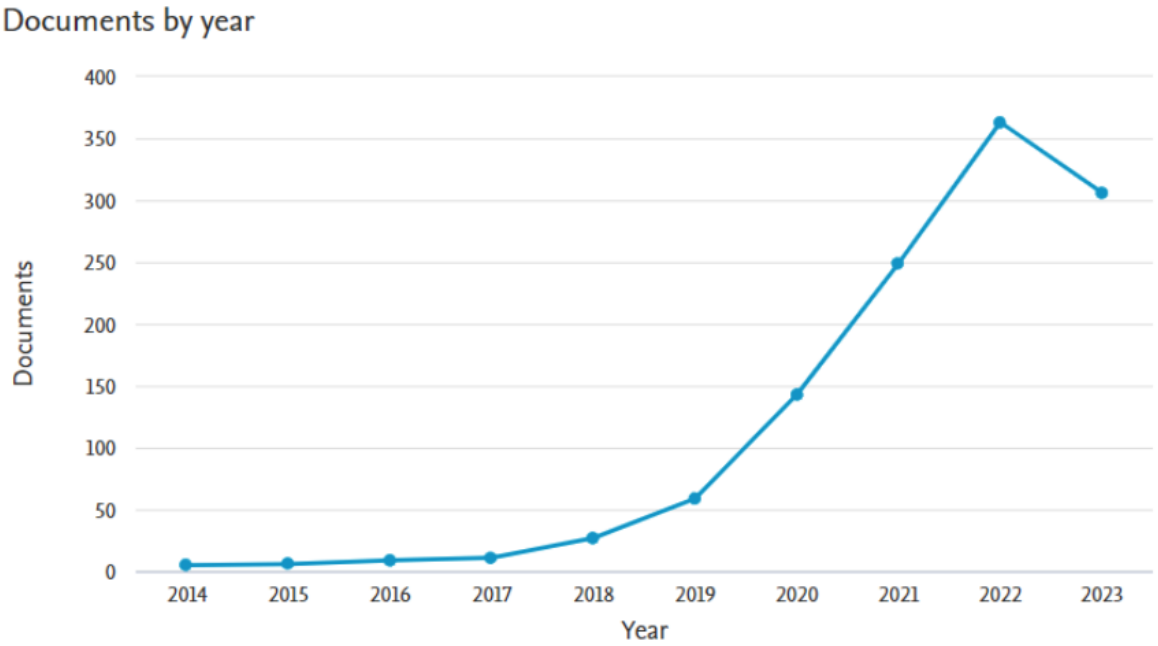


Figure 2. Amount Publication from year 2014 until 2023

Ilham, R., Muhammad, I., Aji , L. J., Rizal , S. U., & Özbilen, F. M. (2023). ARTIFICIAL INTELLIGENCE RESEARCH IN EDUCATION: A BIBLIOMETRIC ANALYSIS. Journal of Education Global, 1(1), 45-55. http://penaeducentre.com/index.php/JEdG/article/view/25

Investigación en IAEd en los últimos años

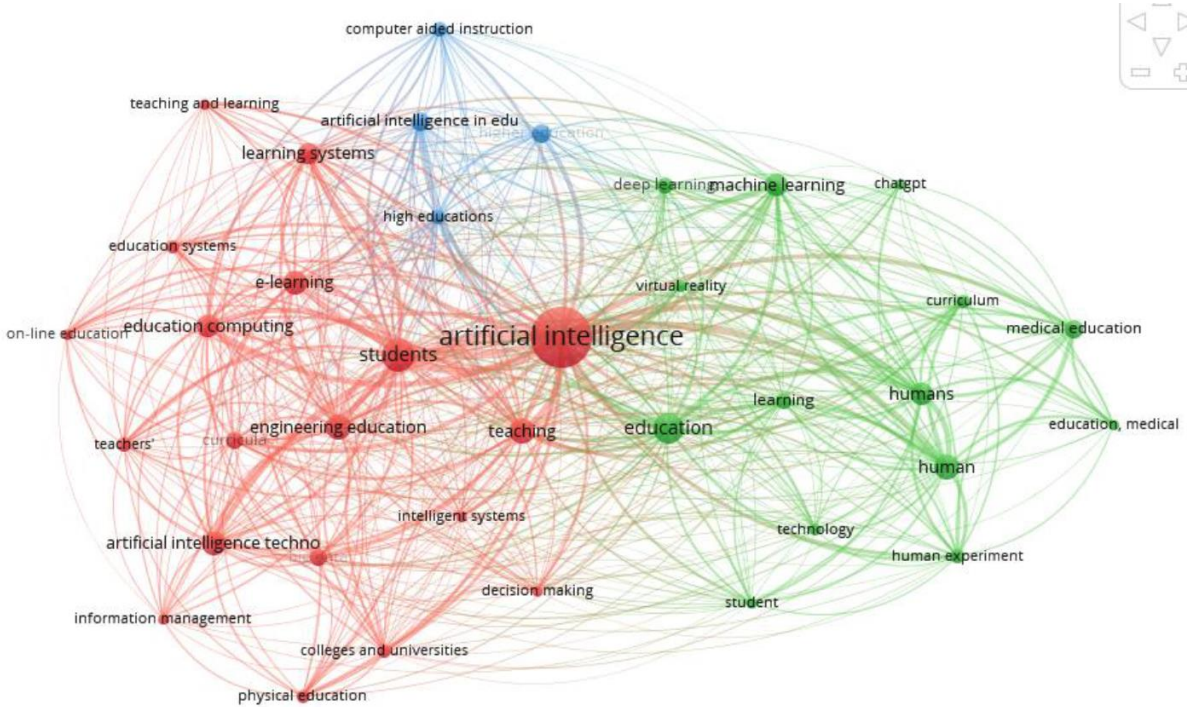
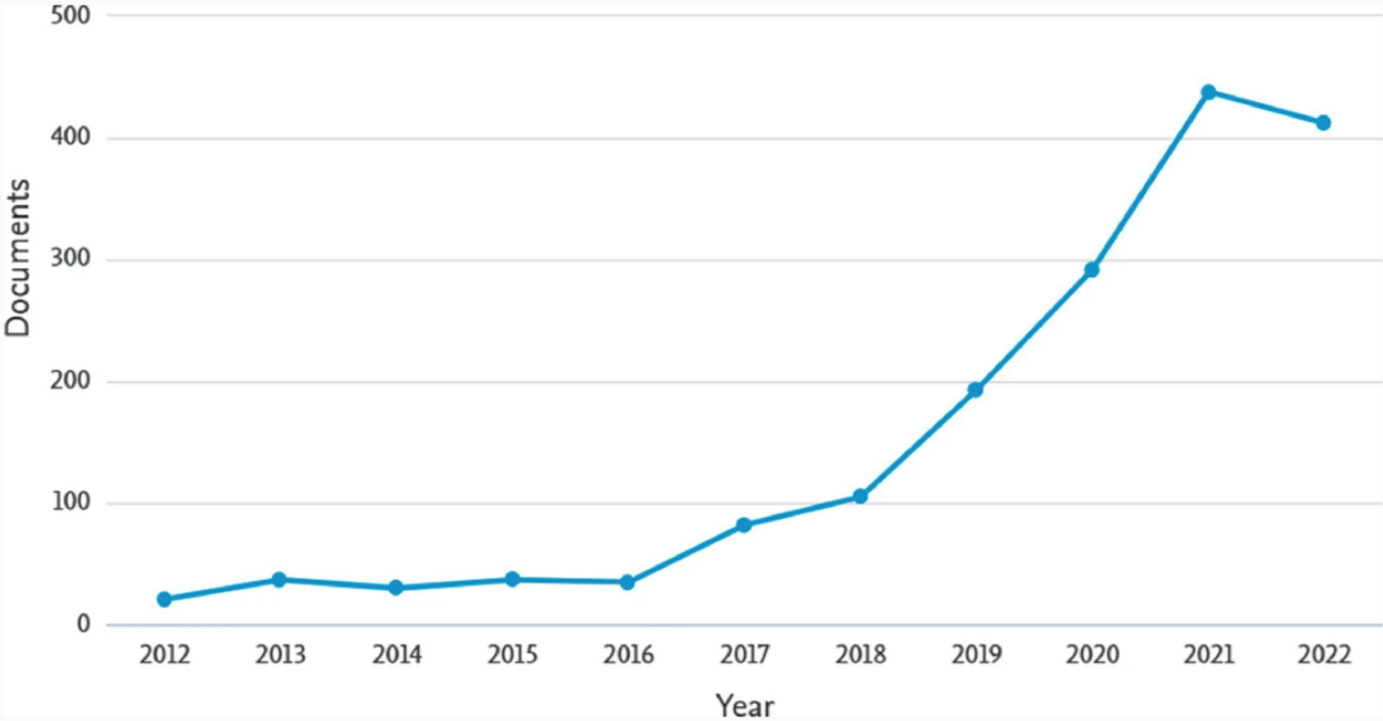


Figure 3. Co-occurrence of Keywords (Occurrence Threshold ≥ 3)

Ilham, R., Muhammad, I., Aji , L. J., Rizal , S. U., & Özbilen, F. M. (2023). ARTIFICIAL INTELLIGENCE RESEARCH IN EDUCATION: A BIBLIOMETRIC ANALYSIS. Journal of Education Global, 1(1), 45-55. http://penaeducentre.com/index.php/JEdG/article/view/25

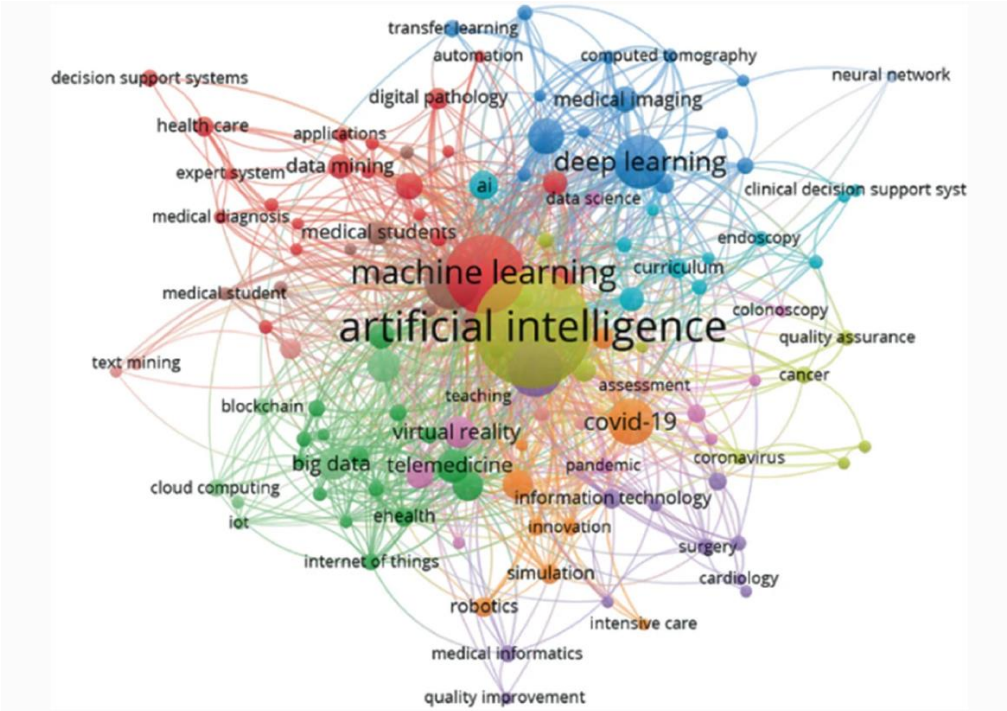
Investigación en IAEd en Ciencias de la Salud



Research publication growth in the last ten years

Maulana, F.I., Zaın, M.Y., Lestari, D., Purnomo, A., Adi, P.D.P. (2023). Mapping the Literature of Artificial Intelligence in Medical Education: A Scientometric Analysis. In: Ranganathan, G., Papakostas, G.A., Rocha, Á. (eds) Inventive Communication and Computational Technologies. ICICCT 2023. Lecture Notes in Networks and Systems, vol 757. Springer, Singapore. https://doi.org/10.1007/978-981-99-5166-6_47

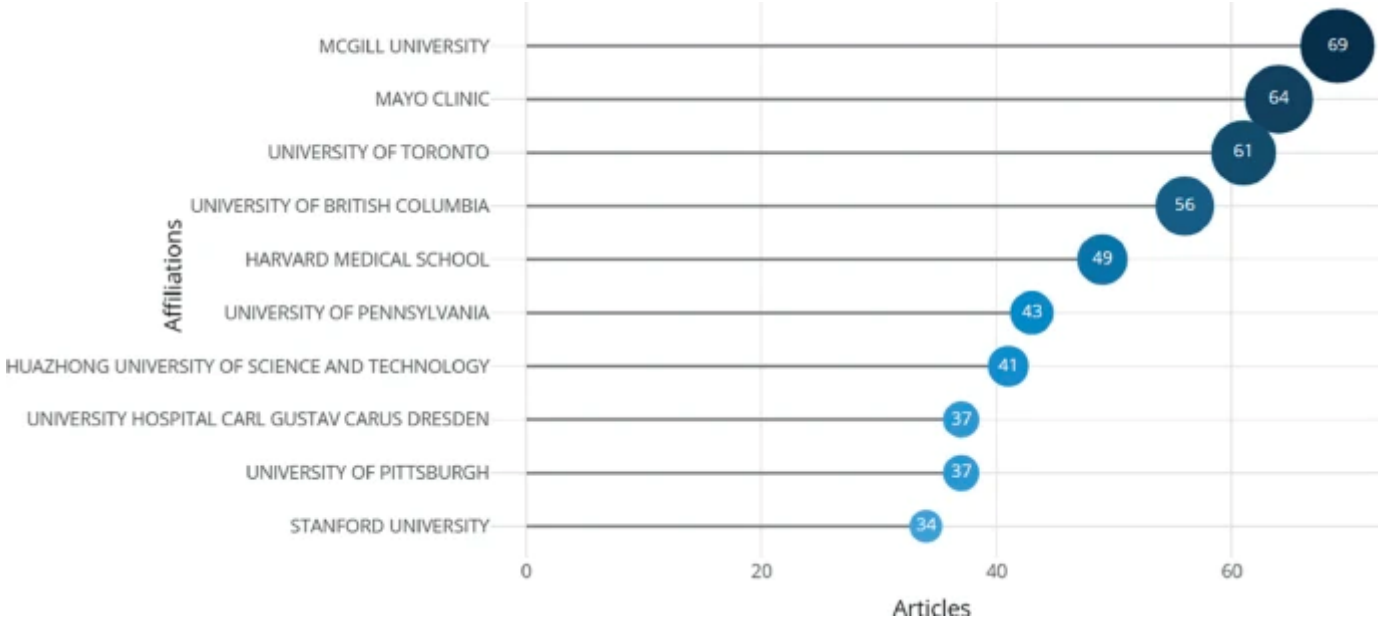
Investigación en IAEd en Ciencias de la Salud



Visualized author keyword co-occurrence analysis of papers on artificial intelligence in medical education: This is one of the field's most frequently occurring terms

Maulana, F.I., Zaın, M.Y., Lestari, D., Purnomo, A., Adi, P.D.P. (2023). Mapping the Literature of Artificial Intelligence in Medical Education: A Scientometric Analysis. In: Ranganathan, G., Papakostas, G.A., Rocha, Á. (eds) Inventive Communication and Computational Technologies. ICICCT 2023. Lecture Notes in Networks and Systems, vol 757. Springer, Singapore. https://doi.org/10.1007/978-981-99-5166-6_47

Investigación en IAEd en Ciencias de la Salud



Maulana, F.I., Zaın, M.Y., Lestari, D., Purnomo, A., Adi, P.D.P. (2023). Mapping the Literature of Artificial Intelligence in Medical Education: A Scientometric Analysis. In: Ranganathan, G., Papakostas, G.A., Rocha, Á. (eds) Inventive Communication and Computational Technologies. ICICCT 2023. Lecture Notes in Networks and Systems, vol 757. Springer, Singapore. https://doi.org/10.1007/978-981-99-5166-6_47

Investigación en IAEd en Ciencias de la Salud

Table 2 Most citation papers in the last ten years

From: Mapping the Literature of Artificial Intelligence in Medical Education: A Scientometric Analysis

Paper	Author	Total citation	Years
"Dermatologist-level classification of skin cancer with deep neural networks [20]"	Esteva, A., et al.	6101	2017
"Online mental health services in China during the COVID-19 outbreak [17]"	Liu, S., et al.	1112	2020
"Digital pathology and artificial intelligence [21]"	Niazi, M.K.K., et al.	335	2019
"Artificial intelligence in medical imaging: threat or opportunity? Radiologists again at the forefront of innovation in medicine [8]"	Pesapane, F., et al.	297	2018
"Human–Robot Interaction [22]"	Sheridan, T.B	290	2016
"Introduction to radiomics [23]"	Mayerhoefer, M.E., et al.	284	2020
"A Survey on Explainable Artificial Intelligence (XAI): Toward Medical XAI [18]"	Tjoa, E., Guan, C	270	2021
"Next-generation of virtual personal assistants (Microsoft Cortana, Apple Siri, Amazon Alexa and Google Home) [24]"	Kepuska, V., Bohouta, G	205	2018
"Robot-proof: Higher education in the age of artificial intelligence [19]"	Aoun, J.E	180	2017
"Medical students' attitude toward artificial intelligence: a multicentre survey [25]"	Pinto dos Santos, D., et al.	166	2019

Maulana, F.I., Zaın, M.Y., Lestari, D., Purnomo, A., Adi, P.D.P. (2023). Mapping the Literature of Artificial Intelligence in Medical Education: A Scientometric Analysis. In: Ranganathan, G., Papakostas, G.A., Rocha, Á. (eds) Inventive Communication and Computational Technologies. ICICCT 2023. Lecture Notes in Networks and Systems, vol 757. Springer, Singapore. https://doi.org/10.1007/978-981-99-5166-6_47

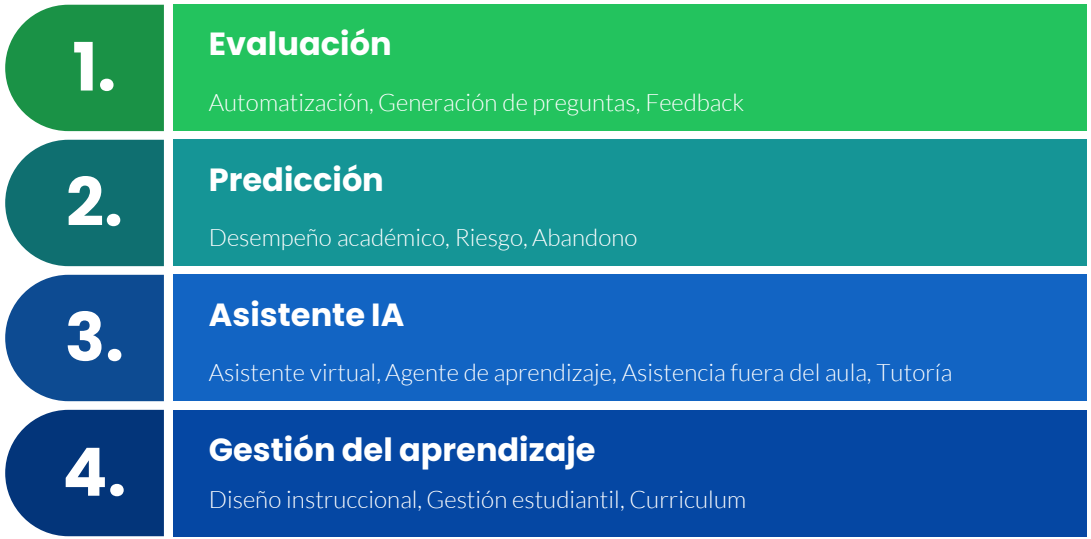
Investigación en IAEd en Ciencias de la Salud

Table 1: Primary objective and types of publication

	Type publication				Total
Main Objectives	**Commentary**	**Correlation Analysis**	**Survey**	**Review**	
The need for integration of AI in medical education	11	1	-	7	19
Correlation of AI/ML in skills training, assessment, and giving feedback.	3	10	-	5	18
Attitude, perception, knowledge of students and residents towards AI	-	-	7	-	7
Application of AI/ML in teaching, learning and clinical reasoning	2	2	1	1	6
Total	**16**	**13**	**8**	**13**	**50**

Burney, I. A., & Ahmad, N. (2022). Artificial Intelligence in Medical Education: A citation-based systematic literature review. Journal of Shifa Tameer-e-Millat University, 5(1), 43–53. https://doi.org/10.32593/jstmu/Vol5.Iss1.183

Ejemplos



Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. International Journal of Educational Technology in Higher Education, 20(1), 22. https://doi.org/10.1186/s41239-023-00392-8

Performance of Large Language Models (ChatGPT, Bing Search, and Google Bard) in Solving Case Vignettes in Physiology

Anup Kumar D. Dhanvijay [1], Mohammed Jaffer Pinjar [1], Nitin Dhokane [2], Smita R. Sorte [3], Amita Kumari [1], Himel Mondal [1]

Evaluating ChatGPT Performance on the Orthopaedic In-Training Examination

Justin E. Kung, MD, Christopher Marshall, BS, Chase Gauthier, BS, Tyler A. Gonzalez, MD, MBA, and J. Benjamin Jackson III, MD, MBA

ORIGINAL ARTICLE

Success of ChatGPT, an AI language model, in taking the French language version of the European Board of Ophthalmology examination: A novel approach to medical knowledge assessment

Succès de ChatGPT, intelligence artificielle conversationnelle, aux annales en français de l'European Board of Ophthalmology : une nouvelle approche dans l'évaluation de l'apprentissage médical

C. Panthier[a,b], D. Gatinel[a,b,*]

Artificial Intelligence in Medical Education: Comparative Analysis of ChatGPT, Bing, and Medical Students in Germany

Monitoring Editor: Taiane de Azevedo Cardoso, Kaushik Venkatesh, and Maged N. Kamel Boulos

Reviewed by Christian Mueller and Syed Latifi

Jonas Roos, MD,[1] Adnan Kasapovic, MD,[1] Tom Jansen, MD,[1] and Robert Kaczmarczyk, MD[2]

ChatGPT Conquers the Saudi Medical Licensing Exam: Exploring the Accuracy of Artificial Intelligence in Medical Knowledge Assessment and Implications for Modern Medical Education

Fahad K. Aljindan • Abdullah A. Al Qurashi • Ibrahim Abdullah S. Albalawi • Abeer Mohammed M. Alanazi • Hussam Abdulkhaliq M. Aljuhani • Faisal Falah Almutairi • Omar A. Aldamigh • Ibrahim R. Halawani • Subhi M. K. Zino Alarki

RESEARCH ARTICLE

Performance of ChatGPT on USMLE: Potential for AI-assisted medical education using large language models

Tiffany H. Kung[1,2], Morgan Cheatham[3], Arielle Medenilla[1], Czarina Sillos[1], Lorie De Leon[1], Camille Elepaño[1], Maria Madriaga[1], Rimel Aggabao[1], Giezel Diaz-Candido[1], James Maningo[1], Victor Tseng[1,4]*

¿Es capaz "ChatGPT" de aprobar el examen MIR de 2022? Implicaciones de la inteligencia artificial en la educación médica en España

Is "ChatGPT" capable of passing the 2022 MIR exam? Implications of artificial intelligence in medical education in Spain.

Carrasco JP[1], García E[2], Sánchez DA[3*], Estrella Porter PD[4], De La Puente L[5], Navarro J[6], Cerame A[7].

1. Evaluación

Automatización, Generación de preguntas, Feedback

Automated essay scoring and the future of educational assessment in medical education

Mark J Gierl,[1] Syed Latifi,[1] Hollis Lai,[2] André-Philippe Boulais[3] & André De Champlain[3]

CONTEXT Constructed-response tasks, which range from short-answer tests to essay questions, are included in assessments of medical knowledge because they allow educators to measure students' ability to think, reason, solve complex problems, communicate and collaborate through their use of writing. However, constructed-response tasks are also costly to administer and challenging to score because they rely on human raters. One alternative to the manual scoring process is to integrate computer technology with writing assessment. The process of scoring written responses using computer programs is known as 'automated essay scoring' (AES).

METHODS An AES system uses a computer program that builds a scoring model by extracting linguistic features from a constructed-response prompt that has been prescored by human raters and then, using machine learning algorithms, maps the linguistic features to the human scores so that the computer can be used to classify (i.e. score or grade) the responses of a new group of students. The accuracy of the score classification can be evaluated using different measures of agreement.

RESULTS Automated essay scoring provides a method for scoring constructed-response tests that complements the current use of selected-response testing in medical education. The method can serve medical educators by providing the summative scores required for high-stakes testing. It can also serve medical students by providing them with detailed feedback as part of a formative assessment process.

CONCLUSIONS Automated essay scoring systems yield scores that consistently agree with those of human raters at a level as high, if not higher, as the level of agreement among human raters themselves. The system offers medical educators many benefits for scoring constructed-response tasks, such as improving the consistency of scoring, reducing the time required for scoring and reporting, minimising the costs of scoring, and providing students with immediate feedback on constructed-response tasks.

Medical Education 2014: 48: 950–962
doi: 10.1111/medu.12517

A 55-year-old male company vice-president presents in your office with a copy of his recent executive physical. His personal health history and family history are negative. He is a non-smoker. As part of the evaluation, he had a random serum cholesterol done, which is reported as 7.00 mmol/L. Serum triglycerides, liver function indices and a resting electrocardiogram are all within normal limits. Examination reveals a rather obese middle-aged man: height 180 cm; weight 98 kg; body mass index (BMI) 30.2; blood pressure 140/88 mm Hg. The rest of the physical examination is unremarkable.

Considering the information provided to you above in the stem, what would you recommend to this patient?

List up to three.

1.
2.
3.

Table 1 Exact agreement and κ-values for six English-language Medical Council of Canada clinical decision-making (CDM) constructed-response (CR) write-in questions

	Performance measure	
Item	**Exact agreement (%)**	**κ-value**
1	97.3	0.91
2	98.2	0.96
3	94.6	0.88
4	98.1	0.94
5	97.9	0.94
6	98.0	0.96

1.

Evaluación

Automatización, Generación de preguntas, Feedback

Artificial Intelligence Screening of Medical School Applications: Development and Validation of a Machine-Learning Algorithm

Marc M. Triola, MD, Ilan Reinstein, MS, Marina Marin, MSc, Colleen Gillespie, PhD, Steven Abramson, MD, Robert I. Grossman, MD, and Rafael Rivera Jr, MD, MBA

Abstract

Purpose
To explore whether a machine-learning algorithm could accurately perform the initial screening of medical school applications.

Method
Using application data and faculty screening outcomes from the 2013 to 2017 application cycles (n = 14,555 applications), the authors created a virtual faculty screener algorithm. A retrospective validation using 2,910 applications from the 2013 to 2017 cycles and a prospective validation using 2,715 applications during the 2018 application cycle were performed. To test the validated algorithm, a randomized trial was performed in the 2019 cycle, with 1,827 eligible applications being reviewed by faculty and 1,873 by algorithm.

Results
The retrospective validation yielded area under the receiver operating characteristic (AUROC) values of 0.83, 0.64, and 0.83 and area under the precision–recall curve (AUPRC) values of 0.61, 0.54, and 0.65 for the invite for interview, hold for review, and reject groups, respectively. The prospective validation yielded AUROC values of 0.83, 0.62, and 0.82 and AUPRC values of 0.66, 0.47, and 0.65 for the invite for interview, hold for review, and reject groups, respectively. The randomized trial found no significant differences in overall interview recommendation rates according to faculty or algorithm and among female or underrepresented in medicine applicants. In underrepresented in medicine applicants, there were no significant differences in the rates at which the admissions committee offered an interview (70 of 71 in the faculty reviewer arm and 61 of 65 in the algorithm arm; $P = .14$). No difference in the rate of the committee agreeing with the recommended interview was found among female applicants (224 of 229 in the faculty reviewer arm and 220 of 227 in the algorithm arm; $P = .55$).

Conclusions
The virtual faculty screener algorithm successfully replicated faculty screening of medical school applications and may aid in the consistent and reliable review of medical school applicants.

1. **Evaluación**

Automatización, Generación de preguntas, Feedback

Surg Endosc (2018) 32:1840–1857
DOI 10.1007/s00464-017-5873-6

Automatically rating trainee skill at a pediatric laparoscopic suturing task

Yousi A. Oquendo[1,2] · Elijah W. Riddle[3] · Dennis Hiller[3] · Thane A. Blinman[3] · Katherine J. Kuchenbecker[1,2,4]

Received: 14 April 2017 / Accepted: 4 September 2017 / Published online: 25 October 2017

Abstract

Background Minimally invasive surgeons must acquire complex technical skills while minimizing patient risk, a challenge that is magnified in pediatric surgery. Trainees need realistic practice with frequent detailed feedback, but human grading is tedious and subjective. We aim to validate a novel motion-tracking system and algorithms that automatically evaluate trainee performance of a pediatric laparoscopic suturing task.

Methods Subjects ($n = 32$) ranging from medical students to fellows performed two trials of intracorporeal suturing in a custom pediatric laparoscopic box trainer after watching a video of ideal performance. The motions of the tools and endoscope were recorded over time using a magnetic sensing system, and both tool grip angles were recorded using handle-mounted flex sensors. An expert rated the 63 trial videos on five domains from the Objective Structured Assessment of Technical Skill (OSATS), yielding summed scores from 5 to 20. Motion data from each trial were processed to calculate 280 features. We used regularized least squares regression to identify the most predictive features from different subsets of the motion data and then built six regression tree models that predict summed OSATS score. Model accuracy was evaluated via leave-one-subject-out cross-validation.

Results The model that used all sensor data streams performed best, achieving 71% accuracy at predicting summed scores within 2 points, 89% accuracy within 4, and a correlation of 0.85 with human ratings. 59% of the rounded average OSATS score predictions were perfect, and 100% were within 1 point. This model employed 87 features, including none based on completion time, 77 from tool tip motion, 3 from tool tip visibility, and 7 from grip angle.

Conclusions Our novel hardware and software automatically rated previously unseen trials with summed OSATS scores that closely match human expert ratings. Such a system facilitates more feedback-intensive surgical training and may yield insights into the fundamental components of surgical skill.

Presented at the SAGES 2017 Annual Meeting, March 22-25, 2017, Houston, Texas.

Electronic supplementary material The online version of this article (doi:10.1007/s00464-017-5873-6) contains supplementary

Fig. 1 Full training setup

Table 5 Averaged automatic scoring performance for the eight models on testing data from participants whose data were not used during training

Model	Summed scores			Rounded average scores		
	±2 Accuracy	±4 Accuracy	Correlation	±0 Accuracy	±1 Accuracy	Correlation
Random	0.24	0.48	<0.01	0.25	0.68	0.03
Median	0.35	0.62	NaN	0.33	0.86	NaN
T	0.52	0.78	0.69	0.44	0.94	0.69
TG	0.52	0.68	0.68	0.54	0.95	0.68
TM	0.46	0.60	0.42	0.38	0.81	0.42
TMV	0.59	0.83	0.78	0.51	0.97	0.78
TMG	0.54	0.70	0.59	0.49	0.89	0.60
TMVG	0.71	0.89	0.85	0.59	1.00	0.85

The abbreviations indicate which features are included in each model: *T* time, *G* grip angle, *M* tip motion, and *V* tool visibility. NaN signifies "not a number" and occurs because correlation with a constant rating is undefined

1. **Evaluación**

Automatización, Generación de preguntas, Feedback

ORIGINAL RESEARCH

Detection of Residents With Progress Issues Using a Keyword–Specific Algorithm

Gaby Tremblay, MSc
Pierre-Hugues Carmichael, MSc
Jean Maziade, MD, FCMF, CCMF, MSc
Mireille Grégoire, MDCM, FRCPSC

ABSTRACT

Background The literature suggests that specific keywords included in summative rotation assessments might be an early indicator of abnormal progress or failure.

Objective This study aims to determine the possible relationship between specific keywords on in-training evaluation reports (ITERs) and subsequent abnormal progress or failure. The goal is to create a functional algorithm to identify residents at risk of failure.

Methods A database of all ITERs from all residents training in accredited programs at Université Laval between 2001 and 2013 was created. An instructional designer reviewed all ITERs and proposed terms associated with reinforcing and underperformance feedback. An algorithm based on these keywords was constructed by recursive partitioning using classification and regression tree methods. The developed algorithm was tuned to achieve 100% sensitivity while maximizing specificity.

Results There were 41 618 ITERs for 3292 registered residents. Residents with failure to progress were detected for family medicine (6%, 67 of 1129) and 36 other specialties (4%, 78 of 2163), while the positive predictive values were 23.3% and 23.4%, respectively. The low positive predictive value may be a reflection of residents improving their performance after receiving feedback or a reluctance by supervisors to ascribe a "fail" or "in difficulty" score on the ITERs.

Conclusions Classification and regression trees may be helpful to identify pertinent keywords and create an algorithm, which may be implemented in an electronic assessment system to detect future residents at risk of poor performance.

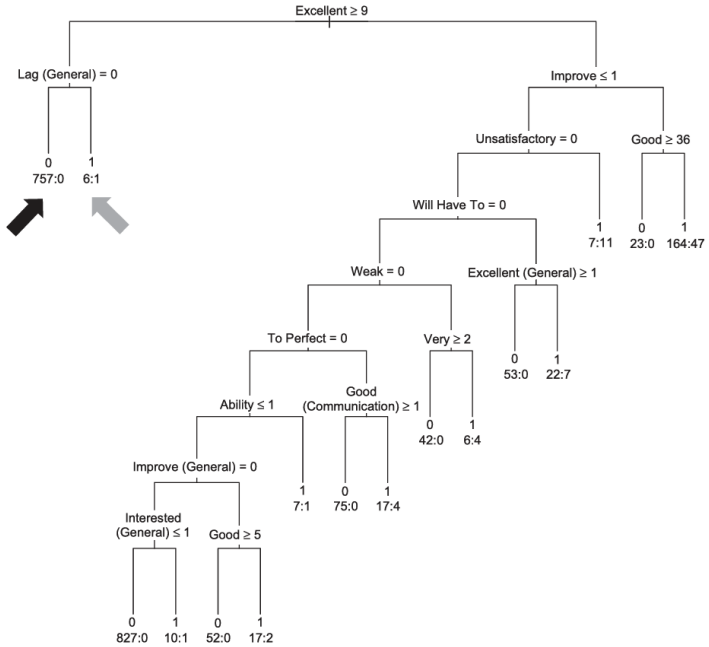


FIGURE 1
Classification Decision Tree for Residents of Royal College of Physicians and Surgeons of Canada Specialties

2.

Predicción

Desempeño académico, Riesgo, Abandono

Han *et al. BMC Medical Education* (2022) 22:830
https://doi.org/10.1186/s12909-022-03898-3

BMC Medical Education

RESEARCH Open Access

Analysis of the effect of an artificial intelligence chatbot educational program on non-face-to-face classes: a quasi-experimental study

Jeong-Won Han[1], Junhee Park[2] and Hanna Lee[3*]

Abstract

Background: Education and training are needed for nursing students using artificial intelligence-based educational programs. However, few studies have assessed the effect of using chatbots in nursing education.

Objectives: This study aimed to develop and examine the effect of an artificial intelligence chatbot educational program for promoting nursing skills related to electronic fetal monitoring in nursing college students during non-face-to-face classes during the COVID-19 pandemic.

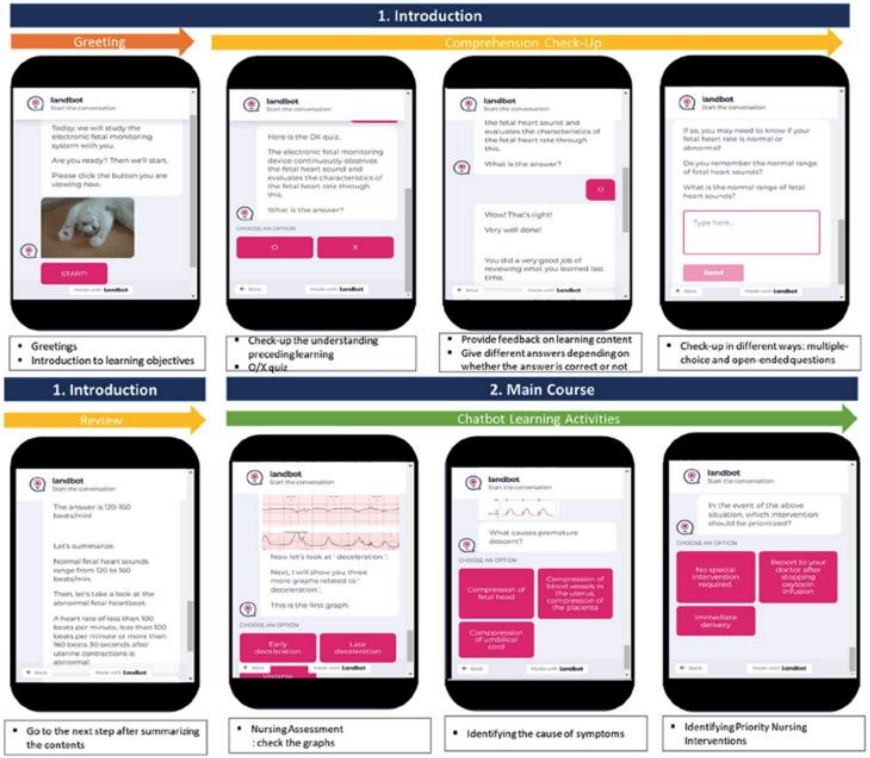
Design: This quasi-experimental study used a nonequivalent control group non-synchronized pretest–posttest design.

Methods: The participants were 61 junior students from a nursing college located in G province of South Korea. Data were collected between November 3 and 16, 2021, and analyzed using independent t-tests.

Results: The experimental group—in which the artificial intelligence chatbot program was applied—did not show statistically significant differences in knowledge ($t = -0.58$, $p = .567$), clinical reasoning competency ($t = 0.75$, $p = .455$), confidence ($t = 1.13$, $p = .264$), and feedback satisfaction ($t = 1.72$, $p = .090$), compared with the control group; however, its participants' interest in education ($t = 2.38$, $p = .020$) and self-directed learning ($t = 2.72$, $p = .006$) were significantly higher than those in the control group.

Conclusion: The findings of our study highlighted the potential of artificial intelligence chatbot programs as an educational assistance tool to promote nursing college students' interest in education and self-directed learning. Moreover, such programs can be effective in enhancing nursing students' skills in non-face-to face-situations caused by the ongoing COVID-19 pandemic.

Keywords: Artificial intelligence, Nursing, Education, Clinical reasoning, Chatbot program, Data processing



3. **Asistente IA**

Asistente virtual, Agente de aprendizaje, Asistencia fuera del aula, Tutoría

PLOS ONE

RESEARCH ARTICLE

The Virtual Operative Assistant: An explainable artificial intelligence tool for simulation-based training in surgery and medicine

Nykan Mirchi[1]*, Vincent Bissonnette[1,2], Recai Yilmaz[1], Nicole Ledwos[1], Alexander Winkler-Schwartz[1], Rolando F. Del Maestro[1]

1 Department of Neurology & Neurosurgery, Neurosurgical Simulation & Artificial Intelligence Learning Centre, Montreal Neurological Institute and Hospital, McGill University, Montreal, Quebec, Canada, **2** Division of Orthopaedic Surgery, Montreal General Hospital, McGill University, Montreal, Quebec, Canada

* nykan.mirchi@mail.mcgill.ca

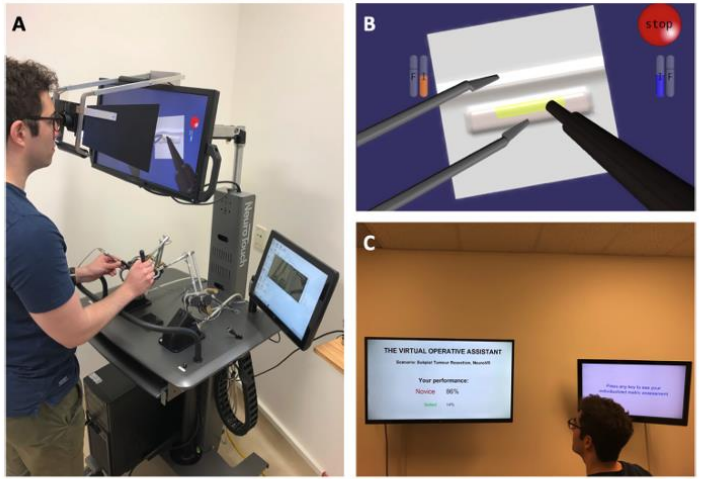


Fig 3. Educational paradigm of the Virtual Operative Assistant. (A) The trainee performs a simulated subpial tumor resection scenario on the NeuroVR (CAE Healthcare, Montreal, Quebec, Canada) platform using a simulated ultrasonic aspirator in the trainee's dominant hand and a simulated bipolar in the non-dominant hand. (B) The scenario involves removal of a cortical tumor (yellow) with minimal damage to healthy brain regions (white). (C) Upon completion of the simulated task, the data is automatically saved and uploaded to the Virtual Operative Assistant software to provide instant feedback on two monitors.

https://doi.org/10.1371/journal.pone.0229596.g003

3.

Asistente IA

Asistente virtual, Agente de aprendizaje, Asistencia fuera del aula, Tutoría

Viewpoint

Introducing Artificial Intelligence Training in Medical Education

Ketan Paranjape[1*], MS, MBA; Michiel Schinkel[2*], MD; Rishi Nannan Panday[3], MD; Josip Car[4], MD, PhD, FRCP; Prabath Nanayakkara[2], MD, PhD, FRCP

[1]Amsterdam University Medical Center, Amsterdam, Netherlands
[2]Department of Internal Medicine, Amsterdam University Medical Center, Amsterdam, Netherlands
[3]Section Acute Medicine, Department of Internal Medicine, Vrije Universiteit University Medical Center, Amsterdam, Netherlands
[4]Lee Kong Chian School of Medicine, Nanyang Technological University, Singapore, Singapore
[*]these authors contributed equally

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Abstract

Health care is evolving and with it the need to reform medical education. As the practice of medicine enters the age of artificial intelligence (AI), the use of data to improve clinical decision making will grow, pushing the need for skillful medicine-machine interaction. As the rate of medical knowledge grows, technologies such as AI are needed to enable health care professionals to effectively use this knowledge to practice medicine. Medical professionals need to be adequately trained in this new technology, its advantages to improve cost, quality, and access to health care, and its shortfalls such as transparency and liability. AI needs to be seamlessly integrated across different aspects of the curriculum. In this paper, we have addressed the state of medical education at present and have recommended a framework on how to evolve the medical education curriculum to include AI.

Civaner et al. BMC Medical Education (2022) 22:772
https://doi.org/10.1186/s12909-022-03852-3

BMC Medical Education

RESEARCH Open Access

Artificial intelligence in medical education: a cross-sectional needs assessment

M. Murat Civaner[1*], Yeşim Uncu[2], Filiz Bulut[3], Esra Giounous Chalil[4] and Abdülhamit Tatli[4]

Abstract

Background: As the information age wanes, enabling the prevalence of the artificial intelligence age; expectations, responsibilities, and job definitions need to be redefined for those who provide services in healthcare. This study examined the perceptions of future physicians on the possible influences of artificial intelligence on medicine, and to determine the needs that might be helpful for curriculum restructuring.

Methods: A cross-sectional multi-centre study was conducted among medical students country-wide, where 3018 medical students participated. The instrument of the study was an online survey that was designed and distributed via a web-based service.

Results: Most of the medical students perceived artificial intelligence as an assistive technology that could facilitate physicians' access to information (85.8%) and patients to healthcare (76.7%), and reduce errors (70.5%). However, half of the participants were worried about the possible reduction in the services of physicians, which could lead to unemployment (44.9%). Furthermore, it was agreed that using artificial intelligence in medicine could devalue the medical profession (58.6%), damage trust (45.5%), and negatively affect patient-physician relationships (42.7%). Moreover, nearly half of the participants affirmed that they could protect their professional confidentiality when using artificial intelligence applications (44.7%); whereas, 16.1% argued that artificial intelligence in medicine might cause violations of professional confidentiality. Of all the participants, only 6.0% stated that they were competent enough to inform patients about the features and risks of artificial intelligence. They further expressed that their educational gaps regarding their need for "knowledge and skills related to artificial intelligence applications" (96.2%), "applications for reducing medical errors" (95.8%), and "training to prevent and solve ethical problems that might arise as a result of using artificial intelligence applications" (93.8%).

Conclusions: The participants expressed a need for an update on the medical curriculum, according to necessities in transforming healthcare driven by artificial intelligence. The update should revolve around equipping future physicians with the knowledge and skills to effectively use artificial intelligence applications and ensure that professional values and rights are protected.

Keywords: Artificial intelligence, Healthcare, Medical curriculum, Medical ethics, Medical students, Medicine

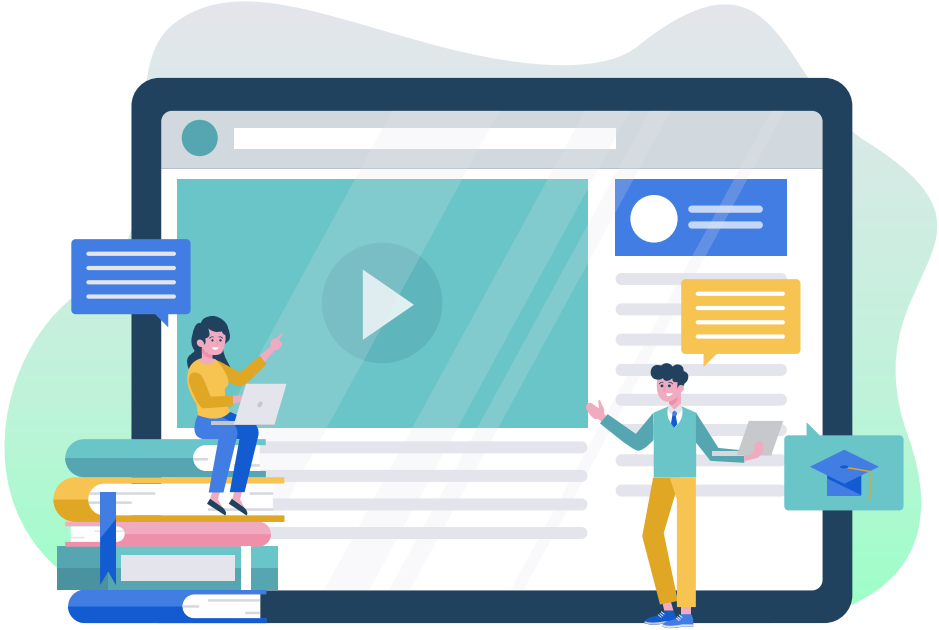
4. Gestión del aprendizaje

Diseño instruccional, Gestión estudiantil, Curriculum

Oportunidades

Investigar

Personalizar



Mejorar procesos

Comunicar

Desafíos

Desafíos éticos

Sesgo, seguridad, equidad

Estar al día

Docentes capaces de usar IA

Infraestructura y soporte

Guías, estándares, infraestructura tecnológica

Inversión

Usar IA tiene costos asociados

Imagen creada con IA Midjourney


Educación
Diseño de estudios
Ciencias cognitivas
Diseño instruccional
Ciencias de la computación
Psicología
Neurociencia
Lingüística
AIEd

Muchas gracias

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