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COMMENTARY

Handling the hype: Demystifying artificial intelligence for memory studies

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Abstract

Artificial Intelligence (AI) has reached memory studies in earnest. This partly reflects the hype around recent developments in generative AI (genAI), machine learning, and large language models (LLMs). But how can memory studies scholars handle this hype? Focusing on genAI applications, in particular so-called 'chatbots' (transformer-based instruction-tuned text generators), this commentary highlights five areas of critique that can help memory scholars to critically interrogate AI's implications for their field. These are: (1) *historical critiques* that complicate AI's common historical narrative and historicize genAI; (2) *technical critiques* that highlight how genAI applications are designed and function; (3) *praxis critiques* that centre on how people use genAI; (4) *geopolitical critiques* that recognize how international power dynamics shape the uneven global distribution of genAI and its consequences; and (5) *environmental critiques* that foreground genAI's ecological impact. For each area, we highlight debates and themes that we argue should be central to the ongoing study of genAI and memory. We do this from an interdisciplinary perspective that combines our knowledge of digital sociology, media studies, literary and cultural studies, cognitive psychology, and communication and computer science. We conclude with a methodological provocation and by reflecting on our own role in the hype we are seeking to dispel.

Keywords: critical AI studies; generative AI; chatbots; mnemonic agency; socio-technical assemblages; interdisciplinarity; ethics; methodology

Introduction

Artificial intelligence (AI) has reached memory studies in earnest and, while not without precedent (Locke 2000), academic attention to its mnemonic consequences is growing (Gensburger and Clavert 2024; Hoskins *et al.* 2024). This partly reflects the hype surrounding recent technological developments, especially in *generative AI* (genAI), *machine learning*, and *large language models* (LLMs). Markelius *et al.* (2024) discuss four characteristics of this hype: (1) the strategic anthropomorphization of *AI systems* leading to false perceptions; (2) the proliferation of techno-determinist experts who stress AI's inevitability; (3) uneven influence over AI narratives; and (4) the insouciant overuse of the 'AI' term. While the current AI hype may in some respects already be dissipating and AI's amplified significance already becoming normalized, the effects of these processes are likely to be long-lasting (Floridi 2024; Widder and Hicks 2024).

AI systems: machine-based systems designed to function with differing levels of autonomy, which may show signs of adaptiveness after deployment, and that, for explicit or implicit goals, infer from the input they receive, how to generate outputs including predictions, content, recommendations, or decisions that may influence their virtual or physical environments. (EU 2024)

Generative AI (GenAI): AI applications that use different types of machine learning models (including LLMs or generative adversarial networks (GANs)) to synthesize textual, image, and audio content, often (but not necessarily) in response to user prompts.

Machine learning: the subfield of computer science that uses algorithms and statistical models to analyse and draw inferences from data and, in the case of deep learning, to develop AI systems that can learn and adapt without instruction.

Large language models (LLMs): probabilistic machine learning models with many parameters (typically more than a billion) designed to interpret and synthesize responses to human language.

The hype that casts AI as desirable, inevitable, and revolutionary is tied to the efforts of big tech companies to use AI to further monetize the large amounts of data and computational resources they have recently consolidated (Whittaker 2021). It is also linked, on the demand side, to the societal crises that make technological solutions enticing (Broussard 2023). AI has always been partly about marketing. As computer scientist Jared Lanier admitted: 'AI is a story we computer scientists made up to help us get funding' (2018, 135). Memory scholars are not immune to such impulses. The question guiding this commentary, then, is how can memory studies handle the AI hype so as to ensure we produce nuanced critiques of its mnemonic consequences, whilst challenging the 'common sense' views about 'AI' that are sold to us?

Exploring this question, we connect with critical AI studies (see Verdegem 2021; Lindgren 2023, 2024) to understand AI's implications for memory studies and vice versa. Primarily focusing on one form of genAI, namely, transformer-based instruction-tuned text generators (commonly known as 'chatbots', such as ChatGPT), we highlight five overlapping areas of critique that can help memory scholars to critically approach these AI systems as they become more mnemonically prevalent. These are: (1) *historical critiques* that complicate the common historical narrative behind the AI hype and historicize genAI; (2) *technical critiques* that emphasize how the different components of genAI systems are designed and work; (3) *praxis critiques* that centre on how people use genAI; (4) *geopolitical critiques* that recognize how geography and international power dynamics shape the uneven global distribution of genAI and its consequences; and (5) *environmental critiques* that stress genAI's ecological impact. For each of these areas, we recount key debates from outside memory studies and consider their implications to our field by highlighting questions and themes that we argue should be central to the ongoing study of genAI within memory studies. Overall, we suggest

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that these five areas of critiques can serve as complementary lenses to inform thorough, interdisciplinary analyses of the relationships between (gen)AI and memory.

In doing this, we suggest that the AI hype has been explicitly problematized across an array of disciplines, including information science, medical science, computer science, and media studies (see Slota *et al.* 2020; Van Assen *et al.* 2020; Vrabič Dežman 2024 ; Markelius *et al.* 2024), predominantly through the adoption of perspectives rooted in critical theory (see Verdegem 2021; Lindgren 2023, 2024). However, memory studies as an interdisciplinary endeavour has yet to explicitly address this matter or draw together the productive critiques being separately pursued by some of its contributory disciplines. In this respect, we also acknowledge the overlap between memory studies and other interdisciplinary fields like heritage studies, but for the purposes of this commentary, we distinguish between them and limit our consideration to the former. While the heritage industry writ large has adopted genAI in a mostly celebratory manner, it should be noted that there is a growing thread of critical research within heritage studies that is both compatible with and helps contextualize the approach we suggest in this commentary (see Foka *et al.* 2023; Foka and Griffin 2024).

Furthermore, in this collaborative commentary, we have intentionally limited the scope of our efforts to a conceptual overview that seeks to encourage rather than provide empirical exploration. So, while we use the commentary to indicate existing primary studies and potential lines of further inquiry, we do not seek to outline these in detail. Instead, we aim to move towards a shared critical research agenda that serves as an invitation to all to contribute empirically in the future. Besides this, we seek to share approaches and research insights from outside of memory studies that, we think, can be helpful to the field. In this respect, our commentary pertains to diverse forms of remembrance – cognitive, collected, collective, and connective – and is pitched primarily to wider memory studies communities, including those only starting to engage with AI as a topic of research.

Throughout we try to avoid abstracting AI. We use 'chatbots' – LLM-supported transformer-based instruction-tuned text generators – as shorthand for genAI but note that all AI systems sit within wider social, political, cultural and environmental assemblages and involve the fluctuating distribution of mnemonic agency between humans and non-humans (Lagerkvist and Reimer 2023; Mandolessi 2023; Merrill 2023; Lindgren 2024; Makhortykh 2024; Smit *et al.* 2024). To this end, we provide inset definitions throughout the commentary. We conclude with a methodological provocation and by reflecting on our own complicity in the hype we are seeking to dispel.

Historical critiques

When historicizing current AI developments, it is common to refer to earlier phases of AI growth and stasis as AI 'summers' and 'winters' (Haigh 2023; Markelius *et al.* 2024). However, this reinforces the narrative promoted by big tech of (interrupted) technological progress that will inevitably lead to so-called 'general' or 'strong' AI. Historical critiques complicate this seasonally inflected narrative by exploring genAI as the outcome of interconnected technological, social, cultural, economic, and political processes (as indicated more in later sections of this commentary) and emphasizing the views of those who narrate AI's history differently.

> **General/strong versus narrow/weak AI:** 'general' or 'strong' AI development pursues human-like consciousness and cognitive abilities while 'narrow' or 'weak' AI systems are restricted to specific tasks without the prerequisite of complex semantic capabilities.

Common histories of AI often begin with the decontextualization of Alan Turing's oft-quoted question, 'can machines think?', shaping present (mis)understandings of genAI (Turing 1950; Proudfoot 2011). Turing was interested in imitation and distinguishing

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between 'discrete-stage' (computers) and 'continuous-stage' (humans) machines. The Turing test that gives 'computer scientists a sense of direction' (Stilgoe 2023) is, thus, often misremembered as seeking to develop machines that think humanly rather than machines that mimic human thinking, foregrounding the deceitfulness of genAI (see Natale 2021).

At the 1956 Dartmouth Summer Research Project on AI, the pursuit of general/strong AI and the idea that all human intelligence could be 'so precisely described that a machine can be made to simulate it' took further hold (McCarthy *et al.* 2006, 12). Some of its participants were later critical of this view (Minsky 1986) and later leading voices in the field like Joseph Weizenbaum – creator of ELIZA, commonly considered the first chatbot (developed in 1964–67) – criticized early AI boosterism as conservatively promoting technical solutions that left existing power hierarchies intact (1976; Birhane *et al.* 2022). More recently the 'mathemorphized' historical narrative of AI that equates the 'precise description' of intelligence with 'mathematical description' and prioritizes the pursuit of general/strong AI has been further problematized by research on AI, race and indigenous knowledge systems that stresses the existence of multiple intelligences and subjecthoods (Buolamwini 2023; Lewis *et al.* 2025; Richardson-Walden and Makhortykh 2024).

In complicating notions of a 'generalised' intelligence that can be modelled, such research offers alternative perspectives which may better serve and represent the diversity of human, social, and cultural memory, and their possible interfaces with computer systems. These critiques sometimes still imply that LLMs are comprehensive and have autonomous agency (Richardson-Walden and Makhortykh 2024), but they also remind us that the rationalist, mathematical way of ordering things that has dominated Western thought since the 18th century (see Foucault 1994) is not the only way. As Lewis *et al.* (2025) argue, indigenous knowledge systems foreground intelligence as a collectively established relationality rather than a property of isolated individuals, making visible the social and cultural matrices in which notions of 'intelligence' emerge and acquire value.

GenAI might then be approached as narrow/weak AI that gains value by posing as general/strong AI (via anthropomorphization) even as its ongoing advancement and integration with other forms of AI complicate this. As part of the future projection of the AI narrative of progress, genAI is frequently credited with excessive levels of agency, reversing Latour's observation that humans typically attribute limited agency to machines (1987; see Smits and Wevers 2022). Still, many earlier technologies have had profound effects on memory, and thus it is important that genAI's mnemonic consequences are sufficiently historicized by interrogating their similarities and differences from older examples of technology-assisted remembrance. While memory scholars have historically conceived technology in a human-centric and instrumentalized manner, opening to wider histories that challenge anthropocentric and anthropomorphized historical accounts that abstract genAI can arguably help us better understand how it contributes to social processes of remembering within which agency is always distributed between human and non-human actors (Merrill 2023; Smit *et al.* 2024).

In short, memory scholars are well-positioned to problematize hype-driven narratives of general/strong AI's inevitability. They can ask what mnemonic shadows are cast by AI's dominant historical narratives, how did these narratives emerge and proliferate, and what can be gained by re-reading them against the grain? Here, memory studies scholars can learn from those working in critical AI studies and in media philosophy who contextualize genAI technologies within longer media debates (Natale 2021; Lindgren 2024) and encourage us to consider to what extent the ontologies, epistemologies, and aesthetics underpinning AI are actually radically new (Fazi 2019, 2024). They can also draw on interdisciplinary perspectives by, for instance, combining science and technology studies, literary studies and media studies to reveal how genAI's accepted historical narratives are linked to the exercise of social and political power in the present (Cave *et al.* 2024; Magalhães and Smit 2025).

Alternatively, the analysis of oral histories, memoirs, and autobiographies could provide insight into the memory of AI's development via the experiences of those directly involved in it. Media archaeological and historical computational science approaches could also be added to the interdisciplinary mix to re-read AI development via, for example, the resurrection and reinterpretation of old and now obsolete computer code (see Kilgrove 2025). Ultimately, problematizing the AI hype to understand the relationship between memory and genAI from a historical perspective requires us to be technologically informed, without being technologically deterministic. This leads us to the next area of critique.

Technical critiques

To understand genAI's implications for memory, it helps to know how it functions. This area of critique problematizes singular, diffuse notions of genAI by stressing the importance of 'deblackboxing' (Dixon *et al.* 2022). This is the effort to make the processes of not only computation but computing generally (i.e. including the effects of sociotechnical infrastructures and power relations on technology) more transparent. This is not straightforward because, as Crawford and Joler (2018) have 'anatomically' captured, the complexity and scale of genAI systems almost exceeds human imagination in relying on a vast (and rapidly changing) capitalistic matrix of hardware and software and human and non-human relations. On the technical level, this means that it is difficult to explain why (especially more complex) AI systems make concrete decisions even under conditions of full transparency because transparency does not automatically lead to comprehension (Esposito 2022). One way to pursue 'deblackboxing' that might be helpful for memory studies researchers is to turn to the computer science texts in which (basic) AI principles and procedures are described and theorized. Exemplifying this, Amoore *et al.* (2023, 1) approach these texts as contested sites 'through which machine learning shapes the world'. For memory studies scholars, such an approach can help reveal how computer scientists understand and approach memory and the processes of remembering and forgetting in computers and software (see Merrill 2023).

Still, genAI systems can generally be technically understood as involving the three pillars of big datasets, high-performance computing infrastructures, and the machine learning algorithms that are applied to data to synthesize content, all underpinned by computer science and mathematics (Van Assen *et al.* 2020). For instance, chatbots, or by their less anthropomorphized name, transformer-based instruction-tuned text generators, are guided by computational training tasks and mathematical principles (e.g. probabilistic reasoning) that are applied to large volumes of training data to create models powering interfaces that respond to user inputs in line with specific patterns in the training data (Smit *et al.* 2024; see Paglen and Downey 2023 on genAI image creators).

GenAI chatbots: computer programs that simulate conversations usually by using LLMs to examine user inputs and provide responses.

An important principle for many genAI applications is to model a baseline (Chen and Chen 2022). For the LLMs behind chatbots, this baseline is conventionally equated to the statistical prediction of units called tokens (e.g. words, letters, and symbols), based on their training data set–mimicking language patterns but without understanding what they are 'chatting' about (Bender *et al.* 2021). GenAI systems are, thus, profoundly dependent on their training data, and the computational, and often implicitly cultural, principles prioritized by their designers and developers, including how to approach outliers, parameterization, and randomization. These principles are rarely divulged publicly. Similarly opaque is how these principles are translated into 'guardrails' that aim to prevent the misuse of genAI. So too, the training data behind different chatbots, including whether it is original or synthetic (e.g. itself AI-generated),

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is often a closely guarded secret, even if this determines the semantics of the content produced, the risks for so-called 'model collapse', and ethical concerns about data ownership and privacy. Critically, it is also unclear how far designers and developers take into consideration the social impacts of their decisions as their hypothetical 'user' becomes millions of users (Salvaggio 2025). While some of these technical critiques apply to other technologies also, collectively they raise important questions when considering genAI and memory's relationship.

Baselines: sets of data points used for training, validating, and testing AI models.

Most fundamentally, we might ask: should genAI be designed to only create factually accurate content, or should it allow greater degrees of mnemonic creativity? Should models forget and machines unlearn (cf. Bourtoule *et al.* 2021)? What might it mean for memory when future outcomes are statistically modelled on past evidence? How far, then, might relinquishing memory to statistical, rather than cultural, weighting create hegemonic, 'line of best fit' forms of remembrance that further diminish the importance of mnemonic outliers? What, in short, are the memory baselines of genAI? Are they based on official historiographies or a greater diversity of sources, and how should the inevitable differences between these be addressed? Are memories that do not match an agreed baseline or fall outside its parameters no longer valid? What might this mean for the contestation of memory and phenomena such as memory activism? Such questions also have implications for the design of genAI systems specifically for mnemonic purposes, whether chatbots in heritage institutions or personalized digital duplicates of historical figures (see Kozlovski and Makhortykh 2025). These and other mnemonic uses should determine the computational logic behind genAI applications, the training data required to implement them, and the guardrails preventing their possible misuse. It encourages memory scholars to be involved in these design processes and decisions, but also discussions about genAI policy, regulation, and law. We consider what all this may mean for users, for example, in terms of who decides on and differentiates between appropriate and inappropriate mnemonic uses of genAI, in the next section dedicated to praxis critiques.

Praxis critiques

A key debate regarding the use of genAI in everyday life relates to whether it will help extend our memory, cognitive capacities, and creativity. Or, alternatively, whether we will offload our memory and knowledge to genAI so much that it compromises our intellectual autonomy. Navigating this debate, which has long characterized the subfield of digital memory studies (Hoskins 2011, 2013) depends, in part, on understanding users' differing levels of expertise and AI literacy (Imundo *et al.* 2024).

Experts in different fields use genAI to acquire synthesized information and feed creative thinking (Javaid *et al.* 2023; Zhu *et al.* 2024). Their specialized knowledge also allows them to better detect incorrect or incomplete genAI outputs related to their field, although they are not immune to genAI's errors, especially if they rely on it as an external memory aid (Fisher and Oppenheimer 2021; Azaria *et al.* 2025). Novices meanwhile may use genAI (e.g. chatbots) to learn because it provides accessible, well-organized, and coherent information, through human-like dialogues, but the lack of specialized knowledge makes novices more vulnerable to errors in the generated content (Fang *et al.* 2019; Hennekeuser *et al.* 2024). No matter then what a user's level of domain expertise may be, expertise in using AI or AI literacy is also important.

Domain expertise: the specialized knowledge of a specific field which can provide insight into, amongst other things, operational requirements and constraints of genAI systems, and the sources and limitations of their training data.

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There is a need for more research on how genAI–human interactions influence human memory capacities and what boundary conditions shape this process. What might be the optimal conditions that unburden human memory through offloading to genAI while maintaining a critical knowledge base when partnering with genAI? How might the discrepancies in human mnemonic capacity that can be both diminished and exaggerated by genAI relate to expertise, but also socioeconomic, racial, gender, or cultural differences? The role of memory scholars here could expand beyond studying genAI's praxis-related implications to becoming 'domain experts' that can co-design AI and influence its surrounding policy and regulation towards cognitively advantageous and societally just outcomes.

Recognizing the impact of differential expertise also connects to debates about whether genAI enables or endangers human mnemonic agency. Does the ability of genAI to synthesize 'the past' deprive our memory of authenticity and render our life stories anti-autobiographical (Hoskins 2024)? Or do individuals and groups retain power in making decisions and choices over what to remember and what to forget despite the technological hype (Wang 2019)?

The urgency of these questions is stressed by genAI 'chatbots' possessing the illusionary appearance of human features that seem to reduce or replace human agency. They can assume various human-like personas, perform highly on tasks that require sensitivity to human emotions, and provide instant insights on complex intellectual questions via dialogues that reinforce the illusion that they possess human-like consciousness (Elyoseph *et al.* 2023; White *et al.* 2023). Chatbots can also automatically acquire and generate information about individual and collective pasts without human approval or control (Hoskins 2024) and shape the mnemonic agency of human users according to how they have been designed and developed, for example, in terms of their parameters of possible interaction.

Designers and developers, as humans, command their own forms of mnemonic agency (Smit *et al.* 2024). Humans also retain agency, in addition to their expertise or AI literacy. They can decide when, how, under what circumstance, and for what purpose to use genAI, just as when they confront other digital technologies (Wang 2019). They often provide both the prompts and the data – typically in the form of information about their individual and collective pasts shared on social media (see Wang and Hoskins 2024) – which are then used to train LLMs and ultimately shape what chatbots 'reassemble' for them as 'memories'. Neither is their remembering only restricted to the content that these chatbots provide them – context is also important with humans and genAI prompting each other to remember (Smit *et al.* 2024). Historicizing genAI, this process is not unlike the transactive, dialogical, and phenomenological constructions of one's autobiographical memory that occur within other online settings (Wang 2022; Merrill forthcoming). It is thus critical that memory scholars work to disentangle how human mnemonic agency interacts with that of genAI and avoid totalizing and sensationalist prognoses of the loss of human agency, which contributes to the AI hype. Indeed, there are good arguments for thinking of the 'A' in 'AI' differently – in terms of augmentation rather than artificiality (Dekeyser and Whitehead 2025).

Geopolitical critiques

Beyond problematizing how users from various global demographics may remember differently with genAI, applying a geopolitical critique highlights how global power dynamics – particularly involving the EU, US, and China – shape the development and distribution of genAI (Larsen 2022; Kennedy 2025) and, in turn, the global battle to control public narratives regarding historical and contemporary events. With AI historically embedded in capitalist logics and driven by government funding priorities and military support for

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scientific research (Nilsson 2010; see also Pilkington 2024), the current hype can thus be understood in the context of major geopolitical and economic uncertainty and AI's increasing use in warfare. Indeed, the companies behind the most prominent commercial 'chatbots' are now pivoting towards military contracts (O' Donnell 2024).

The competition for global genAI dominance and thus political and mnemonic influence has been intensified by the rising economic, technological, military, and political power of China in recent decades. Although the US still holds an edge in advanced AI systems, China is catching up quickly through the development of open-source LLMs, strategic investments, and government support (Kennedy 2025). Pertaining to memory, this genAI geopolitical rivalry will likely increasingly contribute to and coalesce with globally polarizing debates regarding historical nihilism and historical revisionism. Relatedly, there is recent evidence of US-owned genAI 'chatbots' being used to promote Russian geopolitical interests by aiding the censorship of undesired pasts (Urman and Makhortykh 2025).

Global South countries, including in Africa, Latin America, and Southeast Asia, also play an active role in genAI geopolitics through alliances and by setting regulations (see Feakin 2025), but a geopolitical perspective also highlights the uneven global distribution of genAI's costs and benefits between the Global North and South. Many 'chatbots', for example, work discriminatorily by silencing, and under- or misrepresenting different minority groups across the world (Okolo 2023). This perpetuates and amplifies unequal global power relations, further disempowering already marginalized communities and countries. The size of LLM training datasets does not guarantee their diversity (Bender *et al.* 2021). At every stage of their curation – from initial online participation to data collection and fine-tuning, including reinforcement learning with human feedback, current practices favour hegemonic perspectives (Smit *et al.* 2024). Even while genAI can have democratizing mnemonic effects at certain scales, in general, memories of certain hegemonic groups are widely represented, while those related to marginalized groups are underrepresented or absent. As such, the datafied memory of Global South cultures is often missing due to 'algorithmic exclusion' (Albert and Delano 2023), 'digital cultural colonialism' (Kizhner *et al.* 2021) and other processes of digital suppression, including, in some contexts, state-led censorship.

Fine-tuning: the further training of an AI model on a specific dataset to improve its performance with respect to a certain task.

Reinforcement learning with human feedback: A fine-tuning technique that uses human judgement of genAI content to further train AI models.

GenAI's under-representation of non-hegemonic memory is partly linked to the dominance of English in computational linguistics (see Joshi *et al.* 2020; Bender *et al.* 2021). GenAI, thus, can often perpetuate colonial knowledge regimes that disregard alternative ways of understanding and interpreting the world (Birhane and Talat 2023; Lewis *et al.* 2025). In turn, genAI's 'average collective memory', its mnemonic 'line of best fit', can hide a richer diversity of remembrance cultures (Makhortykh 2024; Schuh 2024). This process not only reinforces existing power imbalances regarding which memories can be accessed and which cannot – new forms of memory imperialism – but also erases the distinct meanings that memory, forgetting, or trauma may hold for marginalized communities. Meanwhile, the rapid emergence of LLMs in high-resource languages like Chinese and Russian (e.g. CT-LLM or YandexGPT) but also low-resource languages like Kazakh and Swahili (e.g. KazLLM or UlizaLlama) offers alternatives that may foreground other renderings of the past.

GenAI systems also rely on an uneven international division of digital labour (Fuchs 2014). They are designed and owned by powerful companies in the Global North, but various stages of their implementation are outsourced to the Global South. A significant part of the

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data collection pipeline – data labelling – relies, for instance, on 'ghost workers' in the latter. While this labour helps generate massive earnings, the profits are captured by others, creating a stark disparity between the millions earned by data labelling companies and the low wages of their workers (Okolo 2023). Similarly, 'chatbots' have been tested in refugee camps without adhering to the rigorous ethical procedures applied elsewhere. These practices rework and revitalize 'colonial genealogies through processes of extraction, coloniality, control, and discrimination' (Madianou 2025, 18).

Questioning and overcoming these global mnemonic power imbalances should lie at the heart of memory studies' genAI-related concerns. We need to ask: will global competition for AI dominance benefit end users by creating more divergent narratives, views, and perspectives or polarize the world even further? Whose memories are being preserved, transformed, or erased by genAI? Can genAI accommodate the plurality of mnemonic epistemologies across cultures, or are they only able to reproduce hegemonic views? How might memory scholars work alongside communities affected by digital erasure to resist genAI's technocolonial logics? Can genAI systems be reimagined not as tools of erasure but as platforms for restorative memory work – and if so, under what ethical and political conditions? Such questions are especially important given that those communities least likely to benefit from genAI are also often the most vulnerable to its harms, especially those of an environmental character.

Environmental critiques

Environmental critiques of AI and its surrounding hype complicate claims that digital technology, through its specific temporalities, has radically reformulated human remembering and forgetting, and that this is exacerbated by genAI (Ernst 2013; Hoskins 2013; Hoskins 2024). Whilst notions of decay time and entanglement have been crucial in digital memory studies, this has predominantly focused on acknowledging the relationality of self and machine, and self and data (Hoskins 2013, 2015, 2024). Widening focus to emphasize the wider environment, brings the discussion of AI's mnemonic implications and, in turn, the subfield of digital memory studies into the realm of 'fourth wave' memory studies research (see Erll 2024). Expanding focus to the broader geological plane of 'media' (to include all meaning-making matter), attention is drawn to planetary decay happening at alarming rates, accelerated by an increasing dependence on digital technology (Parikka 2015; Crawford 2021).

This focus resonates with memory studies' 'anthropocentric turn' and the growing consideration of 'planetary memory' (Bond *et al.* 2018), the 'deep-time of the earth' (Chakrabarty 2009), 'terrestrial memory' (Golańska 2023), and attention to those human and non-human relations in ways that hold us 'responsible and accountable for our actions towards' the other (Kennedy 2017, 506). Zooming out further, it brings the wider organic ecosystems of our planet (and beyond) into view. To resist the genAI hype through an environmental critique, then, is to expand the spatial and temporal dimensions of our focus away from only interactions with, and the outputs produced by genAI, towards the entanglement of deep time ingrained in, yet hidden by, the convenient instancy of genAI interfaces. As Reading argues, we need to go further, beneath and beyond the surface level of 'the skin or screen of digital memory' (2014, 753; see also Loots 2024). This goes even further than tracing the capitalistic technological infrastructures and human relations on which genAI relies, in also foregrounding the actors involved in the production of genAI in terms of resources and energy consumption, and the long-term consequences of extraction and power use.

Exemplifying this, Crawford and Joler's 'anatomy of AI' exceeds the technical in acknowledging that whilst our 'encounters with AI are fleeting and brief', behind each lies the 'interlaced chains of resource extraction, human labour and algorithmic processing across networks of mining, logistics, distribution, prediction and optimization' (2018). Thus, whilst typing a quick prompt into a chatbot might seem frivolous, the energy use that enables computation and the material resources required to create, maintain, and extend the hardware necessary for ever-expanding data storage and processing are disruptive to existing ecosystems. As Crawford elsewhere notes, 'from the perspective of deep time, we are extracting Earth's geological history to serve a split second of contemporary technology time' (2021, 31).

In principle, there is nothing new here. Media – digital or otherwise – have always relied on substantial material extraction, production, and waste (Maxwell and Miller 2012; Parikka 2015), and the tension between the illusion of immateriality (e.g. the 'cloud', the AI 'black box') and this continuous geological deep time of media is built into the algorithmic logic of computing. Yet, the mainstreaming of genAI, which promises forms of enhanced computing, and working at complexities, scales, and speeds beyond human capacities, makes us feel unintelligent, irrelevant, and somewhat powerless in its shadow. Meanwhile, these systems propel the destruction of our ecosystems irreparably, leaving their imprint on the planet eternally.

The field of memory studies has paid relatively little attention to the broader material consequences of the 'often obfuscated environmental exploitation and friction between capital and labour that go into these newer forms of mediated memory' (Reading 2014, 749; see Loots 2024). Adopting an environmental critique to genAI calls on us as memory scholars to go beyond the interface encounter and the illusion and deception of this experience (Natale 2021). How can we be attentive to what is not visible in that moment? This demands an infrastructural approach to memory construction; that is, there is a need to scrutinize how current AI-enabled memory practices and technologies are materially supported. Memory scholars could make visible how our planetary and supra-planetary environments and resources – the deep time of our planet and universe – are problematically entangled with our sociotechnical systems of memory. A focus on the environmental dimension of genAI, thus, helps shift our critical gaze towards the memory of the Earth and its universal neighbours. Ultimately, this focus offers a posthuman approach to the entanglements of humans and nonhumans in producing genAI and creating memory. This 'holds the potential to cultivate response-able forms of memory, reshaping how essential interdependence is practiced in the everyday rituals of living and remembering within our more-than-human world' (Gündoğan İbrişim 2024, 101).

Conclusion

This commentary has explored how memory scholars might handle the AI hype by highlighting several lines of critique through which to interrogate genAI's nexus with memory. In doing so, it has considered what memory is *in relation to* the technologies captured under the 'AI' label. Our key takeaway is that the mnemonic study of AI should be specific. Two interlinked questions help reveal this specificity. Firstly, what sort of 'AI' is under scrutiny? Secondly, what form of memory (in relation to AI) is the object of study? At present, most attention in the field seems to be on genAI, but this too demands specification. For example, instead of asking what is the impact of genAI on memory, a more specific research question would be how does the use of transformer-based instruction-tuned text generators shape public memory of political conflicts? Or how do personal digital assistants enable new forms of interaction with a family's past? Or how do image generators fabricate historical representations? Or what are the environmental impacts of heritage institutions' uses of machine learning and cloud services? The list could go on. The point is that for memory studies research to contribute to understanding genAI, it needs to be specific.

This will also help demonstrate the value of (or indeed potentially temper) the plethora of concepts already circulating around genAI and memory.

Specificity demands detailed empirical research and methodological rigor. Thus, we close our commentary with a call for memory scholars to commit to adopting and, where necessary, developing robust methods that allow the close empirical study of the relationship between genAI and memory. Especially, we believe the field will benefit from empirical research that is conscious of the five areas of critique outlined here. While not exhaustive, these encourage empirical research that: (1) problematizes the common histories of AI and historicizes the continuities and ruptures in technology-assisted remembrance that genAI represents, (2) seeks to understand how the disparate technological components of different genAI systems are designed and work in relation to memory, (3) centres on how different types of people practice and experience memory with genAI, (4) acknowledges how global power dynamics surrounding genAI's production and distribution has implications for different memory cultures, and (5) explores the overlaps of memory studies' environmental and digital subfields. Not all these can necessarily be covered in depth in a single study. However, macro-perspectives that consider the historical and technical specificities of genAI systems, acknowledge what they make visible in praxis, while reckoning with the broader geopolitical and environmental consequences of genAI-use that are often invisible, can serve as valuable points of departure and contextualization for studies that might go on to focus on one or more of these areas of critique in more detail. In short, memory scholars would do well to start any critical investigation into genAI (or any other AI) and memory by considering how it could be read through all these different areas of critiques, before narrowing the focus of their study.

These areas of critique, as we have demonstrated, also offer opportunities for collaborative interdisciplinary research, with no single discipline fully equipped to pursue any of them in isolation. Such an interdisciplinary approach to (gen)AI in memory studies then holds the possibility of building on concerns in philosophy, psychological, and cognitive sciences regarding what is 'remembering' (to echo broader debates about what is 'thinking') in the AI age, complementing but also complicating this 'remembering' by situating it in broader technological, social, cultural, economic, political, and environmental contexts. This could be achieved by learning from critical AI studies, whilst remembering the long history of debates – regarding earlier (both pre-digital and digital) technologies – in media studies and sociology. Such an endeavour should still, however, seek to remain sensitive to how particular AI systems work and the computational logics underpinning them, as well as how they are used, thus engaging with the broader field of AI development in computer sciences and again disciplines like sociology and social psychology. Rather than being led by specific case studies and immediately identifying a rupture caused by an abstract 'AI', we suggest it might be more fruitful to begin by considering a chosen case in terms of the five areas of critique highlighted in this commentary, simultaneously exploring the depth and breadth of relationships between AI and memory that the case can foreground. Such an approach would immediately help demystify 'AI'.

The possible approaches for memory studies that we have described throughout this commentary point also to an emerging ethics for studying genAI and memory. Such an ethics demands that memory scholars (ourselves included) interrogate their own complicity in the AI hype. Given what is known about the negative consequences of genAI, ethical tensions arise regarding how far our future empirical analysis of genAI should rely on the technology itself, for instance, when using it to understand AI history (Volynskaya 2024) or how users remember with it (Smit *et al.* 2024). Can memory research always justify the use of these extractive and damaging systems? Might more conventional methods like interviews sufficiently capture the effect/affect of genAI for memory? Likewise, is our call for 'memory domain experts' merely a more morally insulated way of jumping on the bandwagon? Does this commentary itself benefit from and feed the hype? Is its rehearsal of arguments well-known in certain academic quarters for a new memory studies audience, indicative of a mode of academic work that is increasingly aligning with the pleasing and (over-) productive logics of genAI itself? These are the sorts of uncomfortable questions that we all need to ask ourselves when engaging with genAI as a research topic. This commentary has not sought to resolve these quandaries outright, nor the many others raised by one of memory studies' newest research objects, instead it has aimed to highlight them in the hope that as a field we are able to commit to critically working through them, handling the hype and our complicity therein as we go.

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