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Evolution and challenges of ChatGPT in higher education: an analysis of the conceptualization and applications in the first six months of public access

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Abstract. The recent launch of ChatGPT for public use has advanced by leaps and bounds. This is reflected in the proliferation of tools based on Artificial Intelligence, including ChatGPT, which began in its GPT3 version and is currently in its GPT4o version. What challenges do higher education face in this scenario? This study aimed to examine the evolution of knowledge about ChatGPT in the first six months of open access and its implications for the learning structure (what is privileged in teaching, how these concepts are taught, and what those who teach should do) in higher education institutions. Using text mining and natural language processing (NLP) techniques, we examined the evolution of the conceptualization of ChatGPT generated in Wikipedia, analyzing and modeling the groupings, evolution of the conceptualization, and its uses in research in Higher Education through network analysis. The results revealed that (1) the textual descriptions of ChatGPT were primarily technical descriptions aimed at professionally educated users. That is, the terms used are understandable to native English speakers with at least 11 years of formal education, or the standard formal education of a first-year university student. 2) The research strongly focuses on concerns related to the use of ChatGPT, with few studies exploring its positive use in education. Further research is needed to explore the practical applications of the ChatGPT to benefit both students and teachers.
Keywords: higher education, educational innovation, skills, artificial intelligence, network analysis

Evolución y retos de ChatGPT en la enseñanza superior: un análisis de la conceptualización y las aplicaciones en los primeros seis meses de acceso público

Resumen. El reciente lanzamiento de ChatGPT para uso público ha avanzado a pasos agigantados, lo que se refleja en la proliferación de herramientas basadas en Inteligencia Artificial, entre ellas el ChatGPT que comenzó en su versión GPT3 y actualmente se encuentra en su versión GPT4o. ¿Cuáles son los desafíos que enfrenta la educación superior en este escenario? Este estudio tuvo como objetivo examinar la evolución del conocimiento sobre ChatGpt en los primeros seis meses de acceso abierto y sus implicaciones para la estructura de aprendizaje (qué se privilegia en la enseñanza, cómo se enseñan estos conceptos y qué deben hacer quienes enseñan) en las instituciones de educación superior. Utilizando técnicas de minería de texto y PNL, examinamos la evolución de la conceptualización de ChatGPT generada en Wikipedia, analizando y modelando las agrupaciones, la evolución de la conceptualización y los usos en la investigación en Educación Superior a través del análisis de redes. Los
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resultados revelaron que; 1) las descripciones textuales de ChatGPT han sido principalmente técnicas dirigidas a usuarios con formación profesional. Es decir, los términos empleados son comprensibles para los hablantes nativos de inglés con al menos once años de educación formal o la educación formal estándar de un estudiante universitario de primer año. 2) La investigación se centra en gran medida en las preocupaciones relacionadas con el uso de ChatGPT, con pocos estudios que exploren sus usos positivos en la educación. Se necesita más investigación para explorar las aplicaciones prácticas de ChatGPT en beneficio tanto de los estudiantes como de los profesores.

Palabras clave: enseñanza superior, innovación educativa, competencias, inteligencia artificial, análisis de redes.

Evolução e desafios do ChatGPT no ensino superior: uma análise da conceituação e aplicações nos primeiros seis meses de acesso público

Resumo. O recente lançamento do ChatGPT para uso público avançou aos trancos e barrancos, o que se reflete na proliferação de ferramentas baseadas em Inteligência Artificial, incluindo o ChatGPT que começou em sua versão GPT3 e atualmente está em sua versão GPT4o. Quais são os desafios que o ensino superior enfrenta nesse cenário? Este estudo teve como objetivo analisar a evolução do conhecimento sobre o ChatGpt nos primeiros seis meses de acesso aberto e suas implicações para a estrutura de aprendizagem (o que é privilegiado no ensino, como esses conceitos são ensinados e o que aqueles que ensinam devem fazer) nas instituições de ensino superior. Usando técnicas de mineração de texto e PNL, examinamos a evolução da conceituação do ChatGPT gerada na Wikipédia, analisando e modelando os agrupamentos, a evolução da conceituação e os usos na pesquisa no Ensino Superior por meio da análise de redes. Os resultados revelaram que; 1) as descrições textuais do ChatGPT foram principalmente técnicas voltadas para usuários com formação profissional. Ou seja, os termos empregados são compreensíveis para falantes nativos de inglês com pelo menos onze anos de educação formal ou a educação formal padrão de um estudante universitário do primeiro ano. 2) A pesquisa é amplamente focada em preocupações relacionadas ao uso do ChatGPT, com poucos estudos explorando seus usos positivos na educação. Mais pesquisas são necessárias para explorar as aplicações práticas do ChatGPT para o benefício de alunos e profesores.

Palavras-chave: ensino superior, inovação educacional, habilidades, inteligência artificial, análise de rede.

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Introduction

One of the concerns generated after the release of ChatGPT in higher education is the possibility that generative artificial intelligence (AI) will replace the work professors have done to date. Faced with this hypothetical scenario, teachers, and students argue that human teachers possess unique qualities that make them irreplaceable, known as socioemotional competencies (Chan & Tsi 2024). However, there are challenges when it is incorporated into higher education because it does not generate relevant benefits (e.g., in the writing of academic essays) when what ChatGPT elaborates is contrasted with those written by students. In fact, it can generate the opposite effect of perceived poor performance in students who are advantaged in academic writing tasks when they compare their answers with those they believe ChatGPT can generate (Waltzer et al. 2024). In this ambivalent scenario, the following question arises: what do we know about ChatGPT today?

ChatGPT is a chatbot developed by OpenAI, an artificial intelligence research lab founded by Sam Altman and Elon Musk in 2015. The work of OpenAI researchers is based on a set of models called "large language models" (LLMs). This set of models combines state-of-the-art statistical prediction and classification techniques to optimize a computer's performance in language processing and generation, as any human would with any written language, such as Chinese, English, Spanish, German, or French (although ChatGPT can generate language in many other languages).

The sophistication of these LLMs is based on billions of parametric statistical estimates of quantitative relationships between words using a massive amount of text, including a significant portion of what is available on the Web, in addition to other online textbook collections. They are all placed in a gigantic database of several terabytes (Mitchell & Krakauer, 2023).

The publication of LLMs such as ChatGPT is critical to a vibrant debate between researchers and the scientific community (Sanderson, 2023; Stokel & van Noorden, 2023; van Dis et al., 2023). When it comes to AI-based tools, diversity includes tools like Microsoft's Microsoft Copilot, Midjourney, Baidu's Ernie, Google's Bard, and Anthropic's Claude, for example. All these tools promise to contribute to increasing the productivity and creativity of workers, eliminating the monotony of work. Beyond these promises, an initial approximation of the impact of these technologies on the labor market is already available (Eloundou et al., 2023), and these impacts are part of the vibrant debate. For higher education, these benefits are valuable if one understands the usefulness of ChatGPT in aiding and advancing teaching, learning, and preparation of professionals for the job market.

As an extension of this discussion, the contributions of this study are threefold: First, it provides a conceptual framework that paves the way for future empirical research to understand LLMs as

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emerging technologies. Within this framework, readers can appreciate the advantages and disadvantages of using LLMs for education, research and development (R&D), and innovation. Second, this study provides a reproducible methodological approach that allows for the analysis of Wikipedia edits (i.e., a series of changes or modifications made to Wikipedia articles). Based on these analyses, the textual data available in Wikipedia editions can be computationally manageable by integrating natural language processing and bipartite networking techniques to reveal conclusions about LLMs and ChatGPT as a case of contemporary innovation with clear implications for technology transfer purposes. Finally, this article provides three groups of conceptual approaches (roles, concerns, and generic use) existing in Wikipedia in the six months after November 30, 2022, and the main categories of evolution of ChatGPT studies in Higher Education, which studied the acceptance of this technology, the perception of AI as a useful tool for teaching, learning, teaching evaluation, the factors influencing ChatGPT for the development of skills, and the responsibility of institutions to incorporate it integrally and ethically. In this sense, this work has three objectives: 1) to develop a conceptual framework that positions large-scale language models (LLMs), such as ChatGPT, as emerging technologies in education, to facilitate their analysis from a critical and propositional perspective in future research on teaching, learning, innovation, and technology transfer; 2) to implement and validate a reproducible methodological approach that allows the analysis of Wikipedia edits using natural language processing techniques and bipartite network analysis, with the purpose of extracting patterns, trends, and conceptualizations about the use and evolution of ChatGPT as an innovation in higher education; and 3) to classify and analyze the predominant conceptual approaches (roles, concerns, and uses) about ChatGPT in Wikipedia and in recent academic literature, to evaluate how these conceptualizations align with initial projections about its educational impact, and propose future lines of research oriented toward its ethical and effective integration in higher education institutions. It is relevant to mention that three compelling reasons for selecting this time period were considered in this study.

The first is related to the first six months since the launch of ChatGPT for public use, as this period represents the critical phase of adoption and adaptation to the use of technology in higher education, considering that six months involves a full academic semester in most universities worldwide. Second, this period provided a sufficient volume of data to identify emerging patterns in the conceptualization and use of ChatGPT, whereas a shorter period (such as one month) would have been insufficient to observe the evolution of knowledge and concerns in the educational sector. Finally, this period allowed us to capture the initial response of the academic community, including the first institutional policies and curricular adaptations, before the use of the tool was normalized. A full year

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would have diluted the analysis of these critical initial responses of that first widespread use, as after the first six months, a considerable increase in the generation of AI-based tools was reported. This is consistent with Ahmed (2024), who stated that after the first six months, the increase in the development and availability of GenAI tools was remarkable, evidencing a massive response to the use of the tools and new emerging AI applications.

The remainder of this paper is organized as follows. First, a theoretical approach to the definition and understanding of ChatGPT is developed. An analytical method that uses bipartite networks as a complex approach is explained below, and the background of ChatGPT's use in higher education is briefly discussed. Next, the method, results, and section where the findings are documented are presented, and the work closes with conclusions and limitations.

A data-driven description of ChatGPT

The rapid evolution of ChatGPT from its public release on November 30, 2022, to the present day has an intrinsic relationship with scientific disciplines such as computer science and neuroscience and related areas, including but not limited to statistics, machine learning, information retrieval, big data, cloud computing, computer vision, natural language processing, and its unique combination as an accessible chatbot.

Public opinion on ChatGPT can be tracked through online forums (Batchelor, 2023; Edwards & Ziegler, 2022; Hubner & Bond, 2022), blogs, TV news, radio interviews, and online documents. Apart from these sources of information, Wikipedia provides an outlet that reflects knowledge about almost any topic following an encyclopedic style, with content created in a truly collaborative manner (Lehmann et al., 2015). It is now a recognized academic resource in university learning management systems (Selwyn & Gorard, 2016). Wikipedia provides a convenient and open source for analyzing various science-related topics and extracting meaningful information from the perspective of public understanding geared toward non-AI experts (Segev & Sharon, 2017).

The fact that Wikipedia entry for ChatGPT is not flawless is, from our perspective, an essential sign that illustrates public understanding of science. The underlying difference between scientific knowledge and ordinary knowledge allows us to frame Wikipedia as a medium that is not meant for scientists but for ordinary people. The temporal variation in the Wikipedia content for ChatGPT's textual description provides a unique test with meaningful information for the first few months after ChatGPT's public release in 2023. These insights led us to introduce the following research questions:

RQ1: Is there a data-driven method to describe ChatGPT as an emerging technology for learning scaffolding? And if so,

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RQ2: What key ChatGPT concepts or ideas can students and teachers address in educational research on competency development?

RQ3: What is the orientation adopted by the studies in relation to the anticipated projections in the conceptualizations presented on Wikipedia during the first six months of the open use of ChatGPT and what possible avenues of research could be explored in the coming years?

To answer these research questions, we now focus on a conceptual framework that paves the way for examining public understanding of ChatGPT from a data-driven perspective. An interesting feature of this perspective is its versatility in various topics, including those whose relevant data are not fully available as structured data but as unstructured data from various sources. A recent example of this approach was applied to analyze the supply of postgraduate studies (García-Chitiva & Correa, 2023). Furthermore, we used the data provided by the research paper (aim and methodological content) to identify how Higher Education research has used ChatGPT. The main contribution of this study is to explore the understanding and conceptual development of ChatGPT using two main sources: publicly available information on Wikipedia and research publications using this AI-based tool. This contribution provides a comprehensive framework for educators and new researchers conducting studies in non-technical areas (who may find usable the information available on Wikipedia and other similar sources), in areas of applied research identified in our analysis of research articles, in the intersecting themes between the two frameworks presented in our study, or in exploring promising new research areas that we have identified as gaps.

Scrutiny on public understanding of ChatGPT

The role of ChatGPT is now visible across a disparate set of disciplines, including but not limited to public health (Biswas, 2023), mental health (Emsley, 2023; McGowan et al., 2023), higher education (Tsai et al., 2023), and scientific research (Castillo-González et al., 2022; Hill-Yardin et al., 2023; Qasem, 2023). However, these recent concerns are not fundamentally different from those asserted regarding the use of artificial intelligence and machine learning discussed prior to the public release of ChatGPT (Crompton & Burke, 2023; Goretzko and Israel, 2021; Youyou et al., 2015).

Wikipedia serves as an enabler of the social organization of knowledge that reflects the public's understanding of different topics (Roszkowski & Włodarczyk, 2022). Because knowledge organization is not a static behavior but a dynamic and never-ending social behavior (Candia et al., 2019), analysts can use historical versions of a Wikipedia page (i.e., edits) to discover the conceptual evolution of the topic under scrutiny. The implicit purpose of such scrutiny is based on the relationship between past conceptual work and future discoveries (Mukherjee et al., 2017). A symbol illustrating the link between

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past conceptual work and future developments is the "imitation game" coined by Turing (1950) as a test of a machine's ability to mimic human intelligence, which was named the "Turing test" and appears in the "See also" section in the current versions of Wikipedia for ChatGPT.

Our scrutiny is based on describing the ChatGPT as a case of technological development, and it is evident that this guidance has important implications for technology transfer (Lavoie & Daim, 2019). Analysts can rely on quantitative text analysis (Benoit et al., 2018), also known as text mining methods (Silge & Robinson, 2016). The application of these methods in Wikipedia has been aimed at improving search results (Kapugama et al., 2016) and assessing the quality of information using sophisticated machine learning techniques, such as deep learning neural networks (Wang & Li, 2020). Because text-mining methods can be combined with other quantitative analyses that are not necessarily aimed at assessing the quality of information, their application to Wikipedia remains neglected.

For example, Wang and Li (2020) have introduced so-called "readability metrics" as text statistics aimed at understanding the fundamental role of words in a text and the average length of sentences as two of the main causes of reading difficulty. One of the many readability metrics available is the SMOG score coined by McLaughlin (1969). The SMOG formula returns an estimate of the number of years of formal education a person requires to understand a text. Practical applications of this formula have been used in psychology to describe the textual difficulty of peace agreements between the official governments of the three nations and their guerrilla groups in Latin America (Correa et al., 2018). As the SMOG readability formula is applicable at the level of a single text, its iterated application to a series of texts, such as Wikipedia edits, opens the door to another set of analyses, such as those offered by bipartite network modeling. Although bipartite networks are well known in the literature on complex systems and networks (Estrada, 2011), we are unaware of their application in Wikipedia content combined with readability metrics, such as the SMOG score. The contribution of this study can be considered a targeted effort that shows the potential of bipartite network modeling for version control systems typically used in R&D and innovation projects.

Modeling Networks at Odds

Bipartite network modeling studies the relationship between two disjointed sets (Estrada 2011). In our case, ChatGPT's historical edits comprise one of these sets, whereas the list of ChatGPT-related concepts represents the other. The individual items in the first set can be a sample of documents representing Wikipedia's instant edits to ChatGPT (e.g., edits written over a day, week, or month). Individual items for the second set can be a list of common words systematically related to ChatGPT and are computationally manageable, such as trigrams (e.g., "large language model"), bigrams (e.g.,

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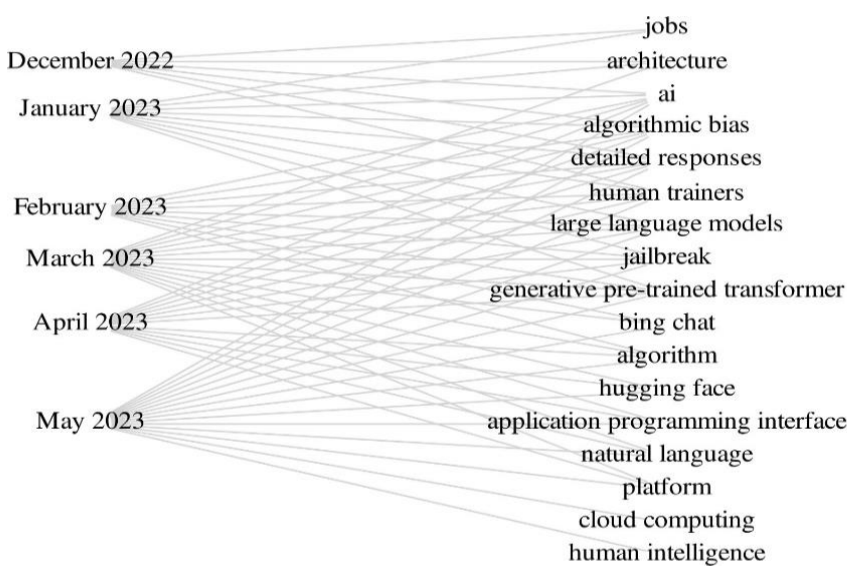
"artificial intelligence"), keywords (e.g., "chatbot"), or acronyms defined as abbreviations formed from the initial letters of other words and pronounced as a word (e.g., "AI" for "artificial intelligence"). As each edit on Wikipedia has a corresponding date, observing how subsequent edits change over time is straightforward and relevant to R&D- and technology-oriented innovation projects. However, before embarking on this model, it is vital to understand how quantitative text analysis focuses on the statistical relationships between words in a system composed of a series of texts. Quantitative analysis of texts modeled as bipartisan networks is not well known, except for the study by Bail (2016), who examined how advocacy organizations stimulate conversations on social media.

Statistical relationships between words and texts are not fixed, as they can change based on the sample of texts under scrutiny and how the content included in these texts has been altered based on external factors, such as facts related to the development of ChatGPT, as reflected in historical edits to Wikipedia. Wikipedia's collaborative content production style is ideal for understanding how, when, and the possible reasons why a text may change, even if all its content is linked to a single topic. An essential ingredient in our approach is the description of ChatGPT as a case of technological development and transfer, as will become apparent immediately.

Figure 1 provides an example of a visual representation of a two-party network. By way of illustration, this bipartite network represents a subsample of the words explicitly used in Wikipedia edits for ChatGPT.

Figure 1.

Bipartite network representing the connectivity between the fundamental concepts associated with ChatGPT and the month year they were used in Wikipedia revision history entries.



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In this two-party network, gray straight lines represent the connection between a list of fundamental concepts associated with ChatGPT (e.g., "pre-trained generative transformer" and "large language model" and large language model) and the month in which these concepts first appeared in the ChatGPT documentation available on Wikipedia. In addition, along with the fundamental concepts, this bipartite network displays other terms that could represent contemporary roles (e.g., "supervised learning," "architecture") and concerns (e.g., "hallucination," "jailbreak") associated with ChatGPT. Mapping the connections between concepts and dates, as illustrated in Figure 1, is a tactical step in this analysis. However, this step does not have significant significance until these connections are considered from the perspective of technological development and transfer, as preconditions for the development of new products. According to Lavoie and Daim (2019), the relationship between technological development (TD) and technology transfer (TT) raises debates about when TT should begin, as some authors believe that TT can start only after TD is completed, while others believe that TT can start in parallel with TD. From this perspective, ChatGPT illustrates a case in which TD preceded TT at some point, after which they were working in parallel. To date, when the ChatGPT TT took place, the milestone was dated February 14, 2019, when a group of computer scientists working at OpenAI published a working paper (Radford et al., 2019), which was established as the conceptual basis for the subsequent TD with the release of the GPT2 model in an online resource called "Hugging Face" (https://huggingface.co/gpt2).

With the evolution of ChatGPT reflected in its subsequent versions 3.5 and 4.0 (OpenAI, 2023), the link between past conceptual work and subsequent technological developments in the contemporary history of ideas in artificial intelligence is not necessarily evident (Vaswani et al., 2017). For example, Frank Rosenblatt and his "perceptron" (Rosenblatt, 1962; Rosenblatt, 1958) defined the beginnings of research in artificial intelligence.

The perceptron is a simple artificial neural network computational model that describes the storage and organization of information in the human brain. Even though the perceptron was a conceptual milestone, Minsky and Papert (1969) emphasized that its limitations (i.e., a simple artificial neural network with a single layer of weights) could not learn non-linearly separable functions. Rumelhart et al. (1986) then helped address some of these problems by developing the concept of "backpropagation." Owing to this concept, neural networks were considered "multilayered" perceptrons that could discover more complex patterns in data, compared to the original single-layer perceptrons of the late 1950s. Geoffrey Hinton's work at the University of Toronto was built on these

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developments. Hinton et al. (2006) provided fundamental insights into both the constraints of simple perceptron networks and how newer architectures could identify complex patterns from data (Hinton et al., 2006).

At this point, it should be apparent that ChatGPT represents the tip of the iceberg; beneath its surface, there is an entire ecosystem developed and maintained by multiple stakeholders, such as Amazon, Baidu, Hugging Face, Google, Meta, Microsoft, among many others that are promoting the so-called "open source" movement (Lerner & Tirole, 2005) towards LLM development (Frank, 2023). The basic idea of this movement is to facilitate and shape the culture of data-driven innovations. We'll explain. Several leading scientists in AI research agree with the claim that LLMs can be regarded as electricity. LLMs and electricity can be used for several purposes. In some cases, LLMs do not require the expertise of a computer scientist to develop new versions of existing LLMs from scratch (which is time-consuming, error-prone, and offers no guarantees of later success). The so-called "fine-tuning" approach can be used to adapt or retrain the existing LLMs with new data. Thus, the fine-tuning process is a shortcut to increasing the chances of achieving success in different objectives, such as computing devices for psychological purposes (Al Hanai et al., 2018).

At this point, the contrast between enthusiasts and detractors of LLMs is worth noting. For enthusiasts, fine-tuning the existing LLMs can be considered an easy game. Online resources such as GitHub, Kaggle, and Hugging Face have promoted and shaped this open-source culture, where registered users can stay up-to-date on the latest machine learning techniques and technologies through access to vast repositories of community-published models with data and code that can be adapted for more projects.

To detractors, LLMs are seen as technologies with the potential to become sensitive and conscious, which can define their own goals that could conflict with humans' self-interest. We regard enthusiasts and detractors as actors who occupy extreme positions, among which there could be many intermediate positions. In any case, the confrontation between enthusiasts and detractors is likely to impact the future agenda of research and development efforts with relevant implications for society, as all efforts and innovations may have known and unknown drawbacks (Smil, 2023).

Our approach, through bipartisan network modeling, offers attractive conceptual and methodological opportunities to understand the functions and concerns associated with ChatGPT. As such, this type of modeling can potentially uncover significant insights into the link between dates and concepts systematically studied by stakeholders vying for leadership positions in a globalized market eager to invest in radical innovations (Thiel & Masters, 2014). Since these innovations appear to be

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better off when led by spin-offs (Pöhlmann et al., 2021), this study also derives alternative perspectives on ChatGPT in this regard.

Background on the use of ChatGPT in higher education

Although AI developments have not been entirely recent, the access of ordinary people to this type of technology and its current uses are recent. Concerns about the aspects of ethics and academic integrity and the possibilities that the use of ChatGPT and AI-based technologies can bring to student learning are topics of recent debate (Sullivan et al., 2023). As ChatGPt is a novelty in the educational field, empirical approaches are beginning to explore the implications for students' personal development and learning. Particularly for teaching and learning in higher education, the implications of ChatGPT on the development of soft skills (*e.g.*, self-learning, leadership, ethics), specific (*e.g.*, knowledge, economics, and administration), and transversal (*e.g.*, written communication), in professional training programs in business, administration, economics, among others at the baccalaureate level, and in postgraduate programs. In a recent study, Chaudhry et al. (2023) analyzed the implications of the use of ChatGPT on the outcomes of students in a business baccalaureate program in a leadership course when they carry out academic tasks in which they had to solve a practical case. They compared the results of the answers using the ChatGPT with the results of students with the highest scores. These tasks were also analyzed using plagiarism detectors, such as Turnitin and ZoteroGPT. The results showed the need to rethink course assessment guidelines to avoid unfair assessments that favor students who use AI, in contrast to those who do not. That is, it creates new ways to ensure academic integrity and depth of learning.

In a subsequent study, Fuchs and Aguilos (2023) conducted an exploratory study in which they analyzed how university students use AI for their studies. Through interviews with students with a bachelor's degree in business administration at a Finnish university, they inquired about students' motivations for using ChatGPT for autonomous learning and mentoring, and the ethical implications of using it for their learning. The results showed three main uses and meanings that students gave to ChatGPT: (1) help with self-learning when they want to learn a topic in an extended or more precise way, (2) digital tutoring to learn complex topics, and (3) ease of access that can favor academic dishonesty and plagiarism.

From a personal perspective, Singh et al. (2023) analyzed the views of 430 students with a master's degree in computer science from a UK university on learning activities. They identified that students considered ChatGPT effective if universities defined clear guidelines for its use. These students perceived that although they were aware of this tool, they did not use it frequently and did not perceive that its use affected their learning. Hmoud et al. (2024) examined the motivations of graduate students

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at a Middle Eastern university who had previously reported their experiences with ChatGPT. They were asked about their motivation to include the ChatGPT in their learning tasks. The interview questions were divided into three categories: experiences, preferences, and efforts when using the ChatGPT.

In an analysis of the implications of ChatGPT on specific skills, Salifu et al. (2024) analyzed the factors that influence economics students at the University of Ghana to use ChatGPT to learn. They examined behavioral intentions, enabling conditions, and actual use of ChatGPT. They assessed whether expectations of effort and ethics influence perceived confidence and behavioral intention. The results indicated that the students' impulse to use the tool was related to how fun it was for them to use it and find support for the concrete development of some tasks. In addition, the students reported no ethical conflicts regarding their use in the development of their work. Regarding the implications of this tool on the development of transversal skills, Rejeb et al. (2024) examined public sentiment about ChatGPT's influence on education and identified ChatGPT as an essential educational tool to enhance writing skills, foster interactive learning environments, and provide personalized educational experiences. However, the study also uncovered challenges related to academic integrity, raising concerns about the responsible use of AI and data privacy. The study's findings have theoretical and practical implications for integrating the ChatGPT into educational settings. In the same vein,

In addition to examining the evolution of knowledge about ChatGPT, this paper provides an analysis of the challenges addressed in higher education to understand the implications of the use of this tool in learning, to incorporate it profitably into professional training processes, and to establish outstanding research topics that are of interest to academics. Curriculum designers and teachers.

Method

The mixed method was used in this study. First, given the recent public release of ChatGPT on November 30, 2022, I relied on Wikipedia's collaborative writing system and its history of revisions as a data source for analysis using the bipartite network analysis method with binary inputs. Critical readers might wonder about the motivation for this decision, given that OpenAI provides a repository where research and development documentation can be consulted. I argue that there are two criteria in favor of the choice I made as a data source. First, the documentation provided by OpenAI is not entirely intended for large audiences. Second, Wikipedia's collaborative writing system is a standalone medium geared primarily toward non-experts. Third, I searched for empirical studies that used the ChatGPT in higher education. This search was performed with the queries “Higher Education” AND “ChatGPT” in the Scopus database. Regarding the inclusion criteria, only research articles were selected, and other documents (e.g., chapters, books, notes, conferences, and reviews) were excluded. Only articles published in 2023 were included, and those published in 2024 were discarded.

Data Sources

Wikipedia's versions of the term "ChatGPT" were explored, which is publicly available to everyone in https://en.wikipedia.org/wiki/ChatGPT. This study focuses on the historical versions. A sample version was printed as a PDF file, which was identified by the date of its creation on Wikipedia. According to statistics from the Wikipedia page, the English entry for the term "ChatGPT" received 1396 edits between December 5, 2022, at 00:11 UTC and May 31, 2023, at 15:20 UTC. This study analyzed a sample of 623 versions of these editions, representing 44.63% of the changes recorded. The focus of this sample was based on Wikipedia's influential role over non-experts in shaping the "public understanding" of ChatGPT, as documented by 514 active volunteer Wikipedia editors who updated the ChatGPT documentation between those dates and times.

A local working directory was created, in which all printed files were saved. Next, an online GitHub repository was created that contained all details to reproduce our findings. A system called "Git Large File Storage" was used, which allowed me to upload and save PDF files to the GitHub repository. An R project file was developed that allowed me to associate more data pre-processing and analysis within the same working directory (Wickham et al. 2023).

These documents were used as computational inputs for analysis within the R system (R Core Team, 2023) using the following R libraries: quanteda (Benoit et al., 2018), igraph (Csardi & Nepusz, 2006), tidyverse (Wickham et al., 2023), and bipartite (Dormann et al., 2009).

Additionally, a Scopus database of 347 scientific documents published in 2023 was obtained using the query (Title) "ChatGPT" AND (Title-Abs-Key) "higher education." This download was made on August 5, 2024, in *.csv format. Only empirical, applied research articles published in English until December 31, 2023, were selected to establish a sample of documents that would allow us to answer RQ3 and RQ4. Other articles, such as meta-analyses, bibliometric analysis, and PRISMA reviews, were excluded. This second selection yielded a total of n = 127 articles. Subsequently, the articles were analyzed by network analysis and Thematic Map analysis using the Bibliometrix library (Aria & Cuccurullo, 2017) in R Core. For this analysis, the field options (Title and Summary) and N-Grams (Trigrams) were activated in the Bibliometrix tool and stop words in English were eliminated. This procedure allowed the studies to be organized into four general categories: *Generative artificial intelligence, Technology acceptance model, Factors influencing ChatGPT, and AI artificial intelligence*. These data were downloaded from *.csv format for processing by content analysis in category identification and analysis

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(Lindgren et al., 2020). In the first step, specific data from each study were reviewed, such as the method, types of participants, activity in which ChatGPT was analyzed (i.e., teaching, learning), objective of the studies, and main results. In the second step, two researchers invited by the author corroborated and provided feedback on the content analysis and categorization carried out by the author, based on the criteria defined for this analysis. Based on this feedback, the author defined seven common categories to classify the studies: *academic integrity, adoption, and use of ChatGPT, Intentional personal use, teaching-learning mediation tool, skills development tool, Perception, and Impact.*

Data pre-processing

The data were preprocessed as follows. First, ChatGPT public entry was provided by the English Wikipedia (https://en.wikipedia.org/wiki/ChatGPT). Then, your view of history in chronological order was examined from the oldest to the most recent edition. Sample edits were made as PDF files from a standard session on Google Chrome. The sampling procedure allowed us to cover Wikipedia edits from December 5, 2022, to May 30, 2023. The sample comprised 623 PDF files from a local repository. This local repository was set up as a public GitHub repository to facilitate quantitative analysis of the content. Based on the ideas proposed by Bail (2016), we analyzed textual data using standard natural processing language techniques and modeled this information using bipartite network data. We developed a document feature matrix, where each revision version of Wikipedia was organized as a column, each word was organized as a row, and the cells had two possible values: 1 if a specific word was present in a specific revision version of Wikipedia and 0 otherwise.

Preliminary analyses of this matrix of document characteristics paved the way for a data-driven procedure. The goal of this procedure was to analyze computationally manageable ChatGPT-related concepts such as trigrams (*e.g.,* "*large language model*"), bigrams (*e.g.,* "*artificial intelligence*"), keywords (*e.g.,* "*chatbot*"), or acronyms (e.g., "*AI*" *for artificial intelligence*) with the corresponding date of their insertion or deletion in Wikipedia revision history versions. For example, the keyword "usability" was explicitly used in the text and references of the initial editions (on December 5, 2022) but disappeared as a term used in the text and remained present in the references of subsequent editions (after December 10, 2022, at 05:51). Similarly, the "large language model" trigram was absent from the edition on December 5, 2022, at 13:43 UTC and was first used in the edition on December 5, 2022, at 13:45 UTC. This series of editions is particularly suitable from the perspective of descriptive network analysis, as illustrated in Figure 1.

The building blocks for this analysis are trigrams, bigrams, keywords, and acronyms, which can be used in an in-context keyword search (Benoit et al., 2018) to analyze the network-based relationship with ChatGPT through an ad hoc dictionary. The combined use of this dictionary and in-context search

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allowed us to construct as many data frames as the trigrams, bigrams, keywords, and acronyms found in each sampled document. These data frames were merged into a single independent data frame and used as computational inputs to model their relationship as a bipartite network, defined as edge lists, graph data frames, adjacency matrices, and incidence matrices (Luke, 2015).

Data analysis

The modeling of concepts and dates as nodes of a bipartite network allows for the estimation of some quantitative characteristics of the network of these nodes, such as those applied in complex networks (Estrada, 2011; Oldham et al., 2019). For example, the centrality-based metrics can be calculated for each node. This helps to understand the relevance or relative importance of a concept compared to other concepts in a bipartite network. Several methods can be used to identify the most relevant nodes in a two-party network. Intuitively, node centrality refers to the "most important" node within a network. One way to estimate this importance is to count the links or links for the node of each network and rank them from the highest to the lowest connection. This count provides a node characteristic called degree centrality. According to Estrada (2011), "a node is more central or more influential than another in a network if the degree of the former is greater than that of the latter" (p. 122). In other words, degree centrality relates to a direct connection between any pair of nodes. In addition, we can also estimate how close each node is to all other nodes, which leads to an alternative called proximity centrality. Luke (2015) defines proximity centrality as "the inverse of the sum of all distances between one node and all other nodes in the network." (p. 94).

Another alternative is known as intermediation centrality, which captures the degree to which a node exists "between" a pair of other nodes; that is, the edge between two nodes must pass through that node. Centrality of the eigenvector is the fourth alternative and measures the transitive influence of nodes. A high eigenvector score indicates that a node is connected to many nodes with high scores. Although these centrality metrics are known to share strong correlations in theoretical network models, their correlations for real-world networks tend to be lower; however, they can be used interchangeably (Oldham et al., 2019; Ronqui y Travieso, 2015). To estimate the centrality of ChatGPT-related concepts, we followed the recommendations of recent studies that modeled natural language as a bipartite network (García-Chitiva & Correa, 2023).

Along with this article, interested readers can access our data, code, and results in our public GitHub repository (https://github.com/pilargarciach/ELLM). The value of this repository is two-fold. On the one hand, it joins the culture of open science, intending to provide sufficient information for

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others to repeat the" experiments" (Stark, 2018, p. 613). In contrast, teachers can use this repository as an online resource to teach the state-of-the-art descriptive statistics of bipartite networks.

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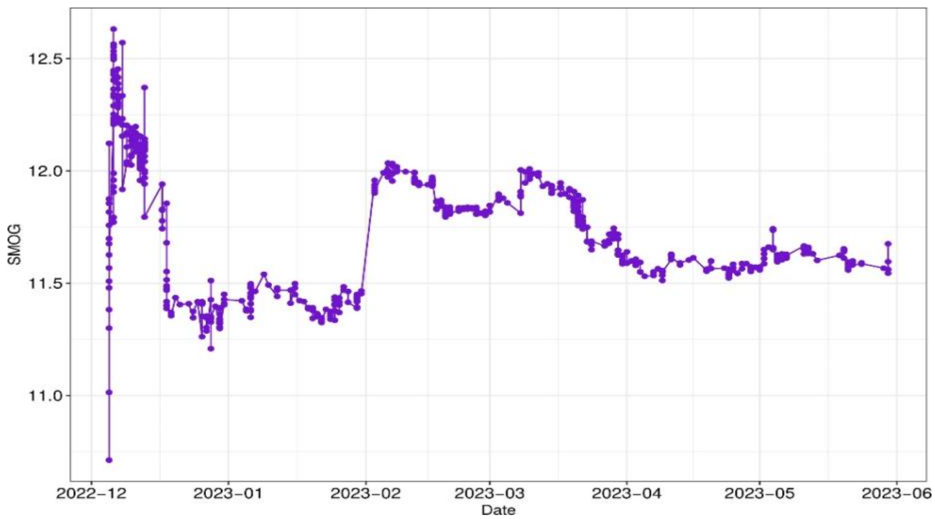
Results

The results begin the analysis by answering RQ1: The share of public understanding of ChatGPT through the readability of English Wikipedia edits (see Figure 2).

Figure 2.

The evolution of the ChatGPT description captured by the SMOG readability index for Wikipedia revision history



In this analysis, the SMOG formula was applied as a proxy to estimate the readability of the texts. The SMOG formula returns an estimate of the number of years of formal education a person requires to understand the description of the ChatGPT available on Wikipedia. Figure 2 shows the SMOG instant readability formula for each sampled edition. The readability of these editions varied from 11 to 12 years of formal education. The significance of this finding is that average American freshman college students can understand these documents. Considering that the average reading time of a person with this educational profile is around 200 to 300 words per minute, the latest Wikipedia edition on ChatGPT on May 30, 2023, could demand between 68 and 102 minutes of reading. Figure 3 complements the previous results by visualizing collaborative writing work on Wikipedia edits by volunteer contributors from December 5, 2022, to May 30, 2023.

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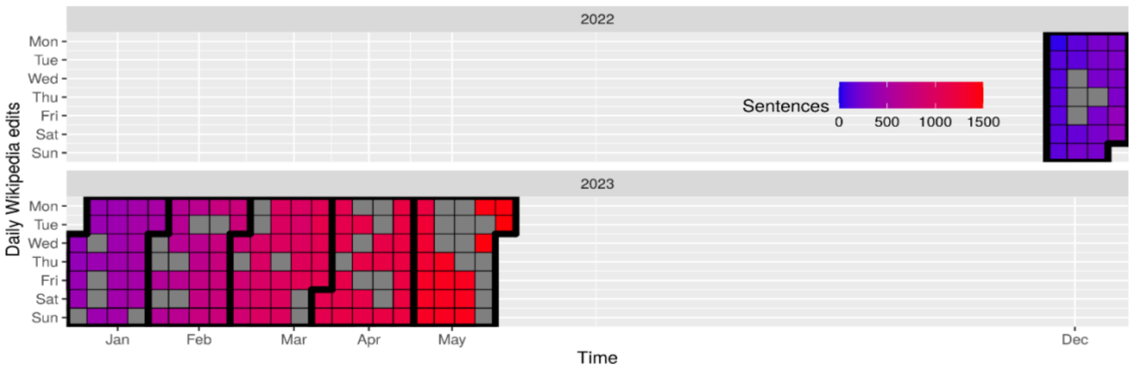
Figure 3.

A calendar heatmap showing collaborative work among volunteers writing Wikipedia edits for ChatGPT between December 2022 and May 2023.



Despite Wikipedia's first edits to ChatGPT between December 2022 and February 2023, the documentation became more refined after March 2023, when Microsoft, a major stakeholder in ChatGPT, announced its pre-trained generative transformer, Microsoft Copilot. While these results are not entirely surprising, given Microsoft's role as a critical player in R&D and innovation in AI applications, further content-based analyses reveal other interesting findings.

After performing bipartite network modelling to map the connection between ChatGPT-related concepts and the dates of their corresponding edits on Wikipedia, we estimated the importance of these concepts by calculating the centrality of the eigenvector and used this network metric in the range of 1 to 10. Figure 4 shows the ranking of the top 10 concepts related to ChatGPT during the first six months after its public release on November 30, 2022.

The acronym "AI" for artificial intelligence and the term "chatbot" were the first two most important concepts throughout the analyzed time window. It is interesting to note that semantically identical terms (e.g., "AI" and "artificial intelligence") differ in terms of their relevance or importance (captured by their centrality from a network perspective). The remaining concepts changed their relative positions in this ranking, starting with the trigram "optimization of upcoming policies" that occupy the third position in December 2022 and occupy less important positions afterward. Figure 4 also differentiates concepts that improved their ranking over time (e.g., the keyword "chat" and the root "hallucination" that groups hallucinations or hallucinations) from those that systematically declined (e.g., the trigrams "large language models," "upcoming policy optimization," and the terms "data" and "InstructGPT").

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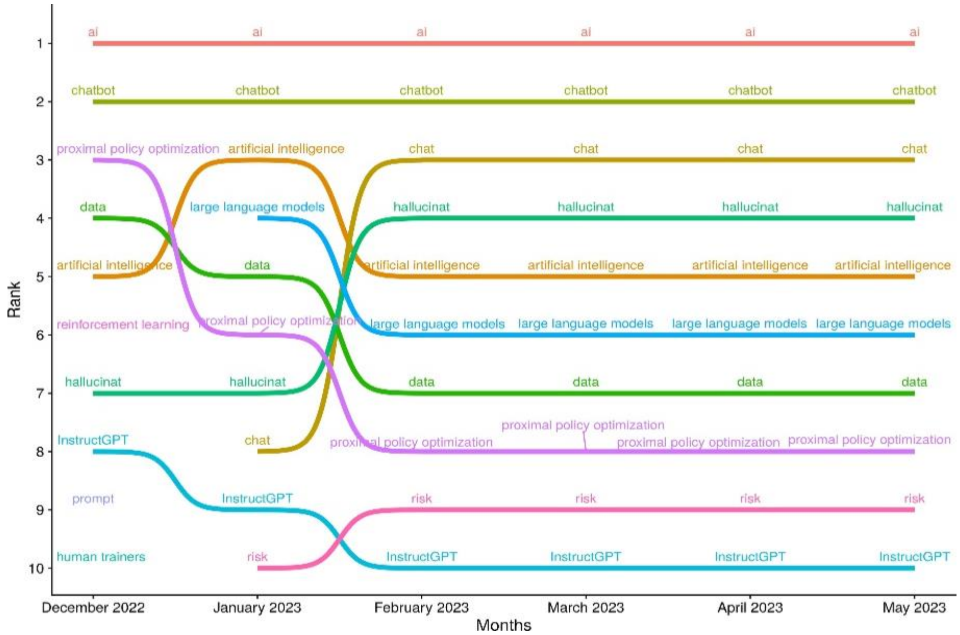
Figure 4.

A highlight chart showing the ranking of the ten most important concepts related to ChatGPT



The final part of the analysis refers to the relevance of the terms associated with ChatGPT from the perspective of an individual working in research and development for business innovation purposes. Here, a monthly analysis of the two-party network helps identify some clues for "early adopters of the technology." Therefore, the focus of network analysis has shifted to growth, as summarized in Table 1.

Table 1.

Bipartite Network Statistics of Terms Conceptually Associated with ChatGPT

Net	Nodes	Edges	Density	Diameter
December 2022	28	27	0.071	2
January 2023	40	39	0.050	2
February 2023	45	44	0.044	2
March 2023	53	52	0.037	2
April 2023	51	50	0.039	2
May 2023	54	53	0.037	2
Complete	64	265	0.131	4

The two-party network statistics in Table 1 show the growth of ChatGPT textual descriptions. Both nodes and edges grew systematically each month with a concomitant decrease in network density. Here, density refers to the ratio of the observed edges or connections between nodes to the maximum possible link in any pair of nodes. One way to understand the significance of this finding is to examine

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the size of the vocabulary associated with the ChatGPT. The number of concepts associated with this vocabulary increased, but their connections became less evident over time. One way to understand this loss of connectivity is to examine the corresponding eigenvector centrality values for terms that did not appear in Figure 4 but are explicitly represented in Figure 5.

Figure 5.

A list of "less important" nodes representing ChatGPT's related terms

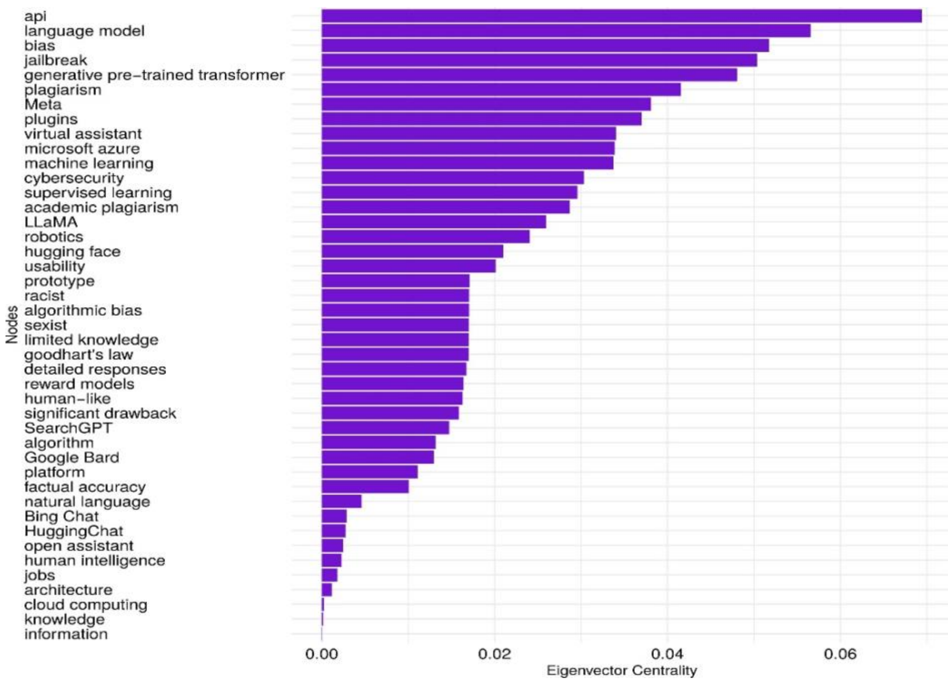

Figure 5 provides more information on ChatGPT. The list of acronyms, bigrams, and trigrams were identified is implicitly tied to three layers of understanding about ChatGPT as one of the representatives of so-called "generative artificial intelligence." These layers of understanding are present in Wikipedia and permeate various online communities, such as Hugging Face, GitHub, and Kaggle, as well as specialized YouTube channels. A complementary method to extract meaningful information about these terms is to model them as nodes in a derived two-party network. In this new network, the set of dates was omitted, and a novel set containing three nodes representing the ChatGPT's level of understanding was defined. The first node of the new set is related to the "concerns" category, under which terms that suggested desirable or undesirable uses of ChatGPT were grouped. The second node relates to "roles," grouping terms with specific meanings in the machine-learning literature. Finally, the third node was named "generic use" to group words that did not fit into previous categories. Figure 6 shows a derived bipartite network that matches ChatGPT-related terms (purple rectangles on the left)

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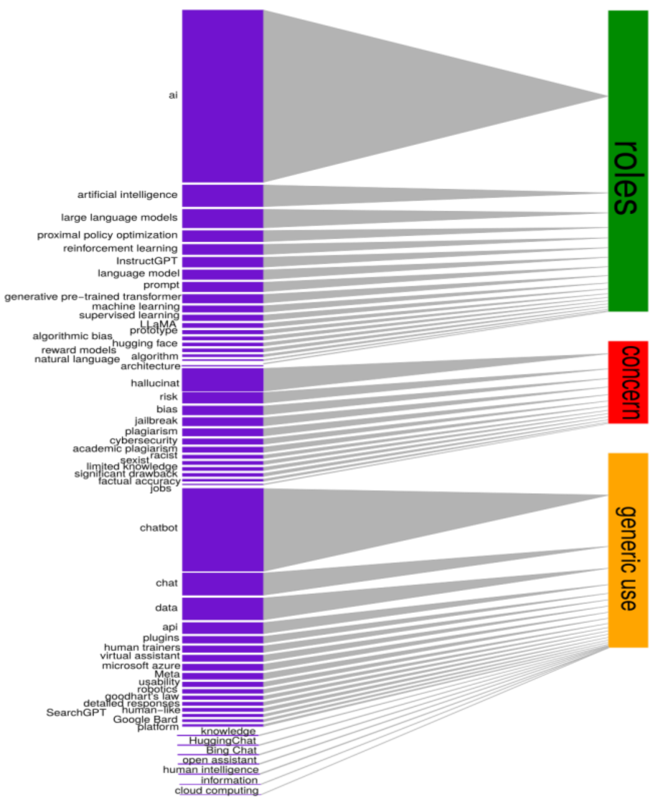
to contemporary roles (green rectangles on the right), concerns (red rectangles), and generic uses (orange rectangles). Here, the area of the violet rectangles is proportional to their centrality when modeled as vertices that constitute the derived bipartite network. Terms related to contemporary ChatGPT functions belong to the central layer of understanding, followed by terms related to the generic use of ChatGPT. Concerns regarding ChatGPT, on the other hand, were less important during the analyzed time window.

Figure 6.

A Derived Bipartite Network Matching ChatGPT's Related Terms to Contemporary Generic Functions, Concerns, and Uses



In response to RQ2, Figure 7 shows the analysis of the set of articles published in 2023. Four categories were identified through thematic bibliometric analysis (generative artificial intelligence, technology acceptance model, factors influencing ChatGPT, and AI artificial intelligence). The contents were examined using these categories (CB), study research object (SRO), empirical setting (ES), and specific analysis (SA). These studies examined the ChatGPT using different methodological approaches and perception measures, thereby developing some skills in students (e.g., self-regulation, self-

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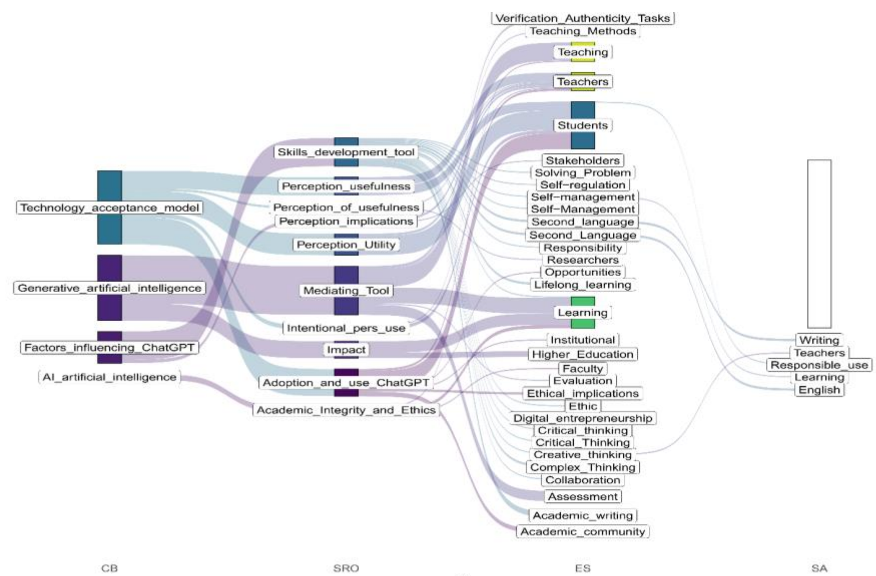
management, and problem-solving). Interestingly, the studies carried out in 2023 (the year in which there was an expanded deployment of the original chatbot known as ChatGPT) covered at least seven topics that sought to examine Academic *integrity and ethics* (4) through focus groups and surveys, *identify through surveys and questionnaires the Adoption and use of ChatGPT* (24), *the Intentional personal use* (4), *the Perceptions* (30) of the educational actors (teachers and students), implementations to measure the effect on the *Teaching-learning mediation tool* (30), on the *Skills development tool* (20), and the *Impact* (15) on learning and Higher Education in general. These studies specifically examined four aspects: 1) the perception of at least seven types of educative actors (teachers, students, researchers, stakeholders, Faculties, Academic community, and higher education institutions) (61); 2) the ChatGPT utility to complement teaching, evaluation, and verification authenticity of the tasks (27), to enhance the learning process (16), to develop skills such as *academic writing, complex thinking, critical thinking, second language, lifelong learning, self-regulation, creative thinking, digital entrepreneurship, solving-problem, and self-management* (21); and specification about ChatGPT use and ethical considerations (2). Finally, some studies developed focus implementations of ChatGPT to improve learning and writing in second language (English) in students, developing creative thinking in teachers, and exploring the responsible use perception of the students.

Figure 7.

Sankey plot of implementations, perceptions, and uses of ChatGPT in Higher Education research in 2023.



Finally, in response to RQ3, the relationships between the three clusters were examined. In this way, 127 studies were identified in the conceptual evolution of ChatGPT on Wikipedia and analyzed. Additionally, diverse approaches have been identified in the analysis of the impact and use of the

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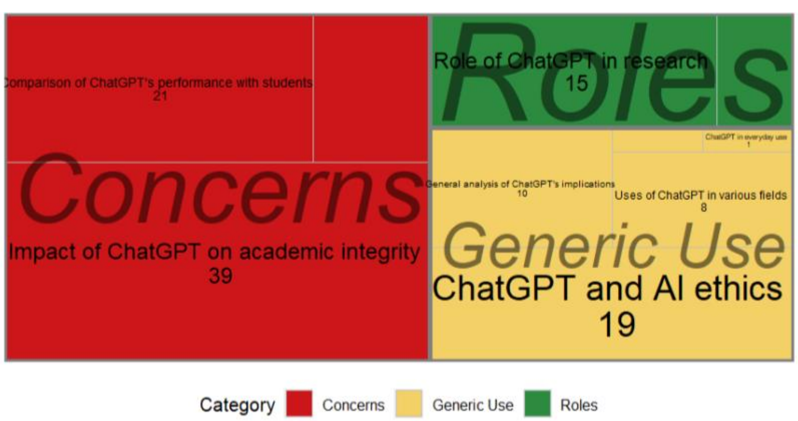
ChatGPT. As shown in Figure 8, the category of "concerns" encompasses studies that address ethical issues, risks, and debates about the desirable or undesirable use of ChatGPT, which suggests a common concern about the social and moral implications of this technology. This type of study highlights a cautious perception of the adoption of artificial intelligence tools, pointing out possible risks such as the impact on academic integrity or the effects on human interaction. In contrast, the "roles" category includes research that focuses on the specific role of ChatGPT in artificial intelligence and machine learning, as well as its integration into processes, such as natural language processing (NLP) and data classification. These studies emphasize the technical and functional potential of ChatGPT, focusing on technological development and optimization. Finally, the category of "generic use" includes studies that, although they recognize the presence of ChatGPT, do not focus on specific aspects of its uses or impacts, suggesting a more generalist view of its application. The distribution of studies among these categories shows a balance between concern for social and ethical effects and interest in the development and technical use of the tool, which reflects the current state of research on AI technologies, a field that seeks to optimize their capabilities while managing their social impact. This empirical classification suggests that the academic community recognizes the versatility of ChatGPT and values the need for a critical analysis of its integration in various contexts. Details of the distribution of the 126 studies examined in these three categories are presented in Appendix 1[1].

Figure 8.

Treemap topics 2023 ChatGPT studies



Discussion

[1] Available in the repository: https://github.com/pilargarciach/LIT_gpt.git

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The launch of ChatGPT on November 30, 2022, marked a milestone in the development of chatbots with immediate response capabilities and a wide variety of user queries. This Artificial Intelligence (AI) has stimulated significant debate among various professionals, including academics (Stokel-Walker, 2022; Van Noorden & Perkel, 2023), lawyers (Hunter & Shannon, 2023), and educators (Zhai, 2022). In this analysis, conceptual development was examined and topics associated with Wikipedia were identified to determine the development and focus of that work. We did something like the studies published in 2023 that used the ChatGPT in higher education. In both cases, a predominant focus on concerns related to the use of ChatGPT was identified, followed by an interest in its general use (generic use), and to a lesser extent, in its specific roles within the educational and technological fields. This distribution revealed several research gaps that deserve further exploration.

The category of "concerns" groups together a significant number of studies (e.g., 39 on evaluating ChatGPT as a learning tool and 19 on its impact on academic integrity). This reflects a common concern regarding the social and ethical implications of using this technology, such as its potential negative impact on the authenticity of academic work (Thorp, 2023). Despite the importance of these analyses, studies exploring the positive and proactive use of the ChatGPT to improve teaching and learning processes are lacking. In comparison, studies that focus on ChatGPT's specific roles (15 in assessment as a learning tool and 10 in comparing its performance with students) point to its technical potential but fail to fully develop practical applications that could benefit both students and teachers.

The high concentration of studies in the concern category suggests a cautious perception of the impact of ChatGPT in the academic field. The existing literature emphasizes the risks associated with ethics, proper use of tools, and potential dependence of students on automatic solutions. This approach is valuable for establishing ethical and normative frameworks to guide the responsible use of artificial intelligence in education (Eloundou et al., 2023; Smil, 2023). However, this perspective can be limited, if not complemented by research exploring practical applications that enrich the learning experience.

In the generic use category, we identified studies that generally addressed the implementation of ChatGPT in educational contexts, and their potential to be used as support tools. Studies such as those by Cobo et al. (2011) suggest that ChatGPT can help improve the learning experience, but there is still a lack of detailed empirical evidence quantifying its direct impact on the development of specific competencies, such as academic writing or self-regulation of learning.

However, studies that analyze the role of ChatGPT tend to focus on technical aspects, such as its integration into natural language processing systems and its role in data classification (Tang et al., 2020; Touvron et al., 2023). These studies reveal the potential of ChatGPT as a technical tool in artificial

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intelligence, which is crucial for its optimization in specific tasks. However, there is still room for research on how these capacities can be harnessed in vocational education and training. In this context, what opportunities do ChatGPT have for training professionals with ideal skills for future jobs?

Clearly, the development of future skills must be adapted to a world in which artificial intelligence technologies, such as ChatGPT, play a central role. Higher education should focus on developing students' skills such as advanced digital literacy, the ability to critically evaluate the results generated by AI, and a solid ethical sense in implementing these tools. This includes fostering critical thinking and complex problem solving, which are increasingly relevant skills in a work environment influenced by automation (Elcoro et al., 2023).

What opportunities can the intentional incorporation of AI-based tools, such as ChatGPT, have for Higher Education? The inclusion and intentional use of ChatGPT in the educational context offers significant advantages, such as the ability to customize teaching to suit the needs of each student and facilitate the understanding of complex concepts. Recent studies by Dave et al. (2023) show that ChatGPT can be used to support second-language teaching, improve academic writing, and foster creativity in both students and teachers. At the institutional level, this represents an opportunity for universities to develop collaborative research projects that explore the use of artificial intelligence as a support tool in education in various areas of knowledge (Perkowitz, 2023).

However, the challenge is to balance the use of these technologies with a clear, conscious pedagogical intentionality and a critical understanding of their limitations and possible risks. As Geoffrey Hinton points out, adopting artificial intelligence must be accompanied by a reflection on its possible consequences, including aspects such as bias in automated decision-making and the risks of its use in sensitive areas such as employment and security (Hassani and Silva, 2023). To address these challenges, a collaborative approach is required between academics, developers, and practitioners from different fields.

Conclusions, possible future approaches, and limitations

This study examined the development of ChatGPT's conceptualization and orientation in higher education research by 2023. This study identified the need to take a balanced perspective in ChatGPT analysis, integrating its potential benefits and legitimate concerns raised by its adoption in education. Future students should focus on broadening their understanding and knowledge of practical applications and identifying ways to harness their capabilities without compromising the integrity of the educational processes. Likewise, a research agenda is needed to explore how professional training in various disciplines can benefit from integrating artificial intelligence, promoting a culture of continuous learning and technological adaptation.

As Perkowitz (2023) mentioned, the challenge of educating machines has been compared to that of educating a child, and in this sense, ChatGPT represents the first step towards collaboration between humans and machines to achieve more effective and adaptive learning. In the future, higher education institutions must lead this process, ensuring that the development of technological competencies is accompanied by the development of soft competencies (e.g., critical thinking, analysis, collaboration, etc.) that allow professionals to perform successfully, ethically, collaboratively, and with professional relevance; that is, as García-Chitiva and Correa (2023) put it, which allows them to improve the dynamics of the developments that are carried out in the workplace.

One of the limitations of this study is the period in which the contents of Wikipedia and research articles were analyzed. Wikipedia's content may have broader aspects and topics associated with the conceptualization of ChatGPT than the one we address here, since we only took six months, covering only the first half of 2023. A similar situation occurred in the studies examined, as only those published in 2023 in the SCOPUS database were considered. The number of articles in 2024 may be substantially higher if they are identified in other indexed databases (e.g., WOS, PubMed) and open access, such as Lens or Google Scholar.

Conflict of Interest
The author declares that they have no conflicts of interest regarding this article.

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