

September 2025

Automated Media: Challenges and Opportunities for Media Literacy Education

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Recommended Citation

Claes, A., Jacques, J., Descampe, A., & Wiard, V. (2025). Automated Media: Challenges and Opportunities for Media Literacy Education. *Journal of Media Literacy Education Pre-Prints*. Retrieved from <https://digitalcommons.uri.edu/jmle-preprints/43>

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Automated Media: Challenges and Opportunities for Media Literacy Education

Abstract:

This paper offers a theoretical reflection on the evolving landscape of automated media, focusing on how automation and so-called Artificial Intelligence (AI) are reshaping traditional media-related practices and the competences required for media literacy. It examines how automated media technologies, such as recommendation algorithms and generative AI, might reshape the critical skills necessary to navigate a complex digital ecosystem. By framing AI-driven media practices through a social-action perspective and treating media as human activities, we argue that media literacy models should encompass competences related to the operation of computational automata, particularly through the management of inbound and outbound information flows. We propose three categories of operative tasks: implementation, orchestration, and evaluation. In the remainder of this article, we apply the aforementioned theoretical framework to discuss significant challenges for media literacy education. By doing so, we aim to underscore how automated media are reshaping user agency, content creation, and human-machine interaction.

Keywords: Automated Media, Media Literacy, Artificial Intelligence, Computational Automata, Algorithmic Literacy

Recommended citation: Claes, A., Jacques, J., Descampe, A. & Wiard, V. (2025). Automated Media: Challenges and Opportunities for Media Literacy Education. *Journal of Media Literacy Education Pre-Prints*. Retrieved from <https://digitalcommons.uri.edu/jmle-preprints/43>

Introduction

In contemporary times, many technical innovations have paved the way for implementing automated media production, circulation, and use processes. The advent and popularization of these innovations generated a spectrum of discourses in the public, professional and scientific discussion, ranging from exaggerated optimism to alarmism. A notable example of this phenomenon is the series of debates—often tinged with a sense of urgency or even panic—that accompanied the launch of ChatGPT and the subsequent discussions surrounding Artificial Intelligence (AI). These debates are far from new and must be situated within a long history of moral panics and often heated discussions about the effects of technological innovations, particularly concerning audiences considered more vulnerable, such as children (Cricher, 2008; Petley et al., 2013). In this context, it appears increasingly challenging for users of these digital tools to cultivate a critical mindset that not only adequately grasps their functionality but also considers their long-term impact on individuals and societies.

Regardless of the diverse approaches and theoretical frameworks employed, the overall aim of media literacy education is a process of empowerment designed to enable individuals to evolve and act in a mediatized world. The growing accessibility of AI innovations to a wider audience, which sparked intense discussions and varied responses, raised many questions about the importance of media literacy and its implementation. Two main bodies of questions arise in this context:

- *What defines a literate media practice* in the context of AI? How do these emerging technologies transform media interactions, and what implications do these transformations have for the competences needed to engage effectively and meaningfully in a mediated environment?
- *How can media education contribute* to the development of media literacy in relation to AI? This raises several questions about the appropriate concepts and pedagogies for analyzing and deconstructing modern innovation. Do "older" concepts developed during the eras of cinema, print media, and the early internet still hold relevance today? Or is there a need to develop new concepts and methods to foster a new set of media literacy competences focused on AI?

To contribute to the discussions on these matters, it is essential to transcend the boundaries that shape current scientific studies regarding the competences required for utilizing AI-driven technologies. In recent years, multiple attempts have already been made to design literacy models fit for new technologies; models focusing on algorithmic literacy (Mateas, 2005; Le Deuff & Roumanos, 2022), data literacy (Khan *et al.*, 2018; Claes & Philipette, 2020), statistical literacy (Gould, 2017), or, more recently, AI literacy (Long & Magerko, 2020). A significant portion of these works is dedicated to the "*daily*" practices of the "*average*" individual, particularly on the use of recommendation algorithms (e.g. Dogruel, 2021 or Oeldorf-Hirsch & Neubaum, 2023).

However, these technologies are increasingly permeating various sectors, significantly transforming the professional practices of their users. For instance, journalists must navigate algorithm-driven news dissemination, which raises concerns about bias and accuracy while offering the potential for more personalized content delivery. Artists encounter new mediums and tools enabled by algorithms, challenging traditional creative processes and opening up innovative artistic expressions. Educators, too, face the dual impact of algorithmic media: It can enhance personalized learning and access to resources but also raises questions about data privacy and the digital divide. These examples illustrate the complex landscape where algorithm-based media pose significant challenges and opportunities for evolving professional practices.

These works are also characterized by the tendency to focus on the algorithm to the detriment of its interface and context of use. By reifying devices such as classification algorithms and text generators, giving them an almost magical ethos, the risk is losing sight of the semiotic space in which the automated tasks unfold. Few studies have examined the influence of human-machine interaction modalities on the inference processes at the origin of users' algorithmic imaginaries (Rader et al., 2018). Additionally, the use of these technologies tends to be studied in isolation from other traditional media practices, falsely implying that they have achieved a kind of monopoly in the media ecosystem.

Finally, most of these studies adopt a protectionist stance, which is not uncommon in media literacy studies (Buckingham, 1998). According to this stance, plagiarism, filter bubbles, fake news and other biases introduced by “algorithms” are all dangers from which users need protection. Resisting (DeVito et al., 2017) or coping (Dogruel, 2021) is the main mode of action. Albeit developing user literacy may serve practical purposes, such as being able to find correct and relevant information, it also involves nurturing life skills allowing civic engagement in a mediated environment and collective problem-solving (Hobbs, 2010).

Research in media literacy should improve the breadth and depth of their inquiries by considering these technologies in their context of use, among a greater variety of audiences and with a broader normative lens. Moving forward requires an analytical framework that allows us to name, qualify, and organize these media technologies. This article aims to contribute to this work by assuming two initial postulates. First, theoretical work is indispensable to structure the frameworks for analyzing these innovations, placing them within the evolution of an existing field beyond a mere logic of disruption. This theoretical work is key to highlighting “what’s different” about these innovations while emphasizing the fruitful continuities that enable critical thought. In particular, in this article, we draw upon the social-action perspective—which conceptualizes media primarily as human activities—to point out the continuities between artificial intelligence tools and the media that preceded them while also enabling us to highlight the specific challenges posed by these innovations. Second, we contend that structuring this theoretical exploration around automated media is pertinent, as it enriches critical examination and empirical research.

Therefore, the objective of this article is to examine the growing automation of the contemporary media landscape to provide a working definition of automated media. The paper aims to advance the theoretical understanding of automated media by highlighting key issues arising from their use. This conceptual effort lays the foundation for identifying key research directions in media literacy education, particularly those focused on the communicative functions played by AI tools nowadays. Rather than offering a final answer to what constitutes a literate practice in the context of automation, this paper aims to serve as a roadmap for further empirical research. It also highlights the importance of moving beyond a restrictive approach to media education—one that primarily seeks to shield individuals from external dangers. This perspective advocates for fostering informed and critical engagement with computational automata as a means to contribute to a more sustainable media landscape.

Automated Media

Media as Human Activities

One may wonder if the innovations mentioned above qualify as media. While a comprehensive review of the research defining media is beyond the scope of this article, we offer a brief overview to highlight the most compelling perspective: Media are best understood as forms of human activity. Historically, theoretical literature has been built through several waves of reflection and debates to define what constitutes a *media*. The first wave, associated with the era of mass media, emphasized the materiality of media, considering their qualities primarily as *physical entities* (e.g. a newspaper, a poster, a movie, etc.) recognizable in the world (Meunier & Peraya, 2010). After this, semiotic approaches describe media primarily as *sense-making entities*, seeing them as *vehicles facilitating* the exchange of meaning. This perspective broadens the concepts of reading and writing to include both the recording and interpretation of linguistic and non-linguistic signs. It therefore recognizes that literacy extends beyond text to include visual, auditory, and digital elements, which can be encoded and decoded on various material platforms. Critical approaches embodied by the Frankfurt School have stressed that media are *institutions* comprising humans within structures driven by intentions and intersected by power dynamics. This approach foregrounds the notion of media not just as passive conduits of information but also as active entities where human engagement and power relations play a critical role. In the steps of McLuhan (1964/1994), multiple contributions have defined media as *extensions of human faculties*, intersecting media ecology with areas like cybernetics and technology studies. This framework focused on the effects of mediated communication on human thought and societal interactions. To this day, media ecologists emphasize the transformative influence of communication technologies on societal worldviews, prioritizing media's production and technological design over content (McLuhan, 1964/1994; Scolari, 2012; Wiard, 2019).

A less explored avenue is the *social action* perspective on mediated communication, proposed by Anderson and Meyer in 1988, which places social interaction and everyday routines

at the core of communication phenomena and mediated interactions. They argue that meanings are not inherently contained within the content; rather, they are actively constructed within the semantic framework surrounding the content: *"Where we will learn about meaning is in the everyday methods and practices that surround the use of media. (...) The effects of media occur when their content is entered into interpretive strategies that we use and the social action in which we participate"* (Anderson & Meyer, 1988, p. 44-45).

From this perspective, a medium is *"a recognizable human activity that organizes reality into readable texts for engagement"* (Anderson & Meyer, 1988, p. 316). In this context, the word *text* here refers more broadly to a *"bounded set of signs presented for interpretation"* (Anderson & Meyer, 1988, p. 339). The content of a medium is not limited to the combination of "usual" textual and visually coded signs but anything that may stand for something else and can be involved in a sense-making performance. This perspective appears to be the most enriching in the context of AI, as it incorporates the previously mentioned viewpoints while emphasizing media's situated and contextualized nature. Considering media as a practice enables us to explore their role in daily life, their contribution to shaping our understanding of the world, and their impact on human communication. This approach underlines media's interactive and participatory dimension, focusing on the dynamic relationship between their technical, semiotic and social dimensions. This perspective invites a comprehensive examination of media, considering its content and structure and the practices surrounding its use and the meanings it generates in various contexts. For Couldry, considering media as a practice has a clear aim: *"to decentre media research from the study of media texts or production structures (important though these are) and to redirect it onto the study of the open-ended range of practices focused directly or indirectly on media"* (Couldry, 2004, p.117).

Media can therefore be understood as the situated performance of production or reception, where "performance" inherently involves variability—ranging from success to failure and from simple to complex. The notion of performance brings us to competences, the ability to mobilize internal and external resources to carry out intentional actions. Although this concept has limitations and has faced legitimate criticism, when carefully applied and grounded in actual practices, it provides a valuable framework for defining media literacy (Fastrez & Jacques, 2024). Various frameworks have been developed to outline the competences associated with media literacy, and the choice of a definition is not without implications, as each interpretation emphasizes specific issues that can determine the key competences needed to interact with media. When considering media as human activities, a challenge lies in precisely delineating the scope of the activities at stake. This involves identifying the concrete elements that constitute media engagement and determining how these insights can be effectively integrated to analyze media practices and related competences.

In this regard, a particularly interesting contribution is that of Fastrez (Fastrez, 2010; Jacques et al., 2013), who conceptualized media literacy as a set of competences “*required to perform different tasks (reading, writing, navigating, and organizing) on a variety of media considered as informational, technical and social objects*” (Tilleul et al., 2015, p. 76). Media are informational objects designed to represent real or fictional entities using various sign systems. They are also technical objects resulting from technical processes grounded in material forms. Furthermore, media are social objects shaped by individual and institutional agents who use, produce, and distribute them, thereby contributing to the fabric of social life. By integrating these four types of media tasks with the three dimensions of media, the authors established a framework of 12 core tasks (see Figure 1 below). This amalgamation of essential tasks gives rise to a spectrum of media practices.

Figure 1

Matrix Definition of Media Literacy (Tilleul et al., 2015, p. 41)

Media as... Tasks:	Informational dimension	Technical dimension	Social dimension
Reading	Decode, understand and evaluate media		
Writing	Create and disseminate media productions		
Navigating	Search (activity with a pre-established objective) and/or explore (open activity)		
Organizing	Categorize using <i>ad hoc</i> typologies and/or implementing tools for organizing documents/technologies/social relations		

Building on this definition of media literacy, the question arises: How do algorithms and artificial intelligence tools influence the deployment of these activities, and how do they question the relation between the semiotic, technical, and social dimensions of media as practices? It is essential to recognize that the innovations under our scrutiny possess distinct features that set them apart from other media forms. Examining the issue of automation is a promising approach to highlight the unique aspects of media based on algorithms and artificial intelligence.

Automation in the Age of So-Called Artificial Intelligence

The technical progress of artificial intelligence has revitalized the concept of automation, which for a long time had been relegated to the economic and social history of the 20th century. Recently, the concept has received renewed academic and industrial interest, and several monographs have already been devoted to the topic, such as *Automating the News* (Diakopoulos,

2019) or *Automating Inequality* (Eubanks, 2019). Automation is commonly defined as executing a task by a technical device without human intervention. Although simplistic, this definition touches upon the tension point between two fundamental processes: on the one hand, the material organization specific to the development of a technical scheme, and on the other hand, the appropriation of this organized material by the individual. In other words, between what Lévy describes as virtualization and actualization (Lévy, 1995). Contrary to what the term might suggest, the virtualization process does not mean dematerialization but rather an elevation to a potentiality, an ontological transition of a solution anchored in a specific initial problem towards a problematic domain (Lévy, 1995). It involves formalizing a problem in more general terms to enable the detachment of a subjective experience, the development of a more abstract function, and its embodiment in a material exteriority. The extent of the problematic field to which the tool aims to respond varies from one device to another.

In an organized externality, this process crystallizes power relations that become materialized, public, and shareable constraints, which then structure collective subjectivities (Lévy, 1995). This structuring effect on behavior manifests while actualizing the device's virtualities. During the resolution of a specific problem, gestures must be acquired to conform to the device's requirements (Davis, 2020). However, because it does not entirely predetermine the resolution of a problem, the actualization of a tool remains sensitive to a field of multiple forces, including the user's skills and the socio-cultural context within which the usage unfolds. Current public discourses about AI generally emphasize the virtualization process by highlighting the automated task, thereby implying a disappearance of the individual proportional to the degree of automation. However, this line of reasoning is incomplete, as a performance must still be delivered. Rather than erasing the individual from the workflow, these artifacts reconfigure an individual's tasks to engage with the actualization process by distributing action across time and alternative semiotic systems (Norman, 1992).

To describe these reconfigurations, a possibility is to use the notion of *computational agent* used in the field of artificial intelligence rather than the more generic terms of *algorithm* and *AI* overly used in social sciences. A computational agent is a device comprising sensors (to perceive the environment), actuators (to act on the environment), and a program (to determine the agent's behavior) (Russel & Norvig, 2016). These components grant the computational agent what the French philosopher Simondon proposed to call *dual informational autonomy* (Simondon, 1968/2005). This dual autonomy pertains to the information from the program devised before the device's activation (whether an explicit script or a model derived from training data) and the information from evaluating inputs during operation (whether new data feeds the model or data from interaction with a user). However, we find the concept of agent and, more broadly agency, which have generated considerable debate in the social sciences, problematic, as both concepts imply possible intentionality inherent in these technical devices. We therefore prefer to use the

concept of *computational automaton* to refer to how their designers endowed these technical tools with the capacity to reconfigure themselves based on this dual autonomy coined by Simondon.

We can roughly distinguish three generations of computational automata that have marked public opinion and digital practices: so-called *expert systems*, *learning agents*, and *generative AIs*. The transition from one generation to another is characterized by a qualitative leap regarding this dual informational autonomy, amplifying these devices' degree of virtuality. Expert systems, which we define as software that uses a knowledge base (mainly a set of rules) and an inference engine to make decisions, are particularly rigid as they process user information without subsequently adapting their processing rules for the next users. Moreover, the processing rules are “manually” crafted by experts and do not derive from an automated learning phase. Examples of such systems are the ones found in banks to grant credits. Then, *learning agents* are systems that allow for the development of complex inferences within large datasets, enabling them to automatically build processing rules (a *model*) during a learning phase and then apply those rules to new data during a prediction phase. The close entanglement of these learning and prediction phases (through reinforcement learning, for instance) allows for real-time consideration of environmental changes. This no longer consists simply of applying rigid rules to input data but of maximizing utility functions with feedback loops allowing the rules applied to be adapted according to the data provided and produced. A typical example of such an adaptive *learning agent* is a recommender system. Eventually, the current generation of generative AIs (specifically, the associated language models) marks a second notable leap in dual informational autonomy. Although their learning component is not technically far from the one instantiated in a recommender system, their ability to generate natural language gives the impression of a much broader spectrum of operation than analytical systems dedicated to a specific task.

The importance of these qualitative jumps is not solely a function of computing capacity but also stems from the reconfigurations at work in terms of interaction modalities. The increasing virtuality of automated artifacts results in a gradual transition from the user's role to that of the operator. Simondon (2005) pointed out that because of this dual informational autonomy, it is no longer the ongoing task that demands the user's work but everything surrounding it. By transforming the user into an operator, the automaton conditions the actualization process to manipulate and manage incoming and outgoing information flows. The operation of a device is a common practice that did not await the advent of artificial intelligence. However, what is worth noting is the new range of operational tasks that may be deployed.

The points raised thus far aim to provide a general description of the effects of automation from the operator's point of view. The following section aims to transpose these considerations to media practices and literacy through the scope we previously introduced.

Automated Media and Media Literacy

The notion of *automated media* has already been used but has never been precisely defined (Andrejevic, 2020; Napoli, 2014). The term automated media has already been used by Andrejevic (2020) and Napoli (2014). Andrejevic describes automated media as “communication and information technologies relying on computerized processes to shape information production, distribution, and use” (p.29, 2020). Although Napoli never gives us a definition, she also uses the term to refer broadly to socio-technical systems that use algorithms to manage information flows. In both contributions, these systems are conceptualized as a media from an institutional perspective. As we introduced earlier, this critical perspective focuses on how the power dynamics inherent to human organizations shape the circulation of meaning in society. In this particular case, the purpose of the critique is to identify how algorithms affect the constitution, embodiment and enforcement of these power relations through the automated management of information flows. While we obviously take these critical considerations as a starting point, a social-action perspective encourages us to reconsider the ongoing accommodation of these systems by individuals in their daily life. How do the potential effects identified by critical approaches are actualised during sense-making performances? Reflecting on these theoretical insights and guided by the work of Anderson and Meyer (1988), we propose to define automated media as:

Any recognizable human activity that operates a computational automaton to organize reality into readable texts for engagement.

As we said previously, the notion of *text* must be understood broadly. The interface of an automaton, whether a generative AI or a recommendation algorithm, is as important for interpreting its output as what is generally referred to as *content* (be it audio, text, or images). This frame directs the user’s attention and the interpretation process. For instance, previous research has shown that social endorsement characteristics associated with social media posts influence how individuals select content online (Messing & Westwood, 2014).

At first glance, the media literacy framework presented earlier remains applicable to automated media. The core competences can be defined by intersecting the proposed activities with the relevant dimensions. For instance, it is essential to technically “read” an automated medium, which requires understanding its algorithmic functioning and the machine learning mechanisms it employs. Additionally, writing within this context demands consideration of the informational dimension, such as questioning the standardization of writing forms inherent to these tools. Furthermore, navigating and organizing these various automated media requires an awareness of their social dimensions, including the diversity of cultural contexts in which the institutions producing them operate and their long-term collective effects on issues like the authenticity of works or the relationship to language.

Nevertheless, it is important to emphasize that introducing a computational automaton fundamentally alters the nature of the media, which is considered a practice. Writing a text with

ChatGPT differs from writing with a pen, parchment, or word processor. The key difference lies in shifting a significant portion of the user's activity towards operational tasks. These tasks are less focused on the direct organization of reality into readable and actionable texts for engagement than on managing the dual informational autonomy of the computational automaton. In this context, a growing portion of the task involves managing the flow of information around the computational automaton, which is anticipated to process this data and, even in fragmented forms, contribute specific elements to these "readable and actionable texts" that are central to the medium-as-practice concept discussed earlier. We already qualified this process as a shift from "utilization" towards "operation".

In a mediation context, we suggest three types of operative tasks revolving around the management of inbound and outbound information flows, which are a derivative of writing, reading, navigational and organizational tasks that we previously discussed: (1) Implementation, (2) Orchestration, and (3) Evaluation:

- (1) The *implementation* of a computational automaton refers to the configuration of its settings, the monitoring of its behavior and the correction of operational incidents. This implies a technical and informational "reading" of the device and a social "reading" through identifying the norms and biases that influence algorithmic decision-making. "Writing" with automated media manifests through the adjustment of input data. For expert and learning systems, implementation implies altering the input data to steer the output in a specific direction (e.g. the recommendation of a recommender system). Numerous studies document the strategies developed by non-expert users, often based on personal folk theories about the computational automaton's behavior (Bucher, 2017; Eslami et al., 2015; Rader & Gray, 2015). The specificity of a learning system is that input data adaptation can influence the output and retrain or refine the actual processing rules (and their underlying model). In the case of a generative AI, refining the prompt sent to a language model, altering the parameters of a chatbot (e.g. temperature, input tokens limit, instructions) or completely retraining a model is another way to ensure a computational automaton's implementation.
- (2) The *orchestration* of several computational automata requires navigating among them and organizing them to perform a complex task. It can be achieved through their "serialization" or "parallelization". Serialization happens either by chaining multiple systems so that the output of one becomes the input of the next (e.g. generating a text description of an image and using this description as part of a prompt to an image generator) or by creating loops, which entails providing a system with its output as input. In both cases, the operator acts as a transmission belt, adapting the information flow to ensure the next computational automaton can properly understand the generated data. In the case of generative AI systems, developing models and app repositories (e.g. GPT stores) will be a key factor for the extension of orchestration tasks. This topic will be addressed in greater detail later in this paper. Parallelization occurs when several computational automata are pitted against

one another to achieve the same task or orchestrated to perform comparable but slightly different tasks (e.g. monitoring several recommender systems to follow the news).

- (3) *Evaluation* is another core activity of automated media. Depending on the nature of the task at hand, most computational automata will not immediately perform well. Configuring such a tool is often done through a trial-and-error process which involves running several simulations and evaluating the outcomes of the computation process. A similar evaluation can be performed when several computational automata are suitable candidates for a specific task. It seems also important to conduct evaluations concerning the long-term maintenance of these tools to guarantee their future effectiveness, establish means to record and archive the results of past interactions and evaluate tradeoffs in resources and results.

We view these activities as preliminary priority areas for investigation that should be assessed regarding the actual practices of automated media users. Rather than a definitive list of questions raised by these innovative tools, they represent initial avenues derived from theoretical work, highlighting potential areas of friction that could be central to media literacy education efforts in the near future. The final section of this paper aims to further explore the challenges posed by automated media and outline several avenues of inquiry.

A Research Agenda for Automated Media Literacy

Following a social action perspective, sensemaking is an accomplishment of interpretation, providing structure and coherence to reality. Texts are resources for achieving common understanding between individuals. Realizing texts' potential in media practices is a complex endeavor whose success is tightly linked to individual and collective interpretative performances. We have therefore defined automated media as a partial delegation of this performance to a computational automaton through operative tasks.

The framework we have developed so far is a theoretical construct describing what an automated media could be, inferred from the capabilities of existing computational automata. This automation principle we have discussed can take many forms depending on the socio-economic context in which it will proliferate. We can rightly wonder if the automation project being promoted by the industry of Silicon Valley is not in complete contradiction with the core purpose of a media, turning the idea of an automated media into nothing more than an oxymoron. Current research seems to indicate that AI models collapse when trained on synthetic data generated by previous models (Shumailov et al, 2024). Can computational automata contribute to shared and meaningful practices of individuation? Or are they rather adding disorder to an increasingly fragmented media environment? What is needed to actualize a computational automaton into an automated media? The rest of this discussion is dedicated to the development of this issue. In the following sections, we therefore present a research agenda with themes that cut across the three tasks: implementation, orchestration, and evaluation.

Beyond predictive butlers

According to Anderson and Meyer, “*any meaning is a local and partial representation of the socially embedded sense-making performances that can be given*” (1988, p.29). Meaning is, therefore, an emergent property of a semiotic device arising from an interpretative process whose product can evolve over time and circumstances. Context is a determining factor of this interpretative process, a concept not foreign to computational automata. The term usually refers to the text sent in a prompt to a language model, but we can more broadly associate this concept with the data collected to train the computational automaton.

Up until now, the single and only interpretative frame used by commercial computational automata to process “context” has been based on principles of efficiency, optimization and, above all else, prediction. The computational automata aims to identify patterns and reproduce them, with the risk of calcifying practices by perpetually reproducing past events. The commercial intent behind these predictions is to create a personal assistant responding to the urges and desires of its operator. This conceptualization can be traced back to the work of Nicholas Negroponte in the MIT Media Lab, who envisioned computational automata as a well-trained English butler capable of responding to commands and anticipating user needs (1995). His vision later became the foundation of speculative technologies and the techno-utopian philosophy of Silicon Valley.

This has been the common criticism directed at recommendation algorithms. These considerations can be more broadly extended to other forms of computational automata: despite this restrictive interpretative frame of computational automata, can automated media be accommodated in our daily lives and contribute to meaningful practices despite this calcifying interpretative frame?

The predecessors of Negroponte and founders of the Environmental Ecology Lab, Avery Johnson and Warren Brodley, advocated for technologies that were modeled on the classroom rather than the living room, whose purpose was to cultivate new tastes and spark new interests (Morozov, 2024). For instance, for a recommender system, this approach is related to the notion of discoverability, defined in the cultural context by Rioux (2022, p.24, our translation) as “*the ability of an artist or work to reach an online audience, using different tools and techniques, to be present, visible and recommended on the Internet*”.

To ensure meaningful informational discoverability, systems must be capable of understanding what is appropriate in a given context and determining when something is noise to one party but meaningful information to another. Unfortunately, such interpretative capabilities are nonexistent as of now. However, we believe common computational automata can nevertheless partially achieve this purpose by allowing operators what Anderson and Meyer call *prolificacy*, the ability to produce several meanings from the same content with added depth and complexity as time passes and circumstances evolve (1988). Media education activities could seek to address

these issues of meaning-making by helping learners consider the goals and operating modes of computational automata beyond mere efficiency and discoverability, incorporating aspects such as surprise, creativity, or collective experience.

Depth and complexity of operative tasks

We have been trying to locate automated sense-making performances on tasks of implementation, orchestration, and evaluation on the periphery of the computational automaton's actualization process. The form taken by these operative tasks is still unstable and highly contingent upon developments in a rapidly evolving socio-technical sector.

Given the computational resources currently required to train and run statistical models used by computational automata, most applications rely on proprietary models hosted on third-party infrastructures through an “AI as a service” economic model, if the owners of these infrastructures do not directly implement them. Two notable evolutions can be envisioned in the coming years within this socio-technical infrastructure. First, the emergence of small lightweight models, tailored to specific tasks, might enable more actors to benefit from advanced language processing capabilities without needing to mobilize third-party infrastructures. Second, the current development of *model-agnostic programmatic interfaces* (e.g., Langchain, openrouter.ai) allows developers to connect their systems to several models and to choose dynamically which model to interact with based on API constraints. It is still unclear whether graphical interfaces will reflect the capabilities offered by this infrastructure by allowing end users to switch models on the fly. The integration of such built-in orchestration tools could facilitate richer media practices involving the coordination of several agents. Without them, we are more likely to observe the development of a centralized infrastructure, relying on a few key players and their flagship models, thereby locking the user into a restricted application ecosystem.

Depending on how users evaluate and orchestrate automated media, they may be able to develop complex practices. Carefully documenting operative tasks deployed by individuals in a real-world context is, therefore, a critical endeavor. Is the level of media literacy a predictive factor? If that's the case, how does the relation between proficiency in media literacy and automated media practices evolve over time? Do the orchestration of computational automata serve primarily as crutches that are abandoned once the individual is more proficient at performing the task than the device? Or, conversely, does the operation of a computational automaton mean that the user stops developing his or her mastery of the task at hand? Although the example may be far-fetched, should we expect that users would no longer be able to decode social cues in an email because a computational automaton would process it for them beforehand? Media education stakeholders could play a role in the future by helping learners discover alternative computational automata beyond the most popular ones and exploring the possibilities of tinkering with new tools.

Metaphors we live by

Most interfaces of popular commercial AI-integrated applications have been dominated by the “butler” mental models. Computational automata are designed as personal assistants with names, faces, or personality traits. These anthropomorphic cues aim to metaphorically represent the system as a human being, making it more user-friendly (Mori, 1970) and increasing trust (Waytz et al., 2014). Using conceptual metaphors (Lakoff & Johnson, 2003) in Human-Computer Interaction (HCI) to improve user experience is not a novel concept. By allowing users to understand a specific domain in terms of another, more concrete domain, metaphorical projections have proved effective in helping users understand the structure (Nielsen, 1995) and functionalities (Smilowitz, 1996) of digital interfaces.

Linguistic interactions (conversations or commands), historically a common interaction technique, is also a strong anthropomorphic cue. The predominance of linguistic interactions has been further amplified thanks to large language models' natural language processing capabilities. As computational automata become increasingly proficient in complex information-processing tasks, they also get more effective at conveying a sense of agency and social competence (Friedman & Kahn, 1992). Consequently, users are more inclined to attribute skills such as joint attention, empathy, and other pragmatic abilities to these systems. Previous research indicates that users are not completely deceived by these representations, even though they may not be fully aware of their inclination to anthropomorphize the device (Natale, 2021). Furthermore, users often rely on metaphorical projections to develop folk theories about algorithmic devices, helping them make sense of their interactions with these technologies (Eslami et al., 2015; Wu et al., 2019). Even if these mental schemas may not always be technically accurate, they influence users' emotional responses to these technologies and their attitudes toward them (Bucher, 2017).

The analysis of automated media practices cannot go without considering the effect of these interfaces on operators' mental models. Although anthropomorphic cues may deceive users, they may stimulate creativity (Marenko & van Allen, 2016) or encourage engagement with operational features (Harambam et al., 2018). The issue of metaphors could be addressed more directly in media education activities, helping learners critically examine the concepts and terms used to describe these innovations, particularly by revisiting the complex concept of intelligence.

Evaluation

Being able to assess the affordances of a media object critically is a core competence in most media literacy frameworks. Computational automata are no exception, and operators must interpret the procedural interpretation made by the automaton. Doing so means elaborating mental models, classification criteria and performance measurements. When properly chained with other automata, these mental constructs may concern the computational automaton itself or its capabilities. Considering the ongoing lack of transparency in this sector, how do people perform,

if they do, this evaluation process? What are the heuristics and mental models elaborated to justify these decisions? Studies focusing on recommender systems mentioned earlier in this paper have already touched upon this concern. Less research has been conducted on newer technologies to understand better which cues influence user choices and configuration preferences.

This evaluation process does not stop at technical and semiotic considerations. Mediated communication is a social process. As pointed out by Anderson and Meyer:

“It is, first, the process of making sense of content in reference to others. It is the fact that all of one’s identities and memberships are in play at the moment of reception even though a particular response may not reveal them. [...] Second, it is the fact that we interpret content in the connections to others that it provides.” (1988, p.116)

The recommendation of media content is a prime example of this double process. Whether we endorse the recommendation or not, our reaction to it says something about us, about the source of the recommendation, the relationship we wish to establish with it, and the relationship we wish to create with others who may also endorse this kind of recommendation. The meaning of a recommendation is, therefore, a function of both the quality of a recommendation and the connection it creates to other elements. Automated recommender systems are, once again, no different. Bucher has highlighted the affective powers of recommender systems and how users react strongly to inappropriate recommendations because they reflect identities that do not suit them (Bucher, 2017). Language models and other computational automata relying on statistical inferences contribute to similar processes.

AI technologies and language models are the subject of much debate, both online and offline. When and how these technologies are discussed is another core determinant of the heuristics users develop to orient themselves in this ecosystem. By negotiating, endorsing, or resisting the social norms and models these technologies perpetuate, individuals affirm identities and join communities that will later determine the meanings they attach to automated media.

Considering these issues, we believe that research in media literacy should further investigate practices resembling what Verbeek calls meta-agency, "agency directed at shaping one's agency" (Verbeek, 2011, p.87). This entails the configuration of one's technical environment in a manner that ensures the actualization of behaviors that are consistent with one's own goals and values. But how to conceive and nurture an autonomous agency under determining forces? According to Meyers (1989), although complete deliberative rationality is not always accessible, a series of competences can be developed to reinforce self-awareness: memory, introspection, and imagination skills can contribute to identifying and interpreting self-referential responses or affective signals. Media education stakeholders could explore agency in digital environments by encouraging learners to reflect on their intentions when using these tools, their effects on them,

and the importance of stepping beyond conventional paths and default settings to engage more deeply with these technologies.

Conclusion

Rather than wiping the slate clean and producing another theoretical framework, we wished to see how older theoretical notions could be reused to explain new socio-technical configurations. New media does not erase older forms of mediated communication. Previous concerns remain relevant. The challenge is to identify how individuals translate traditional media practices to practices involving operation of computational automata, and the issues arising from this translation. By adopting a social-action perspective, our objective is to direct the debate toward an examination of how individuals generate meaning through these computational automata. Therefore, this theoretical construct attempts to disassociate ourselves from the alluring notion of automation of communication. We aim to distinguish the sense-making performance from the partially automated semiotic process and examine the transition between the two through a magnifying lens. Furthermore, the words we use to address technological and semiotic change in our media ecosystem set the frame of the scientific debate. By providing a vocabulary not contingent on current design trends, we wish to sustain research endeavors moving beyond a defensive critique of existing technologies to proactively inquire into alternative socio-technological configurations (Rieder, 2020).

Individuals are no more passive with automated media than they were with legacy media. Reading, writing, navigating, and organizing remain relevant categories that help individuals decompose how they engage with automated media. However, the gradual shift from direct use towards operating a complex technological environment, knowingly or not, merits our attention. This transition requires competences beyond traditional media literacy frameworks: new skills that allow users to navigate the dual informational autonomy of AI systems, manage information flows, and critically assess their role in shaping their media environment. The outlined conceptualization proposes identifying key operative tasks unique to automated media, i.e. implementation, orchestration, and evaluation. By shifting the analytical lens towards active operative practices, we can study how individuals engage with these systems more nuancedly, requiring a deeper understanding of how computational automata function and influence mediated environments.

This proposal must not be considered a definite answer to the question of what a literate practice should be in our continuously evolving media ecosystem. This proposal must be understood as a roadmap for further field-based qualitative research to develop a grounded understanding of how users create and disseminate meaning with computational automata. Beyond research, this paper is also a reminder that overcoming a protectionist approach to media education where individuals should be protected from external dangers, may be advisable. Without ignoring toxic design practices, supporting the informed and critical operation of computational automata is another way to create a more sustainable media landscape.

References

- Anderson, J. A., & Meyer, T. P. (1988). *Mediated communication: A social action perspective*. Sage Publications.
- Andrejevic, M. (2020). *Automated media*. Routledge.
- Bucher, T. (2017). The algorithmic imaginary: Exploring the ordinary affects of Facebook algorithms. *Information, Communication & Society*, 20(1), 30–44.
<https://doi.org/10.1080/1369118X.2016.1154086>
- Buckingham, D. (1998). Media education in the UK: Moving beyond protectionism. *Journal of Communication*, 48(1), 33–43. <https://doi.org/10.1111/j.1460-2466.1998.tb02735.x>
- Claes, A., & Philippette, T. (2020). Defining a critical data literacy for recommender systems: A media-grounded approach. *Journal of Media Literacy Education*, 12(3), 17–29.
<https://doi.org/10.23860/JMLE-2020-12-3-3>
- Couldry, N. (2004). Theorising media as practice. *Social Semiotics*, 14(2), 115–132.
<https://doi.org/10.1080/1035033042000238295>
- Critcher, C. (2008). Making Waves: Historical Aspects of Public Debates about Children and Mass Media. In K. Drotner & S. Livingstone (Eds.), The International Handbook of Children, Media and Culture (pp. 91- 104). Sage.
- Davis, J. L. (2020). *How Artifacts Afford: The Power and Politics of Everyday Things*. MIT Press.
- DeVito, M. A., Gergle, D., & Birnholtz, J. (2017). “Algorithms ruin everything”: #RIPTwitter, Folk Theories, and Resistance to Algorithmic Change in Social Media. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, 3163–3174.
<https://doi.org/10.1145/3025453.3025659>
- Diakopoulos, N. (2019). *Automating the news: How algorithms are rewriting the media*. Harvard University Press.
- Dogruel, L. (2021). What is algorithm literacy? A conceptualization and challenges regarding its empirical measurement. In M. Taddicken & C. Schumann (Eds.), *Algorithms and communication* (pp. 67–93). <https://doi.org/10.48541/dcr.v9.3>
- Eslami, M., Rickman, A., Vaccaro, K., Aleyasen, A., Vuong, A., Karahalios, K., Hamilton, K., & Sandvig, C. (2015). “I Always Assumed That I Wasn’T Really That Close to [Her]”: Reasoning About Invisible Algorithms in News Feeds. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 153–162.
<https://doi.org/10.1145/2702123.2702556>
- Eubanks, V. (2019). *Automating inequality: How high-tech tools profile, police, and punish the poor* (First Picador edition). Picador St. Martin’s Press.
- Fastrez, P. (2010). Quelles compétences le concept de littératie médiatique englobe-t-il ? Une proposition de définition matricielle. *Recherches en Communication*, 33, 35-52.
- Fastrez, P., & Jacques, J. (2024). Documenting media practices to define media literacy competence : A qualitative approach. In P. Fastrez & N. Landry (Éds.), *Media Literacy and Media Education Research Methods : A Handbook* (pp. 23-44). Routledge.

- Friedman, B., & Kahn, P. H. (1992). Human agency and responsible computing: Implications for computer system design. *Journal of Systems and Software*, 17(1), 7–14.
[https://doi.org/10.1016/0164-1212\(92\)90075-U](https://doi.org/10.1016/0164-1212(92)90075-U)
- Gould, R. (2017). Data Literacy is Statistical Literacy. *Statistics Education Research Journal*, 16(1), 22-25.
- Harambam, J., Helberger, N., & van Hoboken, J. (2018). Democratizing algorithmic news recommenders: How to materialize voice in a technologically saturated media ecosystem. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2133). <https://doi.org/10.1098/rsta.2018.0088>
- Hobbs, R. (2010). *Digital and Media Literacy: A plan of Action* (Communications and Society Program). The Aspen Institute. <http://www.knightcomm.org/digital-and-media-literacy-a-plan-of-action/>
- Jacques, J., Fastrez, P., & De Smedt, T. (2013). Organising Media as Social Objects : An exploratory assessment of a core media literacy competence. *The Media Education Research Journal*, 4(1), 42-57.
- Khan, H. R., Kim, J. et Chang, H.-C. (2018). *Toward an Understanding of Data Literacy*. <https://www.ideals.illinois.edu/handle/2142/100243>
- Lakoff, G., & Johnson, M. (2003). *Metaphors we live by*. University of Chicago Press.
- Le Deuff, O., & Roumanos, R. (2022). Enjeux définitionnels et scientifiques de la littératie algorithmique: Entre mécanologie et rétro-ingénierie documentaire. *tic&société*, 15(2–3), 325–360. <https://doi.org/10.4000/ticetsociete.7105>
- Lévy, P. (1995). *Qu'est-ce que le virtuel ?* La Découverte.
- Long, D., & Magerko, B. (2020). What is AI Literacy? Competencies and Design Considerations. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16.
<https://doi.org/10.1145/3313831.3376727>
- McLuhan, M. (1994). *Understanding media: The extensions of man*. MIT-Press. (Original work published 1964)
- Marenko, B., & van Allen, P. (2016). Animistic design: How to reimagine digital interaction between the human and the nonhuman. *Digital Creativity*, 27(1), 52–70.
<https://doi.org/10.1080/14626268.2016.1145127>
- Mateas, M. (2005). Procedural literacy: educating the new media practitioner. *On the Horizon*, 13(2), 101-111. <https://doi.org/10.1108/10748120510608133>
- Messing, S., & Westwood, S. J. (2014). Selective Exposure in the Age of Social Media: Endorsements Trump Partisan Source Affiliation When Selecting News Online. *Communication Research*, 41(8), 1042–1063. <https://doi.org/10.1177/0093650212466406>
- Meunier, J.-P., & Peraya, D. (2010). *Introduction aux théories de la communication* (3rd ed). De Boeck supérieur.
- Meyers, D. T. (1989). *Self, society, and personal choice*. Columbia University Press.
- Mori, M. (1970). Bukimi no tani (the uncanny valley). *Energy*, 7(4), 33–35.
- Morozov, E. (2024, June 28). The AI we could have had. *Financial Times*.

- Napoli, P. M. (2014). Automated media: An institutional theory perspective on algorithmic media production and consumption. *Communication Theory*, 24(3), 340-360.
- Natale, S. (2021). *Deceitful media: artificial intelligence and social life after the Turing test*. Oxford University Press.
- Negroponte, N. (1995). *Being digital* (1st ed). Knopf.
- Nielsen, J. (1995). *Multimedia and Hypertext: The Internet and beyond*. AP Professional.
- Norman, D. A. (1992). Design principles for cognitive artifacts. *Research in Engineering Design*, 4(1), 43-50. <https://doi.org/10.1007/BF02032391>
- Oeldorf-Hirsch, A., & Neubaum, G. (2023). What do we know about algorithmic literacy? The status quo and a research agenda for a growing field. *New Media & Society*, 27(2), 681–701. <https://doi.org/10.1177/14614448231182662>
- Petley, J., Critcher, C., Hughes, J., & Rohloff, A. (2013). *Moral Panics in the Contemporary World*. Bloomsbury Publishing.
- Rader, E., & Gray, R. (2015). Understanding User Beliefs About Algorithmic Curation in the Facebook News Feed. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 173–182. <https://doi.org/10.1145/2702123.2702174>
- Rader, E., Cotter, K., & Cho, J. (2018). Explanations as Mechanisms for Supporting Algorithmic Transparency. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1–13. <https://doi.org/10.1145/3173574.3173677>
- Rieder, B. (2020). *Engines of order: A mechanology of algorithmic techniques*. Amsterdam University Press.
- Rioux, M. (2022). La découvrabilité va-t-elle devenir essentielle pour se frayer un chemin dans notre monde hyperconnecté ? *NECTART*, 15(2), 22–30. <https://doi.org/10.3917/nect.015.0022>
- Russell, S. J., & Norvig, P. (with Davis, E., & Edwards, D.). (2016). *Artificial intelligence: A modern approach* (Third edition, Global edition). Pearson.
- Scolari, C. A. (2012). Media Ecology: Exploring the Metaphor to Expand the Theory. *Communication Theory*, 22(2), 204–225. <https://doi.org/10.1111/j.1468-2885.2012.01404.x>
- Shumailov, I., Shumaylov, Z., Zhao, Y., Papernot, N., Anderson, R., & Gal, Y. (2024). AI models collapse when trained on recursively generated data. *Nature*, 631(8022), 755–759. <https://doi.org/10.1038/s41586-024-07566-y>
- Simondon, G. (2005). *L'invention dans les techniques: Cours et conférences*. Seuil. (Original work published 1968)
- Smilowitz, E. D. (1996). Do metaphors make Web browsers easier to use. *Conference Proceedings of Designing for the Web: Empirical Studies*.
- Tilleul, C., Fastrez, P., & De Smedt, T. (2015). Evaluating Media Literacy and Media Education Competences of Future Media Educators. In S. Kotilainen & R. Kupiainen (Eds.), *Reflections on Media Education Futures. Contributions to the conference Media Education Futures in Tampere, Finland 2014* (pp. 75–89). Nordicom.
- Verbeek, P.-P. (2011). *Moralizing technology: understanding and designing the morality of things*. The University of Chicago Press.

- Waytz, A., Heafner, J., & Epley, N. (2014). The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. *Journal of Experimental Social Psychology*, 52, 113–117. <https://doi.org/10.1016/j.jesp.2014.01.005>
- Wiard, V. (2019). News Ecology and News Ecosystems. *Oxford Research Encyclopedia of Communication*. <https://doi.org/10.1093/acrefore/9780190228613.013.847>
- Wu, E. Y., Pedersen, E., & Salehi, N. (2019). Agent, Gatekeeper, Drug Dealer: How Content Creators Craft Algorithmic Personas. *Proceedings of the ACM on Human-Computer Interaction*, 3(219), 1–27. <https://doi.org/10.1145/3359321>