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An Activity System-based Perspective of Generative AI: Challenges and Research Directions

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Abstract:

With its remarkable ability to generate content, generative artificial intelligence (GAI) has been recognized as a milestone in the development of artificial general intelligence. To understand the challenges, potential impact, and implications associated with GAI, we adopt a socio-technical perspective to analyze them. First, we identify the key characteristics of GAI, which include content generation, generalization ability, and reinforcement learning based on human feedback. Next, we address technological, ethical, societal, economic, regulatory, and governance challenges. Finally, we deploy activity theory to explore research directions in GAI. Research questions that warrant further investigation include how GAI may impact the future of work, how GAI can collaborate effectively with humans, and how we can improve the transparency of GAI models as well as mitigate biases and misinformation in GAI to achieve ethical and responsible GAI.

Keywords: Generative Artificial Intelligence, Activity System Analysis, Activity Theory, AI Challenges, Socio-technical Perspective, Research Directions

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1 Introduction

Large generative artificial intelligence (GAI) models have attracted worldwide attention since the release of OpenAI's ChatGPT, a Large Language Model that integrates the Generative Pre-trained Transformer (GPT) architecture. The GPT architecture uses artificial intelligence (AI), or more specifically, machine learning algorithms, to generate content by pre-training on a large corpus of data and then fine-tuning for specific tasks. ChatGPT can answer users' questions fluently and in a human-like way. It has the ability to not only converse and reason but also remember the context of dialogs. It can generate content such as poems, songs, and codes. The latest release, GPT-4, has powerful capacities for processing multimodal information. GAI, such as GPT-4, comprises a set of algorithms that are capable of extracting information from training data, which include text (e.g., GPT-3.5, Claude), images (e.g., DALLE-2, Stable Diffusion), and audio (e.g., musicLM), and generating novel content after learning the patterns from the data (Sun et al., 2022).

Compared with other AI models, GAI models are distinct in that they have the capacity to generate original content (Hacker et al., 2023). This characteristic stems from their ability to learn patterns and relationships from training data without explicit guidance about specific features to focus on (Hacker et al., 2023). Large generative models utilize several techniques to acquire this ability. For instance, models may use self-attention in transformers to allocate different weights to individual words and capture the dependency and contextual relationships within sequences (Zhang et al., 2023). Also, they may use unlabelled data to leverage a universal representation beyond word-level information (Zhang et al., 2023).

New technologies can introduce novel possibilities and affordances for interacting with humans. In the case of GAI, the ability to produce original content can give rise to many possible applications. The impact of a new technology is not merely determined by the technology itself (Baxter & Sommerville, 2011). A holistic approach is needed to understand the technology in the socio-cultural and organizational contexts in which it is deployed (Hasan & Kazlauskas, 2014). Specifically, we identify and address research gaps associated with GAI by deploying a socio-technical perspective to understand the impact of the technology and propose future research directions. Hence, we first review the fundamental characteristics of GAI, explore the emerging challenges they give rise to, identify research gaps stemming from these characteristics and challenges, and present future research directions based on the framework of activity theory.

2 Characteristics of Generative AI

Prior to situating GAI within a broader context, it is important to identify its key characteristics to better understand its potential, application, and impact in the socio-technical system. In this section, we discuss three key characteristics of GAI: content generation, generalization ability, and reinforcement learning using human feedback.

2.1 Content Generation

GAI refers to a class of algorithms that can learn from training data to generate new content (Sun et al., 2022). The ability to generate original content makes it distinct from other AI models that are designed to make predictions or classifications (Hacker et al., 2023). The mechanism behind this ability lies in the large-scale pre-training in which the model extracts and learns universal representations of information extracted from the training data (Radford et al., 2018). Examples of the representations it can learn include linguistic structures (Radford et al., 2018), image representations (Chen et al., 2020), and relationships between textual descriptions and images (Mu et al., 2022). GAI models can then generate new content after learning these representations. For example, GAI calculates the probabilities of subsequent word-level tokens based on the previously generated tokens and the context for text generation (Lee, 2023). The ability to generate original content increases its potential applications such as art creation and commercial advertisement generation (Cao et al., 2023). They can also be utilized in chatbots to carry out long and context-specific conversations (Dwivedi, Kshetri et al., 2023).

2.2 Generalization Ability

Another key feature of GAI is its enhanced generalization ability in which the model can adapt to previously unseen data and perform well. GAI can be used in a wide range of tasks including creating poems, analyzing data, and coding. Many machine learning systems function as narrow experts - excelling at tasks they were trained for using supervised learning on a large dataset (Radford et al., 2019). However, these systems could fail when the task and data distribution change slightly. Their need for manually labeled data restricts their applicability in domains that are short on annotated data (Radford et al., 2019). According to Radford et al. (2019), the lack of generalization is mainly due to the lack of variety in datasets and tasks. Thus, GPT models utilize pre-training on a large unlabeled text corpus that contains billions of tokens to learn a universal representation that transfers with little adaptation to a wide range of tasks (Radford et al., 2018). High generalization ability not only means the model is applicable to different settings but also implies the model can capture the underlying patterns and structures in the data well which helps to improve creativity, variety, and reasoning in content generation.

2.3 Reinforcement Learning Based on Human Feedback

The use of large-scale, unsupervised pre-training, followed by supervised fine-tuning using human feedback, has characterized GAI's ability to model users' needs and intentions along with human-generated content. The use of extensive input data during the pre-training phase facilitates the model's ability to learn a huge variety of content, but it does not guarantee the output will consistently align with the user's intention (Cao et al., 2023). Thus, reinforcement learning using human feedback is applied in the fine-tuning phase of training, including in generative models such as Sparrow, InstructGPT, and ChatGPT (Ouyang et al., 2022; Glaese et al., 2022). For ChatGPT, humans rate the answers from the GPT model and these ratings are, in turn, used to train a reward model based on reinforcement learning (Ouyang et al., 2022). Through supervised learning using humans' ratings, ChatGPT is able to better identify users' intentions and preferences in their prompts.

Human feedback is also used in subsequent versions and releases of GAI products in which users can further rate responses from the algorithm. In addition, users' prompts may be collected as training data for the model. This process can be seen as an effective co-teaming of humans and algorithms (Dwivedi, Kshetri et al., 2023). The users' prompts are not only one-way instructions but also feedback for the algorithms. The communication loop between humans and GAI models can be viewed as an advancement in human-AI collaboration.

3 What Challenges Does Generative AI Bring?

To understand the challenges, potential, and value of GAI, we need to view it as an integral component of a larger socio-technical system. As an emerging technology, GAI can make significant impacts on society, including economic, ethical, legal, and regulatory. For example, when applied in the content creation industry, intellectual property rights may need to be revisited to acknowledge AI as another source of content generation. Therefore, we need to shift our focus to the broader social context and investigate GAI as a "technology in practice" (Orlikowski, 2000). In this section, we explore the challenges that emerge when GAI is situated within a socio-technical system and offer insights into how GAI interacts with other factors in a socio-technical system.

3.1 Technological Challenges

GAI poses technological challenges and limitations as a user-oriented product. First, GAI models have limited explainability and transparency. It is hard to interpret and know how a GAI model created its output (Dwivedi, Kshetri et al., 2023). The lack of transparency makes it challenging for users to discover mistakes or potential risks in its output (Dwivedi, Kshetri et al., 2023). It will also impede users from trusting it, especially in highly consequential and ethical situations (Doran et al., 2017). Second, GAI models may respond to users' prompts with unreasonable output (Ji et al., 2023). As mentioned earlier, GAI models do not understand the underlying semantics of the given training data, and the content they generate is based on the outcome of the probabilistic computations for the next token (Lee, 2023). Thereby, GAI models may fabricate information and generate misinformation as a consequence (OpenAI, 2022), with such phenomena being referred to as hallucinations. Third, authenticity is another issue associated with GAI-generated content. GAI can create vivid photos and videos about events that look real but have never happened. Users can easily manipulate photos and generate fake faces using DeepFake AI (Gragnaniello et al., 2022). Combined with social media, these fake contents are becoming an increasing menace as they can exacerbate the proliferation of fake news and rumors (Te'eni & Ho, 2022).

3.2 Ethical Challenges

GAI focuses on the optimization of the models' output and response efficiency. However, the optimization of performance may conflict with ethical principles. First, biases may be present in the models' output as AI is constrained by the constructed ground truth of its training data (Lebovitz et al., 2021). When the training data only represents a fraction of the population, exclusionary norms could give rise to biases during training. The patterns, preferences, or needs of a larger population may end up being overlooked (Zhuo et al., 2023). Further, the complex architecture of the GAI models may capture and embed biases in the input, all of which may accumulate through many iterations of the model and become harder to eliminate (Liu et al., 2021). Human-ML (machine learning) augmentation, where humans and algorithms work together in decision-making, is one possible solution to address AI biases (Teodorescu et al., 2021). Another way is to use synthetic data to train the model (Chen et al., 2021). Synthetic data refers to artificial data that captures the structure of real data sets rather than data extracted directly from the real world (Draghi et al., 2021). Machine learning tools, such as the Generative Adversarial Network, have been used to generate data samples that have not been adequately represented in the data set to help overcome biases (Norori et al., 2021).

Second, GAI models may generate harmful content that is violent or offensive. Despite strict rules set by GAI platforms to avoid displaying such content, these rules could be broken by strategic prompts, such as prompts that elicit DAN (Do Anything Now) or other jailbreaker modes of ChatGPT to generate illegal or immoral responses. Third, GAI can raise data privacy and security concerns. Data gathered from crawled web pages may include personal information that threatens privacy (Siau & Wang, 2020). With the widespread adoption of GAI tools, sensitive data involving individuals or organizations could be inadvertently leaked by GAI platforms (Porter, 2023). As GAI gradually becomes an inseparable part of our work and daily life, data privacy and security are important issues that warrant attention.

3.3 Societal and Economic Challenges

GAI may bring challenges to society and the economy. First, it may widen the digital divide in society (Carter et al., 2020). The topic of the digital divide created heated discussions in the mid-1990s when the popularization of the World Wide Web raised concerns of an exacerbated North-South divide (Norris, 2001). Initially, it was used to refer to the gap in accessing the Internet infrastructure due to demographic differences such as income, gender, and region of residence (Norris, 2001). However, this conceptualization was criticized for dichotomizing the difference as "connected" versus "disconnected" (Selwyn, 2004), which suggests that the gap can be easily bridged by providing access to those "disconnected." The digital divide was later reconceptualized by Selwyn (2004) as a hierarchy of access to technologies, leading to a varying degree of involvement with technology and participation in activities.

In the context of GAI, access to the technology may vary across countries or geographical regions. Depending on where one lives, there may be full, restricted, or even no access to GAI products. Such differences can lead to distinct differences in GAI usage, which widen the digital divide in society and across the globe. There is also a second-level digital divide that refers to the gap in Internet skills and usage in different regions (Scheerder et al., 2017). Differing attitudes across different regions and cultures on GAI utilization could also widen the digital divide (Dwivedi, Kshetri et al., 2023). Although GAI may enlarge the digital divide, it may bridge the digital divide from another perspective. GAI can help to simplify our interactions with machines, as well as help generate codes, texts, and images using natural language instructions. It can help those with lower digital literacy, such as some elderly and people without access to digital literacy education, to accomplish complex tasks with the aid of GAI.

Second, GAI may potentially replace jobs and increase unemployment (Wang & Siau, 2019; Zarifhonarvar, 2023). Companies that deploy more industrial AI technologies are hiring less low-skilled workers (Li et al., 2021). Some 'rule-based' jobs requiring little or no creativity, emotions, or physical labor, such as data analysts, interpreters, and customer service agents, may become redundant as GAI continues to advance. On the other hand, there are optimistic opinions about GAI's impact on labor markets. Huang and Rust (2018) hold the view that AI replacement happens more at a task level than job level. Hence, the application of GAI may not lead to job losses per se but may create changes in workforce compositions (Das, 2023).

Third, concerns about income inequality and monopolies associated with the adoption of GAI have also been raised. As mentioned earlier, GAI may increase work efficiency and replace some low-skilled jobs. Those who make a living from jobs that could be replaced by GAI may lack the skills for a job transformation. Moreover, the income gap may widen between those who have upgraded their skills to utilize GAI tools and those who have not. Organizations need abundant resources to train and utilize large personalized GAI. Companies that have the resources to embed GAI into their workflows will gain competitive advantages over companies that do not.

3.4 Regulatory and Governance Challenges

As GAI brings new affordances to human-AI interaction, regulations and governance will face new challenges (Wan et al., 2022). First, current laws and regulations have become inadequate to account for new phenomena brought about by GAI (Hacker et al., 2023). For example, a significant advancement of GAI is original content generation. GAI's content generation is derived from training data that contains the original work of humans in which the artistic styles of writing, speaking, and painting, for example, are learned and imitated by GAI. For example, GAI can learn to write like William Shakespeare (see an example at https://www.hyperwriteai.com/aitools/write-like-shakespeare) and compose like Wolfgang Amadeus Mozart (see an example at https://openai.com/research/musenet). Hence, intellectual property rights are brought into question with GAI.

Copyright laws need to further define or redefine copyright violations in the era of GAI. Examples of issues include appropriate authorship or acknowledgment associated with content jointly generated by GAI (McCormack et al., 2019). Violations of laws associated with GAI will be the impetus for changes to existing laws and regulations (Shneiderman, 2020). AI governance can be another challenge for organizations, governmental agencies, and regulatory bodies (Taeihagh, 2021). Due to the lack of transparency of GAI models, it can be difficult to assess their output for accuracy or control the generation of the output to avoid the display of inappropriate content. It is also hard to control the data flow across the entire life cycle because of data fragmentation that occurs during the training process (Taeihagh, 2021). Thus, it is difficult to assess biases and errors in the data, posing challenges to the governance of GAI.

4 Future Research Directions Based on Activity System Analysis

In this section, we propose research questions and directions in GAI based on activity system analysis. We use activity theory as the overarching framework to guide the system analysis.

4.1 What is Activity System Analysis?

Activity system analysis is an approach used to analyze human activity situated in a collective context (Yamagata-Lynch, 2010; Engeström, 2014). Its origin is based on the Cultural-Historical Activity Theory (CHAT) proposed by Lev Vygotsky. Vygotsky did not agree with the mainstream idea that organisms and the environment are two disembodied entities that should be studied separately (Bakhurst, 2009). Vygotsky believed that human consciousness was developed only through mediated action in cultural, historical, and institutional settings (Hasan & Kazlauskas, 2014). Hence, he proposed building the connection between an individual and the environment by modeling the mediated action. The subject, the object, and the mediating artifact/tool form the mediated action triangle (top half of Figure 1).

Following Vygotsky's (1978) work, his student, Leont'ev (1978), identified object-oriented activity as the unit for analysis. Engeström (2014) further included the components of rules, community, and division of labor into the triangle (bottom half of Figure 1) and developed the activity system analysis. These elements supplemented the socio-historical aspects of mediated action. In general, CHAT posits that human activity is object-oriented (i.e., motivated and directed by specific objects) and is achieved by actions through the use of tools, which can be either physical or psychological (Hasan & Kazlauskas, 2014). Systemic contradictions arise when elements within an activity system or between different activity systems change and conflict with each other. The methodology of activity system analysis involves applying the activity system framework to analyze activities and contradictions in a complex system.

Over the past three decades, activity theory has been studied and applied in the information systems area (Karanasios, 2018; Karanasios & Allen, 2018), including in human-computer interaction (Kuutti, 1996; Clemmensen et al., 2016; Pang et al., 2020; Dolata et al., 2023). The activity theory framework enables simultaneous considerations of human-technology interaction at different levels, including individual, organizational, and societal. It is consistent with the "practice turn" emerging from the human-computer interaction area, which shifts away from focusing on the interaction between users and artifacts toward viewing the whole activity in the historical and social context (Kaptelinin & Nardi, 2012; Kuutti & Bannon, 2014). Activity theory has been applied in system analysis (Kaptelinin et al., 1999) and system evaluation

(Quek & Shah, 2004). It has also been applied in organizational information system usage contexts. For example, applications include studying ambulance service systems in hospitals (Allen et al., 2013) and knowledge flow barriers in healthcare organizations (Lin et al., 2008). The activity system is societally motivated, representing a collective of human ‘doing’ towards organizational and societal objectives (Engeström, 2001). The activity theory helps when designing digital tools by shifting the focus from one-user interaction to the social context and from the lab context into real-world applications (Dolata et al., 2023). The use of activity theory in the information systems field emphasizes connecting the organism with the context, which aligns with our intention to understand GAI from a more holistic perspective.

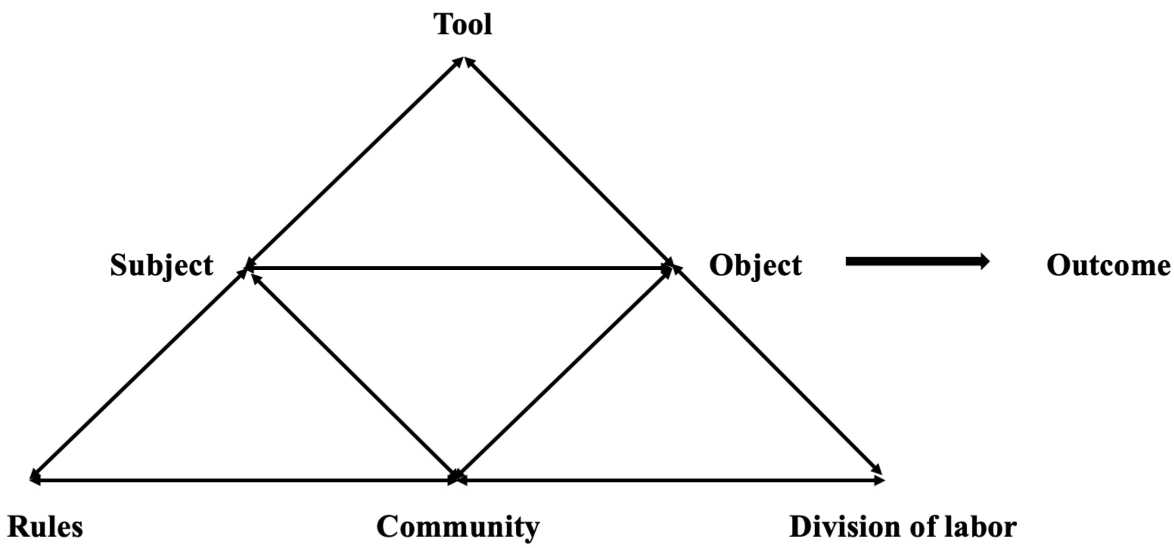

Figure 1. The Activity System by Engeström (Adapted from Engeström, 2014)

The activity system developed by Engeström (2014) provides a meaningful framework to analyze the trends and research directions GAI may bring. Citing Leont’ev (1978), Kaptelinin and Nardi (2006) defined an activity as “a purposeful interaction of the subject with the world, a process in which mutual transformations between the poles of ‘subject–object’ are accomplished” (p. 31). With a focus on users of GAI, the activity in this context refers to individual or organizational users deploying GAI as a tool to achieve certain objectives, while being sanctioned and empowered by rules, community norms, and division of labor. The activity system can be structured as shown in Figure 2.

Table 1 provides descriptions of the various components of the activity system.

4.2 Proposed Research Directions Based on the Activity Theory Framework

Having explained the activity system, this section will utilize the activity system framework to propose future research directions in GAI. The distinctive characteristics of GAI – the ability to generate new content, high generalization capability, and reinforcement learning based on human feedback – can bring about new possibilities for users when they switch from conventional tools to GAI, potentially transforming the nature of their jobs. However, this transformation is also the source of contradictions in the activity system. Contradictions are accumulated structural tensions within and between activity systems heightened by ongoing transitions and transformations (Leont'ev, 1978; Engeström, 2001). They are also the “motive force of further change and development” (Engeström, 2001). By analyzing the potential contradictions brought about by GAI using the activity system, we can better address the gaps and directions for future research.

According to Engeström (2014), there are four levels of contradictions in human activity systems:

1. Contradictions within each element of the central activity system, such as limitations of a tool;
2. Contradictions between elements of the central activity system, such as contradictions between a subject’s expectations of a tool and the usability of the tool;

3. Contradictions between the current central activity system and a more culturally advanced form of activity system, such as the automation of certain activities by a new technology;
4. Contradictions between the central activity system and its neighbor activity systems, such as contradictions between users' technology-using activity and their company's technology-developing activity.

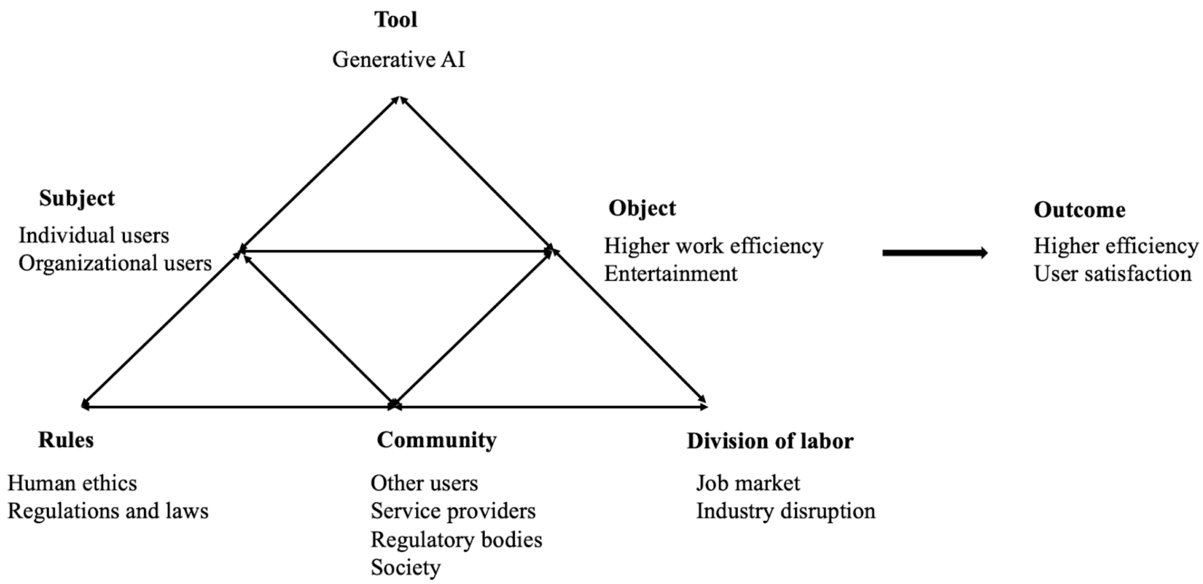

Figure 2. Activity System of Individuals' and Organizations' Use of Generative AI

We discuss the research directions of GAI based on these four levels of contradictions: contradictions within the elements, between the elements, between more advanced activity systems and the central system, and between different activity systems. Figure 3 illustrates these four levels of contradictions.

Table 1. Components of the Activity System

Component	Description
Subject	The individual or group of individuals that executes the activity (Yamagata-Lynch, 2010). In the context of GAI usage, the *subject* refers to GAI users, including individual and organizational users.
Tool	The physical or psychological artifact that mediates the activity and acts as a resource for the subject (Hasan & Kazlauskas, 2014; Yamagata-Lynch, 2010). In the context of GAI usage, the *tool* refers to artifacts/products that incorporate GAI technology.
Object	The focus and purpose of the activity (Hasan & Kazlauskas, 2014). In the context of GAI usage, the *object* refers to users' motives to utilize GAI, such as to increase work efficiency or productivity, to entertain himself/herself, or to get inspiration for a task.
Rules	The formal and informal regulations that restrict or impact activities (Yamagata-Lynch, 2010). In the context of GAI usage, *rules* refer to human ethics, regulations, and laws that are related to the use of GAI.
Community	The collective view of the social context where the subject is situated, such as the social group that the subject belongs to (Yamagata-Lynch, 2010). In the context of GAI usage, the *community* refers to the social groups that the user belongs to, or other social actors that could exert influence on GAI usage.
Division of labor	The task specialization by members of the community (Jonassen & Rohrer-Murphy, 1999). GAI usage may have an impact on the division of labor established before GAI was introduced, such as the replacement and displacement of certain jobs, and the emergence of new jobs. At the macro level, certain industries will face disruptions brought by GAI.
Outcomes	The execution results of the activity (Jonassen & Rohrer-Murphy, 1999). *Outcomes* differ from the object as outcomes could be something unexpected. The use of GAI may have diverse outcomes, such as work efficiency, user habits, and AI literacy.

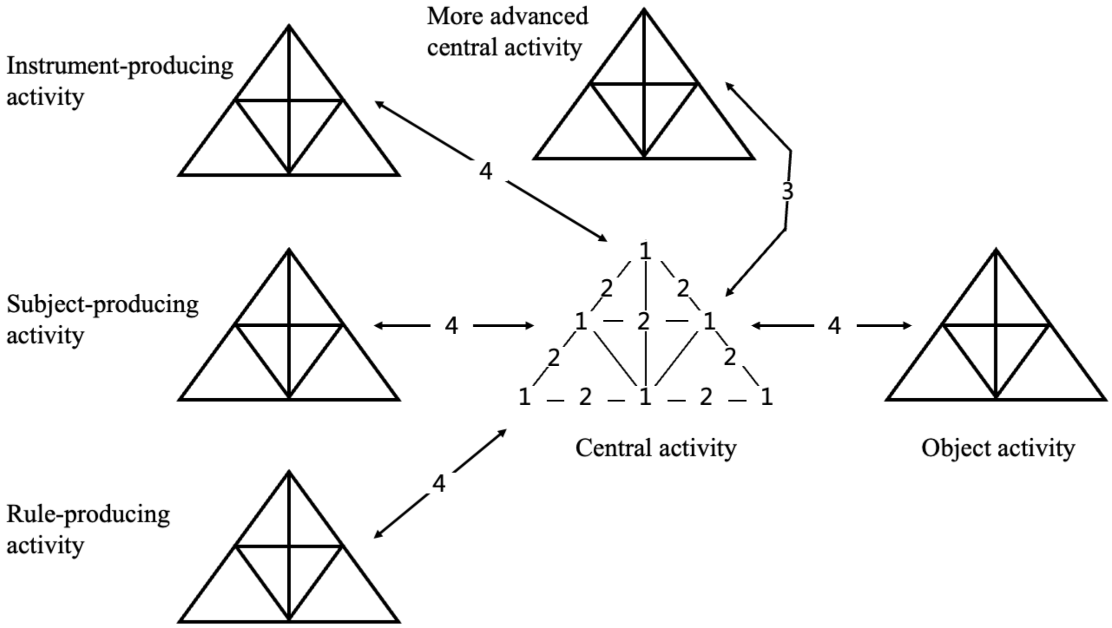

Figure 3. Four Levels of Contradictions within the Human Activity System (Adapted from Engeström, 2014)

First, GAI can cause contradictions within the elements of the activity system. For example, its limitations in transparency and explainability may fail to meet users' expectations. The difficulty in distinguishing between GAI-generated content and human-generated content can also raise concerns for teachers. These limitations of GAI give rise to contradictions within the tool and motivate investigations for further development. The subject (i.e., users) may also face contradictions. As the tool advances, skills needed for GAI usage (e.g., prompting strategies and fact-checking) continue to change, while the basic AI literacies that everyone is expected to possess are also transformed with the advancement of GAI. Users' current literacies may fail to meet these requirements, thus leading to consequences such as unethical use and propagation of misinformation (Li et al., 2022). These problems contribute to contradictions for users. Similarly, the advancement of GAI tools also triggers contradictions within the object, rules, community, division of labor, and outcome, which become sources of research gaps that offer directions for future research. Research directions and research questions arising within elements are outlined in Table 2.

Table 2. Research Directions Arising within Elements

Element	Research directions	Research questions	References
Tool	Transparency and explainability	How can we improve the transparency and explainability of GAI?	Berente et al. (2021), Sun et al. (2022), Dwivedi, Kshetri et al. (2023)
		What kind of transparency and explainability is needed for GAI users?	Jovanovic & Campbell (2022)
	Content assessment	What criteria can be used to evaluate the quality of AI-generated content, such as accuracy, originality, and impartiality?	Dwivedi, Kshetri et al. (2023)
	AI-generated content detection	How can we detect AI-generated content with accuracy?	Chen et al. (2023)
	Interface design	What is the best interface method for GAI to improve its user adoption?	Gursoy et al. (2023)

Table 2. Research Directions Arising within Elements

Subject	User acceptance	What factors impact user acceptance of GAI?	Gursoy et al. (2023)
		What factors influence the acceptance of GAI tools in organizations?	Agrawal (2023)
	Requirements for users	What skills and capabilities are necessary in the era powered by GAI?	Dwivedi, Kshetri et al. (2023)
		What kind of AI literacy is needed for the adoption of GAI?	Bozkurt (2023)
		How can we train or coach users to use GAI in a responsible and ethical way?	Mhlanga (2023)
		What are the key factors for successful GAI implementation in organizations?	Dwivedi, Pandey et al. (2023), Agrawal (2023)
Object	Applicable issues	How can we use generative AI-powered tools to address global grand challenges (e.g., environmental protection, and Sustainable Development Goals)?	Dwivedi, Kshetri et al. (2023)
Rules	Responsible and ethical AI	What are responsible and ethical policies for GAI?	Dwivedi, Kshetri et al. (2023)
		Can we create responsible and ethical GAI through data filtering and AI regulations?	Jovanovic & Campbell (2022)
	Biases	What biases could be introduced into GAI by the training data and processes?	Dwivedi, Kshetri et al. (2023), Susarla et al. (2023)
		How can we reduce the biases in GAI?	Schramowski et al. (2022)
	AI regulation	How can AI laws and regulations be tailored to account for GAI?	Hacker et al. (2023)
	Intellectual property rights protection	Are the current intellectual property rights protection applicable for GAI?	Zhong et al. (2023)
		How can we develop a more comprehensive set of metrics for intellectual property rights protection that applies to GAI?	Zhong et al. (2023)
Community	Impact on social interactions	How will GAI shape social and personal interactions in society?	Dwivedi, Kshetri et al. (2023)
Division of labor	Job market	How will the labor market be reshaped by GAI in the short and long term?	Nah et al. (2023)
		What types of jobs may be replaced by GAI, and what types of new jobs may be created by the deployment of GAI?	Zarifhonarvar (2023)
	Industry disruption	What effects and disruptions may GAI bring to different industries, such as tourism, e-commerce, arts, and entertainment?	Gursoy et al. (2023)
		What new business models can be created by the use of GAI?	Dwivedi, Kshetri et al. (2023)
		How can GAI facilitate the digital transformation of different industries?	Dwivedi, Kshetri et al. (2023)
Outcome	User satisfaction	How can GAI improve consumer experience and satisfaction?	Gursoy et al. (2023)
		How can GAI be used appropriately to improve the learning experience and achievement of students?	Dwivedi, Kshetri et al. (2023)
	Work efficiency	How will the use of GAI impact users' information search behavior?	Gursoy et al. (2023), Pan et al. (2023)
		How will the use of GAI impact users' decision-making process?	Gursoy et al. (2023)

Elements in an activity system are not isolated or stand-alone. Instead, contradictions exist between them. The most prominent contradictions between elements are those between subjects (e.g., users) and the tool (i.e., GAI in this context). Users and GAI are the two fundamental elements underlying our focal activity, in which users utilize GAI to fulfill their needs or goals. Human-AI relationship, human-AI collaboration, the role of GAI, and knowledge co-creation with GAI are potential research topics related to contradictions between the subjects and the tool. Similarly, contradictions are also triggered between rules and the subject, as well as between rules and the community. The development and advancement of GAI make current rules such as human ethics, regulations, and laws inadequate or even inappropriate. Therefore, there is an urgency for adaptation and reformation of existing rules. Before rules and regulations are adapted or reformed, users and the community may contend with the need to abide by extant rules while simultaneously exploring and using the tool. Both the rights and responsibilities of the users and the community should be considered in setting the rules. Research directions and questions arising between elements are listed in Table 3.

Table 3. Research Directions Arising between Elements

Element	Research directions	Research questions	References
Subject-Tool	Human-AI relationship	How can individuals find their position and significance when interacting with GAI?	Saadi & Yang (2023)
		How will human-AI relationships evolve as GAI further improves and advances?	Dwivedi, Kshetri et al. (2023)
		How to build human-machine symbiotic relationships to augment intelligence?	Paul et al. (2022), Zhou et al. (2021, 2023)
	Human-GAI collaboration	How should the human(s) and GAI collaborate in a hybrid team?	Dwivedi, Kshetri et al. (2023)
		What is the most effective design process for creating GAI that collaborates with humans?	Wang et al. (2020)
	Role of GAI	How can GAI play a role in improving human-human collaborations?	Suh et al. (2021)
	Knowledge co-creation	Will GAI expand explicit knowledge production modes and enhance knowledge production efficiency?	Zhu & Luo (2023)
	Impact on organizations	How will the implementation of GAI impact organizations, such as their decision-making process, human resource management, and knowledge management?	Korzynski et al. (2023)
Tool-Object	Context	Is GAI built for specific or dynamic contexts?	Helberger & Diakopoulos (2023)
	Scale of use	What is the appropriate scale of usage of GAI?	Helberger & Diakopoulos (2023)
Subject-Rules	Citizens' rights	How can we promote citizens' rights to file complaints about GAI?	European Parliament (2023)
Rules-Community	Obligations of service providers	What are the obligations of GAI providers?	The Future of Life Institute (2022)
	Risks of GAI	Following a risk-based approach, what kinds of GAI should not be provided?	European Parliament (2023)

Contradictions also arise between more advanced activity systems and the central system. A more advanced activity system refers to a more developed form of activity system compared to the current one (Engeström, 2014; Hasan & Kazlauskas, 2014). As the activity system evolves, such as with the development of tools, contradictions will arise between the current and the more advanced activity systems. We identify two types of contradictions. From a geographical perspective, some countries are less advanced in GAI utilization because of low download Internet speed, the lack of availability of the Internet, or the absence of complementary technology infrastructures (Shamika, 2023). The gap in GAI utilization leads to different levels of efficiencies and capacities, which can be a source of contradictions between GAI utilization and activity systems in different nations. From a temporal perspective, as GAI tools become more advanced, there can be conflicts between the new and old activity systems when other elements in the system cannot adapt to the more advanced tools right away. For example, users may resist the GAI technology when they find advanced GAI autonomy takes over too much control of their lives (Osburg et al., 2022). Research directions and questions arising from contradictions between advanced activity systems and the central activity system are listed in Table 4.

Table 4. Research Directions Arising between Advanced Activity Systems and the Central Activity System

Advancement dimension	Research directions	Research questions	References
Geographical dimension	Digital divide and inequality	Will GAI widen or bridge the digital divide among countries in different stages of technological development?	Baidoo-Anu & Ansah (2023), Bozkurt & Sharma (2023), Dwivedi, Kshetri et al. (2023)
		How will GAI impact low-income countries and shape global resource allocation in the Global North/South divide?	Paykamian (2023)
Time dimension	Conflicts of structure between advanced GAI function and emerging use	Will the “over-automation” of daily routines by advanced GAI technology make users feel a loss of control and create technological resistance?	Osburg et al. (2022)
		Will the structure provided by GAI products conflict with the structure emerging from continuous use?	DeSanctis & Poole (1994)
	Overreliance on GAI	Will users become over-reliant on advanced GAI technology and how to address the risk?	Abd-Alrazaq et al. (2023), Nah et al. (2023)

Contradictions can also occur between activity systems, i.e., between the central activity system and its neighbor activity systems. The central activity system refers to the original target of a study, while a neighbor activity system refers to one that is linked to the central activity (Engeström, 2014). Neighbor activity systems can be categorized into four types, i.e., object activities, tool-producing activities, subject-producing activities, and rule-producing activities. Object activities are “activities where the immediately appearing objects and outcomes of the central activities are embedded” (Engeström, 2014, p. 71). Depending on what element is produced for the central activity system, neighbor activity systems also include tool-producing activities (e.g., science and art), subject-producing activities (e.g., education and schooling), and rule-producing (e.g., administration and legislation) activities.

The objects of GAI usage are diverse and associated with many other neighbor activities, such as news writing (Longoni et al., 2022), business (Sohn et al., 2020), and education (Lawan et al., 2023). Contradictions arise between the central GAI-using activity and these neighbor activities when a novel GAI tool is introduced into industries. For instance, when journalists utilize GAI as a tool for news writing, human subjects who are engaged in a neighbor activity of news reading may encounter trust issues (Longoni et al., 2022). Meanwhile, contradictions may arise from the negative influence of the neighbor activity on the central activity, or vice versa, such as the disruptions created by GAI on traditional or mainstream education (Lawan et al., 2023). Tool-producing activities are activities that aim to produce or enhance GAI. The GAI developing activity of companies may conflict with users’ using activity when their objects clash. Subject-producing activities are mainly related to educating users of GAI, such as students (Pavlik, 2023) and workers (Chetty, 2023). Improving the AI literacy of different groups of people can make the potential of GAI more fully realized. Rule-producing activities include legislation with regard to GAI. Existing laws and regulations on GAI, which have advanced recently, are still inadequate. It is foreseeable that in the near future, legislation activities will be carried out on a large scale. These changes in legislation will influence or even disrupt GAI usage in its current form, resulting in contradictions. Table 5 shows research directions and questions arising between the central activity system and its neighbor activity systems.

5 Conclusion

GAI technology holds tremendous potential for application in a wide variety of contexts and is recognized as a milestone for artificial general intelligence (Zhang et al., 2023). The ‘ripples’ this tool may generate once thrown into the water (i.e., put into practice) are uncertain. The trends and impacts arising from this innovation are a pervasive inquiry and concern for many. We first explore the essence and core characteristics of the GAI technology from the model’s capabilities and technological features. We then summarize the challenges arising from this technology, such as technological and ethical challenges. We also offer research directions for GAI using activity system analysis.

Table 5. Research Directions Arising between the Central Activity System and its Neighbor Activity Systems

Type of neighbor activity	Research questions	References
Object activity	Do people believe in AI-generated news and human-written news to the same degree?	Longoni et al. (2022)
	Why do people evaluate GAN-generated versus non-GAN-generated products differently, such as in fashion?	Sohn et al. (2020)
	How will students' utilization of GAI impact their performance in class, and how to mitigate the adverse effects of GAI in education?	Lawan et al. (2023)
Tool-producing activity	How to balance the need for data collection by a platform and the user's need for privacy and data security?	Wach et al. (2023)
	Will platform censorship promote users' ethical use of GAI or lead to unethical use?	Kreitmeir & Raschky (2023), Petrescu & Krishen (2020)
	How to balance users' need for algorithm transparency and the pursuit of higher performance through advanced deep learning models that are inherently less transparent?	Hulsen (2023)
Subject-producing activity	How should educators better train students to utilize GAI effectively?	Pavlik (2023)
	How to empower workers with fundamental AI literacy to effectively utilize GAI?	Chetty (2023)
Rule-producing activity	What are the unintended consequences of a ChatGPT ban?	Kreitmeir & Raschky (2023)
	Should ChatGPT be banned by academia?	Yu (2023)
	To what degree is the AI Act proposed by the European legislators appropriate for GAI?	Helberger & Diakopoulos (2023)

Using the activity theory framework, we generated a structured list of research questions and directions by analyzing contradictions amid the GAI activity system. Contradictions may appear within the elements, such as within the subject (e.g., users) or the tool (i.e., GAI). For example, research questions to be examined include "What skills and capabilities are needed to utilize GAI effectively?" and "How can transparency and explainability of GAI be improved?". Contradictions also exist between the elements, especially in the relationship between the subject (e.g., users) and the tool (i.e., GAI). Relevant research questions relate to promoting and maximizing the value of human-GAI relationships and collaborations. Contradictions also arise between more advanced activity systems and the central system, which could be created by geographical or time dimensions. Research questions can focus on GAI's impact on the digital divide and the potential conflicts in structures created by GAI. For example, will GAI widen or bridge the digital divide? Additionally, we need to examine the contradictions between different activity systems that use GAI. Examples of research questions include "How do people evaluate GAI-generated content such as news, arts, and fashion?" and "How can we train or enable individuals to utilize GAI more effectively?".

Finally, the impact of an innovation is never solely determined by the innovation itself. Only by situating the technology in a more holistic context of society, culture, and history can we fully understand the 'ripples' or outcomes it may bring. By addressing the contradictions that may arise from novel innovations within the activity system, society can genuinely embrace such innovations and advance their potential to the fullest.

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References

Abd-Alrazaq, A., AlSaad, R., Alhuwail, D., Ahmed, A., Healy, P. M., Latifi, S., Aziz, S., Damseh, R., Alrazak, S. A., & Sheikh, J. (2023). Large language models in medical education: Opportunities, challenges, and future directions. *JMIR Medical Education*, *9*(1), 1-11.

Agrawal, P. K. (2023). Towards adoption of generative AI in organizational settings. *Journal of Computer Information Systems*. Advance online publication. https://www.tandfonline.com/doi/abs/10.1080/08874417.2023.2240744

Allen, D. K., Brown, A., Karanasios, S., & Norman, A. (2013). How should technology-mediated organizational change be explained? A comparison of the contributions of critical realism and activity theory. *MIS Quarterly*, *37*(3), 835-854.

Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI*, *7*(1), 52-62.

Bakhurst, D. (2009). Reflections on activity theory. *Educational Review*, *61*(2), 197-210.

Baxter, G., & Sommerville, I. (2011). Socio-technical systems: From design methods to systems engineering. *Interacting with Computers*, *23*(1), 4-17.

Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS Quarterly*, *45*(3), 1433-1450.

Bozkurt, A. (2023). Generative artificial intelligence (AI) powered conversational educational agents: The inevitable paradigm shift. *Asian Journal of Distance Education*, *18*(1), 198-204.

Bozkurt, A., & Sharma, R. C. (2023). Challenging the status quo and exploring the new boundaries in the age of algorithms: Reimagining the role of generative AI in distance education and online learning. *Asian Journal of Distance Education*, *18*(1), 1-8.

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

Carter, L., Liu, D., & Cantrell, C. (2020). Exploring the intersection of the digital divide and artificial intelligence: A hermeneutic literature review. *AIS Transactions on Human-Computer Interaction, 12*(4), 253-275.

Chen, C., Fu, J., & Lyu, L. (2023). *A pathway towards responsible AI generated content*. arXiv. https://arxiv.org/abs/2303.01325

Chen, M., Radford, A., Child, R., Wu, J., Jun, H., Luan, D., & Sutskever, I. (2020, November). Generative pretraining from pixels. In *Proceedings of the International Conference on Machine Learning* (pp. 1691-1703).

Chen, R. J., Lu, M. Y., Chen, T. Y., Williamson, D. F. K., & Mahmood, F. (2021). Synthetic data in machine learning for medicine and healthcare. *Nature Biomedical Engineering*, *5*, 493-497.

Chetty, K. (2023). AI literacy for an ageing workforce: Leveraging the experience of older workers. *OBM Geriatrics*, *7*(3), 1-17.

Clemmensen, T., Kaptelinin, V., & Nardi, B. (2016). Making HCI theory work: An analysis of the use of activity theory in HCI research. *Behaviour & Information Technology*, *35*(8), 608-627.

Das, D. (2023). Understanding the choice of human resource and the artificial intelligence: ‘Strategic behavior’ and the existence of industry equilibrium. *Journal of Economic Studies*, *50*(2), 234-267.

DeSanctis, G., & Poole, M. S. (1994). Capturing the complexity in advanced technology use: Adaptive structuration theory. *Organization Science*, *5*(2), 121-147.

Dolata, M., Katsiuba, D., Wellnhammer, N., & Schwabe, G. (2023). Learning with digital agents: An analysis based on the activity theory. *Journal of Management Information Systems*, *40*(1), 56-95.

Doran, D., Schulz, S., & Besold, T. R. (2017). *What does explainable AI really mean? A new conceptualization of perspectives*. arXiv. https://arxiv.org/abs/1710.00794

Draghi, B., Wang, Z., Myles, P., & Tucker, A. (2021, September). Bayesboost: Identifying and handling bias using synthetic data generators. *Proceedings of Machine Learning Research*, *154*, 49-62.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). Opinion paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 1–63.

Dwivedi, Y. K., Pandey, N., Currie, W., & Micu, A. (2023). Leveraging ChatGPT and other generative artificial intelligence (AI)-based applications in the hospitality and tourism industry: practices, challenges and research agenda. *International Journal of Contemporary Hospitality Management*. https://doi.org/10.1108/IJCHM-05-2023-0686

Engeström, Y. (2001). Expansive learning at work: Toward an activity theoretical reconceptualization. *Journal of Education and Work*, *14*(1), 133-156.

Engeström, Y. (2014). *Learning by expanding: An activity theoretical approach to developmental research*. (2nd ed.). Cambridge University Press.

European Parliament. (2023, May 11). *AI Act: A step closer to the first rules on Artificial Intelligence*. https://www.europarl.europa.eu/news/en/press-room/20230505IPR84904/ai-act-a-step-closer-to-the-first-rules-on-artificial-intelligence

Glaese, A., McAleese, N., Trębacz, M., Aslanides, J., Firoiu, V., Ewalds, T., Rauh, M., Weidinger, L., Chadwick, M., Thacker, P., Campbell-Gillingham, L., Uesato, J., Huang, P., Comanescu, R., Yang, F., See, A., Dathathri, S., Greig, R., Chen, C., ... Irving, G. (2022). *Improving alignment of dialogue agents via targeted human judgements*. arXiv. https://arxiv.org/abs/2209.14375

Gragnaniello, D., Marra, F., & Verdoliva, L. (2022). Detection of AI-generated synthetic faces. In C. Rathgeb, R. Tolosana, R. Vera-Rodriguez, & C. Busch (Eds.), *Handbook of digital face manipulation and detection: From DeepFakes to morphing attacks* (pp. 191-212). Springer International Publishing.

Gursoy, D., Li, Y., & Song, H. (2023). ChatGPT and the hospitality and tourism industry: An overview of current trends and future research directions. *Journal of Hospitality Marketing & Management*, *32*(5), 579-592.

Hacker, P., Engel, A., & Mauer, M. (2023, June). Regulating ChatGPT and other large generative AI models. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency* (pp. 1112-1123).

Hasan, H., & Kazlauskas, A. (2014). Activity theory: Who is doing what, why and how. In H. Hasan (Ed.), *Being practical with theory: A window into business research* (pp. 9–14). THEORI.

Helberger, N., & Diakopoulos, N. (2023). ChatGPT and the AI Act. *Internet Policy Review*, *12*(1), 1-6.

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, *21*(2), 155-172.

Hulsen, T. (2023). Explainable Artificial Intelligence (XAI): Concepts and challenges in healthcare. *AI*, *4*(3), 652-666.

Ji, Z., Lee, N., Frieske, R., Yu, T., Su, D., Xu, Y., Ishii, E., Bang, Y. J., Madotto, A., & Fung, P. (2023). Survey of hallucination in natural language generation. *ACM Computing Surveys*, *55*(12), 1-38.

Jonassen, D. H., & Rohrer-Murphy, L. (1999). Activity theory as a framework for designing constructivist learning environments. *Educational Technology Research and Development*, *47*(1), 61-79.

Jovanovic, M., & Campbell, M. (2022). Generative artificial intelligence: Trends and prospects. *Computer*, *55*(10), 107-112.

Kaptelinin, V., & Nardi, B. A. (2006). *Acting with technology: Activity theory and interaction design*. MIT Press.

Kaptelinin, V., & Nardi, B. (2012). *Activity theory in HCI: Fundamentals and reflections*. Morgan & Claypool Publishers.

Kaptelinin, V., Nardi, B., & Macaulay, C. (1999). The activity checklist: A tool for representing the "space" of context, interactions. *Interactions*, *6*(4), 27-39.

Karanasios, S. (2018). Toward a unified view of technology and activity: The contribution of activity theory to information systems research. *Information Technology & People*, *31*(1), 134-155.

Karanasios, S., & Allen, D. (2018). Activity theory in information systems research. *Information Systems Journal*, *28*(3), 439-441.

Korzynski, P., Mazurek, G., Altmann, A., Ejdys, J., Kazlauskaite, R., Paliszkiewicz, J., Wach, K., & Ziemba, E. (2023). Generative artificial intelligence as a new context for management theories: Analysis of ChatGPT. *Central European Management Journal*. *31*(1), 3-13.

Kreitmeir, D. H., & Raschky, P. A. (2023). *The unintended consequences of censoring digital technology--Evidence from Italy's ChatGPT ban*. arXiv. https://arxiv.org/abs/2304.09339

Kuutti, K. (1996). Activity theory as a potential framework for human-computer interaction research. In B. Nardi (Ed.), *Context and consciousness: Activity theory and human-computer interaction* (pp. 17-44). MIT Press.

Kuutti, K., & Bannon, L. J. (2014, April). The turn to practice in HCI: Towards a research agenda. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 3543-3552).

Lawan, A. A., Muhammad, B. R., Tahir, A. M., Yarima, K. I., Zakari, A., Abdullahi II, A. H., Hussaini, A., Kademi, H. I., Danlami, A. A., Sani, M. A., Bala, A., & Lawan, S. (2023). Modified flipped learning as an approach to mitigate the adverse effects of generative artificial intelligence on education. *Education Journal*, *12*(4), 136-143.

Lebovitz, S., Levina, N., & Lifshitz-Assaf, H. (2021). Is AI ground truth really true? The dangers of training and evaluating AI tools based on experts' know-what. *MIS Quarterly*, *45*(3), 1501-1526.

Lee, M. (2023). A mathematical investigation of hallucination and creativity in GPT models. *Mathematics*, *11*(10), 1-17.

Leont'ev, A. N. (1978). *Activity, consciousness, and personality*. Prentice Hall.

Li, S., Wang, H., & Wang, S. (2021). Research on the factors that influence the labor structure of the manufacturing industry in the context of artificial intelligence–taking the development of industrial robots as an example, *Management Review*, *33*(3), 307-314.

Li, Y., Marga, J. J., Cheung, C. M., Shen, X., & Lee, M. (2022). Health misinformation on social media: A systematic literature review and future research directions. *AIS Transactions on Human-Computer Interaction, 14*(2), 116-149.

Lin, C., Tan, B., & Chang, S. (2008). An exploratory model of knowledge flow barriers within healthcare organizations. *Information & Management*, *45*(5), 331-339.

Liu, X., Zhou, Q., Chen, X., Fan, L., & Cheng, C. T. (2021). Bias-error accumulation analysis for inertial navigation methods. *IEEE Signal Processing Letters*, *29*, 299-303.

Longoni, C., Fradkin, A., Cian, L., & Pennycook, G. (2022, June). News from generative artificial intelligence is believed less. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* (pp. 97-106).

McCormack, J., Gifford, T., & Hutchings, P. (2019). Autonomy, authenticity, authorship and intention in computer generated art. In *Computational Intelligence in Music, Sound, Art and Design: 8th International Conference, EvoMUSART 2019, Held as Part of EvoStar 2019, Leipzig, Germany, April 24–26, 2019, Proceedings 8* (pp. 35-50). Springer International Publishing.

Mhlanga, D. (2023). *Open AI in education, the responsible and ethical use of ChatGPT towards lifelong learning*. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4354422

Mu, N., Kirillov, A., Wagner, D., & Xie, S. (2022, October). Slip: Self-supervision meets language-image pre-training. In *European Conference on Computer Vision* (pp. 529-544). Springer Nature.

Nah, F. F.-H., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023). Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. *Journal of Information Technology Case and Application Research*, *25*(3), 277-304.

Norori, N., Hu, Q., Aellen, F. M., Faraci, F. D., & Tzovara, A. (2021). Addressing bias in big data and AI for health care: A call for open science. *Patterns*, *2*(10), Article 100347.

Norris, P. (2001). *Digital divide: Civic engagement, information poverty, and the Internet worldwide*. Cambridge University Press.

OpenAI. (2022). *ChatGPT: Optimizing language models for dialogue*. https://web.archive.org/web/20230226100839/https://openai.com/blog/chatgpt/

Orlikowski, W. J. (2000). Using technology and constituting structures: A practice lens for studying technology in organizations. *Organization Science*, *11*(4), 404-428.

Osburg, V. S., Yoganathan, V., Kunz, W. H., & Tarba, S. (2022). Can (A)I give you a ride? Development and validation of the CRUISE framework for autonomous vehicle services. *Journal of Service Research*, *25*(4), 630-648.

Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C., Mishkin, P., Zhang, C., Agarwal, S., Slama, K., Ray, A., Schulman, J., Hilton, J., Kelton, F., Miller, L., Simens, M., Askell, A., Welinder, P., Christiano, P. F., Leike, J. & Lowe, R. (2022). Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, *35*, 27730-27744.

Pan, S. L., Nishant, R., Tuunanen, T., & Nah, F. F.-H. (2023). Literature review in the generative AI era – how to make a compelling contribution. *Journal of Strategic Information Systems*, *32*(3), Article 101788.

Pang, N., Karanasios, S., & Anwar, M. (2020). Exploring the information worlds of older persons during disasters. *Journal of the Association for Information Science and Technology*, *71*(6), 619-631.

Paul, S., Yuan, L., Jain, H. K., Robert, L. P., Spohrer, J., & Lifshitz-Assaf, H. (2022). Intelligence augmentation: Human factors in AI and future of work. *AIS Transactions on Human-Computer Interaction, 14*(3), 426-445.

Pavlik, J. V. (2023). Collaborating with ChatGPT: Considering the implications of generative artificial intelligence for journalism and media education. *Journalism & Mass Communication Educator*, *78*(1), 84-93.

Paykamian, B. (2023, March 8). *Will AI chatbots raise digital equity concerns for students?* GovTech. https://www.govtech.com/education/higher-ed/will-ai-chatbots-raisedigital-equity-concerns-for-students

Petrescu, M., & Krishen, A. S. (2020). The dilemma of social media algorithms and analytics. *Journal of Marketing Analytics*, *8*, 187-188.

Porter, J. (2023, March 21). *ChatGPT bug temporarily exposes AI chat histories to other users*. *The Verge*. https://www.theverge.com/2023/3/21/23649806/chatgpt-chat-histories-bug-exposed-disabled-outage

Quek, A., & Shah, H. (2004, September). The activity theoretical iterative evaluation method. In *Proceedings of the First International Workshop on Activity Theory Based Practical Methods for IT-Design* (pp. 85-95).

Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018, June 11). *Improving language understanding by generative pre-training*. Open AI. https://openai.com/research/language-unsupervised

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., & Sutskever, I. (2019). Language models are unsupervised multitask learners. *OpenAI Blog*, *1*(8), 9. https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf

Saadi, J., & Yang, M. (2023). Observations on the implications of generative design tools on design process and designer behaviour. In K. Otto, B. Eisenbart, C. Eckert, B. Eynard, D. Krause, & J. Oehmen (Eds.), *Proceedings of the Design Society: 24th International Conference on Engineering Design* (pp. 2805-2914). Cambridge University Press.

Scheerder, A., Van Deursen, A., & Van Dijk, J. (2017). Determinants of Internet skills, uses and outcomes. A systematic review of the second-and third-level digital divide. *Telematics and Informatics*, *34*(8), 1607-1624.

Schramowski, P., Turan, C., Andersen, N., Rothkopf, C. A., & Kersting, K. (2022). Large pre-trained language models contain human-like biases of what is right and wrong to do. *Nature Machine Intelligence*, *4*(3), 258-268.

Selwyn, N. (2004). Reconsidering political and popular understandings of the digital divide. *New Media & Society*, *6*(3), 341-362.

Shamika N. Sirimanne. (2023). How artificial intelligence chatbots could affect jobs. United Nations Conference on Trade and Development. https://unctad.org/news/blog-how-artificial-intelligence-chatbots-could-affect-jobs

Shneiderman, B. (2020). Human-centered artificial intelligence: Three fresh ideas. *AIS Transactions on Human-Computer Interaction*, *12*(3), 109-124.

Siau, K., & Wang, W. (2020). Artificial intelligence (AI) ethics: Ethics of AI and ethical AI. *Journal of Database Management*, *31*(2), 74-87.

Sohn, K., Sung, C. E., Koo, G., & Kwon, O. (2020). Artificial intelligence in the fashion industry: Consumer responses to generative adversarial network (GAN) technology. *International Journal of Retail & Distribution Management*, *49*(1), 61-80.

Suh, M., Youngblom, E., Terry, M., & Cai, C. J. (2021, May). AI as social glue: uncovering the roles of deep generative AI during social music composition. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (pp. 1-11).

Sun, J., Liao, Q. V., Muller, M., Agarwal, M., Houde, S., Talamadupula, K., & Weisz, J. D. (2022, March). Investigating explainability of generative AI for code through scenario-based design. In *Proceedings of the 27th International Conference on Intelligent User Interfaces* (pp. 212-228).

Susarla, A., Gopal, R., Thatcher, J. B., & Sarker, S. (2023). The Janus effect of generative AI: Charting the path for responsible conduct of scholarly activities in information systems. *Information Systems Research*, *34*(2), 399-408.

Taeihagh, A. (2021). Governance of artificial intelligence. *Policy and Society*, *40*(2), 137-157.

Te'eni, D., & Ho, S. Y. (2022). HCI that makes and breaks online fake: An introduction to the special issue. *AIS Transactions on Human-Computer Interaction*, *14*(2), 107-115.

Teodorescu, M. H., Morse, L., Awwad, Y., & Kane, G. C. (2021). Failures of fairness in automation require a deeper understanding of human-ML augmentation. *MIS Quarterly*, *45*(3), 1-18.

The Future of Life Institute. (2022, May). *General Purpose AI and the AI Act*. https://artificialintelligenceact.eu/wp-content/uploads/2022/05/General-Purpose-AI-and-the-AI-Act.pdf

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.

Wach, K., Duong, C. D., Ejdys, J., Kazlauskaitė, R., Korzynski, P., Mazurek, G., Paliszkiewicz, J., & Ziemba, E. (2023). The dark side of generative artificial intelligence: A critical analysis of controversies and risks of ChatGPT. *Entrepreneurial Business and Economics Review*, *11*(2), 7-24.

Wan, W. Y., Tsimplis, M., Siau, K. L., Yue, W. T., Nah, F. F.-H., & Yu, G. M. (2022, June). Legal and regulatory issues on artificial intelligence, machine learning, data science, and big data. In *International Conference on Human-Computer Interaction* (pp. 558-567). Springer Nature.

Wang, D., Churchill, E., Maes, P., Fan, X., Shneiderman, B., Shi, Y., & Wang, Q. (2020, April). From human-human collaboration to Human-AI collaboration: Designing AI systems that can work together with people. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1-6).

Wang, W., & Siau, K. (2019). Artificial intelligence, machine learning, automation, robotics, future of work, and future of humanity – a review and research agenda. *Journal of Database Management*, *30*(1), 61-79.

Yamagata-Lynch, L. C. (2010). *Activity systems analysis methods: Understanding complex learning environments*. Springer Science & Business Media.

Yu, H. (2023). Reflection on whether Chat GPT should be banned by academia from the perspective of education and teaching. *Frontiers in Psychology*, *14*, Article 1181712.

Zarifhonarvar, A. (2023). *Economics of ChatGPT: A labor market view on the occupational impact of artificial intelligence*. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4350925

Zhang, C., Zhang, C., Li, C., Qiao, Y., Zheng, S., Dam, S. K., Zhang, M., Kim, J. U., Kim, S. T., Choi, J., Park, G., Bae, S., Lee, L., Hui, P., Kweon, I. S., & Hong, C. S. (2023). *One small step for generative AI, one giant leap for AGI: A complete survey on ChatGPT in AIGC era*. arXiv. https://arxiv.org/abs/2304.06488

Zhong, H., Chang, J., Yang, Z., Wu, T., Mahawaga Arachchige, P. C., Pathmabandu, C., & Xue, M. (2023, April). Copyright protection and accountability of generative AI: Attack, watermarking and attribution. In *Companion Proceedings of the ACM Web Conference* (pp. 94-98).

Zhou, L., Paul, S., Demirkan, H., Yuan, L., Spohrer, J., Zhou, M., & Basu, J. (2021). Intelligence augmentation: Towards building human-machine symbiotic relationship. *AIS Transactions on Human-Computer Interaction*, *13*(2), 243-264.

Zhou, L., Rudin, C., Gombolay, M., Spohrer, J., Zhou, M., & Paul, S. (2023). From artificial intelligence (AI) to intelligence augmentation (IA): Design principles, potential risks, and emerging issues. *AIS Transactions on Human-Computer Interaction, 15*(1), 111-135.

Zhu, Q., & Luo, J. (2023). Generative transformers for design concept generation. *Journal of Computing and Information Science in Engineering*, *23*(4), 1-16.

Zhuo, T. Y., Huang, Y., Chen, C., & Xing, Z. (2023). *Exploring AI ethics of ChatGPT: A diagnostic analysis*. arXiv. https://arxiv.org/abs/2301.12867

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