4.4. Planning, Scheduling, and Optimization in News Media

Automated stories are commonly found in the subfield of planning, scheduling, and optimization. The process involves running data through an algorithm that organizes that data into a readable story. Therefore, using algorithms to plan, publish, and refine stories is usually implemented to produce data-driven stories; such stories often relate to crimes, natural disasters, elections, finance, and sports. After the success of the *LA Times'* QuakeBot, which can create a write-up within minutes of an earthquake, newsrooms started to embrace story automation (Salaverría and de-Lima-Santos 2020).

In general, narrative structures are repetitive, which makes them good candidates for automation (Carlson 2015; Dörr 2016; Graefe 2016; van Dalen 2012). For example, The Associated Press and *Newsday* automated the coverage of 124 school districts in the US, and *The Washington Post* published 850 automated articles in 2016. These examples highlight the potential that AI brings to news production since it allows newsrooms to produce more stories while using fewer human resources (Broussard et al. 2019). However, using automated stories raises ethical and quality concerns (Guzman and Lewis 2020).

Many news media outlets saw the COVID-19 outbreak as an opportunity to automate their production processes since the global death toll and infection rates were structured data that could fit into predictable story frames (Danzon-Chambaud 2021). For example, The Times (UK) automated a powerful charting tool to build graphics for coronavirus coverage. The BBC released a project called Salco ("Semi-Automated Local Content") to generate over 100 unique stories per month. The BBC allowed Salco's coverage to focus on local audiences who could learn about their hospitals' performance during the COVID-19 pandemic. These examples highlight another level of AI systems that includes the subfields of NLG and computer vision.

5. Discussion and Conclusions

Overall, this study argues that AI can take different forms in the news industry. Our findings reveal three major subfields that are more present in the news ecosystem: machine learning, computer vision, and planning, scheduling, and optimization. Machine learning is used in different parts of the news production workflow. However, we commonly found two applications in our cases. The first involves a great interest in boosting public engagement using machine learning recommendation engines. The second involves news outlets using machine learning models to adjust their business strategies to individual readers. For example, machine learning may be used to predict subscription cancellation or build paywalls that bend to the individual reader. Thus, machine learning algorithms are often used to strengthen news outlets' business models and boost revenue streams. In line with previous studies, third-party organizations build some of these solutions and sell them to newsrooms, such as Piano in the US and Deep BI in the UK (Cook et al. 2021). Similarly, large tech platforms, especially Google, provide solutions such as Jigsaw, which is a tool that is used to help community managers manage toxic comments or posts that might violate community guidelines (Rashidian 2020).

Automated journalism governs the subfield of planning, scheduling, and optimization. Although journalism is related to textual content, our findings suggest that NLP models are used less frequently in the industry than planning, scheduling, and optimization. We speculate that this might be associated with the fact that it is not easy to replicate NLP models in different languages, such as Portuguese (Rodrigues et al. 2014). Furthermore, automated journalism does not necessarily focus on adopting machine learning or NLP approaches. Automated journalism constitutes, at times, a basic application of computational models, which, in many cases, are used to fill in the blanks of template stories. These dumb algorithms—those which may adapt but ultimately seek to achieve very simple instructions—are far more likely to be found in the news industry, as they do not require much effort or time to deploy (Biswal and Gouda 2020).

Computer vision is a subfield of AI that helps practitioners deal with visual content in different ways. Thus far, most of the cases deal with CV as a tool for investigative reporting, including fact-checking content on social networks. According to this perspective, CV seems limited to being a one-goal project, which hampers its replication and, consequently, its application on a larger scale. Although we could identify small news outlets that rely on computer vision algorithms to produce investigative stories, we found that large newsrooms use these algorithms the most. We understand that since CV requires technological infrastructure, qualified personnel to develop codes, and a significant investment, only large newsrooms can afford it (de-Lima-Santos and Salaverría 2021). However, we found that most of the applications that use AI in the news industry rely on grants from big tech companies such as Google and Facebook to develop them (Rashidian et al. 2018; Rashidian 2020). This brings serious challenges to the development of technological innovations in news media since these organizations decide who receives their money, when they receive it, and where it goes.

We found that few of the news outlets we studied use social bots. Most of the bots that we researched were news bots that write stories. Social bots are the most easily applicable form of technological assistance in news production and dissemination (DalBen and Jurno 2021; Lokot and Diakopoulos 2016). However, we believe that there are two reasons why they did not appear on this list. First, social bots such as Twitter bots do not necessarily use AI. We speculate that this might be the reason why social media bots did not appear on the list of cases. Second, this list is not extensive enough, which might leave some examples of AI applications in the news industry out. This can result in a biased sample of the population. Because of this potential limitation, we treated the study as an initial approach to the subject. Future research could explore this topic, especially from practitioners' points of view. Furthermore, it would be interesting to have more ethnographic studies about the development of AI in newsrooms since they would shed light on limitations and hurdles that relate to deploying AI algorithms in the field. Given that AI has ethical considerations and societal consequences, these computational models need to be constructed and simulated with the most up-to-date datasets to reduce biased behaviors, which can affect the public and professionals involved (Guzman and Lewis 2020). Future studies can address these ethical and societal consequences in each subfield.

In conclusion, we were able to highlight the different uses of AI subfields in the news industry, despite the limitations discussed. Our study contributes to scholarly literature by stressing the limits and opportunities that relate to using AI in news media and providing input for practitioners to expand its applicability.

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AI in academia: An overview of selected tools and their areas of application

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REVIEW PAPER

AI IN ACADEMIA: AN OVERVIEW OF SELECTED TOOLS AND THEIR AREAS OF APPLICATION

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ABSTRACT

As a result of OpenAI's ChatGPT, there has been increasing interest in AI and web-based natural language processing (NLP), including in academia. In this article, we provide an overview of the tools that can be used for academic purposes. The overview was conducted from the perspective of a university educator and was intended to guide educators in higher education on emerging AI technologies. The tools discussed ranged from searching the literature and attributions to peer-reviewed articles, scientific writing, and academic writing and editing. The objective is to foster an informed approach to the integration of AI tools in academic settings, ensuring that educators are well-equipped to leverage these technologies to enhance the quality and output of academic work.

Keywords: ai in academia, natural language processing, generative ai, ethical considerations

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Introduction

In recent years, the academic landscape has undergone a transformation largely driven by the integration of technology. Among various technological advancements, artificial intelligence (AI) has emerged as a game changer, particularly in natural language processing (NLP). The ability of AI to understand, interpret, and generate human language has opened new avenues for the enhancement of academic research and education. The article examines the growing field of AI and NLP services and their applications in academia. Researchers, educators, and students in the academic community are constantly seeking tools and resources to improve and facilitate the acquisition and dissemination of knowledge. In the academic sector, AI has led to the development of various tools for literature search, content analysis, scientific writing, and editing. The use of these tools promises not only to streamline academic processes, but also to add depth and insight to the content of academic studies. However, with great potential comes great responsibility. Integration of AI integration into academia is not without ethical considerations and challenges. Authenticity, privacy, and bias potential are of great importance. In addition, researchers should distinguish between the use of AI tools and their own knowledge, research, writing style, as well as their own creativity, so that AI does not replace them but complements them.

This study aimed to provide an overview of the current state of AI tools in an academic context. This study explores the selection of various AI tools available through the lens of a university educator. The goal is to equip educators and the broader academic community with brief descriptions that will serve as a starting point for judiciously integrating AI tools into their work.

Methodology

To navigate the complex landscape of artificial intelligence in academia, a narrative synthesis of recent publications from academic and non-academic sources was undertaken. This chapter explains the methodological approach used to collect, summarize, and interpret relevant literature and sources for this review.

Search strategy

A systematic and exhaustive search of electronic databases was conducted. ScienceDirect, Google Scholar, ABI/Inform Global, Springer Link, and Emerald were chosen as resources for their extensive coverage of the educational and AI-related literature. In addition, specialized scientific journals were consulted, namely the International Journal of Artificial Intelligence in Education (IJAIED), Computers & Education, and Artificial Intelligence Review, given their specific focus on the intersection of technology and education. Since AI technology is dynamically and rapidly evolving, non-academic sources such as newspapers, blogs, and AI-oriented online platforms have been considered in research to ensure that the latest advances and discussions in the field are considered to create a comprehensive collection of current AI tools for use in academia.

The keywords used for the search were “AIEd”, “AI in higher education”, “Technology-Enhanced Learning”, and “AI Tools for Education”. These keywords were used individually and in combination to maximize coverage of the relevant literature and search results.

Inclusion and Exclusion Criteria

The scope of the search for AI applications was narrowed based on the specific inclusion and exclusion criteria. Only articles published in English were considered. Papers specifically related to the use and impact of AI tools on academic writing were selected. Therefore, articles that addressed the application of AI outside of higher education were excluded. Similarly, studies related to educational technologies but not AI in particular were excluded. Similarly, administrative and IT AI applications related to higher education institutions, such as overarching learning management systems throughout the organization, were excluded from this study.

Data Extraction and Analysis

As this article is dedicated to AI tools in the academic field, such applications have also been used to search the literature on this topic. Services such as *Elicit*, *Litmaps*, and *Scite* have been used to expand the literature search and support the analytical process. To facilitate analysis, productrelated information was extracted from each of the producer's websites and compiled into an organized system using notion.so[1]. The analysis excludes pricing information. However, free services were also observed. The AI tools are classified into three application areas, as listed in Table 1. A narrative synthesis approach was adopted to interpret and synthesize the data from the extracted products to create a condensed description of the AI applications analyzed.

Table 1.
Application areas of Academic AI Tools

Application areas (Primary Usage)	**Description**
Literature Search	Tools in this category use AI algorithms to help researchers efficiently search for relevant academic literature and map connections between papers. They can analyze content, extract key information and visualize relationships among academic papers, aiding in comprehensive literature reviews.
Analyzing Research Articles (Papers)	These tools use AI to enhance the reading experience of (peer-reviewed) articles. They can provide summaries, extract key insights, and offer a conversational interface for asking questions. These tools are designed to make complex academic papers more accessible and understandable.
Academic Writing and Editing	These tools use AI to improve the quality and coherence of scientific writing, as well as structure and format research papers. Academic writing and editing tools ensure that academic texts are clear, coherent, and adhere to writing standards through grammar checks, language feedback, and suggestions for improving structure and style. This is especially helpful for nonnative English speakers and for ensuring high-quality manuscripts.

Note. The scope of features of some of the apps spans several functions, which does not always allow a clear classification. Assignment to one of the three proposed application areas was based on the specific primary usage interpreted by the author.

Bias and Limitations

This article provides an overview of specific academic AI tools as a narrative review and, in this regard, it is inevitably influenced by the authors' perspectives. The methodology used was designed to ensure the most comprehensive and unbiased review possible while acknowledging the inherent limitations of the narrative review approach. Despite the comprehensive search strategy, some relevant studies may have been missed, particularly those published in languages other than English, or in less accessible databases. In addition, such an overview carries the risk that the results could lose their topicality and thus relevance, owing to rapid and dynamic developments in this market niche. Although this article is intended as a starting point for the presentation of such a novel software, future studies may consider the use of systematic reviews and meta-analysis techniques for a more quantitative analysis of the topic or focus groups.

Literature Review

The Evolution of AI: A Brief History

Crevier (1993) chronicles the successes and failures of the AI field, including the early prediction that machines can simulate human intelligence. This book is based on interviews with major players in the history of AI, including Marvin Minsky and Herbert Simon. Buchanan (2005) traced the beginning of AI to philosophy, fiction, and imagination, and highlighted early milestones in problem-solving, learning, knowledge representation, and inference. Since its inception in the 1950s, AI has progressed in several evolutionary stages. An early foundation for the field can be traced back to the work of British mathematician Alan Turing, who proposed the concept of a "universal machine" capable of performing calculations from other machines. This concept laid the foundation for contemporary computing (Turing, 1937, pp. 230–265). In 1956, the Dartmouth Conference formalized AI as a distinct field of academic inquiry. The term 'Artificial Intelligence' was first introduced during this event by John McCarthy, and a research agenda on the topic was proposed, marking the beginning of AI (McCarthy et al., 2006). During the subsequent decade, there was considerable enthusiasm and funding directed towards artificial intelligence (AI), with a particular focus on problem-solving and symbolic methods. A period of disillusionment in the late 1970s was referred to by McCorduck

1 https://notion.so

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(2004) as the first "AI Winter" because of the lack of practical and scalable applications. AI research experienced a revival in the 1980s, often referred to as the 'AI Spring'. This period saw the development of "expert systems", which sought to emulate the decision-making ability of human experts (Buchanan & Shortliffe, 1984). However, these systems are extremely expensive and inflexible, leading to a second period of decreased interest. As AI research moved towards statistical models and data-driven approaches during the 1990s, the field of machine learning was born (Vapnik, 1998). The ensuing era of big data in the 2000s enhanced the effectiveness of machine learning algorithms and catalyzed the emergence of deep learning, a subset of machine learning that employs structures inspired by the human brain. Impressive results have been achieved in deep learning applications for image and speech recognition (LeCun et al., 2015). The 2010s marked the integration of AI into everyday life with applications, such as voice assistants (e.g., Apple's *Siri* and Amazon's *Alexa*) and recommendation algorithms. Advancements have also been observed in fields such as NLP (Nath et al., 2022), computer vision, and reinforcement learning (Goodfellow et al., 2016). The use of artificial intelligence continues to evolve into the 2020s and beyond, finding applications in a wide range of fields. Therefore, the ethics of AI is an emerging area of focus (Russell, 2020).

Key terms

Artificial intelligence

AI is a broad field that encompasses a wide range of technologies and applications (Jordan & Mitchell, 2015). At its core, AI involves the development of algorithms and models that can perform tasks that would normally require human intelligence, such as perception, reasoning, and decision-making. A key area of AI research is machine learning, which involves training models on large datasets to make predictions or decisions based on learning (Jordan & Mitchell, 2015). Machine learning has been used to develop a wide range of applications from image and speech recognition to natural language processing and predictive analytics. AI has the potential to transform many other areas of our lives, from transportation to finance to education (R.Baker & Siemens, 2014; Bengio et al., 2013). However, AI also has limitations, such as the challenge of developing transparent and explainable models (Rudin, 2019).

Machine learning

Machine learning is a subfield of AI that focuses on the development of algorithms and models that can learn from data and make predictions or decisions based on this learning (Jordan & Mitchell, 2015). Machine learning is a powerful tool for a wide range of applications, including image and speech recognition, natural language processing, and predictive analytics (Goodfellow et al., 2016). There are several types of machine learning algorithms, including supervised, unsupervised, and reinforcement learning (Sutton & Barto, 2018). Supervised learning involves training a model on labeled data, where the correct output is known for each input. Unsupervised learning involves training a model on unlabeled data, where the goal is to identify patterns or relationships in the data. Reinforcement learning involves training a model to make decisions based on environmental feedback. One of the key challenges in machine learning is bias (Zou and Schiebinger, 2018). Machine learning models can inadvertently learn and perpetuate biases that exist in the data, leading to unfair or discriminatory outcomes. It is important that researchers are aware of these issues and take steps to mitigate them.

Neural Networks

Neural networks are a type of machine learning algorithm that is modeled after the structure and function of the human brain (Goodfellow et al., 2016). They consist of interconnected nodes, or "neurons," that process and transmit information (LeCun et al., 2015) Neural networks are used in a variety of applications, including image and speech recognition, natural language processing, and predictive analytics (Schmidhuber, 2015).

Natural Language Processing & Large Language Models

The history of NLP can be traced back to the 1950s, when researchers began to explore the possibility of using computers to process and analyze natural languages (Manning & Schu¨tze, 1999). Early NLP efforts focused on developing rule-based systems that can analyze and generate natural language. These systems are limited in their ability to handle the complexity and variability of natural language, and progress in this field has been slow. Large language models are a type of neural network specifically designed for natural language processing tasks (Vaswani et al., 2017). They are trained on massive amounts of text data, such as

https://doi.org/10.53880/2744-2373.2023.4.37

books, articles, and websites, and can generate human-like texts in response to prompts or questions (Brown et al., 2020). Large language models have become increasingly popular in recent years, with models such as GPT-3, GPT-4, and ChatGPT achieving impressive results on a wide range of language tasks (Brown et al., 2020; Radford et al., 2019). These models are a type of neural network that is specifically designed for natural language processing tasks. GPT-3, or Generative Pre-trained Transformer 3, is a language model developed by OpenAI that has been generating waves in the AI community since its release in 2020 (Brown et al. 2020). It has 175 billion parameters, making it one of the largest language models developed to date. GPT-3 has been used in a wide range of applications, from generating creative writing, answering trivia questions, and creating chatbots. GPT-4 was the successor of GPT-3. It is important to note that the development of large language models such as GPT-4 raises ethical concerns regarding data privacy, bias, and the potential misuse of these models. ChatGPT is a variant of GPT-3 specifically designed for chatbot applications (Radford et al., 2019). It has been used to create chatbots that can conduct conversations with humans in a natural and engaging manner. Although large language models, such as GPT-3, GPT-4, and ChatGPT, have the potential to transform many aspects of our lives, it is important to be aware of their limitations and potential risks (Zou & Schiebinger, 2018).

AI is a complex and rapidly evolving field with numerous definitions reflecting its multifaceted nature. Each of the following definitions encapsulates different perspectives on AI capabilities.

Weak AI or Narrow AI

Weak AI or *Narrow AI* refers to artificial intelligence systems that are designed to perform specific tasks within a limited domain. These systems exhibit intelligence in a selective and specific manner, but lack the broader cognitive abilities and general intelligence of human beings. They are highly specialized tools that excel in specific tasks but do not possess true thinking or consciousness. These systems are extremely good at the specific tasks they are designed for, but cannot operate outside those tasks (Russell & Norvik, 2010). Furthermore, these systems do not possess the broader cognitive abilities or general intelligence of humans (Condello et al., 2021; Ducao et al., 2020; Goretzko & Israel, 2022; Laurent, 2018; Leszkiewicz et al., 2022; Liem et al., 2018; Park & Park, 2018; Schachner et al., 2020; Süße et al., 2021; Weidener & Fischer, 2023). Weak AI is characterized by its focused nature, excelling in well-defined tasks or areas of application, but lacking the ability to generalize knowledge or skills to other domains (Condello et al., 2021; Liem et al., 2018). This is often contrasted with strong AI, which aims to replicate human-level intelligence and possesses general intelligence (Schachner et al., 2020; Süße et al., 2021). Weak AI systems are typically developed using machine learning algorithms and trained on large datasets to perform specific functions with a high degree of accuracy (Park & Park, 2018). Examples of weak AI applications include virtual personal assistants, such as Apple's *Siri* and Amazon's *Alexa*, which can understand and respond to voice commands but are limited to specific tasks, such as setting reminders or playing music (Park & Park, 2018). These systems are designed to act as if they are intelligent within their specific domain, but do not possess true thinking or consciousness (Condello et al., 2021).

Strong AI or General AI

Strong AI or General AI is the notion of a machine that can perform any intellectual task that a human being can perform. It is not just about mimicking human intelligence, but about possessing an understanding akin to human cognition. As of 2021, this level of AI remains largely theoretical (Searle, 1980). The pursuit of strong AI has been a long-standing goal in the AI field of artificial intelligence. Researchers have used various approaches, such as modeling cognitive architecture, to advance the development of strong AI (Chollet, 2019). Achieving strong AI is a significant milestone in this field as it represents the creation of intelligent systems that can match or surpass human cognitive abilities.

Superintelligence

The term *superintelligence* refers to a future form of AI that surpasses human intelligence in practically all fields of interest, including creativity, general wisdom, and social skills. Although it is a speculative concept, many AI theorists and futurists believe that superintelligence is a potential outcome of continued advancements in AI (Bostrom, 2014). Larson (2021) challenged the notion of superintelligent computers and singularity (Kurzweil, 2014; Vinge, 1993), argued that we are not close to achieving superintelligence, and questioned the basic premise of singularity.

Larson discusses the limitations of AI in terms of inference and highlights that AI falls short of human intelligence in its ability to handle uncertain rules and formulate new ones. This perspective provides a critical view of the feasibility and implications of superintelligence.

Human-Centered AI Approach (HCAI)

Human-centered artificial intelligence (HCAI) seeks to shift the focus of AI development from technology to people (Bingley et al., 2023). The advent of AI has led to a growing interest in understanding the human facets of AI, with the goal of cultivating AI that complements rather than replaces human capabilities. Notable initiatives in this regard include the European Humane AI project and the Stanford Institute for Human-Centered Artificial Intelligence (Xu, 2019).

HCAI has emerged as a design philosophy that places humans at the epicenter of AI development. While lacking a rigid definition, HCAI is generally perceived as an approach that aims for AI development to be purposeful for human benefit, transparent, and maintain human agency and control over data and algorithms. Shneiderman (2020) encapsulated HCAI akin to a modern Copernican revolution, in which AI systems are designed with humans at the core. Considering that such *EdTech* or AI-Enhanced Education tools (AIEd) are used in the context of university thinking spaces as sites of humanism, the term Digital Humanism (*Wiener Manifest Für Digitalen Humanismus*, 2019) seems attractive and appropriate to the author. Schmölz (2020) engaged in an intellectual inquiry into the philosophical roots of digital humanism and deduced that the conceptualization of *Conditio Humana* as rational thinking and logical operation for the demystification of nature was an intellectual feat of the Age of Enlightenment. However, within the realm of digital humanism, Conditio Humana has undergone a transformation in relation to machines, as rationality and logical operations are now attributed to machines. Creativity and individual articulation in the digital domain have emerged as new facets of Conditio Humana in digital humanism. This paradigm shift alleviates postmodern humans from the constraints of calculable rationality, without regressing into mythological frameworks.

AI Tools in the Context of Academia and Education

AI tools have the potential to change the way research is conducted in academia (Jordan & Mitchell, 2015). They can be used to analyze large datasets, generate insights, and automate repetitive tasks (Brynjolfsson & Mitchell, 2017). Neural networks and large language models are just two examples of AI tools available to researchers (Kitchin, 2014). Other examples include computer vision algorithms, natural language processing tools, and predictive analytics models, which are not addressed in this study.

Holmes et al. (2021) argue that most AI researchers are not trained to address emerging ethical issues and that an ethical framework for AI is imperative. According to Prunkl et al. (2021), submitting authors should provide a statement describing the broader social implications of their research. Larsson (2020) discussed the use of ethics guidelines as a governance tool in the development and application of AI, who emphasized that AI governance must move from principles to processes and that data-dependent AI requires multidisciplinary research to be successful. These contributions suggest that ensuring the ethical use of AI in academic research requires a multidisciplinary approach and a set of robust guidelines. Science journals face a problem when so-called *paper mills* produce and distribute fake or fraudulent papers. It is common for these articles to contain text, data, and images that are partially or completely plagiarized or fabricated, often due to ghostwriting. It is likely that such manuscripts corrupt the scientific literature, lead to misdirection of the readers, and result in the distortion of systematic reviews. The advent of AI tools such as ChatGPT has amplified this concern. Furthermore, paper mills strain the time and resources of journals, as they require time-consuming examinations to detect and retract fraudulent articles (Barnett, 2023; Brainard, 2023; Liverpool, 2023).

Perspectives on AIEd

To meaningfully integrate AI as a tool in academic and pedagogical work practices and contexts, educators must be well prepared and have a good understanding of AI. Such applications in higher education have the potential to significantly enhance learning and teaching experiences (Crompton & Song, 2021). AIEd Applications are not limited to learners or teachers. They also have implications for the general organization and administration of higher education institutions. Baker and Smith (2019) highlighted various perspectives from which AI applications in higher education can be viewed. Their analysis of educational AI tools examined them from three distinct viewpoints: learner-facing, teacher-facing, and system-facing.

Learner-facing tools

Learner-facing AI tools, within the context of AI in Education (AIEd), encompass a range of technologies that aim to improve the learning experience of students. These tools use artificial intelligence for personalized instruction, feedback, and interactive learning experiences and adapt to individual needs (Sobel & Kushnir, 2006). Learner-facing AI tools also have the potential to improve student engagement and motivation through the incorporation of gamification elements such as badges and leaderboards (Ghaban & Hendley, 2019). Such tools can assist in the development of skills such as decision making and problem solving by providing opportunities for learners to actively engage with the learning environment (Sobel & Kushnir, 2006). For example, AI-powered writing assistance tools can help students improve their writing skills (Alharbi 2023). Additionally, learner-facing AI tools can assist instructors in identifying struggling learners and provide timely support to prevent dropouts (Topali et al., 2019).

Teacher-facing tools

With recent developments in AIEd, teachers may have to orchestrate AI and other digital tools and environments in the future (Niemi, 2021). To effectively utilize AI in their teaching practices (Ng et al., 2023), teachers may need to develop AI digital competencies and skills of the 21st century. Furthermore, teachers and higher education lecturers' perceptions and experiences of AI in education can contribute to the formulation of effective AI teaching strategies (Lin et al., 2022). AIEd offers teachers several tools. These tools aim to support teachers in their work practices and enhance their efficiency and effectiveness (Chounta et al., 2021). One tool that teachers may encounter is AI-based educational technology (EdTech). This technology uses artificial intelligence to provide personalized learning platforms, automated assessment systems, and facial recognition systems to aid teachers in their teaching practices (Akgun & Greenhow, 2021). AI-powered assessment tools, such as AI-Grader, have been used to assess student performance, provide feedback, reduce teachers' workload, and improve their trust in AI-EdTech (Nazaretsky et al., 2022).

System-facing tools

Unlike educator- or learner-facing tools, system-facing tools often involve the sharing of data among multiple schools and colleges rather than being confined within a single organization. This may have contributed to the relative scarcity of these tools. System-facing AIEd encompasses a broad spectrum of tasks that extend beyond the functionalities of educators and learner-facing tools. Its applications range from timetable organization to inspection prediction, providing valuable assistance to ensure smooth operation within the educational system (Baker et al., 2019).

Results (22 AI applications and brief descriptions)

AI Tools for Literature Search

AI-enabled literature search tools analyze vast databases using algorithms and data mining techniques. These tools are capable of identifying literature based on contextual similarities, citations, and thematic associations in addition to keyword searches. These tools utilize semantic search capabilities to comprehend the researcher's intent and provide more relevant results based on the context of the keywords. Tables 2 and 3 present the tools to find, summarize, and extract information from research articles.

Table 2.
AI tools for Literature Search

AI Tool	Description
Consensus[2]	Consensus is an AI-powered search engine that additionally provides evidence-based answers from scientific research. It uses AI to extract key findings from peer-reviewed sources and present them in a distilled and easily digestible format. Consensus is 100% ad-free, making it a valuable resource for accessing unbiased knowledge.

2 https://consensus.app

Elicit[3]	Elicit is an AI-powered research assistant that uses language models to find relevant academic papers, even without a perfect keyword match. It can also summarize and extract key information, support various research tasks, and integrate with citation managers. Elicit is available for free.
Inciteful[4]	Inciteful is a free and open-source research tool that uses citations to help users explore and discover relevant academic literature. Its unique features include the literature connector tool for interdisciplinary studies and integration with Zotero. The platform is expanding rapidly and currently consists of two different tools, with more under development.
Laser AI[5]	Laser AI is an application designed to streamline systematic reviews, particularly Living Systematic Reviews. Its semi-automated data extraction module reduces extraction time without compromising quality, and promises to save 50% of time on average when compared to manual workflows. Laser AI also offers robust security and compliance standards.
Litmaps[6]	Litmaps is a tool that streamlines the literature review process by generating a visual map of relevant articles and articles. It analyzes citation patterns to find the most relevant and related articles, reducing the time it takes to complete a literature review while enhancing its quality. Litmaps seems to be popular among PhD candidates, science communicators, and universities and offers benefits such as finding overlooked articles, keeping users informed about new publications, and facilitating effective communication and collaboration among colleagues.
Research Rabbit[7]	Research Rabbit is a digital platform that simplifies the search and management of the literature for researchers. It offers personalized recommendations, interactive visualizations, and collaboration options, and it integrates with citation managers. The platform is free for researchers and has received positive feedback for its intuitive interface and features.

Table 3.
Apps for Literature Search (continued)

AI Tool	Description
System Pro[8]	System Pro is an AI-powered tool that revolutionizes the search and analysis of scientific literature, particularly in health and life sciences. By efficiently synthesizing peer-reviewed research, it provides users with accurate, up-to-date overviews and transparent citations. It also contextualizes searches by recommending and visualizing related topics, facilitating the discovery of new insights. The tool stands out for its reliability, transparency, and capacity to break down disciplinary silos. System Pro is built on a proprietary architecture that combines large language models with structured data, making it faster and more reliable than traditional search engines.
Scite[9]	Scite.ai's AI-powered research assistant helps researchers, students, and writers by searching through millions of research articles to provide reliable answers to questions and aid in writing tasks. It can also find competing evidence, summarize content, and help find sources for specific statements.
Semantic Scholar[10]	Semantic Scholar is a free AI-powered research tool that provides access to a vast database of scientific literature. The Semantic Reader is an augmented reader that aims to transform scientific reading by providing enhanced context and accessibility.

AI tools for analyzing research articles (Papers)

AI-Enhanced Education (AIEd) tools have emerged as essential tools for analyzing research articles in the ever-expanding arena of academic research. By employing artificial intelligence techniques, such as natural language processing and machine learning, AIEd tools streamline the literature review process and enable more in-depth analysis. These tools include automatic summarization to extract the crux of articles, synthesis tools to integrate information across sources, and semantic search tools for contextualized literature retrieval. Additionally, they offer citation analysis to track the impact of research, network visualization for graphical representation of relationships among articles, and text mining to extract insights

3 https://elicit.org
4 https://inciteful.xyz
5 https://laser.ai
6 https://app.litmaps.co
7 https://www.researchrabbit.ai
8 https://www.system.com
9 https://scite.ai
10 https://www.semanticscholar.org

from large textual datasets. AIEd tools also include sentiment analysis to assess content tone and bias detection to protect the integrity of research. The tools used to analyze and summarize the research articles are listed in Table 4.

Table 4.
Apps for analyzing research articles (papers)

Tool	Description
Chat PDF[11]	Helps researchers read and understand complex academic papers. Chat PDF uses AI to provide a conversational interface, allowing researchers to ask questions about the paper and receive answers in real-time. A chat-based interface makes it easy to get information and answers from PDF documents.
Explain Paper[12]	Explain Paper is an online tool designed to make reading and understanding research papers faster and easier. Users can upload a research paper to the platform, highlight any text, and receive an explanation. This functionality aims to make research papers, which often contain dense and complex language, more accessible. It provides clear and concise summaries of academic papers.
Lateral AI[13]	Lateral is an AI-powered app that offers features such as text search, organization of findings, easy sharing, and document view. The app aims to make research more organized using AI to help locate text and organize findings.
Open Read[14]	Enhances engagement with peer-reviewed papers by providing succinct summaries. It provides AI-powered interactive papers, promotes open access, and offers a library of books and personalized reading plans. However, it is still in the early stages of development and may have limitations in coverage of topics or disciplines.
Scholarcy[15]	Scholarcy is an AI tool that summarizes scholarly content, extracts structured data and knowledge summaries, and saves the time required to extract key information from an article. Create summary flashcards in Word or PDF format and supports collaborative notetaking and annotation. It also offers a browser extension and is continually improving its algorithms for summarization techniques.
SciSpace Copilot[16]	SciSpace is a research platform designed to simplify research discovery and learning. It offers an end-to-end workspace that automates repetitive tasks and aids in the quick discovery of information. The platform contains metadata of over 200 million papers and 50 million open-access full-text PDFs.
Unriddle[17]	Unriddle is an AI-powered research tool that simplifies complex topics, summarizes content, and allows users to ask questions and receive instant answers. It can create a custom AI using any document as a data set, which makes it useful for guiding users through complex topics. Unriddle is built on GPT-4 and can handle around 500,000 words. It is ideal for students, researchers, and professionals who need to quickly find and understand relevant information.

AI Tools for Academic Writing and Editing

In addition, such applications help to organize longer articles with more complex structures for better readability.

Table 5 lists the tools that provide functionality to improve language expression and compliance with academic writing standards in research papers. In addition to using AI to provide suggestions and corrections to improve writing quality, these tools can help identify areas that might require improvement and provide targeted feedback on these areas. In addition, such applications help to organize longer articles with more complex structures for better readability.

Table 5.
Tools for Academic Writing and Editing

Tool	Description
Jenni.ai[18]	Jenni AI provides functionality such as AI autocompletion, in-text citations, and paraphrasing, and can assist with various content types. It uses a combination of its in-house AI systems, GPT4 and ChatGPT, and fine-tunes each user's controls and custom data to generate content. The tool supports multiple languages and can generate text in the language of your choice, with a translation feature that allows you to switch between languages. Currently, it is only available on the desktop. Jenni AI has a built-in plagiarism checker and promises to create 100% plagiarism-free content.

11 https://www.chatpdf.com
12 https://www.explainpaper.com
13 https://www.lateral.io
14 https://www.openread.academy
15 https://www.scholarcy.com
16 https://typeset.io
17 https://www.unriddle.ai
18 https://www.jenni.ai

Paper Pal[19]	An AI tool that assists in the editing of academic texts. It uses AI to ensure clarity, coherence, and adherence to academic writing standards. Thus, a manuscript check of the provided documents is offered to analyze its elements to point out weaknesses to be checked and to offer improvements. Paper Pal checks for technical compliance and language quality standards set by journals. The application is certified to ISO / IEC 27001-2013.
Quillbot[20]	Quillbot is an AI-powered writing enhancement tool that includes a grammar checker, a paraphrasing tool, and a summarizer. It suggests alternate ways to write your text, aiding nonnative English speakers in articulating their ideas more fluently. Used as a Summarizer, the app is capable of condensing various types of content, into concise key points.
Trinka[21]	An AI-powered writing and editing tool designed specifically for academic and technical writing. It helps researchers improve the clarity and coherence of their writing and ensures that the text adheres to academic writing standards.
Wisio[22]	Wisio.app is an AI-powered platform that simplifies the scientific writing process. It offers personalized text suggestions, citation extraction, translation, and English correction tools. Users can choose from multiple pricing options, including a free Starter plan and paid plans with unlimited features. Wisio. app promises additional features such as a reference manager, tables and figures, and journal templates in the future.
Writeful[23]	An AI tool that assists in the editing of academic texts. It uses AI to ensure clarity, coherence, and adherence to academic writing standards. Writefull also provides language feedback and helps nonnative English speakers improve the language quality of their manuscripts.

Conclusions

The use of academic AI-based tools that use natural language processing and large language models, as well as machine learning techniques, is changing the way research is conducted. Artificial intelligence tools offer researchers new avenues and access points to search, analyze, and summarize research articles. The use of such tools opens new possibilities for research in the literature. In this regard, it is important to determine which databases are being used by the search algorithms. It is the primary promise of using such tools to save time, so that more attention can be directed to critical aspects of research, such as data analysis and interpretation. Another area where AI tools have shown great promise is the analysis and summarization of research. Several AI-based tools, such as Chat PDF, Explain Paper, Lateral AI, Open Read, Scholarcy, SciSpace Copilot, and Unriddle, are used to analyze and summarize scientific papers. The use of these tools can make recommendations that can help researchers identify areas for improvement and provide targeted feedback on these areas. Moreover, these tools can facilitate the organization of longer articles with complex structures, making them more readable. The use of artificial intelligence tools in academic writing and editing has also shown great promise. AI algorithms are being used in tools such as Jenni.ai, Paper Pal, Quillbot, Trinka, Wisio, and Wordtune to improve academic writing standards and linguistic expressions. In addition to suggesting alternative spellings, these tools also assist non-native speakers to express their ideas more fluently and to advocate adherence to academic writing standards. Despite the versatility and impressive performance of AI tools in academia, they present potential limitations in their application. Some of these tools require extensive training to be effective, which may represent a significant time commitment that researchers should consider. In addition, AI tools influence the stylistic forms of scientific writing, each of which needs to be examined. Although these tools hold great promise for academic operations, they also raise new questions regarding the ethics of science. Assessment and verification of the authenticity and quality of academic work poses new challenges for researchers, academic institutions, and journal publishers. As a result, the number of submissions to be critically evaluated in terms of paper mills is expected to increase. Teachers and academic researchers in the field of higher education are in urgent need of addressing the impact of technology on work practices. Despite the increasing number of academic tools and the development of new options, certain routines of use will be established over time despite the increasing number of AI tools. To teach students and junior researchers meaningful workflows with AI, universities will also have to make decisions regarding tool selection after consulting with the teaching faculty.

Academic research is a rapidly growing market niche for AI tools and developers that

19 https://www.paperpal.com
20 https://www.quillbot.com
21 https://www.trinka.ai
22 https://www.producthunt.com/posts/wisio-app
23 https://www.writefull.com

Available Online on
https://mapub.org/mapeh/4/ai-in-academia-an-overview-of-selected-tools-and-their-areas-of-application/
https://doi.org/10.53880/2744-2373.2023.4.37

offers a range of low-threshold applications. Individuals and institutions in higher education can take advantage of these resources. Although this article can only present a selection of available applications, educators should recognize that engagement with these tools is inevitable as the number of these tools increases. Thus, it is important to preserve academic integrity and authenticity. Therefore, academics must keep up to date with the latest developments and critically evaluate the applicability and relevance of AI tools. Using these tools, researchers can save time, focus more on critical aspects of their research, and improve the quality of their work. Intelligent and responsible integration of AI can serve as a powerful aid for academic research and education. This article aims to contribute by presenting an overview of AI tools for the academic field and to enable teachers in the field of higher education to get started on the topic.

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