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Should ChatGPT be Banned at Schools? Organizing Visions for Generative Artificial Intelligence (AI) in Education

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Completed Research Paper

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Abstract

Several sectors, including education, have experienced rapid growth in the utilization of artificial intelligence (AI). The emergence of generative AI (GAI) models, such as GPT-4, hold the potential to transform teaching and learning. However, GAI in education presents unique challenges and risks, such as potential violation of academic integrity, negative effects on critical thinking skills, and propagation of biases and inaccuracies. This study examines organizing vision functions in the digital world to explore the opportunities and threats posed by GAI, specifically ChatGPT, in education. By identifying the main actors contributing to the early development of organizing visions of ChatGPT in education, we aim to provide valuable insights into the shared visions concerning ChatGPT in education. Understanding these implications will be crucial for educational stakeholders and society at large as they navigate the complex challenges associated with GAI in education.

Keywords: Organizing Vision, Generative AI, Artificial Intelligence, AIED, Social Media

Introduction

The role of artificial intelligence (AI) in our lives is expanding rapidly (Dennehy et al., 2023; Järvelä et al., 2023), and the recent development of generative AI (GAI) has attracted significant attention and debate, especially regarding its potential impact on academic integrity and education systems (Nguyen et al., 2022). GAI allows text, audio, image, and other media to be generated in a way that mimics human behavior. The emergence of powerful GAI models, such as BERT, GPT-4, and its successors, has shown the transformative potential of AI in various educational contexts (Abuzayed & Al-Khalifa, 2021; Dwivedi et al., 2023). These models can enhance teaching and learning experiences by enabling personalized and adaptive instruction, automated feedback, and collaborative learning environments (Chen et al., 2022; Nguyen, Gardner, et al., 2020). However, integrating GAI into educational settings presents unique challenges and risks (Hong et al., 2022). One of the primary concerns is that students may become overly reliant on AI-generated solutions, which could erode critical thinking and problem-solving skills (Kasneci et al., 2023; Yan, 2023). Furthermore, the potential for AI-generated content to perpetuate biases, inaccuracies, and misinformation poses a significant threat to the integrity of educational resources and processes. As a result, it is crucial to understand the implications of AI including its opportunities and threats for the field of education.

Recently, considerable attention has also been drawn to Italy's groundbreaking decision to become the first Western nation to ban the use of the advanced AI chatbot, ChatGPT (Shiona McCallum, 2023). This unprecedented action has prompted extensive discourse and initiated the examination of pivotal concerns regarding the prospective function and ramifications of ChatGPT in societal domains, with a specific emphasis on its potential impact within educational settings. At the same time, this decision also raises questions about the appropriate balance between innovation and regulation in the development and deployment of AI technologies. While the potential benefits of GAI-based technologies, such as ChatGPT, are significant, so are the risks associated with their misuse or abuse (Dwivedi et al., 2023; Holmes et al., 2021; Nguyen et al., 2022). Finding the right balance between fostering innovation and protecting public safety and ethical values is a complex and ongoing challenge for policymakers, industry stakeholders, and society at large.

In Information Systems (IS) innovation, organizing visions has emerged as a key concept for understanding how novel technologies are adopted and integrated into an organization, community, or society (Ramiller & Swanson, 2003; Swanson & Ramiller, 1997). The organizing vision theory consists of three functions (i.e., interpretation, legitimation, and mobilization) that frame the development, implementation and adoption of innovative technologies. Interpretation involves conveying the usefulness of innovative technologies to a broader community, legitimation involves demonstrating its applicability to current challenges, and mobilization involves motivating community actors to adopt and diffuse the innovation (Davidson et al., 2015; Parameswaran et al., 2023). In the process of engaging with and comprehending IS innovations, organizing visions play a crucial role in recognizing potential benefits and drawbacks. In a recent study by Amadoru et al., (2021), the authors proposed a framework for how organizing vision functions operate differently in the context of the digital realm. Following this line of research, this study aims to examine organizing vision functions in the digital world to investigate the opportunities and threats of GAI, specifically ChatGPT, in education. In particular, we seek to answer the following research questions:

1) Who are the main actors contributing to the early development of organizing visions of ChatGPT in education?
2) How do organizing vision functions operate during the early development of organizing visions of ChatGPT in education?

In the following sections, we will provide an overview of the role of IS research in the context of AI in education, with a specific focus on GAI in education. We will subsequently outline the data collection and analysis methods in our study. Our findings follow this, and we will discuss the main contributions and potential implications of our study and conclude with limitations and suggestions for future research directions.

Information Systems (IS) Research and Artificial Intelligence (AI) in Education

Throughout the last few decades, IS have played a crucial role in supporting and transforming education to meet society's growing demands (Leidner & Jarvenpaa, 1995; Nguyen et al., 2021; Nguyen, Gardner, et al., 2020). IS have been applied by educational institutions to support learning and teaching activities, administrative operations, and decision-making. In addition to being indispensable to modern education, IS have become an integral part of it. Accordingly, IS research has enabled the creation and evaluation of more efficient tools utilizing emerging technologies to address the increasing demands of different stakeholders in educational sectors.

IS research plays a vital role in analyzing learners' behavior and their learning processes by providing tools, techniques, and methodologies to collect, manage, analyze, and interpret data related to learners' behavior. Utilizing data generated by learning management systems, educational apps, and other digital learning tools, IS researchers can gain insights into student engagement with course materials and their progression through the learning process (Baker et al., 2021; Romero & Ventura, 2015). This understanding can inform the development of more effective teaching strategies and personalized learning experiences (Siemens, 2013).

IS research also significantly contributes to designing, developing, and implementing new digital learning tools and platforms specifically tailored to support effective teaching and learning (Nguyen et al., 2021; Rubel & Jones, 2016). For instance, Nguyen et al. (2021) conducted a design science research study to establish and evaluate a set of design principles for IS utilizing learning analytics in higher education. Their research, which involved testing the developed artifact across four courses with 1,173 enrolled students, lays the groundwork for future development and implementation of learning analytics systems to enhance learning and teaching in higher education settings. By incorporating theories of learning and behavior analysis into the design of these systems, IS researchers can create tools that are optimized for student engagement, motivation, and achievement.

Recently, IS research has recognized that AI has the potential to be a powerful technology for education (Nguyen, Gardner, et al., 2020; Wambsganss et al., 2022). AI refers to the development of computer systems capable of performing tasks that typically require human intelligence, such as seeing, recognizing sounds, making decisions, and translating languages. An AI system learns from data through algorithms and mathematical models, identifies patterns, and makes predictions or decisions based on that learning. Education is not a new concept when it comes to AI; it has been a research and development area for several decades (Chen et al., 2022). For instance, Chen et al. (2022) have identified and analyzed 4 519 publications related to AI in education (AIED) from 2000 to 2019. The study also reported main topics have been investigated in the domain of AIED involve educational data mining for performance prediction; discourse analysis in computer-supported collaborative learning; natural language processing for language education; neural networks for teaching evaluation; and affective computing for learner emotion detection; intelligent tutoring systems; recommender systems for personalized learning; and educational robots.

AI in education is also recognized as a multidisciplinary research domain involving knowledge and expertise from various disciplines, including IS, computer science, education, psychology, and cognitive science. The integration of multiple disciplines facilitates a more holistic understanding of the complex nature of the learning process. Furthermore, this interdisciplinary approach enables the development of advanced AI tools to enhance the quality of educational experiences.

This research aims to investigate the ramifications of GAI models such as GPT-4 and its subsequent iterations. As these models evolve, they bring forth fresh prospects and obstacles that significantly influence the trajectory of the education sector. Accordingly, IS research is pivotal in comprehensively tackling these advancements and their associated implications.

Generative Artificial Intelligence (GAI) in Learning and Teaching: Opportunities and Threats

GAI refers to a subset of AI models that are capable of generating new content or predicting outcomes based on input data. In these models, various AI techniques, including computer vision and natural language processing (NLP), are often used to produce information on request, create patterns, or perform tasks by themselves with minimal human interaction. GAI has experienced significant growth in recent years, particularly with the advancement of large language models (LLMs). The recent release of ChatGPT by OpenAI has generated intense public discourse around this topic. As GAI gains momentum, its impact on various domains, including education, becomes increasingly apparent.

The potential for GAI to revolutionize learning and teaching is immense, offering a plethora of opportunities to enhance educational experiences and outcomes. For instance, one of the promising applications of GAI is in personalized learning. Researchers have explored using GAI models to create tailored learning experiences based on individual students' learning patterns, strengths, and weaknesses. Studies have demonstrated that GAI can improve learning efficiency and increase student engagement by providing customized content and exercises that adapt to each student's needs (Bond et al., 2019).

Another important aspect of GAI in the literature is its application in intelligent tutoring systems (ITS). GAI models have been employed in developing ITS that provide real-time feedback, hints, and scaffolding to learners, simulating the support of a human tutor (Wambsganss et al., 2022). Researchers have reported positive outcomes associated with the use of GAI in ITS, such as increased mastery of learning and individual growth (Amershi & Conati, 2006).

The use of GAI for assessment and evaluation has also been a focus of research. Studies have investigated the potential for GAI to automatically evaluate and grade written assignments or exams, thereby reducing the workload for educators and providing timely feedback to students (Zawacki-Richter et al., 2019). Additionally, some research has explored the use of AI for generating adaptive assessments that align with students' current knowledge levels, ensuring accurate and informative evaluations (Kabudi et al., 2021). In the context of creative problem-solving, GAI has been found to support students by offering novel ideas or approaches that may not be immediately apparent to the learner (Lund et al., 2023). Research suggests that AI-enabled tools could introduce unique perspectives and encourage exploration, fostering students' innovation and critical thinking skills (Nguyen, Gardner, et al., 2020; Zawacki-Richter et al., 2019).

However, alongside the potential benefits of GAI, there are also challenges and threats that must be addressed. Ethical concerns have been raised regarding GAI implementation in education (Hong et al., 2022; Kitto & Knight, 2019; Nguyen et al., 2022). One such concern is the potential to perpetuate existing biases present in training data (Hong et al., 2022), which could result in AI systems reinforcing stereotypes or discriminatory practices. This underscores the need for careful consideration of data sources and the importance of incorporating diverse perspectives in the development and evaluation of AI systems.

Another challenge is related to privacy and security concerns arising from the collection and analysis of large amounts of student data (Holmes et al., 2021; Hong et al., 2022). The use of AI in education often necessitates processing sensitive information, such as academic performance, personal interests, and demographic data. This raises questions about data ownership, consent, and appropriate safeguards to protect students' privacy. IS researchers must develop strategies to ensure that AI-driven educational applications adhere to robust data protection standards and comply with relevant legislation.

Furthermore, the digital divide presents a critical challenge, as the integration of AI in education may exacerbate existing disparities in access to technology or digital literacy levels (Bennett et al., 2008; Nguyen, Hong, et al., 2020). Ensuring that AI-driven learning opportunities are accessible to all students, regardless of socioeconomic status or geographical location, is essential to promote equity and inclusivity in education. Researchers and policymakers must work collaboratively to address these disparities and develop solutions that facilitate equal access to AI-based learning resources.

Understanding the early development of organizing visions for GAI, such as ChatGPT, in education plays a crucial role in identifying and addressing challenges to ensure equitable access to AI-driven learning opportunities for all students. By examining the interplay between technological advancements and societal needs, organizing visions can help identify both opportunities and challenges associated with the implementation of GAI in education. Nevertheless, through fostering shared understanding among stakeholders and guiding the development of AI applications that address the identified challenges, organizing visions can contribute to the responsible and equitable integration of GAI technologies in educational settings.

Organizing Visions for Information Systems (IS) Innovation

The concept of organizing visions has been central to the study of IS innovation as it provides a macro-level framework for understanding how a community of actors comes to implement, adopt and diffuse new technologies (Parameswaran et al., 2023). Originally introduced by Swanson and Ramiller (1997), organizing visions refer to a community's collective understanding and shared expectations surrounding an IS innovation that guides organizational decision-making and facilitates technology adoption. This literature review will examine the key themes and findings in the literature on organizing visions for IS innovation.

While the field is still developing (Kim & Miranda, 2018), the role of organizing visions in shaping the adoption and diffusion of IS innovations has been well-established in the literature. Research has highlighted the importance of a compelling and coherent organizing vision in generating interest and fostering a shared understanding of the potential benefits and implications of an innovative IS (Ramiller & Swanson, 2003). Studies have also demonstrated that the presence of an organizing vision can accelerate the diffusion of IS innovations by providing a common language and reference point for organizational actors to discuss, evaluate, and make sense of IS innovations (Amadoru et al., 2021; Davidson et al., 2015).

The process through which organizing visions emerge and evolve has also been a focus of research. Swanson and Ramiller (1997) proposed that organizing visions are formed and disseminated through a process of interpretation and communication among a community of interest, including technology vendors, consultants, researchers, and industry analysts. These stakeholders contribute to constructing and shaping the organizing vision, which, in turn, influences the perceptions and expectations of potential adopters (Amadoru et al., 2021; Wang, 2021).

In addition to the process of organizing vision formation, the literature has explored the factors that contribute to the success of an organizing vision. Some studies have suggested that the credibility and legitimacy of the stakeholders promoting the organizing vision play a crucial role in its acceptance (Wang, 2021). Other research has emphasized the importance of the organizing vision's alignment with existing organizational values, goals, and practices, as well as the broader industry trends (Amadoru et al., 2021; Bunduchi et al., 2019).

The relationship between organizing vision and the institutionalization of IS innovations has also been examined in literature. Research has shown that a well-developed organizing vision can facilitate the institutionalization of an IS innovation by providing a shared understanding of the innovation's value and potential applications, thereby increasing the likelihood of its adoption and routinization within organizations (Amadoru et al., 2021).

Despite the valuable insights the literature provides on organizing vision for IS innovation, some challenges and limitations have been identified. For instance, the concept of organizing visions has been criticized for its emphasis on the role of external stakeholders. Research has argued that the internal dynamics within adopting organizations should be given greater consideration (Wang, 2021). Additionally, the relationship between organizing visions and other factors influencing IS innovation adoption in the digital realm warrants further investigation. In particular, resources, spanning technological, knowledge-based, human, and financial categories (Amadoru et al., 2021) are crucial in the context of education. Different types of resources vary greatly between educational institutions and localities, reflecting the likelihood of GAI adoption. Lastly, ChatGPT’s unique positioning towards non-technical end users impacts the underlying mechanisms that drive the formation of organizing visions and the ultimate adoption of IS innovations. With ChatGPT reaching 100 million users at an unprecedented rate, surpassing the pace of any prior digital platform (Chow, 2023), GAI has the potential to reshape voluntary technology adoption. Thus, this work focuses on both internal stakeholders (e.g., educators) and external stakeholders (e.g., influencers) to explore the multifaceted landscape of early-GAI discourse and adoption.

Methodology

As GAI, specifically ChatGPT, is an emerging area of interest (Dwivedi et al., 2023), we focus on gathering and analyzing digital trace data generated by social media platform, Twitter. Digital trace data, such as event logs and social media updates, are the byproduct of interactions with digital technologies (Berente et al., 2019). While digital trace data is not originally intended for research purposes, it can provide valuable insights into real-world technology use and behavior (Howison et al., 2011). Furthermore, Twitter, in particular, is recognized as a central hub for discussions and debates on emerging technologies (Amadoru et al., 2018, 2021), making it a key source of data for this research.

However, the collection and analysis of large-scale digital trace data pose significant challenges (Pentland et al., 2021). To overcome these challenges, the IS field has increasingly adopted computationally intensive approaches to generate, reformulate, replace, and extend through the analysis of digital trace data (Berente et al., 2019; Lindberg, 2020; Miranda et al., 2022). These approaches draw from computational theory discovery and computational social science, grounded theory methodology and mixed methods research, “but is not reducible to any one of them” (Miranda et al., 2022, p. iv). Thus, we employ this broad and diverse approach to analyze the emerging discourse of GAI on Twitter.

At a high level, we follow the first three iterative phases of Computationally Intensive Theory Development (CITD): (1) sampling and data collection, (2) synchronic analysis, and (3) lexical framing (Berente et al., 2019). We plan to address the fourth step (diachronic analysis) in future work. In addition, Miranda et al. (2022), noted that research may utilize either synchronic analysis, diachronic analysis or a mix of approaches when analyzing data. We go through each of the three phases below.

Phase 1: Data Collection and Sampling

Data was collected through Twitter API v2's full-archive endpoint, which is freely accessible to researchers upon approval from Twitter (Twitter, 2022). This endpoint provides access to the entire archive of tweets dating back to 2006 which enables replication. To focus our data collection efforts, we used the hashtag #chatgpt and keyword "chatgpt" as seed parameters to iteratively identify other relevant parameters. ChatGPT has been at the forefront of the GAI debate, particularly in educational settings (Lim et al., 2023), which led us to focus on this technology specifically. After multiple rounds of data exploration, we arrived at our final query: *(#chatgpt OR chatgpt OR "chat gpt" OR #chatgpt3 OR chatgpt3 OR "chat gpt3" OR "chat gpt 3" OR #chatgpt4 OR chatgpt4 OR "chat gpt4" OR "chat gpt 4") lang:en -is:retweet*. Retweets and non-English tweets were excluded. Data was collected between December 1, 2022, and March 31, 2023, a period of four months following the release of ChatGPT on November 30, 2022. All data was collected on the 14th of March and 14th of April using a custom toolkit developed by the author team (Kishore et al., 2019). Initial data collection resulted in 2,408,153 English tweets.

As shown in Table 1, the dataset was reduced to 1,260 tweets using multiple approaches. The process of data reduction and aggregation facilitates deeper levels of analysis, thereby supporting the formulation of novel theoretical insights (Errmann et al., 2023; Kar & Dwivedi, 2020). First, all education-related tweets were identified using a partial string match. Then, the topic modeling package, BERTopic, was applied to identify salient topics (Grootendorst et al., 2023). BERTopic generates document embeddings by utilizing the pre-trained transformer-based language model, BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2019). BERT and GPT-3 represent the two most popular language models available today, and BERT has been shown to outperform existing topic modeling approaches such as Latent Dirichlet Allocation (LDA) (Abuzayed & Al-Khalifa, 2021). BERTopic also helps uncover interpretable topics that may reveal a specific discourse, thus, making the analysis contextually richer. While BERTopic identified multiple topics which were interesting, a specific discourse on banning ChatGPT consistently emerged. Thus, our initial analysis focuses on this specific discourse.

Step	**Explanation**	**Tweets**
Initial data collection	Number of tweets mentioning ChatGPT between December 1, 2022, and March 31, 2023.	2,408,153
Identifying education-related tweets	Restricted dataset to tweets containing *educ*, teach* universit*, school*, or college**.	91,842
Unsupervised topic modelling (BERTopic)	Restricted dataset to a specific topic discussing banning ChatGPT in an educational setting.	1,260

Table 1: Data reduction approach.

Phase 2: Synchronic Analysis

The process of synchronic analysis encompasses various approaches to classify and identify associations within a dataset. This includes approaches such as qualitative coding and cluster analysis (Berente et al., 2019). We have already used one approach, topic modeling, to gain an initial understanding of the data. Additionally, we utilize synchronic analysis by segmenting tweets into actor groups (Kotlarsky et al., 2022; Mirbabaie et al., 2020) and by conducting thematic analysis (Braun & Clarke, 2006, 2012). Table 2 outlines and defines the features of Twitter that were analyzed.

The categorization of users into actor groups allows us to differentiate between users with distinct characteristics, behavioral intentions and access to different types of resources. For instance, media organizations tend to be more active on social media platforms, and usually have a larger following, than the general public (Mirbabaie et al., 2020). By understanding the diverse intentions of users participating in early discourse related to banning ChatGPT, we familiarize ourselves with the dataset. Further, this categorization allows us to examine how different groups engage with a specific topic and how others interact with the content generated by these groups. In this way, we can explore the dynamics of online discourse and gain deeper insights into the behavior and motivations of different actors within our dataset (Miranda et al., 2016). As actors often belong to multiple categories (Kotlarsky et al., 2022), we utilize a cascading categorization approach to fit user accounts into the most meaningful categories, as discussed in the Results and Findings section.

Twitter Feature	Definition
Tweets	The number of original pieces of content (e.g., text, images, and media) generated by users.
Retweets	The number of times a tweet was redistributed or reposted by other users.
Replies	The number of responses to a tweet.
Followers	The number of users following the creator of a tweet.

Table 2: Definitions of Twitter features.

Phase 3: Lexical Framing

Lexical framing involves situating concepts and patterns within an existing body of knowledge to extend a specific discourse (Berente et al., 2019). It provides researchers with a language to generate and formulate relevant findings. We engage in thematic analysis to generate more robust concepts and associations between concepts as it provides us with a flexible approach to understanding the meaning and patterns within qualitative data. Thematic analysis typically involves an initial stage of data familiarization, which entailed re-examining tweets, and then proceeded to the coding phase. During coding, an open coding approach was utilized, whereby each tweet was examined and assigned codes. Next, assigned codes were reviewed again to uncover overarching patterns of significance, resulting in the identification of potential themes. Thematic analysis is especially useful in this context as it allows the co-authors to apply their understanding of the body of knowledge to construct a relevant contribution. Thus, thematic analysis enables lexical framing as it unveils deeper relationships both within and between actor groups (Braun & Clarke, 2006, 2012).

Results and Findings

RQ.1 Who are the main actors contributing to the early development of organizing visions of banning or allowing ChatGPT in education?

To identify the main actors contributing to the early development of organizing visions of ChatGPT, we employed a cascading categorization method to group actors. Due to the frequent overlap of actors across various groups, we determined their primary group membership based on their profile description and overall involvement in the relevant discourse. To accomplish this, all co-authors engaged in multiple iterations of categorization as a diverse range of actor groups surfaced and underwent continual redefinition over multiple rounds. At the end of this process, we identified nine high-level actor groups that participated in early online discourse, as shown in Table 3. If a particular user fit into both the academic and influencer actor groups, for example, they were included in the academic actor group, as the academic actor group contains more salient information than the influencer actor group. This cascading prioritization is also represented in the order of the table, with academic and educator actor groups taking priority over individual and influencer actor groups when a user account was identified as an individual.

Actor Group / Description	Tweets (Sum)	Retweets (Sum)	Retweets (Avg.)	Retweets (Std. Dev.)	Replies (Sum)	Replies (Avg.)	Replies (Std. Dev.)	Followers (Sum)	Followers (Avg.)	Followers (Std. Dev.)
Academic: Those affiliated with higher education institutions engaging in teaching, research, and consultation services.	137	275	2.01	10.54	140	1.02	2.46	664,554	4,850.76	12,907.91
Educator: Individuals involved in teaching K-12, either formally affiliated with schools or providing education services. These educators are frequently also consultants and entrepreneurs.	130	118	0.91	2.30	156	1.20	2.84	476,251	3,663.47	11,259.52
Individual: Those that are not explicitly associated with education or any formal organization or community. These individuals express themselves as technology enthusiasts, consultants, data scientists, writers, gamers, etc.	455	81	0.18	1.44	182	0.40	0.92	119,029	261.60	257.64
Influencer: Influencers are individuals with a high number of followers. We identified influencers as individuals with 1,000 or more followers. Includes individual reporters.	319	640	2.01	12.54	599	1.88	8.35	7,318,613	22,942.36	79,923.42
Media: Online media and news channels related to diverse fields of interest including education, technology, politics, science, trade, finance, etc.	101	135	1.34	4.57	140	1.39	4.96	145,445,000	1,440,049.51	6,922,863.64
Organization: Technology service or consultation related businesses; Non-governmental organizations; Institutions.	66	255	3.86	22.01	126	1.91	7.88	2,285,719	34,632.11	129,348.74
Community: Communities of interest (CoI); Communities of practice (CoP); Not-for-profit communities.	22	21	0.95	2.36	8	0.36	0.79	1,000,817	45,491.68	132,691.07
Student: Self-identified students.	16	3	0.19	0.54	12	0.75	2.24	5,421	338.81	887.43
Bot: Automated retweeting accounts.	14	4	0.29	0.47	6	0.43	0.76	109,104	7,793.14	21,526.88

Table 3: Cascading actor group categorizations.

Table 3 shows that individuals posted the highest number of updates (455) yet received the lowest average number of retweets (0.18). In crisis scenarios, individuals tend to be perceived as credible sources of first-hand information and, thus, receive a large number of retweets (Kotlarsky et al., 2022). However, this was not the case in the context of ChatGPT. Instead, in the context of individual user accounts, influencers and academics received the highest average number of retweets (2.01). Despite possessing a significantly smaller average network size compared to influencers, academics received the same average number of retweets. We hypothesize that this is because academics often included their academic affiliations in their profiles, which added to their perceived legitimacy. In contrast, influencers were typically associated with technology startups or large tech organizations, which provided them with legitimacy through their perceived understanding of innovative technologies. Thus, in the context of ChatGPT, academics and influencers were perceived as key sources of information as they represented both active users of the technology and those that were directly impacted by the popularization of the technology. Conversely, educators did not receive a large volume of retweets, but did receive more replies, on average, than academics which shows that an active discussion was occurring within these networks.

In the context of non-individual user accounts, we find that organizations possessed the largest number of average retweets (3.86) and replies (1.91) overall. As organizations include universities, schools, and technology firms participating in online discourse, this makes logical sense when viewed from the perspective of legitimacy. Yet, the media's relatively low participation in the discourse is surprising as the media usually dominates online discourse in terms of volume (Mirbabaie et al., 2020). On average, media also possessed the largest networks yet received limited interactions (i.e., retweets and replies). Thus, organizations were seen as a more valuable source of information to the public in comparison to the media.

RQ2. How do organizing vision functions operate during the early development of organizing visions of ChatGPT in education?

Regarding the organizing vision of ChatGPT in education (i.e., the lexical framing), thematic analysis of synchronic data in combination with available literature, reveals two overarching themes: 1) The Need for Education Redesign and Preparedness and 2) Digital Inclusion and Exclusion in the Age of AI. Each of these themes, along with the subthemes, are discussed below.

The Need for Education Redesign and Preparedness

The first overarching theme encompasses the need for curriculum and assessment redesign and the need for training educators and students in the appropriate use of learning technologies. As the integration of advanced technologies such as ChatGPT into society is an inevitable reality that cannot be ignored, it may be more effective for education to adapt and redesign assessment methods instead of banning these tools altogether.

Leveraging Emerging Technology to Enhance Learning

One of the prominent subthemes in tweets with positive sentiment towards the use of ChatGPT in education is to capitalize on emerging advanced technologies as a means to enhance the quality of learning and teaching. The integration of advanced technologies like ChatGPT into education presents numerous opportunities for personalized learning and a better learning experience for students. For instance, Denny et al., (2015) identified the potential of NLP technologies, including chatbots, for personalized learning in higher education. These technologies can analyze individual learning patterns and adapt instructional strategies to meet the unique needs of each student. Additionally, advanced technologies such as ChatGPT can enhance the learning process for students with real-time responses upon requests.

> "Academia has to embrace ChatGPT - it's here to stay. It would be insane to ban it. It's an opportunity to shift the focus from memorisation to focusing on learning how to learn. Would they ban it for teachers too? It will likely be a great tool for preparing course material." (Academic, ID 967)

> "Instead of simply banning #ChatGPT, using it in a rational way can free scholars, teachers and students from repetitive and thoughtless work and learning so that they can be more devoted to complex learning and creativity, some education insiders believe." (Media, ID 976)

> "Schools really should be teaching students how to correctly use ChatGPT instead of outright banning it, it's like not allowing people to use Google or an online dictionary, makes no sense moving forward into the future." (Student, ID 1190)

As highlighted by Nguyen et al. (2020), AI-enhanced learning analytics can provide immediate feedback to students and offer personalized support, leading to improved engagement, motivation, and performance. Additionally, the use of advanced technologies can enhance communication between students and teachers, providing students with access to assistance at any time and promoting a more collaborative and interactive learning environment (Järvelä et al., 2023; Mousavinasab et al., 2021).

Assessment and Evaluation Reform

Furthermore, traditional curriculum and assessment designs may no longer be fit for purpose, mainly as technology can quickly take over tasks that once required human effort (Dwivedi et al., 2023; Lund et al., 2023). To avoid discouraging learning or encouraging lazy learning behaviors, testing methods should change to better incorporate emerging technology meaningfully into the syllabus (Kabudi et al., 2021; Lawless & Pellegrino, 2007).

> "Instead of banning ChatGPT in schools, teachers should learn to use it to create better lesson plans. Focus on how you can define action-oriented objectives that can generate curiosity in the learner. Remember: use cases / problems first, facts / process later." (Individual, ID 515).

> "Banning #ChatGPT from schools and colleges would be a difficult thing to achieve in this hyper connected world. As a faculty, we have to innovate and challenge students differently. It is going to be another exciting moment for teaching. But information is not knowledge." (Influencer, ID 464)

The main concern expressed in tweets expressing negative sentiments about the use of ChatGPT in education is the possibility that it may encourage academic dishonesty and cheating, resulting in poor learning habits.

> "Are you kidding me? There are many Academic Integrity cases being caught due to students misusing ChatGPT by letting it do their entire homework in university. What are you talking about? This is about integrity and I am glad that Microsoft is pushing it to this direction." (Organisation, ID 1114)

> "ChatGPT should be banned. Amazingly surprised to see a public university providing workshop on how to use ChatGPT in teaching and learning. Irreversible damage in students critical thinking and problem solving skills, leading to a generation of illiterate graduates." (Academic, ID 966)

Educators' Responsibility and Empowerment

Nonetheless, in tweets expressing positive sentiments towards using ChatGPT in education, a notable subtheme, educators' responsibility to keep up with time, emphasizes the importance of teacher preparedness in the age of AI. Educators and students require training in both technical skills and learning pedagogies before implementing emerging technologies like ChatGPT into the classroom (Dwivedi et al., 2023; Ertmer & Ottenbreit-Leftwich, 2010).

> "ChatGPT can advance education and banning it would be counterproductive. However, it's crucial that teachers are properly trained and guided in using the tool effectively and responsibly. Teachers play a critical role in ensuring that it's used for learning purposes." (Organisation, ID 1127)

> "How will this ban work exactly? You might block access to the site through the school/university firewall but that is not going to stop students using #ChatGPT. Instead of fighting the future, embrace it. Focus on equipping young people with the skills for tomorrow's jobs." (Individual, ID 393)

> "Blocking #chatgpt in schools is a short-sighted solution that deprives students of valuable learning opportunities. Instead, schools should teach responsible usage and internet safety to empower students to make informed decisions online." (Individual, ID 90)

Students' Preparedness for AI

On the other hand, it is equally important to acknowledge that students should be aware of the potential negative consequences and take proactive measures to mitigate them, while also preparing themselves to effectively leverage advanced technologies such as ChatGPT to enhance their learning and competencies. Tweets expressing negative sentiment towards using GAI in education commonly raise concerns about the accuracy and potential harm of the generated content.

> "Yes, schools should block ChatGPT because it can be used to bypass traditional filters and is not suitable for academic purposes. It can also be used to access inappropriate content, which can be harmful to students." (Individual, ID 64)

> "Last time I checked, #ChatGPT is still in validation mode. Schools are right in refusing to allow it within their premises at this stage. Of all people, should know the importance of Verification and Validation (VandV) before release to human consumption/use." (Academic, ID 105)

This highlights the importance of not only ensuring the reliability and quality of AI-generated educational material in the implementation of such technologies but also promoting students' awareness and preparedness for AI, including its potential benefits and limitations, to enable them to use these tools effectively and responsibly.

Digital Inclusion and Exclusion in the Age of AI

The second overarching theme surrounding the use of ChatGPT in education involves both the potential for learning inequity caused by these technologies as well as their potential to reduce learning inequity by providing more personalized and accessible educational experiences. This theme also highlights the importance of digital inclusion, which is also an EU-wide (European Commission, 2022) and worldwide effort to ensure that everyone has the opportunity to contribute to and benefit from the digital world, particularly in the context of education where AI and other advanced technologies have the potential to either exacerbate or address existing educational inequities.

Digital inclusion refers to the equal opportunity for all individuals to access and benefit from digital technologies, irrespective of their socioeconomic status, location, or other factors (Nguyen, 2022). It encompasses access to devices, internet connectivity, digital literacy, and the ability to use these resources effectively. Conversely, digital exclusion refers to the lack of access or inability to fully participate in the digital world due to barriers such as limited connectivity, financial constraints, or inadequate digital skills.

Technological Accessibility to Counter Learning Inequity

The findings of our study support the importance of addressing learning inequity before the deployment and implementation of technologies such as ChatGPT in classrooms, highlighting the critical role of ensuring accessibility to devices and internet connections in and out of schools to promote equitable access to education.

> "Any school district whose first reaction is to block #chatGPT is just making sure the kids who can afford devices at home have access and the kids who can't won't. It be the biggest technological catalyst in generations." (Educator, ID 12)

> "Am not sure that's the best idea. Not unless schools can give ALL their young people laptops for their own personalised learning. And to access #ChatGPT" (Influencer, ID 1248)

> "I am very concerned about the equity issue already emerging in districts that just "block ChatGPT" and consider problem solved. Students with means and access individually already have an advantage in education, and this could exacerbate that exponentially." (Influencer, ID 558)

Educators have a responsibility to prepare learners for a technologically driven workplace (Thomas & Brown, 2011) and empowering them by providing technology training (Ertmer & Ottenbreit-Leftwich, 2013). ChatGPT has the potential to reduce learning inequity by supporting diverse groups of learners, including those with learning disabilities (Nguyen et al., 2018; Rose & Meyer, 2002), and to enhance learning experiences by aligning with learning pedagogies (Kirschner & De Bruyckere, 2017).

Educational Accessibility to Promote Learning Equity

On the other hand, another cohort of the digital community argues that ChatGPT can actually reduce learning inequities by supporting diverse groups of learners, including those with learning impairments, to allow for learning at their own pace and by providing access to educational resources for learners who are deprived of formal education, ultimately promoting more equitable access to education.

> "By banning chatGPT from classrooms, schools risk depriving students from these communities of the opportunity to access new technologies and ways of learning. This can further widen the already significant gap between these students and their more privileged counterparts." (Educator, ID 66)

> "You can actually ask ChatGPT for endless ideas about how to incorporate this technology into schoolwork and lessons. But that would be too obvious. Hey look! Here's a new teaching tech that actually engages autistic or learning-impaired children. LET'S BAN IT!!" (Influencer, ID 160)

This apparent contradiction is consistent with the argument made by (Nguyen, Hong, et al., 2020) that while digital learning activities can support digital inclusion by providing more equitable access to education, they can also contribute to the digital divide by reinforcing existing inequities in access to technology and digital literacy skills.

Discussion

By examining the organizing visions of GAI, specifically ChatGPT, in education, we provide valuable insights into the opportunities and threats posed by such systems, which can guide the integration of AI into educational settings. From a theoretical perspective, this study expands on the framework proposed by Amadoru et al. (2021) to explore the organizing vision functions in the specific context of GAI in education by focusing on actor groups with access to different types of resources. By identifying the main internal and external actors contributing to the early development of organizing visions of ChatGPT in education, and examining how organizing vision functions operate, we offer a more nuanced understanding of how educational stakeholders can navigate the complex landscape of AI. This research contributes to the literature on organizing visions, particularly in the context of AI and education, by providing empirical evidence that helps refine and extend existing work.

The theoretical contributions of this study center around the extension and refinement of the organizing vision framework in the context of GAI in education. By applying elements of the framework proposed by Amadoru et al. (2021) and investigating the main actors contributing to the early development of organizing visions of ChatGPT in education, as well as examining how organizing vision functions operate during this process, we expand the understanding of organizing visions in the digital realm. Furthermore, our study offers valuable insights into the dynamics between different stakeholders and their influence on the trajectory of GAI integration in education.

First, by identifying the main actors involved in the early development of organizing visions of ChatGPT in education, we contribute to the literature by highlighting the varying roles and influence of different stakeholder groups, such as policymakers, educators, administrators, students, and technology developers. This comprehensive mapping of stakeholders enriches our understanding of the complex interplay between various actors, enabling a more nuanced analysis of the factors that drive the formation and evolution of organizing visions in the educational technology domain.

Second, our study extends the organizing vision framework by examining how organizing vision functions operate during the early development of ChatGPT discourse and adoption in an educational context. We delve into the mechanisms through which these functions interact and influence each other, shedding light on the intricate dynamics governing the development of organizing visions. This enhanced understanding of organizing vision functions can inform future research on adopting and diffusing innovative technologies, such as GAI, in other sectors and contexts.

Methodologically, this study provides several contributions to the field of educational technology and IS research. Our research design allows for a robust investigation of organizing vision functions in the context of GAI in education, which can serve as a foundation for future studies exploring similar phenomena. By employing a computationally-intensive approach (Miranda et al., 2022), we combine the strengths of qualitative and computational research methods to provide a more comprehensive understanding of the underlying processes and dynamics (Pentland et al., 2021).

First, the qualitative component of our study offers an in-depth exploration of the perspectives and experiences of various stakeholders involved in the early development of organizing visions of ChatGPT in education. We collect rich data that allows us to uncover the nuances and complexities of the organizing vision functions and their interactions. This qualitative approach enables us to capture the multifaceted nature of GAI integration in education, providing a strong foundation for understanding the opportunities and threats posed by these technologies.

Second, the computational component of our study complements and strengthens the qualitative findings by providing evidence to support our theoretical assertions (Miranda et al., 2022). By analyzing a large-scale digital trace dataset, we identified patterns that helped to validate and generalize our findings. This computationally intensive approach allows us to rigorously examine the relationships between different organizing vision functions and the influence of various stakeholder groups on the development of organizing visions.

Our findings have several practical implications for educational stakeholders, including policymakers, educators, administrators, students, and technology developers. As GAI technologies like ChatGPT continue to evolve (Kasneci et al., 2023; Lund et al., 2023), educational stakeholders must be aware of their potential benefits and risks to make informed decisions about their implementation. For policymakers, our study highlights the importance of striking a balance between innovation and regulation to ensure that AI technologies are used responsibly and ethically. Policymakers must collaborate with educational institutions and technology developers to establish guidelines and standards that address concerns surrounding AI-generated content, including biases, inaccuracies, and misinformation.

Educators and administrators can use our findings to identify the best practices for incorporating GAI technologies into the teaching and learning process. This includes developing strategies to prevent over-reliance on AI-generated solutions, which can undermine critical thinking and problem-solving skills. Educators should also be prepared to address the potential ethical and societal implications of using AI in the classroom, engaging students in meaningful discussions about AI's role in education and its broader impact on society.

For students, understanding the opportunities and threats associated with GAI can empower them to use such technologies responsibly and effectively without compromising their academic integrity. They should be encouraged to critically evaluate AI-generated content and develop the skills needed to distinguish between reliable and unreliable information.

Finally, technology developers have a significant role in mitigating the risks associated with GAI. By incorporating the feedback and concerns of educational stakeholders, they can work towards developing AI systems that are more transparent, fair, and accountable. This includes addressing issues related to biases, inaccuracies, and misinformation in AI-generated content and promoting the responsible use of AI in educational settings.

In summary, this study contributes to the ongoing conversation on the integration of AI technologies, particularly GAI, in education (Dwivedi et al., 2023; Lund et al., 2023; Nguyen, Gardner, et al., 2020) by examining the organizing visions of ChatGPT. Our findings have important theoretical and practical implications for various educational stakeholders as they navigate the complex landscape of AI technologies in education. While GAI offers numerous benefits, addressing the associated risks and challenges is essential to ensure the responsible and ethical use of these technologies in educational settings. Future research could further explore the long-term impact of GAI on education and examine the effectiveness of specific interventions and strategies for mitigating the associated risks.

Conclusion

While ChatGPT and other GAI models present both opportunities and challenges for education, an outright ban may not be the most effective solution. Instead, a more nuanced approach that involves developing responsible use policies, providing appropriate support for educators with access to different types of resources, and engaging stakeholders in the decision-making process can help harness the potential of AI in education while mitigating its risks. While further research is required, the approach and findings may also inform other domains that are considering adopting IS innovations. Categorizing and understanding different actor groups (Kotlarsky et al., 2022; Mirbabaie et al., 2020) has the potential to reveal salient information on who is contributing to the development of organizing visions throughout different phases. This extends beyond education, AI, and GAI, as it offers an approach to enrich theory development beyond these domains.

This study should be viewed in light of its intrinsic limitations. As the primary dataset is only a few months old, discourse may evolve or expand rapidly over time. New relevant hashtags and keywords may emerge over time that were not included as part of this study. For the next phase of our study, we plan to continually rework our data collection and analysis approach to account for this. Collecting data from Twitter API v2 only provides access to public Twitter accounts; therefore, this dataset does not include data generated by private Twitter accounts. While Twitter in particular is known as a platform where discursive social engagement can emerge (Amadoru et al., 2018), we will also consider integrating other data sources as well as conducting an empirical case study in future research. Subsequently, a diverse spectrum of perspectives encompassing students, guardians, and non-academic personnel would foster a richer understanding of the intricate dynamics and provide deeper insights into the practical ramifications of AI within educational contexts. We also aim to expand our theoretical contribution in future research with a particular focus on a resource-based view. Lastly, BERTopic may not reveal all tweets on banning ChatGPT. While we went through multiple rounds of topic modeling and found a reasonably consistent discourse, we plan to explicitly discuss this process in future research.

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