Vol.7 No.1 (2024)

Journal of Applied Learning & Teaching

ISSN : 2591-801X

Content Available at : http://journals.sfu.ca/jalt/index.php/jalt/index

Artificial intelligence in higher education database (AIHE V1): Introducing an open-access repository

Fadhil Ismail[A] — A Kaplan Higher Education Academy, Singapore

Joseph Crawford[B] — B University of Tasmania, Australia

Shannon Tan[C] — C Kaplan Higher Education Academy, Singapore

Jürgen Rudolph[D] — D Kaplan Higher Education Academy, Singapore

Eunice Tan[E] — E Singapore Institute of Management, Singapore

Pauline Seah[F] — F Kaplan Higher Education Academy, Singapore

Fiona Xiaofei Tang[G] — G Kaplan Business School, Perth, Australia

Florence Ng[H] — H University Partnership (Coventry University), PSB Academy, Singapore

Laura Visser Kaldenbach[I] — I Singapore Institute of Management, Singapore

Anand Naidu[J] — J Murdoch University, Perth, Australia

Vanessa Stafford[K] — K Kaplan Business School, Sydney, Australia

Michelle Kane[L] — L University of Portsmouth, United Kingdom

Keywords

AI;
AIEd;
Artificial intelligence;
artificial intelligence in education;
ChatGPT;
GenAI;
generative AI;
higher education;
literature survey;
PRISMA.

Abstract

Generative artificial intelligence (GenAI) has fired the world's imagination. The higher education sector is not immune from the GenAI hype, panic, and mania. The emergence of artificial intelligence, in its newest form, into curriculum, student life, and learning has created an entanglement of technology, people, and learning. Yet, there is still a lack of cohesive accounts of the emergent literature used to inform practical learning and teaching decisions. Our manuscript responds with the deployment of a previously published systematic literature review to create the first version of the Artificial Intelligence in Higher Education Database (AIHE V1). Published in conjunction with this article, we pioneer an open-access resource to support learning and teaching scholars to gain timely access to pre-examined literature on AI and higher education. This first version documents 160 manuscripts published between 30 November 2022 and 31 December 2023. Using a rigorous systematic review method, engaging in the PRISMA approach, we offer a first glance at the metadata of articles published on AI and higher education during the first year of ChatGPT.

Correspondence

fadhil.ismail@kaplan.com [A]

Article Info

Received 9 March 2024
Received in revised form 28 March 2024
Accepted 3 April 2024
Available online 18 April 2024

DOI: https://doi.org/10.37074/jalt.2024.7.1.35
DOI: https://doi.org/10.37074/jalt.2024.7.1.35D

Introduction

ChatGPT's launch in late 2022 unleashed an avalanche of scholarly investigations that examine the intersections of ChatGPT, generative AI, and higher education (Rudolph et al., 2023a, 2023b). These inquiries have been disseminated across an array of academic journals and preprint repositories. Despite the high volume of these publications, they offer only fragmented views of a domain evolving at breakneck speed. Considering the rapid proliferation of such scholarly work, it is imperative to critically evaluate the corpus of existing literature. This endeavour is not merely academic. Our findings and database provide a foundation for elucidating the roles and repercussions of AI technologies within higher education contexts. Specifically, they are instrumental in identifying both the prospects and perils AI presents to teaching and learning in tertiary education (Rudolph et al., 2024).

Many authors optimistically underscore the potential of ChatGPT and similar generative AI-driven chatbots to enrich and augment educational outcomes and experiences in higher education (e.g., Rasul et al., 2023). However, there is a need to investigate GenAI's pitfalls, safeguard against unethical or ineffectual deployment, and promote its ethical, effective, and responsible use. As the body of literature expands, the importance of not only aggregating and scrutinising these studies through thorough literature reviews but also of employing meta-analytical methods to dissect the broader implications of this burgeoning academic discourse within varied educational milieus becomes paramount. Part of the novelty of what we do in this article lies in the systematicity of our approach. There are no systematic literature surveys that evaluate generative AI chatbot models within higher education, longitudinally or otherwise. Moreover, current publications on AI applications in relation to higher education still tend to be in their infancy. Efforts to establish coherence among these publications tend to be disjointed and, often, are conducted at a granular level (Ismail et al., 2023).

Familiarity with existing literature precludes inadvertent rediscovery. As a result, the following survey of the literature, available by the time of drafting this manuscript (April 2024), focuses on literature reviews and surveys that include generative AI (GenAI). Earlier chatbots (dating back to ELIZA in the 1960s) and voice-activated virtual assistants such as Siri or Alexa (in the 2010s) are, to varying extents, 'generative' (see Rudolph et al., 2023b). Whilst GenAI's most popular form in the shape of ChatGPT only burst onto the global scene in November 2022, it is preceded by foundational large language models (LLMs) and text-to-image GenAI such as DALL-E (Cao et al., 2023; Rudolph et al., 2023b). Succinctly put, GenAI can create human-like, AI-generated content, encompassing digital content such as images, music, video, and natural language (Hart, 2024; Michel-Villarreal et al., 2023).

As a consequence, there is a dearth of literature that surveys academic discussions of generative AI and higher education. Thus, for instance, Chiu et al.'s (2023) article is different from our pursuit, as it systematically reviews the opportunities and challenges of AIEd by examining the literature from 2012–2021. Similarly, Marengo et al.'s (2024) not yet peer-reviewed study has understandably little to say about GenAI and higher education as it reviewed empirical studies published between 2013 and 2022 to examine the characteristics of published research in the field of AI in higher education. Yet another example is Dogan et al. (2023), who employ a multifaceted methodological approach (integrating traditional bibliometric analysis with data mining techniques) to analyse peer-reviewed, Scopus-indexed publications that are focused on AI and written in English between 1999 to 2022. Finally, Bearman et al. (2023), while adopting a critical literature review methodology to scrutinise how AI is conceptualised within leading higher education journals, mention 'generative' AI only once in passing.

Tlili et al.'s (2023) deliberations on how AI literature reviews can be more transparent and their methodological approach is indirectly relevant to our research as it employs the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to systematically collect and evaluate 61 literature reviews on AI in education. Tlili et al. (2023) provide a detailed analysis of literature review practices in AI education research by systematically evaluating transparency through a coding scheme and identifying methodological areas needing enhancement.

While Tlili's scope is broader than ours (as it includes both K-12 education and non-generative AI), it is worthwhile noting that Stracke et al.'s (2023) study is both broader and narrower compared with our research. Stracke et al. (2023) look beyond higher education by talking about education in general terms while focusing on trustworthy and ethical AI. They introduce a unified protocol for conducting systematic reviews in AI and education (AIEd), covering both the integration of AI in teaching and learning and literacy education about AI. By aligning with the PRISMA guidelines, Stracke et al.'s (2023) protocol aims to streamline research efforts, enabling consistent analysis and comparison of findings across studies. They demonstrate its utility with a review focused on trustworthy and ethical aspects of AIEd, developed in tandem with the protocol to ensure mutual refinement. Stracke et al. (2023) plan to extend their innovative approach to additional key terms and extend its application over time, facilitating trend analysis and comparative research within AIEd.

The above brief review shows that Ismail et al.'s (2023) observation of a dearth of systematic and macro-level research on our topic continues to be true. Our research team (based in Australia, Singapore and the UK) applied a rigorous research protocol to examine research on AI applications and higher education. In a recent protocol paper, a systematic search strategy was proposed to critically review extant research longitudinally across generative AI chatbot models within higher education (Ismail et al., 2023). Our paper applies this protocol and introduces the first version of an open-access database that systematically surveys the pertinent academic literature from November 2022 to December 2023. Our endeavour seeks to support fellow higher education researchers in gaining access to pre-examined literature on different forms of generative AI and their impact on higher education. Using a rigorous, systematic approach, we analyse the metadata of articles published on specific types of generative AI and higher education to explore their impact on the future of higher education. In this review, the focus was on ChatGPT. By providing an open-access database (see Ismail et al., 2024), we aim to facilitate future research. In adherence to the principles of a sound and systematic review methodology, which necessitates meticulous design and execution within the bounds of established research themes (Crawford & Cifuentes-Faura, 2022), our study sets forth this research objective:

> To implement a detailed research protocol designed for the systematic curation and analysis of literature on GenAI applications (such as ChatGPT), our study aims to facilitate evidence-based decision-making processes among policymakers, educators, and scholars in the higher education sector.

Consequently, our article and the resulting database employ a methodological framework intended to enable a detailed examination of the metadata and substantive findings of scholarly articles focused on GenAI applications pertinent to higher education.

Methods

Ismail et al. (2023) provide a more detailed version of our methodical approach through an updated summary. Systematic reviews methodically compile and analyse existing knowledge within a research domain. They employ a structured approach to evaluate collective findings against predefined criteria (Higgins et al., 2011; Motyka, 2018). While research metrics serve as vital tools for assessing the quality and impact of these findings (Moed & Halevi, 2015), their inherent limitations necessitate a multifaceted evaluation approach, eschewing reliance on a single metric (Nestor et al., 2020). Our review thus selected databases based on a composite of recognised metrics, including Journal Impact Factor, h-index, g-index, Eigenfactor score, and Altmetrics, to ensure a thorough and balanced assessment of research quality (Ismail et al., 2023).

Search strategy

Our literature survey used a systematic approach for article selection guided by PRISMA (Moher et al., 2009; Page et al., 2021). Specifically, it employed the reporting recommendations for systematic reviews suggested in the PRISMA 2020 guidelines to reflect recent developments and protocol suggestions in systematic review methodologies (see Bearman et al., 2012; Butler-Henderson et al., 2020, 2021; Page et al., 2021). Following PRISMA search guidelines, our systematic review conducted a database search of all published journal articles and preprints that relate to the topic of ChatGPT and teaching and learning in higher education.

All research outputs published between 30 November 2022 and 31 December 2023 in the following sources were considered: (1) Academic Search Ultimate, IEEE Xplore, Informit Online, Ovid, Proquest, ScienceDirect, Scopus, and Web of Science; and (2) Google Scholar (the first ten pages for each search string were reviewed). A snowball reference analysis was also conducted based on the extracted articles. Our search strategy clearly aligned the search phrases (search terms, keywords and Boolean Operators) to the thematic dimensions relevant to the research objectives. For each search, the first core strings (higher education, artificial intelligence, and 'focal artificial intelligence') were paired with one of the other strings to complete five strings. 'Focal AI' could include reviews on diverse generative AI chatbots (e.g., ChatGPT, GPT-4, Bard/Gemini, Bing Chat, Claude, or Ernie) and generative non-chatbot AI (e.g. DALL-E, GitHub Copilot, GPT-4 plugins, Midjourney, Runway, or Synthesia), although our review focused on ChatGPT.

Table 1: Concepts, search strings and reviews guiding frames (Ismail et al., 2023, p. 58).

Concept	Search string	Review that guided this frame.
1. **Higher education**	"Higher education" OR university* OR college OR tertiary OR undergrad* OR graduate OR postgrad*	Butler-Henderson et al. (2022); Zawacki-Richter et al. (2019)
2. **Artificial intelligence**	"artificial intelligence" OR "machine intelligence" OR "intelligent support" OR "intelligent virtual reality" OR "chat bot*" OR "machine learning" OR "automated tutor" OR "personal tutor*" OR "intelligent agent*" OR "expert system" OR "neural network" OR "natural language processing"	Zawacki-Richter et al. (2019)
3. Focal artificial intelligence	ChatGPT* OR "Chat Generative Pre-trained Transformer"	*Use specific tool related text.*
4. **Learning Setting**	Curricul* OR learn* OR student*	Zawacki-Richter et al. (2019)
5. **Education policies**	Polic*	Aikens et al. (2016)
6. **Assessment**	Assess*	Struyven et al. (2005)
7. **Teachers and lecturers**	Teach* OR Lectur*	Spelt et al. (2009)
8. **Pedagogical Approaches**	Pegagog*	Spelt et al. (2009)

Eligibility criteria and selection procedure

Our search was limited to English-language academic journals and pre-prints, with the review covering manuscripts published up until 31 December 2023. We included articles focusing on aspects of teaching, curriculum development, education, and student engagement in higher education, specifically those that address assessments, teaching practices, and course design related to the targeted AI tool. Exclusions were made for articles that deal with university administrative processes not pertinent to teaching or learning, as well as studies on students that do not directly relate to educational or pedagogical contexts. For instance, articles without a clear link to higher education contexts were omitted from our review (Ismail et al., 2023).

A double screening procedure was adopted in the systematic review during the verification process across the initial title and abstract screening and full-text screening to determine the final selection of sources of evidence for analysis. An appropriate reliability check (e.g., Cohen's Kappa) was conducted with at least fair agreement between all pairs required prior to progression. In the title and abstract stage, Cohen's kappa ranged between .47 and .86 across all author review pairs, except for one reviewer whose pairs were .28 and .39. These were all checked a third time for posterity ahead of progression. The quality of the evidence gathered in the systematic review was evaluated using Cochrane

Collaboration's tool for risk of bias assessment (Higgins et al., 2011; Page et al., 2021; Zeng et al., 2020) to minimise bias. The flow of information through this systematic review and aggregated findings based on the prespecified criteria was subsequently reported through a PRISMA Statement (Figure 1).

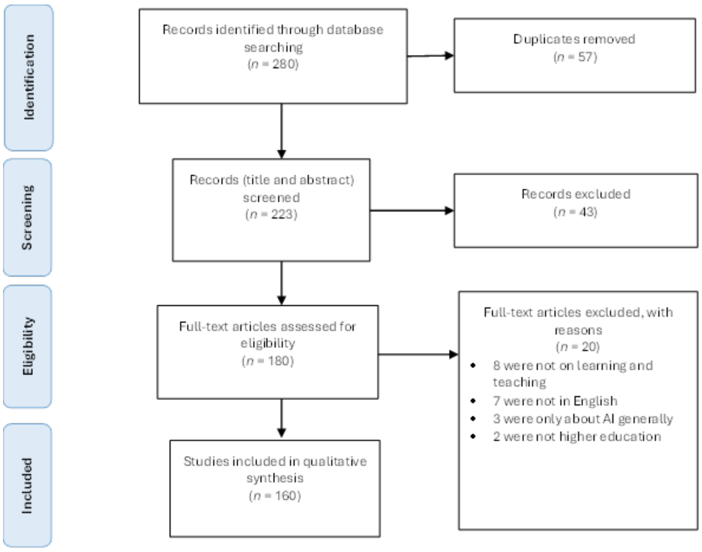

Figure 1: PRISMA statement.

Study validity assessment

We used the PRISMA checklist and critical appraisal tools suited to the methods of the included studies to appraise and critically assess the validity of the studies (Moher et al., 2009, 2015). The PRISMA checklist is a document that guides reporting systematic reviews and meta-analyses clearly and transparently. It ensures that the systematic review is written comprehensively and transparently so that readers can assess the quality and validity of the evaluation (Page et al., 2020).

research, the field will be left blank. For participants, possible categories were academics, practitioners, or students – undergraduate, postgraduate and doctoral (see Butler-Henderson et al., 2020; Ismail et al., 2023).

Table 2: Description of data elements.

No.	Data Element	Field Type	Description
1.	Country of First Author	Alphabetic	Country that the Author is based in
2.	Article Type	Alphabetic	**The 10 categories:** Action research Autoethnography Case study Commentary Descriptive Opinion/Perspective Reflection Research Study Review Theoretical
3.	Type of Studies	Alphabetic	**The three categories:** Quantitative Qualitative Mixed
4.	Participant Type	Alphabetic	**The five categories:** Academics Practitioners Students Others All
5.	Discipline	Alphabetic	**The six categories:** Health Education Humanities/ Social sciences STEM Others All
6.	Title	Alphabetic	Title of the publication
7.	Author(s)	Alphabetic	Last Name, Initial of First Name of the author(s)
8.	Abstract	Alphabetic	Summary of the publication
9.	Year	Numeric	Year of Publication
10.	Journal	Numeric	Name of Journal
11.	Volume Number, Issue Number, Pages	Numeric	Details of the journal
12.	DOI/Hyperlink	URL	Digital Object Identifier / URL of the publication where available

Data coding and extraction strategy

Our data coding and extraction strategy included the production of a detailed spreadsheet that is being made available as an open-access database for scholarly reuse (Ismail et al., 2024) in conjunction with the publication of this article. In constructing the database, we incorporated certain theoretical assumptions detailed in Table 2. These are shared to present our reflexivity as researchers and to help others understand the adaptability of the data for their respective contexts. Although many data elements are clear and can be readily used in future research (like DOI, journal metadata, and country of origin), others, like the quality assessment score, study type, and participant type, necessitate further explanation.

The discipline and sub-discipline categories require some elaboration. The discipline category is grouped into four categories: health science, humanities and social science, STEM (science, technology, engineering and mathematics), and 'others' (see Butler-Henderson et al., 2020; Ismail et al., 2023). The type of study is defined as quantitative, qualitative, or mixed methods. Should there be no empirical

To test the replicability of our process, the description of the above data elements was executed with different researchers. The outcomes from each repetition were recorded and compared for consistency using the metrics described in Table 2. To ensure intercoder reliability, all coders underwent standardised training using Table 2 as a shared coding manual. Their outputs were periodically cross-checked against one another to assess consistency. Reliability was statistically measured and established using Cohen's Kappa (Warrens, 2015). Conflicts in the review decision were deferred to a consensus meeting for the team to come to a resolution. This streamlined and coherent approach ensured the integrity of the database and led the team to the extraction phase of our research project.

Results and discussion

Despite its long and rich history, AI development has made significant and noteworthy progress in the past couple of years (Haenlein & Kaplan, 2019). This includes the launch of AI-powered chatbots such as ChatGPT (Susnjak, 2022). Expectedly, the body of research examining the use of AI-related technologies, including ChatGPT, has also expanded dramatically over the course of a year since the launch of ChatGPT-3.5 in November 2022 (Gupta et al., 2023). The geographical distribution of publications on AI can be observed through the heat map in Figure 2.

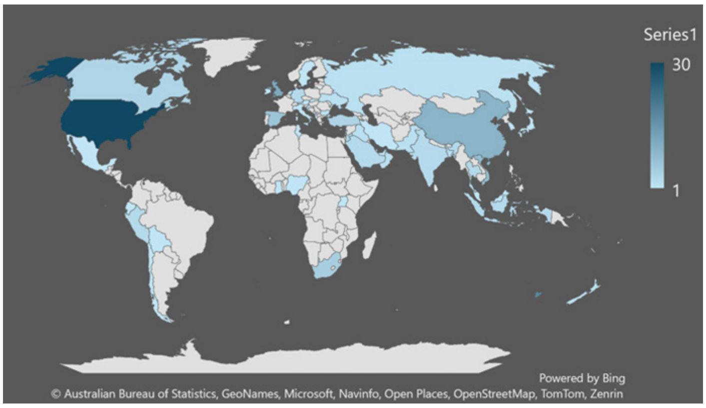

Figure 2: Heat map of geographical distribution of publications.

The first authors of the articles in our database were based in the coincidentally round number of 50 countries. The heat map indicates that the largest number of studies from a single country came from the US (28). Australia has the second-largest number of studies (18). 12 studies originated in the UK and nine in the UAE. China and Vietnam are represented with seven articles each. In terms of continents, Asia contributes 61 (38.1%), the Americas 38 (23.8%), Europe 33 (20.6%), Australasia 20 (12.5%), and Africa eight (5%) articles.

The articles include a broad range of empirical research, such as surveys, interviews, evaluations, and case studies. There were also theoretical pieces, including opinion pieces, commentaries, and reviews, as summarised in Table 3. In studies involving empirical research, qualitative studies (73; 45.6%) account for nearly half of the studies in the database, while quantitative ones (26; 16.3%) and studies using a mixed methods approach (14; 8.7%) were less popular. Nearly a third of the studies in the database were non-empirical (47; 29.4%).

The majority of the articles involved students as the primary participants (65; 40.6%) and studies having mixed groups of participants (65; 40.6%). There were fewer studies involving practitioners (7, 4.4%) and academics (18, 11.3%). Only ten studies (6.3%) were from the STEM discipline, and 14 (8.8%) were from the humanities. The 24 studies from the health discipline make up 15 per cent, but studies broadly located in education (89, 55.5%) formed more than half of the studies reviewed.

The data presented in this review provide insights into the current state of research on generative artificial intelligence in higher education. Our database offers an opportunity for research scholars to undertake future research involving AI in higher education. Given the immense potential and threats that GenAI holds for higher education, we encourage scholars to draw upon our method and database to facilitate their own research. An appropriate citation can be found in our reference list (Ismail et al., 2024).

Table 3: Summary of article characteristics.

Article Types	Numbers	%
Action research	2	1.3
Autoethnography	1	0.6
Case study	4	2.5
Commentary	8	5
Descriptive	2	1.3
Opinion/Perspective	13	8.1
Reflection	1	0.6
Research Study	89	55.6
Review	39	24.4
Theoretical	1	0.6
Total	**160**	**100%**
Types of study	**Numbers**	**%**
Quantitative	26	16.3
Qualitative	73	45.6
Mixed	14	8.7
Others	47	29.4
Total	**160**	**100%**
Participant Types	**Numbers**	**%**
Academia	18	11.3
Practitioners	7	4.4
Students	65	40.6
Others	5	3.1
All	65	40.6
Total	**160**	**100%**
Disciplines	**Numbers**	**%**
Health	24	15
Education	89	55.5
Humanities/ Social sciences	14	8.8
STEM	10	6.3
Others	10	6.3
All	13	8.1
Total	**160**	**100%**

Conclusion

The database attached to this manuscript provides opportunities for scholars to extract specific components of the published literature for their own studies. This database and its future versions will open the door to facilitate easy access to undertake future research based on a clear and transparent understanding of the database. We encourage scholars to download filtered versions of the database and draw on our systematic efforts in their own research (see

Ismail et al., 2024).

A note on the significance of open access (OA) publications is in order. Their growing popularity offers widespread benefits, including free and immediate access to research, enhancing its reach, impact, and efficiency, and ensuring equitable access. This stands in contrast to traditional models where taxpayer-funded research often remains inaccessible behind paywalls, a practice that limits scientific engagement (Butler-Henderson et al., 2020; Max Planck Society, 2003; Schiltz, 2018; Science Europe, 2013). Many funding bodies now mandate OA publication to ensure unrestricted access to research findings. Among OA models, Diamond OA stands out for not imposing fees on authors, thus preserving their copyright (Butler-Henderson et al., 2020; Chen & Olijhoek, 2016; cOAlition S, 2020; Fuchs & Sandoval, 2013; Olijhoek et al., 2015). The necessity of open availability of research for scientific progress is emphasised, with recent findings suggesting the value of extending open practices to data sharing (cOAlition S, 2020). We advocate this approach in our work to promote transparency but also accelerate research efforts, particularly in urgent and vital issues like AI and higher education.

Our paper details the development and research underpinning the open-access Artificial Intelligence in Higher Education Database (AIHE V1: Ismail et al., 2024). Employing a comprehensive systematic review methodology, we aimed to maximise the utility and accessibility of the data and metadata within the database. Our approach included a thorough literature review, database examination, and online resource search to encompass a wide range of publications. The process involved meticulous double-screening and double full-text review, all meticulously documented to aid fellow academics. In addition, we carefully selected and organised this database to facilitate collaboration and synergy among researchers (Butler-Henderson et al., 2020).

To the best of our knowledge, this database is the first of its kind in the higher education literature to curate the existing literature for higher education practitioners and researchers. By centralising the literature within a single database, we aim to streamline the research process, saving time for scholars while guaranteeing that a robust methodological foundation informs new studies. This convenience is anticipated to boost the production of studies exploring the diverse effects of AI on learning and teaching (see Butler-Henderson et al., 2020). Actively disseminating this resource will play a vital role in advancing the scholarship surrounding GenAI's role in education.

We will consider periodically updating and refining this methodology, incorporating future time segments, revising coding protocols, and expanding our database selection to enhance this resource's robustness and relevance over time (Ismail et al., 2023). This strategy aims better to address the effects of AI and other educational technologies, supporting the global higher education community's transition towards fresh insights in learning and teaching within the dynamically changing landscape challenged and transformed by AI applications.

References

Bearman, M., Ryan, J., & Ajjawi, R. (2023). Discourses of artificial intelligence in higher education: A critical literature review. *Higher Education, 86*(2), 369-385. https://doi.org/10.1007/s10734-022-00937-2

Bearman, M., Smith, C. D., Carbone, A., Slade, S., Baik, C., Hughes-Warrington, M., & Neumann, D. L. (2012). Systematic review methodology in higher education. *Higher Education Research & Development, 31*(5), 625-640. https://doi.org/10.1080/07294360.2012.702735

Butler-Henderson, K., Crawford, J., Rudolph, J., Lalani, K., & Sabu, K. M. (2020). COVID-19 in Higher Education Literature Database (CHELD V1): An open access systematic literature review database with coding rules. *Journal of Applied Learning & Teaching, 3*(2), 11-16. https://doi.org/10.37074/jalt.2020.3.2.11

Butler-Henderson, K., Tan, S., Lalani, K., Sabu, K. M., Kemp, T., Rudolph, J., & Crawford, J. (2021). Update of the COVID-19 higher education literature database (CHELD v2). *Journal of Applied Learning & Teaching, 4*(1), 134-137. https://doi.org/10.37074/jalt.2021.4.1.22

Cao, Y., Li, S., Liu, Y., Yan, Z., Dai, Y., Yu, P. S., & Sun, L. (2023). *A comprehensive survey of AI-generated content (AIGC): A history of generative AI from GAN to ChatGPT*. arXiv preprint arXiv:2303.04226.

Chen, X., & Olijhoek, T. (2016). Measuring the degrees of openness of scholarly journals with the open access spectrum (OAS) evaluation tool. *Serials Review, 42*(2), 108-115. https://doi.org/10.1080/00987913.2016.1182672

Chiu, T. K., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2023). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 4*, 100118. https://doi.org/10.1016/j.caeai.2022.100118

cOAlition S. (2020). *Plan S. Making full and immediate open access a reality*. https://www.coalition-s.org/

Crawford, J., & Cifuentes-Faura, J. (2022). Sustainability in higher education during the COVID-19 pandemic: A systematic review. *Sustainability, 14*(3), 1879. https://doi.org/10.3390/su14031879

Dogan, M. E., Dogan, G. T., & Bozkurt, A. (2023). The use of artificial intelligence (AI) in online learning and distance education processes: A systematic review of empirical studies. *Applied Sciences, 13*(5), 3056. http://dx.doi.org/10.3390/app13053056

Fuchs, C., & Sandoval, M. (2013). The diamond model of open access publishing: Why policy makers, scholars, universities, libraries, labour unions and the publishing world need to take non-commercial, non-profit open access serious. *TripleC: Communication, Capitalism & Critique, 11*(2), 428-443. http://dx.doi.org/10.31269/vol11iss2pp428-443

Gupta, B., Mufti, T., Sohail, S. S., & Madsen, D. Ø. (2023). ChatGPT: A brief narrative review. *Cogent Business & Management, 10*(3). https://doi.org/10.1080/23311975.2023.2275851

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review, 61*(4), 5–14. https://doi.org/10.1177/0008125619864925

Hart, R. (2024, February 16). *OpenAI's Sora has rivals in the works, including from Google and Meta*. Forbes. https://www.forbes.com/sites/roberthart/2024/02/16/openais-sora-has-rivals-in-the-works-including-from-google-and-meta/?sh=700ecc282843

Higgins, J. P., Altman, D. G., Gøtzsche, P. C., Jüni, P., Moher, D., Oxman, A. D., Savović, J., Schulz, K. F., Weeks, L., & Sterne, J. A. C. (2011). The Cochrane collaboration's tool for assessing risk of bias in randomised trials. *BMJ, 343,* 1-9. https://doi.org/10.1136/bmj.d5928

Ismail, F., Crawford, J., Tan, S., Rudolph, J., Tan, E., Tang, F., Seah, P., Ng, F., Visser Kaldenbach, L., Naidu, A., Stafford, V., & Kane, M. (2024). *Artificial intelligence in higher education database (AIHE V1)*. https://doi.org/10.37074/jalt.2024.7.1.35D

Ismail, F., Tan, E., Rudolph, J., Crawford, J., & Tan, S. (2023). Artificial intelligence in higher education. A protocol paper for a systematic literature review. *Journal of Applied Learning and Teaching, 6*(2), 56-63. https://doi.org/10.37074/jalt.2023.6.2.34

Marengo, A., Pagano, A., Pange, J., & Soomro, K. A. (2024). The educational value of artificial intelligence in higher education: A 10-year systematic literature review. *Interactive Technology and Smart Education*. http://dx.doi.org/10.20944/preprints202311.0055.v1

Max Planck Society. (2003). *Berlin declaration on open access to knowledge in the sciences and humanities*. https://openaccess.mpg.de/Berlin-Declaration

Michel-Villarreal, R., Vilalta-Perdomo, E., Salinas-Navarro, D. E., Thierry-Aguilera, R., & Gerardou, F. S. (2023). Challenges and opportunities of GenAI for higher education as explained by ChatGPT. *Education Sciences, 13*(9), 856. https://www.mdpi.com/2227-7102/13/9/856

Moed, H. F., & Halevi, G. (2015). Multidimensional assessment of scholarly research impact. *Journal of the Association for Information Science and Technology, 66*(10), 1988-2002. https://doi.org/10.1002/asi.23314

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & PRISMA Group. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *Annals of Internal Medicine, 151*(4), 264-269. https://doi.org/10.7326/0003-4819-151-4-200908180-0013

Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., ... & Prisma-P Group. (2015). Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. *Systematic Reviews, 4*, 1-9.

Motyka, B. (2018). Employee engagement and performance: A systematic literature review. *International Journal of Management and Economics, 54*(3), 227-244. https://doi.org/10.2478/ijme-2018-0018

Nestor, M. S., Fischer, D. L., Arnold, D., Berman, B., & Del Rosso, J. Q. (2020). Rethinking the journal impact factor and publishing in the digital age. *The Journal of Clinical and Aesthetic Dermatology, 13*(1), 12. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7028381/pdf/jcad_13_1_12.pdf

Olijhoek, T., Bjørnshauge, L., & Mitchell, D. (2015). Criteria for open access and publishing. *ScienceOpen Research*. https://doi.org/10.14293/S2199-1006.1.SOR-EDU.AOFRQA.V1

Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffman, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., McGuinness, L. A., Stewart, L. A., Thomas, J., Tricco, A. C., Welch, V. A., Whiting, P., & McKenzie, J. E. (2021). PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews. *BMJ, 372*. http://dx.doi.org/10.1136/bmj.n160

Rasul, T., Nair, S., Kalendra, D., Robin, M., de Oliveira Santini, F., Ladeira, W. J., Sun, M., Day, I., Rather, R. A., & Heathcote, L. (2023). The role of ChatGPT in higher education: Benefits, challenges, and future research directions. *Journal of Applied Learning and Teaching, 6*(1), 41-56. https://doi.org/10.37074/jalt.2023.6.1.29

Rudolph, J., Tan, S., & Tan, S. (2023). ChatGPT: Bullshit spewer or the end of traditional assessments in higher education?. *Journal of Applied Learning and Teaching, 6*(1), 342-363. https://doi.org/10.37074/jalt.2023.6.1.9

Rudolph, J., Tan, S., & Tan, S. (2023b). War of the chatbots: Bard, Bing Chat, ChatGPT, Ernie and beyond. The new AI gold rush and its impact on higher education. *Journal of Applied Learning and Teaching, 6*(1), 364-389. https://doi.org/10.37074/jalt.2023.6.1.23

Rudolph, J., Ismail, M. F., & Popenici, S. (2024). Higher education's generative artificial intelligence paradox: The meaning of chatbot mania. *Journal of University Teaching and Learning Practice, 21*(6). Ahead of publication.

Schiltz, M. (2018). Science without publication paywalls: cOAlition S for the realisation of full and immediate open access. *Frontiers in Neuroscience, 12*. https://doi.org/10.3389/fnins.2018.00656

Science Europe. (2013). *Science Europe principles on open access to research publications.* http://scieur.org/opennew

Stracke, C. M., Chounta, I. A., Holmes, W., Tlili, A., & Bozkurt, A. (2023). A standardised PRISMA-based protocol for systematic reviews of the scientific literature on artificial intelligence and education (AI&ED). *Journal of Applied*

Learning and Teaching, 6(2), 64-70. https://doi.org/10.37074/jalt.2023.6.2.38

Susnjak, T. (2022). *ChatGPT: The end of online exam integrity?*. arXiv preprint arXiv:2212.09292.

Tlili, A., Huang, R., Mustafa, M. Y., Zhao, J., Bozkurt, A., Xu, L., Wang, H., Salha, S., Altinay, F., Affouneh, S., & Burgos, D. (2023). Speaking of transparency: Are all artificial intelligence (AI) literature reviews in education transparent? *Journal of Applied Learning and Teaching, 6*(2), 44-55. https://doi.org/10.37074/jalt.2023.6.2.15

Warrens, M. J. (2015). Five ways to look at Cohen's kappa. *Journal of Psychology & Psychotherapy, 5*. https://doi.org/10.4172/2161-0487.1000197