What Memory?
Artificial Intelligence, Lucid Hallucinations and Other Errors

Beba Molinari[*]

Abstract. This article aims to investigate how the very concept of memory can be influenced by algorithms, with a particular focus on the different ways in which a whole series of errors produced by Artificial Intelligence (AI) can be encountered. These errors take various forms, ranging from extremely obvious manifestations to much more subtle ones that are difficult to recognize, foremost among which are those commonly known as lucid hallucinations. The latter, in particular, can have a clear influence on the construction of memory, just as in the early 1980s, new electronic external storage media affected not only memory but also the concept of memory itself.
***Keywords*:** Artificial Intelligence, Lucid hallucinations, Error, Memory.

Riassunto. *Quale memoria? Intelligenza artificiale, allucinazioni lucide e altri errori*. L'articolo si propone di indagare come il concetto stesso di memoria possa essere influenzato dagli algoritmi, con particolare attenzione alle diverse modalità con le quali si possono riscontrare tutta una serie di errori prodotti dall'Intelligenza Artificiale (*Artificial Intelligence* [AI]). Tali errori si presentano in diverse forme, sia palesandosi in modalità estremamente evidenti, sia in forma molto più subdola, di difficile riconoscimento prime tra tutte quelle più comunemente conosciute come allucinazioni lucide. Queste ultime in particolar modo possono influire in modo evidente nella costruzione del ricordo, così come nei primi anni Ottanta del secolo scorso i nuovi media elettronici di memorizzazione esterna hanno inciso non solo sul ricordo, ma più in generale sul concetto di memoria stesso.
***Parole chiave*:** Intelligenza artificiale, Allucinazioni lucide, Errore, Memoria.

1. Introduction

Several times a day, we are led to remember an event, sometimes simply as a causal link to some stimulus that triggered the memory, other times because it is necessary to understand today's events, which require a higher level of understanding and not just a simple interpretation of the facts that occurred in the immediate past. The cultural nature of the concept of memory itself is therefore evident, understood not only as purely linked to the individual, as an internal processing of an event experienced and therefore of a purely physiological cerebral nature, but rather as a reworking through a series of other external (variable) factors that affect memory, i.e. conditioned by other social and cultural events (Halbwachs, 1968).

This article aims to investigate how the very concept of memory can be influenced by the algorithms underlying Artificial Intelligence (AI), with a particular focus on the different ways in which a whole series of errors produced by AI can be encountered. These errors take different forms, ranging from extremely obvious to much more subtle and difficult to recognise, foremost among which are those commonly known as lucid hallucinations. The latter in particular can have a clear influence on the construction of memory, just as in the early 1980s, new electronic external storage media had an impact on memory itself.

If we look to the future, we are led to believe that we are living in a period of cultural revolution, just as printing and, before that, writing changed the perception of events and had a strong influence

[*] Researcher in General Sociology, Department of History, Cultural Heritage, Education and Society, Tor Vergata University of Rome, Via Columbia 1, 00133 Rome, Italy, e-mail <beba.molinari@uniroma2.it>.

DOI: 10.12869/TM2025-2-06

ISSN 2282-0043

on collective memory. We cannot help but think that today, through new media and, even more so, AI, we are in a period of great technological ferment linked to increasingly innovative and high-performance forms of communication. The acceleration of digital technology has taken place over the last ten years and, without us realizing it, has conquered our daily lives by simplifying the resolution of increasingly complex and specific questions with the help of a growing number of practical applications, most of which are based on AI (Thottoli, 2024).

The author is fully aware that the concept of memory cannot be explained solely through the changes brought about by media technologies (Luhmann 1990), but at the same time she does not believe that the only interpretative key can be traced back to historiographical and spiritual events, espousing Weber's theory (1922) first and foremost with the general concept of culture, followed by Jaspers in his personal conceptualization of history (1949). In this regard, AI offers a range of opportunities that are currently unexplored, allowing us to perform multiple tasks of varying complexity, but at the same time, the general public is unaware of the procedures and methods by which AI operates with great adaptability on our devices. Being aware of the types of errors AI can make allows us to develop a set of antibodies that help us understand critical thinking and co-construct collective memory.

But what is the relationship between AI and memory? It is necessary to clarify the many faces that AI can take. Machine learning is based on data produced by our interactions with the web environment. Our digital traces, produced consciously but in most cases unconsciously, feed machine learning. It is therefore necessary to shift our attention to the latter and the definitions that derive from them, but it is equally essential to understand which of the many different definitions of AI is the most appropriate to adopt. We are not dealing with an exact science, but rather with predictive models that lay the foundations of machine learning and which, precisely because they are predictive, are subject to possible distortions (bias).

In this regard, it is essential to make a clarification that lays the foundations for this article. While we have a series of assumptions on which the methodology of social research useful for understanding various social phenomena, including memory, is based, we must also ask ourselves how many of these assumptions are still valid given the immense amount of information and data provided and analyzed by the internet, shifting the focus to the data used by AI.

In this process of constructing and reconstructing memory, AI skills will become increasingly effective, particularly in terms of becoming ever closer to human skills. We are already at the stage where AI is able to navigate complex systems and understand its environment, relate to what it perceives and solve problems accordingly. That is why it is no longer so much a question of representativeness; the boundaries are already extremely blurred because they are extremely fast, changeable and have a level of continuous implementation that is difficult to even imagine.

The following paragraphs will explore aspects related to AI and its many facets in order to define its boundaries of interest with regard to its impact on collective memory and how new forms of communication can intervene in the process of co-constructing memory. Subsequently, the limits of AI use will be discussed through an in-depth analysis of the different forms of error that machine learning can reproduce.

2. From Artificial Intelligence to Memory

The art of memory has always been linked to the individual. Even in the earliest writings dating back to the 1st century BC, a distinction was made between natural and artificial memory, linking the latter to rhetoric, a concept that was never forgotten and was taken up again in the 17th century by the cultural historian Frances Yates (1968). Many others followed, including Blum (1969), Eickelmann (1978) and, more recently, Assmann and Harth (1991), continued Yates' studies, albeit with different meanings. However, in this case, it is not so much the focus on the individual that is of interest in the field of AI, but rather a broader view of the community (Bauman, 2007). The idea of educating people to remember is strongly linked to the overlapping of multiple pieces of information of different natures and origins in which we live. It is therefore necessary, if not essential, to understand what stimuli lead a community to create and/or co-construct a true 'culture of remembrance'.

There is a great deal of ambivalence surrounding the concept of AI itself, depending on the field and/or studies in which it is approached. AI is aimed at simulating human behavior, designed with anthropic capabilities such as reasoning, learning, planning and creativity. AI adapts quickly to its surroundings, relates to what it perceives, solves problems and acts towards a specific goal, all through a process of receiving data (already prepared or collected via sensors, such as a video camera), analyzing it and providing an output with responses it deems appropriate. AI systems are able to adapt their behavior by analyzing the effects of previous actions and working autonomously.

More specifically (European Parliament, 2020), AI is divided into two broad macro areas: software and embedded intelligence. The former includes virtual assistants, image analysis software, search engines, facial and voice recognition systems, while the latter includes robots, autonomous vehicles, drones and the Internet of Things. While the former are those we use most commonly in our everyday lives, the latter are those we initially refer to as AI[1].

Let's take a look at how AI actually works, albeit in broad terms. What we usually see and interact with when we deal with AI as users is a chatbot (Xu, 2019). This is software that simulates and processes human conversations, whether written or spoken, in order to allow users to interact with digital devices while giving them the impression that they are communicating with a real person, thus facilitating human-machine interaction. Chatbots vary depending on how they are programmed. Some are extremely simple and respond to a single question and/or on a single topic, while others are much more complex, such as digital assistants that learn from their mistakes and from data provided by the web in order to provide increasingly personalized levels of service that reflect the user's interests. To give a concrete example, we could program a chatbot in the guise of a famous historical figure and be able to talk to Michelangelo, Hitler, Queen Elizabeth, etc.

Apart from the purely ethical aspect, which is by no means negligible, chatbots must be trained before they are able to respond2 and it is at this stage that Machine Learning comes into play (Liu, Wang, Whang, 2012) comes into play, through which the model underlying the chatbot learns through a huge amount of data of various kinds (text, images, videos) that are provided free of charge and directly from the web without any type of filter.

[1] While most people do not have a clear idea of what AI is, they are certainly surrounded by it in their daily lives, providing useful data for processing a range of information that changes our lifestyles: dietary, relational, educational, cultural, etc. We are talking about an amount of information that is difficult to even imagine, from a total of 33 zettabytes in 2018 to an estimated 175 zettabytes by the end of 2025, where one zettabyte is equivalent to a thousand billion gigabytes. With this amount of data, it is difficult to imagine a repository that could contain it all.

[2] The learning phases are divided into three successive steps: the first involves learning linguistic skills and general knowledge, and by learning from its mistakes, the chatbot becomes autonomous in its ability to give correct answers, but only with regard to linguistic competence. In this phase, the programmer comes into play, 'adjusting' the errors made by randomizing the correct words and using a predictive process formulated as a 'learning model'. In the second step, the chatbot learns specialist skills through a series of multiple-choice questions, for which the model formulates tasks. In the third and final step, a team of computer scientists verifies the effectiveness of the responses and defines the 'style' and genre with which the chatbot responds.

Once the chatbot software has been trained, there is no need for the program to be constantly connected to the network. It will still function, providing the most reliable response possible based on previously acquired information, but it will not receive the continuous data updates that allow it to 'train' its skills in relation to specific questions.

It is important to emphasize that AI and Machine Learning are not synonymous. They are two closely related but completely different technologies. The former designs an intelligent architecture, while the latter allows us to develop a learning system with ease.

What has been described so far is an overview that does not claim to be exhaustive, but aims to show a variety of extremely innovative tools that are, at the same time, always different and changing. There are several noteworthy tools related to the culture of memory, understood as the direct evolution of chatbots. The most interesting are undoubtedly those that fall within Information Retrieval (Kruschwitz, Petrocchi, Viviani, 2025), i.e. a set of Machine Learning techniques used to manage different aspects, including the representation, storage, organization and access to objects containing information such as documents, web pages, online catalogues and multimedia objects. Information Retrieval aims to provide users with the information they have previously searched for, already providing an initial selection of topics that it considers most relevant. Unlike other more common chatbots, those used in Information Retrieval make use of platforms that provide detailed analyses from historical archives, scientific and journalistic articles, official statistics, etc.3

At the heart of all this is a system based on Machine Learning: the more it is used, the better the performance and accuracy of the information provided by the AI, regardless of the platform or chatbot used. However, it is important to be aware that machine learning systems are not all the same. Some are based on artificial neural networks, i.e. models that mimic the human brain, and when the question asked becomes complex, the neural network needs a so-called deep network, which is where deep learning comes into play (Abadi, Chu, Goodfellow *et al*., 2016): the greater the problem to be solved, the more complex and deeper the network will be. This complexity stems from the fact that everything we see is actually 'assembled' by our brain, which has been trained since childhood to recognize things and attribute the right meaning to them by placing them in a well-defined context, effectively using memory. We must therefore be aware that Deep Learning simulates this process. The key point is that we have now reached a situation where, given a multitude of layers, the model is able to learn by itself (Thompson, Greenewald, Lee *et al*., 2020). It is in this context that errors that can be made by AI and how these errors can change cultural memory come into play.

At this juncture, it is natural to think about the concept of natural and artificial memory. AI represents both, because on the one hand, Deep Learning simulates the human brain in its process of understanding and in its mnemonic aspect, while on the other hand, the use of AI can influence, as with traditional media tools, the vision of a collective memory.

There are therefore several aspects that remind us of the link between AI and the concept of memory. Conscious use of new digital tools can easily become testimony, but this does not mean that

---

[3] First and foremost among these are GPT technologies, which are the new frontier of research, albeit still under discussion and undergoing continuous updating. Among these, one of the first to be available for free is Google Studio IA, which aims to create prompts tailored to our needs, such as a specific professional figure who responds to a series of skills and, through these, provides answers to solutions in specific areas.

The second free tool is NotebookLM, a retrieval system with algorithms that use only data of interest to us, such as PDF documents, so the system will only document sources that we have previously entered. The platform's response is to provide us with a summary, or a timeline, a briefing document, posts to be included in social networks, reports, etc. In other words, it processes content and returns it in a new lexical form. Among other things, there is also the possibility of subsequent dialogue with a chatbot. The best known, most downloaded and most used in Italy is undoubtedly ChatGPT, which aims to provide the most accurate and contextual answers possible, improving interaction with users and supporting human work. We also have the option of creating our own virtual agents using content chosen directly by us.

such testimony is necessarily a point in favor of the collective memory process; it could also turn into a point against it. Access to a flood of uncontrolled information can alter the message conveyed by the chatbot and/or the platform used. In this case, we enter fully into the realm of possible errors that can occur when using Machine Learning, which we will discuss in the next section.

There is another noteworthy aspect, namely the form of language that could be used by the chatbot. Language is 'taught' or, rather, programmed by the computer scientist, and it is not certain that this form of language will not change over time, just as language changes in society.

Obviously, there is a link between AI and memory that has not yet been considered, the most obvious being AI as a repository, as a simple large container of information to draw on when needed, just as we do with our memory. However, we are dealing with an issue that is as obvious as it is evident in its human-machine connection. As a simple repository, it does not make much sense, because there are no specific selection criteria, whereas social actors draw on their own experiences, acquired cultural skills and their perception of the self and the other.

According to Halbwachs (1956, p.79) '*There is no memory possible outside the frameworks that people living in society use to fix and retrieve their* memories'. The premise of this assumption is that the social actor draws on their own memory, constructed through their personal experiences in the culture and group to which they belong, a sort of cultural 'filter' dictated by living in a community. While AI once disregarded this aspect and stopped at indiscriminately searching for useful information through a predefined algorithm, today the research on which the algorithm is based is much more sophisticated and requires a series of 'filters' on which the algorithm processes the data.

3. Lucid Hallucinations and Other Errors

In order to highlight the many errors we may encounter along the way, it is essential to understand not so much the mechanisms underlying the analysis, or rather the algorithms used by AI, which are not the responsibility of the individual or the community and/or group to which they belong, but rather of the programmer; Rather, we should not underestimate the fact that there are different platforms and chatbots, some more effective for certain uses than others, and that, above all, some AI tools use Deep Learning, algorithms based on more purely predictive neural networks, which change the algorithms underlying the analysis at an impressive speed (Quarteroni, 2020).

In order to eliminate the possibility of risk with regard to 'false' information, social actors should have solid IT and mathematical skills. It is therefore almost impossible to have both skills and, on the other hand, to be able to devote the time necessary to verify information as it is conveyed. The very fact that every single piece of information has to be verified renders it useless. However, AI allows us to analyze online contexts, opening up new areas of interest, so the focus shifts to our ability to identify errors.

It is worth noting that there is no single type of error. There are systematic errors, more commonly known as distortions, accidental errors, selection errors, and errors made during indication, operationalization, selection and observation. In fact, these errors are purely related to so-called traditional analysis, and in other contexts it has been repeatedly discussed that error, in its various meanings, is an aspect that is very often overestimated in the social sciences, especially when it comes to sampling (Molinari & Corposanto, 2022). If we think about error from a mathematical, statistical and/or probabilistic point of view and if we think we can 'control' it using AI, we are making another mistake. These are completely different realities, two different epistemological points of view.

Having said that, when we talk about bias, we tend to attribute a purely negative connotation to it, but this is not always true; in fact, unexpected influences should not always be perceived as 'errors', i.e. 'mistakes' that contaminate the quality of the recorded information and therefore render the information itself unusable. Instead, we could think of bias as a space-time continuum, in which possible distortions can effectively alter the quality of data to varying degrees and, in some cases, allow us to discover new aspects that had not been given much weight, opening up new interpretative scenarios (Shapin, 1982). Obviously, upstream of the process, there must be strong social skills related to the historiography of the area of interest and a critical capacity of a geopolitical and cultural nature. The latter aspect is strongly anchored in the real life of the social self of the individual, who recognizes certain objects and places as status symbols of specific contexts, becoming social facts (Appadurai, 1986).

In this regard, it is easy for data from the web to be influenced to varying degrees by distortions that we can distinguish into two macro categories: on the one hand, we may encounter errors due to discriminatory criteria that are inadequate for the task at hand; in other cases, however, biases derive from Big Data and the Data Warehouses themselves, which AI draws on to carry out its processing (Burrows & Savage, 2014). The latter type of error is much more difficult to identify as it requires sector-specific IT and mathematical knowledge.

Therefore, the processing that arises from user requests regarding certain phenomena that occurred in historically significant contexts (wars, epidemics, traumatic events, etc.), as we remember and interpret them today, is still the result of a collective memory that derives from the combined memory of the members of a social group. Memory is the processing of multiple aspects, personal, lived experiences, stories told by loved ones, what we have learned from the media, so we rework a memory with respect to a series of 'other' variables that intervene in the process of remembering from our earliest socialization. In fact, taking this a step further, we could say that the processing carried out by Machine Learning is nothing more than a series of data (information) from the web in other contexts and for other purposes of analysis, i.e. the famous digital traces, which represent our online preferences, experiences, events, etc., with all the strengths and weaknesses that come with them.

To better understand what has been discussed so far, let's take a closer look at the most widely used BOT in recent times, which is not only downloaded and present on our mobile phones with an average of 1.6 billion visits per month in 2025, but is also used by users approximately every 7 minutes. We are talking about ChatGPT (Cong-Lem, Soyoof & Tsering, 2024). Unlike many other BOTs, the latter has the advantage of not requiring any kind of preparation, does not need to be implemented with information, and does not need to be trained on specific documentation. Asking a question about a specific historical event, such as a war, does not lead to errors because it is documented on multiple platforms, but the situation becomes more complicated when a higher level of specification is required, with the question also involving historical and cultural analysis, such as a diaspora. It is precisely in these situations that the most serious errors occur, some of which are extremely obvious as they are subject to various types of discrimination. These issues arise because, as there is no real control over the origin of the information processed by the BOT, the output is not always impartial.

To reduce this problem, it is possible to use a different tool, namely a BOT created and 'trained' by us through limited use of web-based ' ', asking it to explore topics only in relation to a series of documents and articles provided exclusively by the user.

The biggest obstacle currently limiting the use of AI, especially generative AI, is what are known as AI hallucinations, a phenomenon that occurs when the output generated is incorrect, but not so much so as to be obvious (Spennemann, 2023). The underlying problem is that in a state of hallucination, a plausible, comprehensive, effective, clear, but above all logical response is provided that is completely unfounded in reality. This is mainly due to several factors, in particular overfitting, i.e. when the machine learning model 'feeds itself' by reprocessing information on data already processed by AI, introducing into the analysis what is statistically referred to as ‘noise’ within a dataset. On the other hand, when we think about memory in the real world, we must consider that it is maintained over time thanks to communication. If communication fails and the frames of reference of reality are lost (Goffman, 1977), memory is destined to disappear. The similarity between AI lucid hallucinations and memory in the real world is extremely evident: we have repeatedly mentioned that AI ‘works’ by simulating human memory, especially if we consider the need to possess a set of information, which for Goffman are frames of reference, where the absence of the latter for the social actor reveals the possibility of memory loss, of forgetting a given event; while for AI, the scenario of statistical noise arises and the output loses its ‘clarity’.

This type of error cannot be programmed, but can easily escape the user requesting information precisely because they are not particularly knowledgeable about the subject of the query. This is why it is necessary to use appropriate search engines and not rely exclusively on generative AI. It is important that this content can be evaluated by people who are knowledgeable on the subject, who can think critically and who are able to judge whether what emerges from these algorithms is useful or misleading. These are often intrinsic errors that are not generated because there is an error in the coding and/or analysis of Big Data, but rather because they emerge from the vast and perhaps excessive amount of information available on the web, which reflects the biases of the sources used for analysis. This shows how easy it is for errors related to stereotypes and prejudices, from gender to ethnicity to political ideology, to arise.

There are many "obvious" errors that have been discussed by experts in the field. Among these, it is very complex for programmers, for example, to eliminate gender stereotypes that emerge with constant frequency, errors that are often dangerous because they are not always particularly evident to an inattentive reader. Others are related to more purely visual aspects, such as the video production of a person or specific scenarios with glaring errors related to the reproduction of the body, such as six fingers on a hand, eyes of unlikely colors, etc. Obviously, the latter errors are the least dangerous because they do not lead to false beliefs; on the contrary, they can be a wake-up call to view the video and content in question with a more critical eye and ensure that the social actor pays more attention and does further research than what has been done by AI.

Having access to images and videos, even with minor errors (hands, eyes, iridescent skies, etc.), is a futuristic version of Habwachs’ (1952) images of memory, which highlights their importance in relation to what we might today consider basic requirements: a temporal and spatial reference, a further reference to the group and, finally, reconstructivity. If these three aspects are present in the video/image produced by AI, we can think that in some way the latter may have created a sort of *‘memory image’*, contributing concretely to the construction of a shared memory aimed at reducing the mechanisms linked to forgetting.

4. Concluding Considerations

The importance of building cultural memory while considering AI as an integral part of the process is now clear, given that we can no longer ignore this increasingly used tool, which is being entrusted with an ever-growing number of unimaginable tasks, from medical applications to driving commercial and non-commercial vehicles.

Starting from the assumption that: “people produce knowledge based on the knowledge inherited within their culture, their collectively situated goals and the information they receive from the natural world and, last but not least, from the role played by the *social*, i.e. the importance of pre-structuring”

(Shapin 1982, pp. 196-198), the Edinburgh Science Studies Unit (SST) focused its attention, when AI was not yet a topic of discussion, on the ability to make conscious and culturally defined choices. More than 40 years after these considerations, it is essential to be aware that memory can also be culturally defined by AI and that the introduction of this new tool for human-machine dialogue does not necessarily have to be characterized exclusively by negative aspects. The awareness of the social actor drastically limits the "noise" of Machine Learning, which translates into lucid hallucinations, allowing the algorithm to be remodeled in due course.

On the other hand, it is equally true that the more we use AI, the greater the possibility of encountering errors, whether visible or not.

Here too, there are many similarities between AI and memory, starting with the concept of forgetting a memory (Gadamer, 1960). From this perspective, AI becomes a simple tool for searching for one memory over another in order to select what is best to remember. The "forgotten" memory ends up in a "repository" of information, perhaps much closer to Ricoeur's (2000) idea of the concept of "oblivion of erasure", where what is to be forgotten is set aside and destined to be "searched for" only when it has some use for the social actor.

In this regard, therefore, the approach with which we relate to error cannot be understood in a statistical sense, because we do not have the cognitive tools to identify them correctly in algorithms (Buhmann, Paßmann, Fieseler, 2019), but we can intervene upstream by trying to use the most appropriate AI tool. Being more aware that there are multiple search engines, being able to use BOTs in different ways, and knowing that it is still possible to "build" a BOT upstream and train it through our own choice of documentation creates antibodies at our disposal for conscious use.

When we approach new technologies, we are used to expecting a high level of performance from the *machine,* even more so in the field of machine learning. In reality, it is wrong to assume that machines are not prone to error, just as social actors are prone to error, especially when it comes to memory. Testimonies are primarily a combination of several factors: life experiences, mental patterns, expectations, stereotypes, typifications, memories from other people and/or the media, etc. (Mastrobernardino, 2011). The co-construction of memory is, in any case, a combination of different factors, a sort of mediation of different aspects that manifest themselves through external stimuli, some cultural, others personal, etc. These aspects are not necessarily correct, free from political bias, stereotypes, gender differences, etc.

For this reason, I believe that while we must deal with any incorrect outputs as social actors, on the other hand, errors will certainly be reported and corrected in real time, not only by the user but by the AI itself, because we are already at the stage where AI learns from itself and its own mistakes. A series of "corrective" algorithms have been in development for several years now, particularly with regard to the most obvious forms of discrimination, and since memory is co-constructed through the support of groups, "memory", or rather, the processing of socio-cultural events produced by AI are the result not only of multiple datasets and algorithms, but also of multiple social actors who interact every day with increasingly powerful technological innovation.

The picture that emerges is much more complex than it may appear, because apart from lucid hallucinations, which develop only to a much lesser extent than the set of correct information recreated by AI, and are therefore unable to influence a collective idea, according to the author, the most significant problem lies upstream. If we start from the fact that cultural memory is created through the memories of group members, in this case, which group are we talking about? Is AI capable of altering a memory, or even creating multiple individual memories of group participants and then recreating a collective memory? To date, we do not have a real answer to these questions. We can only speculate that it would be extremely interesting to address these issues through ad hoc research, combining multiple interdisciplinary aspects, starting with the IT skills not only of each of us, but rather the shared construction of an algorithm among multiple experts.

There is also an aspect related to the temporal dynamic. If we start from the assumption that collective memory is constructed over time and can only be fully understood in retrospect, it is highly unlikely that this is the historical moment in which we will see the greatest shifts in thinking attributable to AI. but we are nevertheless aware of the present, which allows us to hypothesise a series of possible interpretative scenarios, as generative AI itself does. In this regard, we must not forget that among the many areas in which AI is used, both BOTs and information retrieval platforms are used to identify and delimit the boundaries of the object of investigation and the related hypotheses. Delegating such important aspects of the world of research, social or otherwise, is certainly a rather futuristic gamble, but it is not impossible that machines will surpass humans in the near future; just think of the giant strides made in the field of telemedicine. We are within boundaries that are poorly defined, too blurred at present, but so fragile that they force us to reflect on new areas of study between the real and virtual worlds. AI should be considered a sort of intermediate storage tool, a mediator of the communication system, where communicative acts and information tout court find a virtual place in which to be archived, processed and then codified and subsequently re-proposed in the form of virtual output, an innovative version of what Leroi-Gourhan (p. 64) considered the first computers to be a sort of "*Mémoire Extériorisée* " where the holder is not the individual but rather the "*collectivité ethnique*".

However, there is a warning that we must always bear in mind, namely that AI must be better trained on an ethical and social level, with strong values that lay the foundations so that the transcription of the algorithms underlying Machine Learning is not self-reproduced by the ever-evolving machine itself, but is guided by people, for a process that is no longer machine-centric, but human-centric.

References

Abadi Martin, Chu Andy, Goodfellow Ian, McMahan Brandan H., Mironov Ilya, Talwar Kunal, Zhang Li (2016). Deep learning with differential privacy. Proceedings of the 2016 ACM SIGSAC. In: *Conference on Computer and Communications Security. ACM*, Wien, pp. 308-318.

Airoldi Massimo. *Machine Habitus. Toward a sociology of algorithms*. Cambridge: Polity Press, 2022.

Appadurai Arjun (editor). *The Social Life of Things. Commodities in Cultural Perspective*. Cambridge, 1986.

Assmann Jan & Harth Dietrich. *Mnemosyne*. Frankfurt am Main: Suhrkamp, 1991.

Amershi Saleema, Cakmak Maya, Knox Bradley W., Kulesza Tood (2014). Power to the People: The Role of Humans in Interactive Machine Learning. In: *AI Magazine*, 35(4), 105- 120.

Bauman Zygmunt. *Voglia di comunità*. Bologna: il Mulino, 2007.

Benanti Paolo & Maffettone Sabastiano. *Noi e la macchina. Un'etica per l'era digitale*. Milano: LUISS University Press, 2024.

Blum Richard H. *Die antike Mnemotechnik*. New York: Hildesheim, 1969.

Buhmann Alexander, Paßmann Johannes, Fieseler Christian (2019). Managing algorithmic accountability: Balancing reputational concerns, engagement strategies, and the potential of rational discourse. In: «Journal of Business Ethics.» Doi: 10.1007/s10551-019-04226-4.

Burrows Roger, Savage Mike (2014). After che Crisis? Big Data and the Methodological Challenges of Empirical Sociology. «Big Data and Society», n. 1, pp.1-6, doi: 10.1177/2053951714540280.

Power Daniel J. (2008). Decision Support Systems: A Historical Overview. In «Handbook on Decision Support Systems», 1 (pp. 121-140). https://doi.org/10.1007/978-3-540-48713-5_7

Cloitre Michel & Shinn Terry (1985). Expository practice: Social, cognitive and epistemological linkages. In Shinn T., Whitley R. (editors). *Expository Science. Forms and Functions of Popularization*, Reidel Publishing Company, Dordrecht-Boston, pp.31-60.

Cong-Lem Ngo, Soyoof Ali & Tsering Diki (2024). A Systematic Review of the Limitations and Associated Opportunities of ChatGPT. In: «International Journal of Human-Computer Interaction», *41*(7), 3851-3866. https://doi.org/10.1080/10447318.2024.2344142

Corposanto Cleto & Molinari Beba (2018). Analizzare dati di microblogging con la Sentiment Analysis. Quale rappresentatività? In: «Sociologia Italiana», n. 11, Egea.
Corposanto Cleto & Molinari Beba (2020). Dai Big Data alla valutazione passando per la metodologia della ricerca sociale", in Gozzo S., Pennisi C., Asero V., Sampugnaro R. (editors), Big Data e processi decisionali. Strumenti per l'analisi delle decisioni giuridiche, politiche, economiche e sociali. Milan: Egea.
Eickelmann Dale F. (1978). The Art of Memory: Islamic Education and its Social Reproduction. In: «Comparative Studies in Society and History», XX, pp. 485-516.
Gadamer Hans G. Verità e metodo. Milano: Bompiani Editori, 2000.
Goffman Erving. *Rahmen-analyse. Ein Versuch uber die Organisation von Altagserfahrungen.* Frankfurt am Main, 1977.
Halbwachs Maurice. *La mémoire collective*, Paris: Michel, 1968.
Kissinger Henry, Huttenlocher Daniel & Schmidt Eric, Piccato Aldo. *L'era dell'intelligenza artificiale. Il futuro dell'identità umana*. Milano: Mondadori, 2003.
Jaspers Karl (1949), *Vom ursprung und Ziel der Geschichte,* Mumchen [trad. it. *Origine e senso della storia*. Milano: Franco Angeli. 1965].
Kitchin Rob (2014). Big Data, New Epistemologies and Paradigm Shifts. In: «Big Data & Society", I, 1, pp. 1-12, doi: 10.1177/2053951714528481.
Kyriakidis Miltos, De Winter Joost, Stanton Neville *et al.* (2019). A Human Factors Perspective on Automated Driving. Theoretical Issues in Ergonomics Science. In Kish L., Frankel M.R., *Inference from Complex Samples, Journal of the Royal Statistical Society*: Series B (Methodological), Volume 36, Issue 1, September 1974, Pages 1-22, https://doi.org/10.1111/j.2517-6161.1974.tb00981.x
Kruschwitz, Udo, Petrocchi Marinella, Viviani Marco (2025). ROMCIR 2025: Overview of the 5th Workshop on Reducing Online Misinformation Through Credible Information Retrieval. In: Hauff, C., *et al*., *Advances in Information Retrieval. ECIR 2025. Lecture Notes in Computer Science*, vol 15576. Springer, Cham. https://doi.org/10.1007/978-3-031-88720-8_52
Kruskal William & Mosteller Frederick (1980). Representative Sampling, IV: The History of the Concept in Statistics 1895-1939. In: *The International Statistical Review*, XLVIII, pp. 169-195.
Leroi-Gourhan André. *Le geste et la parole II. La mémoire et le rhythmes*. Paris, 1965.
Liu Yanli, Wang Yourong & Zhang Jian (2012). New machine learning algorithm: Random forest. Lecture Notes. In Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 7473 LNCS, 246-252. https://doi.org/10.1007/978-3-642-34062-8_32
Luhmann Niklas (1990). Meaning as sociology's basic concept, in *Essays on Self-Reference*. New York: Columbia University Press, pp. 21-79.
Mastrobernardino Serena. L*'intervista cognitiva.* Roma: Carocci, 2011.
Molinari Beba & Corposanto Cleto (2022). How does the error from sampling to big data change? In: «Italian Sociological review» 12 (7S), 665-684 http://dx.doi.org/10.13136/isr.v12i7s.576
Quarteroni Alfio. *Le equazioni del cuore, della pioggia e delle vele. Modelli matematici per simulare la realtà*. Bari: Edizioni Dedalo, 2020.
Randazzo Luca, Iturrate Inaki, Perdikis Serafeim & Millan Jose (2018). mano: A Wearable Hand Exoskeleton for Activities of Daily Living and Neurorehabilitation. In *IEEE Robotics and Automation Letters*. 3(1), 500-507. https://doi.org/10.1109/LRA.2017.2771329
Shapin Steven (1982). History of Science and its Sociological Reconstructions. In: «History of Science», 20, 157 - 211. DOI:10.1177/007327538202000301
Spennemann Dirk HR. (2023). What has ChatGPT read? The origins of archaeological citations used by a generative artificial intelligence application. In: «arXiv», https://doi.org/10.48550/arXiv.2308.03301.
Thottoli Mohammed M. (2024). Leveraging information communication technology (ICT) and artificial intelligence (AI) to enhance auditing practices. In: «*Accounting Research Journal*», Vol. 37 No. 2, pp. 134-150.
Thompson Neil C., Greenewald Kristjan, Lee Keeheon & Manso Gabriel F. (2020). The computational limits of deep learning. In: «ArXiv», preprint, arXiv:2007.05558.
THRON. (2020). THRON: Digital Content Management Software. Retrieved December 8, 2020, from https://www.thron.com/en/
Xu Wei (2019). Toward Human-Centered AI: A Perspective from Human-Computer Interaction. In: *INTERACTIONS*, July-Augus T 2019 42-46.
Weber Max (1922). Wirtschaft und Sesellschaft, Tubingen 1956 [trad. It. Economia e società. Milano:Donzelli Editore. Ristampa, 2019]
Yates Frances A. *L'arte della memoria*. Torino: Einaudi, 1972.