Journal for Re Attach Therapy and Developmental Diversities
eISSN: 2589-7799
2022 December; 5 (2): 124-144

# Modeling The Behavior Of Social Machines According To Cybernetics Research

**Dobashi Mohammad Mohsen[1*], Rahmanzadeh Seyed Ali[2], Aqili Seyed Vahid[3], Hashem Zehi Nowroz[4], Keya Ali Asghar[5]**

[1] * Ph.D. Student, Islamic Azad University, North Tehran Branch, Tehran, Iran, Mohsen.Dobashi@Gmail.Com
[2] Assistant Professor, Department Of Social Communication Sciences, Islamic Azad University, North Tehran Branch, Tehran, Iran Salirahmanzadeh@Yahoo.Com
[3] Associate Professor, Department Of Social Communication Sciences, Islamic Azad University, Central Tehran Branch, Tehran, Iran , Seyyed_Vahid_Aqili@Yahoo.Com
[4] Assistant Professor, Department Of Social Communication Sciences, Islamic Azad University, East Tehran Branch, Tehran, Iran , No_Hashemzehi@Yahoo.Com
[5] Associate Professor, Department Of Journalism, Allameh Tabatabai University, Tehran, Iran , Keya@Atu.Ac.Ir

***Corresponding Author:** Dobashi Mohammad Mohsen
* Ph.D. Student, Islamic Azad University, North Tehran Branch, Tehran, Iran, Mohsen.Dobashi@Gmail.Com

**Abstract**

The social machine refers to a combination of humans and communication technologies through the cooperation and interaction between which social structuration is formed. In this concept, machines represent technological communication tools, and humans represent people who have individual or social actions using these tools. In the ubiquitous computing era where artificial intelligence applications are used, social machines act as a powerful framework for understanding and interpreting interactions in social relations, leading to the addition of topics including socio-algorithmic ecosystems or computational social sciences to the social science literature. Moreover, researchers have largely used it to analyze interactions between people and model different levels of communication. On a more specific note, social machines can be used as a framework for policy-making in the field of communication and its relevant technologies. The present study provided a five-point framework for classifying influence processes in socio-algorithmic ecosystems and examined several aspects of social machines from a cybernetic perspective. For this purpose, the factors affecting the concept of social machines were extracted from different sources using an analytical-inferential method and then analyzed and combined. Next, a conceptual model was defined as a framework for structurally evaluating social machines according to the findings. Moreover, the interactions between people and algorithms were formed and categorized through the understanding of social machines according to cybernetics research. Case studies were used to explain how people and algorithms interact in online social networks and algorithmic decision-making systems and describe how this framework can guide scientists in further research and help managers in policy-making.

**Keywords**: Social machines, Sociotechnical systems, Algorithmic bias, cybernetics, Artificial intelligence

## 1. Introduction

The social machine is a new concept in the field of social technologies and refers to a combination of humans and communication technologies. According to this concept, a new and dynamic space can be formed for performing social activities through the cooperation and interaction between humans and communication technologies. Social machines originally operate based on the interaction and cooperation between humans and computing systems. In these machines, humans interact with each other and technologies and perform their activities using communication technologies such as social networks, blogs, online collaboration platforms, and so on. For example, on social networks such as Facebook, Twitter, or LinkedIn, users can share their information, opinions, experiences, and resources and participate in group discussions and activities. These interactions are classified as social machines.
Consolidation of the position of the Internet as the main communication network and its acceptance by the society following the development of hardware, increasing the efficiency of computing systems, increasing the rate of use of smartphones, etc., which has led to the phenomenon of social data creation and the formation of new communication and information processes. It has affected all aspects of society. Algorithmic decision-making systems, artificial intelligence algorithms, social network platforms, data sharing systems, forecasting tools, and decision-making tools lead to changes in social behaviors at different levels of society, which must be carefully followed in order to understand them accurately. Using social machines, people can collectively make decisions and carry out collaborative activities in different fields to achieve common goals. Also, this concept enables us to better understand the effects of technologies on societies and social, cultural, economic, and political systems and to provide new solutions for existing and coming challenges.

One of the most intensive consequences of technological advancement is the degree of digitalization of social processes, making decision-making difficult, i.e. a condition that was not understood before. Although access to the Internet on different devices facilitates information exchange in different situations, computational capabilities and the progress of data storage technologies lead to the constant transformation of individual behavior into cloud data being processed and stored. Therefore, algorithms, society, and communication combine in complex and continuous ways, creating new forms of social ecosystems. Tim Berners-Lee, the founder of the World Wide Web, defined such ecosystems where individuals and algorithms participate and interact as social machines (Shadbolt et al. 2019; Berners-Lee 1999). Social machines are not machines per se, nor do they depict mechanistic deterministic phenomena. On the contrary, they are systems of systems in which individuals and algorithms are separated from their materiality, forming complex interaction patterns (J. A. Hendler and Mulvehill 2016).
Social networks, algorithmic decision-making (ADM) systems, and search engines are all types of social machines where individuals, software, and hardware are constantly interacting and resulting in emergent system states.
As a result, social machines are a concept that provides new opportunities for social interactions by combining individuals and communication technologies. This concept can be a basis for research and policy-making in the field of communication and media to know the effects of technologies and the opportunities provided by them at different levels of society.

**2) Research goal**

Although researchers have greatly analyzed socio-algorithmic systems as social machines, the policy-making of these systems in a similar framework has not been examined so far. Studies mainly focus on investigating the politics of separate parts of these systems, such as legislation, algorithmic function, or user behavior. Therefore, there is a significant knowledge gap in understanding how processes interact and influence each other, as well as how they change systems from a holistic perspective. For example, there are many questions about how changes in recommendation systems on social media platforms affect circulated content or how web mapping services such as Google Maps change traffic patterns and user consuming habits (Shadbolt et al. 2019; J. Hendler and Berners-Lee 2010; Burégio, Meira, and Rosa 2013; Cristianini and Scantamburlo 2020).
Understanding the aspects of social sciences in social machines enables us to improve our understanding of social effects and interactions in the digital world and the function of machines in this context. Understanding the aspects of social sciences in social machines mainly includes:

- **Human behavior and interaction:** Understanding human behavior and interaction in social machines is of great importance. For example, studying the factors influencing an individual's decision to disseminate or choose content, the effect of social networks on the formation of public opinions and social behavior, the role of recommendation algorithms in intensifying the separation of people or interaction between them, the convergence or differences of opinions and social motives, etc.
- **Power and influence:** Social machines can greatly influence people's behavior and opinions. Investigating how these machines affect people's decisions and collective behavior, how they intensify or reduce social differences, and what opportunities and challenges are caused by the concentration of power in social media platforms can provide a better understanding of the factors influencing social machines.
- **Trust and Security:** Users usually expect their personal information and communications to be secure in digital social environments. Studying the issues such as user privacy, exploitation of users' data, and management of information security in social machines can help maintain users' trust and security.
- **The role of organizations and policymakers:** Studying the role of organizations and policymakers in regulating and controlling social machines, determining the relevant rules and regulations, the influence of policies and political decisions on the content and behavior of users, and analyzing the social and political effects of these systems can bring a better understanding of the role of organizations and policymakers in this field.

Understanding the aspects of social science in social machines enables us to provide more appropriate approaches, policies, and solutions to manage and organize these systems to improve social and political interactions in the digital world. Understanding the aspects of social science in social machines in cases such as the above is necessary for three reasons:
(1) The need for a new level of knowledge is felt in this department, which studies with an interdisciplinary nature and with an additional and holistic view on how algorithms affect society. Most of the studies in this field are case-specific and face serious methodological and processing limitations due to the predominance of the data-oriented view as well as the predominance of the engineering technical view in data-oriented.
(2) The policy view in this field emphasizes more on intervention and tries to find ways to intervene in social-algorithmic systems based on law. This policy concern attempts to reduce the unjust, unethical, and illegal outcomes of these systems, but there is no framework to guide such interventions.

(3) System designers are interested in understanding how the insertion of a technical component, or the presence of regulation, might directly or indirectly affect the function of their socio-algorithmic ecosystem. This study develops the theoretical foundation for answering questions such as the above by introducing a framework that classifies the rules of socio-algorithmic ecosystems. This framework reduces the existing complexity of the interpretation of social processes in social machines. It achieves this by seeking answers to the following research questions:

- How can researchers analyze and classify social processes in social machines from a systemic perspective?
- How can researchers use the above framework as a guide for understanding socio-algorithmic ecosystems?

**3) Research contributions**

- This research studied social machines under a cybernetic framework to describe the characteristics of systems to show that social machines can be a valuable tool for the ecosystem and help managers in determining policies and policy-making in the field of communication and its relevant infrastructure.
- This study explained the framework of social machines to prove the framework for the normative statement that technology is not a neutral participant in society. In turn, algorithmic implementations transform social functions in unexpected ways. So, they must be considered in decision-making.

**4) Method**

The present study was carried out using an analytical-inferential method. This method is a combination of the ijtihad method and thematic analysis. Using the ijtihad method, the data are scientifically collected from various sources, examined in terms of documentation and concept, and implication, and analyzed in rational steps to create initial codes and then, combine them to create sub-categories. That is, using the ijtihad method, the stages from data collection to initial and secondary coding in the thematic analysis are followed, and initial codes and sub-categories are extracted but the next steps of thematic analysis are not followed because in the ijtihad method typically used in the field, to infer an order, first all relevant data are searched. This step is called data review in thematic analysis. Next, the documents are reviewed (Khalili, Pour-Ezzat, and Jafari 2018). In this method, after the problem statement, the textual data related to the topic studied are examined, the discussed categories are categorized, and the findings are categorized by forming categories and themes.

**5) Research background**

- **Social machines**

  Social machines are a concept referring to a system or network where humans and machines cooperate and interact to achieve specific goals or perform tasks. Social machines combine human intelligence, social interactions, and technological capabilities to find new ways of collective problem-solving, knowledge-sharing, and decision-making. The term "social machine" was coined by Berners-Lee, the inventor of the World Wide Web. He defined social machines as a way to harness the collaboration between humans and machine intelligence to solve complex social challenges. There are various forms of social machines, such as web-based communities, crowdsourcing platforms, collaborative systems, social media, social networks, etc. These systems use collective intelligence and human engagement by facilitating technologies, to generate valuable outputs and insights. In a social machine, people interact with each other and with automated systems, creating a dynamic ecosystem where information is shared, ideas are exchanged, and actions are coordinated. Composing human and machine capabilities in social machines enables efficient problem-solving, innovation, and collective decision-making. In general, the concept of social machines emphasizes the synergy between human intelligence and machine and highlights the potential of joint and collective efforts to address complex social challenges and improve various aspects of human life.

Social machines are considered a model for examining, evaluating, and understanding socio-algorithmic ecosystems, mainly influenced by computer science thought. It emerged as a scientific solution for dealing with excessive social datafication and enhancing the interconnectedness of social and technological processes (J. Hendler and Berners-Lee 2010). As a scientific model, it aims to combine computational, technological, and social processes under the same framework (Burégio, Meira, and Rosa 2013), supporting explanations, which are beyond the traditional boundaries set by scientific disciplines. In social machines, people and technology are both participants in systemic processes. By adopting systems theory, scientists can trace the inputs, outputs, interactions, constraints, and states forming a particular social machine (Meira et al. 2011) to correctly understand what is human and what is artificial. This, in turn, reduces complexity when studying phenomena and facilitates the practical understanding of socio-algorithmic ecosystems.

- **The approach of social machines to social science research**

What distinguishes social machines from other research is their approach to the interaction between humans, computers, and artificial intelligence interaction. Other approaches address collective intelligence, crowdsourcing, web-based communities, social structurization, etc. separately, mostly leading to the development of abstract frameworks. For example, contribution itself is an issue that seriously affects the perspective from which the discussion is started, that is determining whether social contribution is discussed as a sociological matter or it is considered from a technical perspective in the design of the platform algorithm. Authenticating each can shift the direction of the discussion. In this sense, the contribution of social machines is similar to approaches such as actor-network theory (ANT), which aims to describe complex socio-technological processes by placing humans and technology on the same level (Latour 2005b). Such frameworks aim to help researchers explore ecosystems rather than to provide structured theoretical knowledge (Moll 2010). However, the social machine framework has the following distinguishing properties (Shadbolt et al. 2019):
(1) It assumes that the system reinforces inputs due to the pervasiveness and effectiveness of technology;
(2) Unlike networks in ANT, whose formation background has not been investigated, the studied ecosystem is the result of a design process (Latour 2005a).

(3) The ecosystem has specific goals and features, which arise from the interactions between humans and technologies.
The abovementioned systemic perspective and the roles of humans and technologies are what distinguish social machines from critical data studies and sociotechnical systems approaches. Both critical data studies and sociotechnical systems theories examine the necessary epistemological concepts and questions that must be answered to understand and shape the ethics, manifestation, and influence of technology in society (Iliadis and Russo 2016; Dalton, Taylor, and Thatcher 2016; Selbst et al. 2019; Norman and Stappers 2015). In contrast, social machines do not theorize specific cases but provide an ecosystemic framework placing key participants in the interaction of technology and society and their interrelationships descriptively to help such approaches in their scope. This framework can be useful for scientists (from social sciences to engineering) to develop and evaluate narratives and conceptualization of sociotechnical phenomena (Papakyriakopoulos 2022a).
Numerous phenomena have been studied through the lens of social machines so far. Crowdsourcing platforms, online social networks, smart cities, Internet of Things (IoT) applications, and web-based communities are only some of the cases analyzed by this paradigm, mainly for computer-scientific objectives (Ahlers et al. 2016; Shadbolt et al. 2019; Burégio, Meira, and Rosa 2013; Martin and Pease 2013). Nevertheless, the structured definition and analysis of social machines is not a trivial task, and since humans and technology adopt various roles, goals, and behaviors it is difficult for researchers to develop absolute classification schemes for ecosystems that are quite distinct from each other. To this end, researchers have suggested various frameworks and classifications for the evaluation of social machines. For example, Burégio et al. (2013) classify social machines based on the contribution of systems, their motivation, as well as who participates, and how (Burégio, Meira, and Rosa 2013). Similarly, De Roure et al. (2015) presented methods on what to observe in social machines and how and investigate the prominent similarities and differences of systems (De Roure et al. 2015; Smart, Simperl, and Shadbolt 2014).
Despite existing ambiguity, this framework provides new opportunities when dealing with social ecosystems to make it possible to apply new scientific findings on complex systems to understand and normatively assess how social machines affect society. Researchers have developed theoretical foundations for evaluating the contribution of social machines to society (Palermos 2017) as well as the design principles for social machines from the perspectives of ordinary people and participatory movements (Papapanagiotou et al. 2018). However, a great number of social processes in social machines have not been extensively studied under this paradigm, a gap that this study aims to bridge
.

- **Examining society's action toward social machines**

The study of society's action toward social machines includes the investigation of how people and communities interact and behave in these systems. How users interact with social machines, the dynamics and level of social contribution, the ability of a society to create an approach and make decisions, and social effects including the role of systems in social issues, shaping public opinion, facilitating social changes, and helping to disseminate information, issues such as privacy, security, fairness, transparency, and user empowerment and other significant aspects in community studies are of topics that can be examined in the interaction between humans, artificial intelligence, and social networks.
Numerous phenomena have been studied through the lens of social machines so far. Crowdsourcing platforms, online social networks, smart cities, Internet of Things (IoT) applications, and web-based communities are only some of the cases analyzed by this paradigm, mainly for computer-scientific objectives (Ahlers et al. 2016; Shadbolt et al. 2019; Burégio, Meira, and Rosa 2013; Martin and Pease 2013). Nevertheless, the structured definition and analysis of social machines is not a trivial task, and since humans and technology adopt various roles, goals, and behaviors it is difficult for researchers to develop absolute classification schemes for ecosystems that are quite distinct from each other. To this end, researchers have suggested various frameworks and classifications for the evaluation of social machines. For example, Burégio et al. (2013) classify social machines based on the contribution of systems, their motivation, as well as who

participates, and how (Burégio, Meira, and Rosa 2013). Similarly, De Roure et al. (2015) presented methods on what to observe in social machines and how and investigate the prominent similarities and differences of systems (De Roure et al. 2015; Smart, Simperl, and Shadbolt 2014).
Despite existing ambiguity, this framework provides new opportunities when dealing with social ecosystems to make it possible to apply new scientific findings on complex systems to understand and normatively assess how social machines affect society. Researchers have developed theoretical foundations for evaluating the contribution of social machines to society (Palermos 2017) as well as the design principles for social machines from the perspectives of ordinary people and participatory movements (Papapanagiotou et al. 2018). However, a great number of social processes in social machines have not been extensively studied under this paradigm, a gap that this study aims to bridge.
Crowdsourcing platforms are an example of a phenomenon made possible by new technologies such as the Internet, smartphones, social media, artificial intelligence, and the Web. They connect people on a small scale to accomplish a small mission. The key here is collaboration and organization. Social changes occur not just by disseminating information or collecting donations through a network. A society (in any legal form) must be formed so that it can reproduce itself according to its goal, and the achievement of the goal needs information, motivations, and culture to be aligned. Social processes may become larger and new ones may be activated to solve problems, enhance reality, generate new value, and disrupt the existing function.

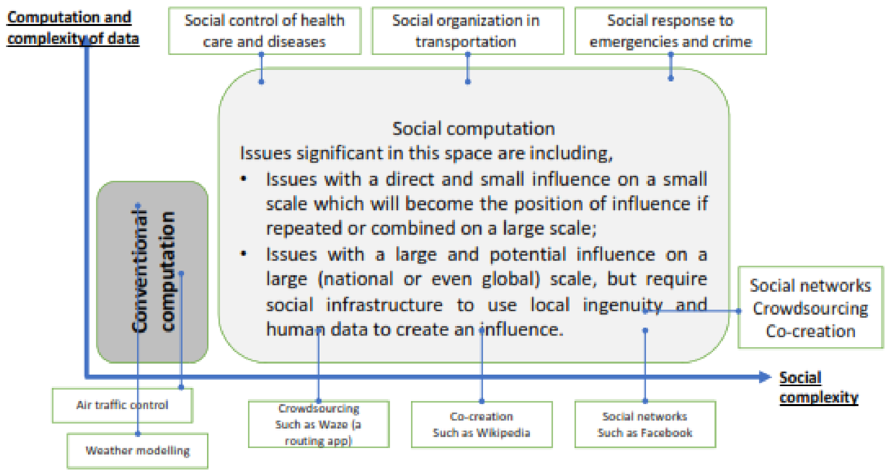



**Figure 1 –** Increase of complexity in computation and social interaction

Figure 1 shows the dimensions along which growth has taken place to enable social machines. First, the computational complexity (both in terms of software and hardware) and the amount of data increase, as shown along the vertical axis. These increases raise very difficult problems in terms of safety and data volume, from air traffic control to weather pattern modeling. The horizontal axis shows the increase in social complexity as technology allows dispersed communities to collaborate to solve problems and issues. More complex computational requirements and more complex social conditions allow for solving problems from a different perspective. This point is where both computation and social interaction are more complex than what current systems can support. However, social machines provide new solutions to manage complex and difficult problems. Social computing can make significant changes in problems in the fields of health, transportation, or security. For example, Uber, as a foreign case, or Snap and Tapsi, as domestic cases, are examples of solving problems in the field of transportation using social computing.
Social machines are co-created by human participants and their technological components, so it is right to use the term co-creation here. Meanwhile, there is no line separating humans and technology, and it is not acceptable to envisage such a line from the social machine perspective. To better understand the issue (as mentioned in Figure 1), it should be noted that a precise idea of the social machine is born in conditions where there are increased data and increased complexity of computation, along with the increased social complexities. In fact, one can say that technology practically allows certain features of social complexities to emerge.
Researchers have extensively studied social machines, unveiling the features and behaviors constituting these systems. However, most studies are case-specific. A set of studies have analyzed the behavior of social groups under the influence of algorithms to show the algorithmic influence on public thoughts and behaviors (Pariser 2011; Bakshy, Messing, and Adamic 2015; Barberá et al. 2015). Other studies have examined information dissemination and opinion formation (Yang 2016; Faris et al. 2017; Stieglitz and Dang-Xuan 2013; Tufekci and Wilson 2012; Shahrezaye et al. 2019). Some studies have tried to understand the features of true or false information dissemination by non-real users in social machines such

as social media or search engines. (Del Vicario et al. 2016; Vosoughi, Roy, and Aral 2018; Ferrara et al. 2016; Papakyriakopoulos, Serrano, and Hegelich 2020). Given this, many researchers investigate how people in power use personalized advertisements to influence people's minds and whether they affect people's social actions and the electorate (Endres 2016; Kruikemeier, Sezgin, and Boerman 2016; Schipper and Woo 2018).

The emergence of social computation has also led to the generation of additional data sources that can be used by decision-makers. In addition to classical systems used in fields such as mechanical and electrical engineering and weather forecasting, new systems are being developed for various purposes such as vehicles, health care, economics, finance, employment, policing, and public administration with human computation, being of increasing importance. These systems use data-intensive algorithms and create inferences about individuals that were not possible before. Most researchers who develop these models are mainly interested in testing their efficiency and accuracy compared to other models and human factors. Other researchers focus on the ethical consequences of these methods: whether they are fair or discriminatory, how biases can be mitigated, and how these systems should be regulated (Buolamwini and Gebru 2018; Bolukbasi et al. 2016; Barocas, Hardt, and Narayanan 2017; Dressel and Farid 2018; Erickson et al. 2017). Explaining and understanding algorithms is not only related to justice and ethics but also to accountability and transparency. Given that legal frameworks, algorithmic design, and algorithmic influence interact with each other, scientists try to pose the right questions to be answered. To this end, researchers analyze the interaction between data regulation, accountability, ethics, and the right to explanation (Wachter, Mittelstadt, and Russell 2017). Additionally, they seek to unveil further cases of algorithmic bias and to identify further challenges in algorithmic fairness to form regulations and systems that are in accordance with social imperatives (Mehrabi et al. 2021; Chouldechova and Roth 2018; Bird et al. 2019). This enhances the importance of understanding social machines for making policies and determining communication policies.

Although the features of social science in social machines have been analyzed by many researchers, the abovementioned shows that social processes are not only of high complexity but also appear in numerous parts of different social machines, indicating that there are many unknowns in social machines, which wait to be discovered and understood. The most integrated approach to this topic comes from the newly emerged field of machine behavior, which focuses on the study of intelligent machines as a class of actors with specific behavioral patterns and ecology. Accordingly, this field attempts to answer how the introduction of artificial intelligence algorithms influences society, and which social factors form the integration of algorithms in society and examines the set of human, social, and technological constituting social processes in socio-algorithmic ecosystems (Rahwan et al. 2019).

- **Social machine cybernetics**

  Cybernetics is multidisciplinary. It is a concept originally proposed by Norbert Wiener in the 1940s. Wiener derived this word from the Greek word "cybernetike", which means to steer or to support. In a general sense, cybernetics is the study that interactively examines the relations between machines, humans, and living systems.

Cybernetics tries to act as a control process and provide useful models and tools to analyze and improve systems. This discipline has been developed based on mathematical principles as well as philosophical and historical concepts. In cybernetics, systems communicate with their environments interactively and in a feedback manner and attempt to reach a desirable and targeted state by intervening and setting up their inputs. This approach can be applied to living systems such as animals and humans as well as artificial systems and machines. Cybernetics is used in various fields such as control engineering, artificial intelligence, robotics, neuroscience, and biological sciences. Considering the advancement of technology and network connections, cybernetics has become very important as a strategy for studying and optimizing complex systems in the modern world.

Systems theory and cybernetics are important as they provide models in which there is no need for the two components of agency and teleology to investigate complex behaviors. In the field of complex systems, researchers have been common in the following issue: How to describe complex physical, biological, human, and even social phenomena and behaviors abstractly and in the form of a system. What is important in systems theory is that behavior is the result of the system's activity, not an internal factor. If a system has some features or conditions, targeted behaviors will appear in it. Some of such systems have the feature of self-regulation, which are called cybernetic systems. Cybernetic systems refer to systems with the ability to receive, store, and process information to control themselves. One of the key components in cybernetic systems is the possibility of using information and feedback. By receiving feedback, the systems behave purposefully and obtain the ability to self-regulate.

To discover social processes in social machines, there is a need for a framework providing an overview of how socio-algorithmic ecosystems behave. Cybernetics is the most prominent scientific theory that deals with systems and their behavior. Cybernetics does not study systems only by looking at them as a set of inputs, outputs, and interacting components but, unlike other theories, wants to understand systems as they exist in a given environment, how their states change according to the environment, what systems' identity is, which constraints exist, what the processes of feedback, communication, and control leading to the transformation and self-organization of the system are (Wiener 1961; Ashby 1957; Von Foerster 2007; Mead 1968; Rosenblueth, Wiener, and Bigelow 1943).

In cybernetics, communication is not limited to human or animal communication, which includes the explicit exchange of symbols and signs. Any kind of interaction or influence between elements, systems, or environment can be considered information that updates related entities about the differences taking place, resulting in a higher form of communication. Understanding the difference is of importance in cybernetics because it can discover operators and operants in the system, i.e. what changes what and how? Studying feedback loops enables the cyberneticist to discover the purpose of elements and systems, as well as their specific structure and intrinsic organization (Bateson 1972; Novikov 2016; Ruesch et al. 2017; Ashby 1957; Rosenblueth, Wiener, and Bigelow 1943).

Cybernetics, as a framework, has already been used to investigate the study of politics and the study of socio-technological processes. Karl Deutsch argued that cybernetics provides the vocabulary required for understanding political systems and power relations while being economically and empirically valid (McLuhan and Deutsch 1965). This is because politics can be considered processes coordinating system components. Similarly, Luhmann also argued the coordinating role of technology in society and stated that the function of media and technologies such as artificial intelligence can be set as communication vocabularies, leading to the creation of systems of heterogeneous components, albeit of different nature than that of culture (Luhmann 1999). Despite the successful application of cybernetics to the study of socio-technological ecosystems, there have been strong criticisms, one of the most prominent which was presented by Jonas (1953), who argued that cybernetics determines goals in objects such as technological artifacts or systems that do not necessarily exist. Similarly, cybernetics reduces social processes to mechanistic descriptions. According to Jonas, these transformations are not justified and lead to empty descriptions of systems only replicating the purposefulness and instrumentality assigned to them by the researcher (Papakyriakopoulos 2022b).

In social machines, computability is not the exclusive right of machines. Moreover, sociability is not the exclusive right of humans. The cybernetic framework allows us to consider human behavior computable and technological participation sociable. For example, human behavior is anticipated in metadata that is turned into recommendation algorithms, deep learning models, or computer vision software. Similarly, the decision of a system decision to hire or fire a person replaces the human resources manager in the social network of a company. Given that all these interactions are anticipated in the forms of communication and control, they appear in a cybernetic domain disregarding their initial significance. What complements their regulations are design frameworks guiding people's behavior and use of technologies (Figure 1). The design framework includes values, infrastructure, accurate algorithms, interfaces, rules, and any other material or non-material properties that form the behavior of system elements. For example, social media platform is typically designed based on companies' business models and in this design, interactions promote efficient advertisement placement rather than optimal interaction between users (Smart, Simperl, and Shadbolt 2014; Murray-Rust et al. 2018).

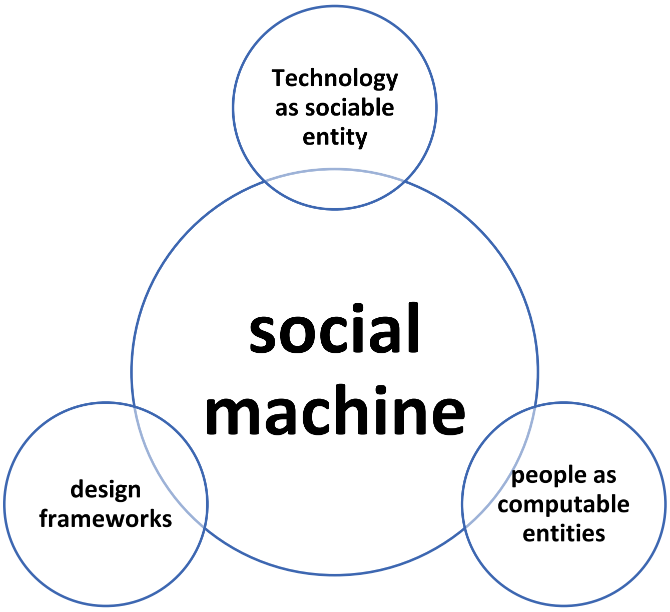



**Figure 2**- Social machines are formed based on human behavior, technological implementations, and design frameworks

The study of social machines from a holistic framework such as cybernetics becomes more important due to the nature of contemporary human algorithmic ecosystems. In the era of ubiquitous computing, people and computers are integrated into circular communication and control systems. People are permanently enhanced by algorithms integrated with most technological artifacts, including navigation tools, social network platforms, or search engines. This pervasive, persistent, invisible, and continuous existence of algorithmic applications creates limitations in every aspect of human life, distorts

people's decisional independence, and creates a network in which the roles of operator and operand are constantly exchanged between humans and algorithms (Murray-Rust et al. 2018).
Social computing is a good example showing that technology is no longer a tool aiding humans, and humans have also become a tool aiding technology. The efficiency of data-intensive algorithms is mainly based on the quality of the input data, which should clearly reflect every aspect of social behavior in an accurate and unbiased way. Therefore, humans turn themselves into digital data and present all aspects of their lives to algorithms to optimize the function of the algorithms (Martin and Pease 2013). For example, in the electorate, the framework of metadata analysis, which is based on the generation of data-intensive models about voters and the extraction of information from them about the interests and behaviors of voters, is used to produce content and advertisements (Hersh 2015; Kreiss 2016). Thus, voters are transformed into data for algorithms, which then provide specific inferences to political actors, and then are transformed into actions influencing voters, producing a circular loop containing social and computational mechanisms, where the concepts of cause and effect cannot be easily separated.

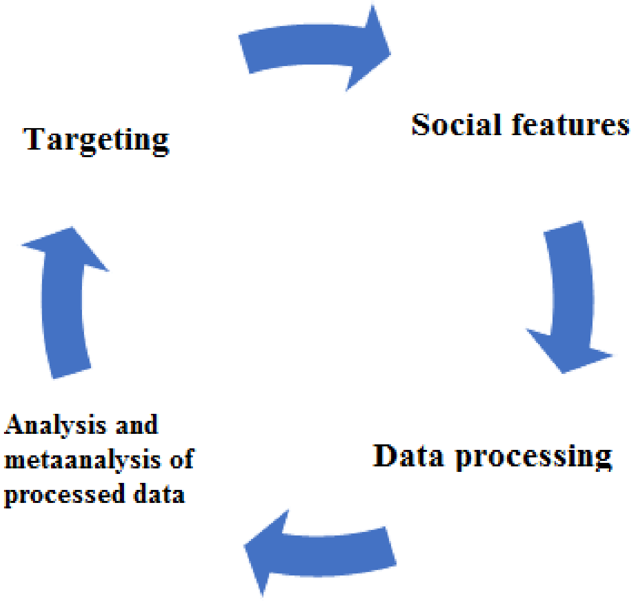



**Figure 3** - Data-driven targeting cycle, with social and computational mechanisms processing and analysis

What remains constant in such computational social science ecosystems is not the quantifiability of humans and algorithms, where computability and sociability are interchangeable, but system behaviors formed by communication processes, which depend on how humans and algorithms interact and how they influence each other. The participants of these systems, in time-space, create a dynamic network of interactions, extract information, and adapt their behavior, often generating fabrics of sociability that remain in the behavioral memory of the community. For example, online dating platforms depend on both the behavior of users and the data generated on that platform by them and its algorithm's ability to match people according to their attitudes. Similarly, deploying an algorithm for recidivism purposes is feasible if it can remember and retrieve people's general behavior based on the data it was trained on.

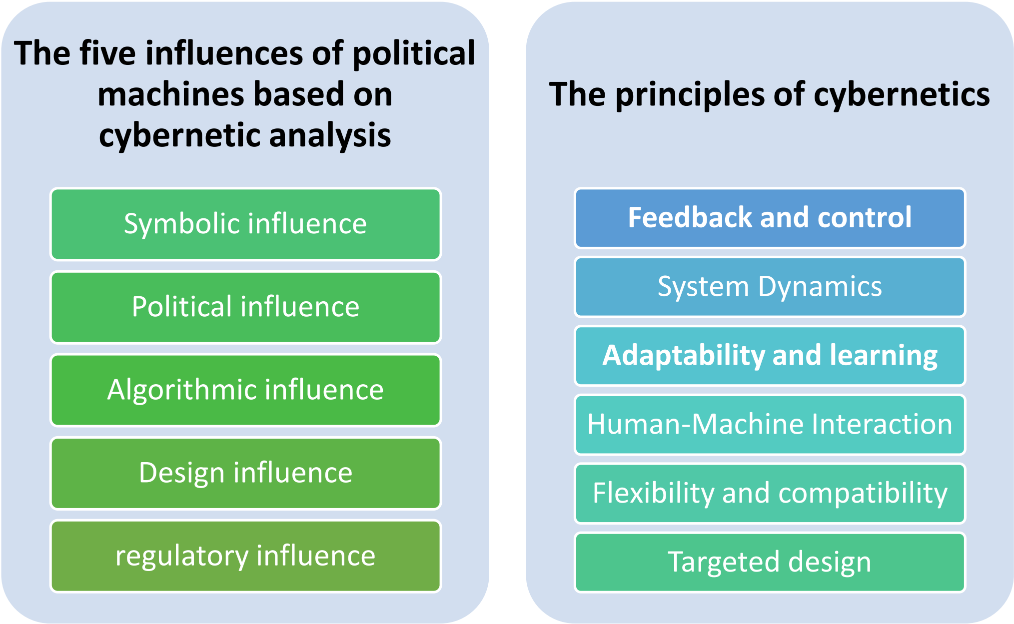
- **Analysis of social machines based on the cybernetic approach**
  Social machines refer to machines and systems interacting with humans and societies. Cybernetics, as a discipline, analyzes and enhances communications between humans and machines. Therefore, the relationship between cybernetics and social machines is such that cybernetics can help design and analyze social machines and apply cybernetic methods and principles to enhance the function and interaction of these machines. Social machines can include a variety of examples such as social robots, smart transportation systems, traffic management systems, group decision support systems, and online social systems.

Social machines try to improve human interactions and increase cooperation and coordination between individuals. These machines usually include a communication technology platform (such as the Internet), artificial intelligence algorithms, sensing equipment, and user interfaces that can acquire and analyze information through their interaction with humans and populations. These machines can be used in various fields such as healthcare, urban management, education, learning, etc. Cybernetics and the use of its principles in the development of social machines can facilitate the improvement of the concept and design of these machines, including the investigation of interactions between humans and machines, feedback management, improvement of artificial intelligence algorithms, and the design of effective user interfaces.

Using the principles of cybernetics in the design and optimization of social machines can significantly improve the function and interaction of these machines. The following examines some approaches to using cybernetics principles in the design of social machines:

1) Feedback and control: One of the basic principles of cybernetics is the use of positive and negative feedback. Feedback loops are necessary for cybernetic studies. Incorporating feedback mechanisms into machine design allows continuous regulation and adjustment of machine behavior based on intended results. Machines can adapt and adjust their actions to achieve optimal function by analyzing feedback signals. In the design of social machines, this principle can facilitate the enhancement of interactions and cooperation between humans and machines. Negative feedback can be used to regulate and balance interactions to help the system reach a desirable and stable state. Positive feedback can also facilitate encouraging and enhancing the function of human and machine colleagues.
2) System Dynamics: Cybernetics emphasizes the understanding of the dynamics of complex systems. It is very important to pay attention to interactions and interdependencies between different components or subsystems in the design of machines. Designers can identify potential bottlenecks, enhance function, and ensure stability and flexibility by modeling and simulating system behavior.
3) Adaptability and learning: The principles of cybernetics can be used to design machines to learn and adapt. Using machine learning algorithms and artificial intelligence techniques, machines can improve their function over time by adjusting their behavior based on data and experience. This adaptability enables machines to effectively adapt to changing conditions and user needs.
4) Human-Machine Interaction: Cybernetics emphasizes the interaction between humans and machines. Designing machines using intuitive and user-friendly interfaces promotes integrated communication and collaboration between humans and machines. Understanding human behavior, cognitive processes, and ergonomic considerations can result in the design of machines that are more intuitive, responsive, and easier to use.
5) Targeted design: Cybernetics emphasizes setting clear goals and objectives. In the design of machines, defining intended outcomes and incorporating goal-oriented behavior enable machines to work towards specific goals. Machines can permanently measure their progress, compare it to intended goals, and make the necessary adjustments to achieve optimal function.
6) Flexibility and compatibility: Cybernetics recognizes the importance of adaptability and flexibility in systems. Designing machines with the ability to detect unexpected events or failures and respond to them can enhance their robustness. Incorporating additional components, fault-tolerant systems, and self-healing mechanisms enables machines to eliminate disruptions and continue to operate efficiently.
By incorporating these cybernetics principles into the design and optimization processes, machines can be developed to operate more effectively, adapt to changing conditions, effectively interact with humans, and achieve intended goals.
On the other hand, in social machines, people influence algorithms, and algorithms, in turn, influence human behavior. Therefore, any framework aiming to study society must have a clear definition of what is social and what is not. In fact, society is a whole unit whose dimensions cannot be easily detached. Therefore, in the following, it has been tried to design the dimensions of a social machine based on the cybernetic approach to social machines.
Attention to the role of social machines in changing society's behavior, along with the literature on cybernetics, guides us to the point where this role can be assessed. In the study of social machines, influence acts as a meta-concept and includes processes institutionalized at the individual, social, and even political levels. Regardless of the form of influence and its appearance, the fact that the meta-concept involves different cases of power and influence, makes it possible to compare and understand complex patterns within ecosystems that might otherwise seem unrelated.
Influence often emerges in the social domain when individuals want to meet their economic, physiological, or socialization needs. However, such processes always have a political aspect because how the influence changes the behavior of the audience of the organization impacts the values, hierarchies, and outcomes of a socio-algorithmic ecosystem. For example, the feeling a user interface color gives an individual can affect how they evaluate a message, leading to a chain of changes with possibly unanticipated effects. Therefore, any social interaction involving an influence process automatically has a potential social component. This component not only includes institutionalized macro policies and group behavior of people but also the attitudes and behaviors of people shaping the rights, obligations, possibilities, and boundaries of an individual or social group in society.
Since this study aims to provide a framework aiding to understand all these cases of socio-algorithmic ecosystems, first, influence processes in social machines should be identified and their different aspects both in their design and in their integration into society should be examined. In a study on political machines, it was attempted to provide a framework for the study of politics in social machines. In this study, five levels of influence have been studied, including symbolic influence, political influence, algorithmic influence, design influence, and regulatory influence (Papakyriakopoulos 2022a).

In the following, it is tried to present a framework for understanding social machines to connect influence processes that may seem unrelated to provide a tool to understand social phenomena shaped by humans and technology simply and efficiently.




**6) Conceptual framework for understanding social machines**

Modeling social systems using the principles of cybernetics can help to better understand behavior and interactions within social systems. Here, cybernetics research and model-based studies in social machines are reviewed to examine the following approaches in order to model social machines using the principles of cybernetics.

1) Social machine structure modeling: In the modeling of social machines, the principle of cybernetics justifies the understanding of the machine structure. The structure and relationship between the members of the social machine can be identified and modeled using approaches such as artificial neural networks, agent-based modeling, or multi-agent systems.

2) Simulation of behavior: Using the principles of cybernetics makes it possible to simulate complex behaviors in social machines. Simulation methods such as agent-based modeling, system dynamic modeling, or differential equation modeling can be used to predict and simulate changes in machine members based on the behavior and interactions between machine members.

3) Dynamics and change: The principle of dynamics and change is important in cybernetics. The modeling of social machines should be able to adapt to the changes in population, environment, and goals. The models can change dynamically and take into account positive and negative feedback so that the machine achieves an optimal and stable state.

4) Interactions and social behaviors: Modeling social machines according to the interactions and social behaviors between members can help to understand the function and complexity of the machine. By modeling concepts such as game theory, social networks, collective behavior, or group decision, social behaviors can be analyzed and predicted.

Using the principles of cybernetics in modeling social machines can help us better understand the behavior and interactions within social systems and enhance them. Also, cybernetic modeling can be used to simulate and test different examples of social machines and facilitate the improvement of the function of social systems.

- **Analytical modeling of social machines**

  Cybernetic modeling is a process through which complex systems and processes are studied and analyzed using the principles of cybernetics. Modeling social machines based on the principles of cybernetics aims to understand, identify, and enhance the function of social machines. During the cybernetic modeling process, machines are modeled as a set of components and the communications between them.

In this cybernetic modeling, the following steps are investigated.

1) To identify and define the social machine: In this step, the studied machine is identified and defined. Components and communications between components are determined in the studied system.

In the analysis of social machines, the most fundamental part is limited to the recognition of humans and has an identity and symbolic nature. A person uses symbols to understand, explain, or represent the world. Human language and thinking consist of words that are nothing rather symbols formed by signifiers and signifieds (De Saussure 2011). These symbols bring the understanding of social conditions and meanings and inform the person and influence him/her. For example, the explicit inclusion of a text for opting into a platform's terms and conditions has the potential to change the user's decision to use that service. It also happens when users converse about different issues with produced text and discussions showing and reproducing the dominant attitudes and perceptions of social groups, conveying a message to the reader.

Such recognition doesn't appear only in the language context. Non-verbalized information, in the form of stimuli such as seeing shapes or colors, can also influence people. Such information is stored in human memory as mental representations or information schemas, which are reactivated depending on the newly received information. Therefore, the appearance and structure of a user interface and the linked user experience can always influence the participants of social machines and change their behaviors. So, this recognition and definition of the social machine is a significant part of the influence of the machines. For example, the color of a platform's user interface can influence the amount of time a user spends with a service (Shneiderman et al. 2016) or how much and how he/she would interact with it (Benyon, Phil, and Turner 2010). Recognition of social machines is influenced by symbols, and symbolic influence encompasses such processes by focusing on the symbols' ability to shape reality and behavior.

Since implicit or explicit symbols always appear in social machines, symbolic influence is the most subtle and penetrating type of influence on the recognition of social machines. It always exists but it is practically impossible to measure it precisely. However, in certain cases, researchers can investigate and understand its properties through appropriate experimental design (King, Churchill, and Tan 2017).

2) To collect data: This stage is to collect data necessary for machine modeling. The data can include information on the behaviors, inputs, and outputs of the machine, and other variables related to the machine's function, which can be analyzed in the social machine algorithm.

One of the most significant questions about social machines is how algorithms can influence people. The data are collected based on these algorithms and the machine operates based on the analysis of these big data. Algorithmic influence is an essential part of many social machines, as services and actors explicitly apply algorithms to automate processes and influence people and society. Algorithmic influence includes the processes induced by the mathematical structure, predictions, and inferences of an algorithm. Of course, under which criteria these features are implemented are strongly influenced by the goals, needs, and values of those in power. These decisions depend on the influences of the design, which will be analyzed later.

Algorithmic influence occurs in society and covers every aspect of socialization using online-data-based computing technologies. From maps presented by routing software to online content suggestions, human behavior is continuously reshaped by algorithmic implementations, and valuable data are collected. For example, in social media, platform designers deploy algorithms to suggest personalized content to users, place targeted advertisements, and filter and review user-generated content. All three algorithmic implementations have the potential to change human behavior in different ways.

By choosing the content that is intended to be visible for the user's news feed, an algorithm matches the user's behavior to his declared and non-declared interests (Just and Latzer 2017). The user's perception of the world will change according to the selected information, leading to algorithm-mediated subjective knowledge. Next, that knowledge is transformed into action, and users form their opinions about the world and actively behave according to them in the online and offline worlds. In this context, it has been largely hypothesized that algorithms can lead to filter-bubble phenomena (Pariser 2011). Bubble filters are segregated opinion clusters formed by algorithms, where users are only in contact with conforming opinions, but not with opposing ones, a social setting that can easily lead to opinion polarization. In fact, these algorithms separate the user from real society by creating a bubble and will direct his behavior by filtering the information available to him. In such conditions generated by algorithms, information is collected that leads to behaviors leading society towards polarization when being used by the user based on the algorithm. Even if this content regulation does not lead to polarization, it always creates a bias, because the algorithmic reality depends on the structure of the algorithm and the related input data, leading to the emergence of data politics (Ruppert, Isin, and Bigo 2017), that addresses how algorithms operate (Seaver 2019), what biases they introduce (Lazer 2015; Bozdag 2013) and how they influence individuals and social groups (Taylor 2017; Beer 2017). Data politics are not limited to recommendation algorithms in social media but also include platform services for personalized advertisement in the form of micro-targeting (Kreiss 2016; Hersh 2015). These obscure algorithms offer advertisements to users according to demographic and behavioral criteria with the aim of effectively influencing user behavior. Micro-targeting is a state-of-the-art technique, and the business models of these platforms largely depend on convincing companies and political actors to rent these services for advertising.

Another dimension of algorithmic influence on social media is related to content filtering algorithms. In addition to being analyzed, the collected data must be made available to the user in various ways. To this end, machines mainly use automated processes that scan uploaded images, videos, and texts and search for content that violates the platforms' terms and conditions. Therefore, the algorithms decide what is allowed to become part of the community's discourse and what should be restricted from the start. How freedom of speech is formed on platforms leads to the development of user behavior according to applied policies. But, in the application of these policies, the key point is being aligned with the target community or not, which may lead to the non-use of that platform. This issue needs to be further addressed.

Algorithm influence also exists in other types of social machines such as ADM algorithms. ADM systems are widely used for risk assessment and warning (Mosier and Skitka 2018), for automating and predicting tasks such as image recognition, speech understanding, medical consulting, and police services (Larus et al. 2018; Ensign et al. 2018; Dressel and Farid 2018). ADM systems lead to two-sided algorithmic influence. First, they influence the behavior of users who apply the models because they generate knowledge that is exploited in multiple decision-making processes, and the data required by the machine are collected. Second, if algorithms also make decisions about individuals and social groups, their decisions affect these groups as well. For example, a hiring algorithm not only influences the company by offering a candidate but also influences the candidates themselves, deciding who gets what job (Ajunwa et al. 2016). An algorithm recommending the type of treatment for patients to the doctor not only helps the doctor to make optimal decisions but also chooses whether patients should be operated on or not, how long their recovery period will be, etc. In such cases, epistemological concerns are raised about the predictive power, accuracy, and general adequacy of algorithms to provide reliable evidence for an algorithmic decision, meaning what behavior the collection of this volume of targeted data will lead to. Since algorithmic implementations are vague, they provide no adequate evidence for their inference, and sometimes, they provide no hard answers, and in other words, the application of algorithms in many fields remains questionable.

3) To design the model: In this step, the system model is developed according to the collected data using the principles of cybernetics. This model can include mathematical equations, block diagrams, neural networks, or other modeling methods as needed.

Examining the various influences of social machines depends on the structure and design of social machines, which are mainly achieved by the design of their components. Each component of a social machine takes its final shape according to the objectives of the designers and existing environmental constraints. This final form contributes to the equilibrium in a social machine. For example, the design principles of a social credit system affect citizens' behaviors in society, determine people's action space, and form their social goals. Similarly, a social media recommendation system suggests content to users in a way that aligns with the goals of the company's business model.

Design constraints also greatly influence the formation of social machines. Hardware or software constraints can lead to discriminative predictions even if that is not part of the designers' intention. In medical predictions, the ability of a model to make good decisions depends on the available data, which may be scarce due to privacy issues and thus lead to the deployment of a model with lower predictive ability.

In addition to the objectives of designers and environmental constraints, design ethics are another parameter strongly influencing the formation of social machines. A tech company's decision to collect data about users' interests, characteristics, demographic information, and behaviors, and exploit them to develop better algorithms, always depends on the owners' understanding of what is ethical. The fact that companies do not disclose how their systems work and maintain a high level of transparency in every aspect of model development and deployment is a design feature that prevents understanding of systems and determines accountability and transparency. Such design features prevent research from the interpretation of phenomena and good societal governance.

Since many technological ecosystems are driven by financial incentives with unknown transformative effects on politics and society, issues such as the abovementioned raise questions about how to ideally design social machines that serve society. For example, although social communication mainly takes place on social media, these media are not public and do not always try to remain impartial (Engelmann, Grossklags, and Papakyriakopoulos 2018; Leskovec, Huttenlocher, and Kleinberg 2010). This is also true of ADM systems established by governments. Reasoning, justifying, and legitimizing an action based on a probability can be problematic, because a probability scientifically assesses a situation and does not deterministically lead to an inference.

The above are just a few examples of how design values, creators' motivations, and environmental constraints can influence the formation of social machines. Analysis of any social machine can reveal the many design features based on which the interaction between participants is formed. Therefore, their accurate evaluation requires a detailed analysis.

4) To test and analyze the model: A model can be tested with real data after being designed. Analyzing the results of the tests evaluates the function of the studied system. The results of the evaluation of the social machine function represent the influence expected to be generated on social behavior.

The influence most obviously emerges in social machines when they are used as a tool to improve their status and increase their power based on changing the behavior of the subjects by those in power. What is analyzed and evaluated here as model analysis is the effect intended by the primary designers including different layers of those in power, which includes any social group, individual or institutionalized action that explicitly and consciously has the motivation to change. This includes cases existing in the political actions of participants in social machines actively seeking to change society and influencing existing hierarchical and power structures.

This influence often appears in online social networks and ADM systems. Although most prominent social media platforms were not designed to promote in-depth content discussions, today they serve as central spaces for the exchange

of opinions and the creation of various discussions. Users use platforms to comment on political issues, publicize their ideologies, and form online groups to create their intended actions (Gustafsson 2012; Rainie et al. 2012). To better understand this influence, one can refer to the area of political activities. This wide space for political interactions creates hopes and promises for a more diverse and participatory political discourse. Social media platforms are considered a space for more independent political actions that can contribute to the dissemination of voices that are systematically suppressed by authoritarian regimes and power structures. These expectations were mainly created since social media can be a space for information, communication, mobilization, consultation, and diversity.
All of the above constitute social media as very complex political media. Even the political processes explicitly taking place on them are in many forms, and various participants use the services for their specific purposes. In this context, many discussions have been formed to examine whether social media really contribute to the democratization of society or whether they have a negative political influence (Effing, Hillegersberg, and Huibers 2011; Zuckerman 2014; Gorham 2020; Bennett 2012). Here, it is emphasized that the model testing and analysis are not limited to the technical and algorithmic functions, and evaluating the effectiveness of social machines is focused.
5) To optimize and modify: If the function of the machine is not sufficient for the intended goals, its function can be enhanced by modifying the model and applying optimizations. Regulatory frameworks are of great importance for optimization and modification.
Since social machines are embedded within a society, and since societal action is controlled by institutionalized processes, political and legal structures form the space in which social machines can operate. In algorithmic applications, the legislator decides how these systems should be established and how the interests of designers and the public can be protected. The issues related to data properties and privacy, algorithmic opacity, and discrimination of social groups are considered the main regulatory issues for algorithmic applications.
Data properties and privacy are considered one of the main reasons for the limited use of algorithms. Considering the huge amount of generated data related to human behavior, they can be used for multiple purposes with no limitations. Data are generated, collected, processed, and combined, and new algorithms are born unstoppably for decision-making, leading to the posing of various questions about who owns this data, what kind of rights the data collector has, and whether data collection and processing violates people's privacy rights. To answer such questions, countries have developed and adopted different regulatory frameworks that define what is allowed and what is not.
Algorithmic opacity is one of the main rights of designers in algorithmic implementation that are supported by the law in not disclosing the inputs, structures, and outputs of models. This is because a developed model can provide its owner with better market opportunities, therefore, its features can be remained uncovered in commercial competition. However, algorithmic opacity prevents the auditing and understanding of such systems, especially when it comes to the effects of an algorithm violating the law.
Discrimination and freedom of speech are legal frameworks that interfere with discriminative social machinery in two ways. First, as discussed earlier, algorithmic implementation may lead to discriminatory decisions against individuals and social groups. Especially for ADM applications, it proves practically that such events can happen repeatedly, raising questions about the extent to which existing laws regarding protected social groups and individual rights and freedoms are violated. Second, in social media and other online platforms, algorithms are deployed to filter content. This happens for two reasons: First, platforms remove content containing harmful and discriminative speech or violating the laws. Second, platforms want to protect the function of their services, thereby removing content not complying with their imperatives. In the process, the following questions should be answered accurately: when does a given content violate the law, how is individual freedom of speech defined and where does society set its limits, who is legally responsible for the content wrongly unfiltered, and how free companies should be in choosing what to filter or not considering their financial incentives.
Generally, algorithmic implementations in social machines remain largely unregulated. Considering this, many discussions have been formed about algorithms and their definition, how their current and ideal functions can prevent biases inserted by algorithmic applications, and who should be countable in cases of possible misconduct. Therefore, regulation emerges as one of the most important categories of influence because it has the potential to change the nature of social machines.
The regulatory frameworks used for optimizing and modifying social machines emphasize the frameworks that can influence social behavior rather than the technical engineering principles of social machines.
Cybernetic modeling is used in various fields of social sciences. Using this approach enables us to investigate the improvement and optimization of the function of complex systems at different scales.

- **Research achievements – A conceptual framework for analyzing social machines**
  The influence categories in social machines can be considered neither static nor independent variables. They constantly interact, dynamically change the states of systems, and form how individuals and society behave. Each form of influence in modeling social machines not only modifies social machines but also has its specific space that is influenced by other parts of the model. In the following, two case studies are presented focusing on the importance

of social machines and examining how the processes of different categories influence each other to show how this framework can reduce social complexity in social machines, help understand explicit and implicit systemic changes, and guide researchers, policymakers, and designers in examining how interventions can form ecosystems. This is done by applying diagrams as a means for connecting influence processes of different natures and using tables to relate events in a cybernetics framework. To increase accuracy and precision in the analysis and understanding of social machines, the two studies presented in the article entitled "Political Machines: A Framework for Studying Politics in Social Machines" are re-examined to show the difference between the models (Papakyriakopoulos 2022a).

- **Study 1 - Reducing exposure to alt-right content**
  As an example of how certain changes in social machines can influence multiple components directly and indirectly, one can refer to YouTube's decision to reduce users' access to alt-right political content in 2019 (Ribeiro et al. 2020). This decision was partly made based on scientific evidence showing strong radicalization patterns on the platform, and users gradually shifted from consuming alt-right moderate content to far-right ideological content. This decision on content management was related to the design values of the platform, but it was operationalized by removing certain content from the platform's recommendation algorithms. This algorithmic change actually changed user behavior, reducing the popularity of such content. However, the researchers showed another indirect impact of this decision. The change in algorithm function not only influenced YouTube, but a similar decreased consumption of such content was observed on Twitter and Reddit (Buntain et al. 2021). This indicates that making changes in political communication on a platform can affect users' behavior on other social media platforms. In this study, the change in the social machine started from the "model design". Figure 4 shows the interconnectedness of influence processes in the YouTube social machine model based on the study of cybernetics, in which the whole social media ecosystem is considered a social machine. This model shows a cascade of influence processes in the model where changes in design values lead to multiple feedback loops from a cybernetic perspective, meaning that the outputs of systemic processes recursively transform into inputs and have further effects. Finally, an equilibrium was reached in the system with less consumption of alt-right content on three different platforms.

This change in the consumption pattern first shows itself in the model design, and this model influences the data collection algorithm. Based on the recognition and identity of the social machine studied, the influence appears in the optimization and modification layer. The ultimate goal was originally to defeat the alt-right part, which was targeted by consuming less alt-right content in the design and data collection algorithm. Here, it should be emphasized that data collection refers to the collection of everything that can provide us with a correct understanding of the user's behavior.

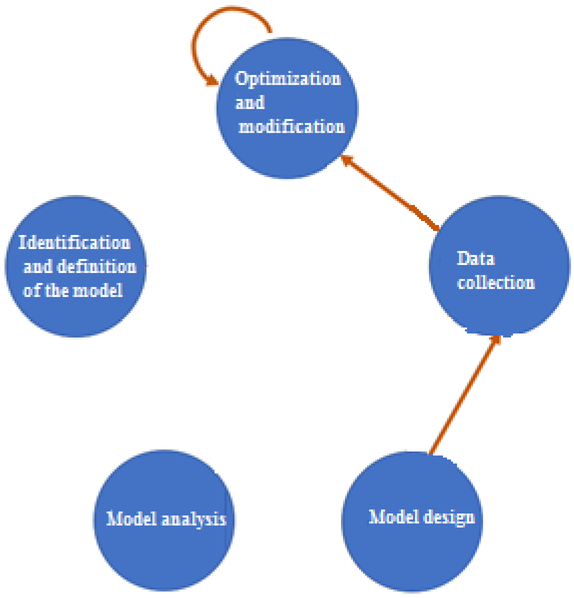



**Figure 4.** Analysis of YouTube's decision to reduce users' access to alt-right political content

| Targeting | Modeling process | Action in the modeling process | The expected output of the action | Cybernetic impact |
|---|---|---|---|---|
| **To reduce access to alt-right content** | **Model design** | **Change of recommendation algorithm of the content** | **Change of algorithm** | **Investigation of the feedback loop in content consumption** |
| **Change of recommendation algorithm of the content** | **Data collection** | **Change of political content consumption on YouTube** | **Changes in the political behavior of the community outside the context of the platform** | **Investigation of the feedback loop in content consumption on other platforms** |
| | | | | |
| **Change of political content consumption on YouTube** | **Optimization and modification** | **Change of political content consumption on** other platforms | **Changes in political behavior** | **Feedback loop** |

**Table 1.** Analysis of YouTube's decision to reduce users' access to alt-right political content

**• Study 2- Data-driven political microtargeting, Facebook and the GDPR**

Data-driven political microtargeting, as a campaign strategy, uses ADM systems to make inferences about voters and targets this with personalized advertising (Hersh 2015). This campaign method made the platforms adapt their advertising targeting systems to attract customers. For example, Facebook offers options to target people based on their inferred political preferences, a feature whose algorithm is used to decide who will see political content and who will not. However, this option is only available in the US since the specific regulatory framework of this country allows it. In contrast, such a platform service is not feasible in Europe, because the European General Data Protection Regulation (GDPR) clearly defines the limits and possibilities of using data for political purposes. Figure 5 analyzes the above processes using the framework of social machines from a cybernetics perspective. This figure indicates that political campaigns influence Facebook's design, which, in turn, adapts its algorithmic structure and changes who will be targeted. In addition, political campaigns are also adapting their political behavior because they use Facebook advertising services to reach voters. Thus, regulatory frameworks act as systemic constraints because they define the feasible space for how political advertising can be placed for each country. From a cybernetic perspective, the above interactions reach an equilibrium where political campaigns in the United States and Europe can use Facebook advertising services in different ways.

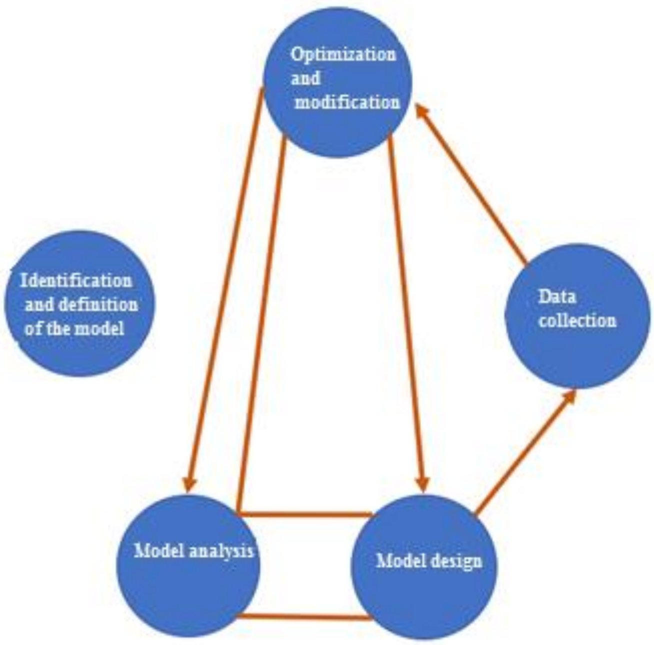



**Figure5.** Analysis of data-driven political microtargeting from the perspective of Facebook

| Targeting | Modeling process | Action in the modeling process | The expected output of the action | Cybernetic impact |
|---|---|---|---|---|
| To launch the campaign | Optimization and modification | Introduction of the GDPR<br><br>Adaptation of platform business model | Model analysis<br><br>Change of the model design | Constraints<br><br>Feedback loop |
| | | | | |
| Adaptation of platform business model | Change of the model design | Change of targeting algorithm | Change of algorithm | Feedback loop |
| | | | | |
| Change of targeting algorithm | Algorithmic influence | Use of algorithms by political actors to target voters | Optimization and modification | Feedback loop |

**Table 2.** Analysis of data-driven political microtargeting from the Facebook perspective

- **Study 3- The behavioral influence of Filimo on the media consumption pattern**

One of the considerable social machines in today's world is the home cinema platform, which created a new space for its users with the outbreak of Coronavirus. This change of interest in user action-based cultural micro-targeting is a matter whose influence emerges in behavioral actions. The emergence of this behavioral action has been increasingly observed in users' interest in TV series more than their interest in movies in recent years, and in home-show broadcasting platforms, this strategy has changed the media consumption pattern, which has also been more effective by creating side campaigns. This campaign method caused platforms to adapt their advertising targeting systems to attract users. For example, in the report of the Filimo platform in 2020, the monthly internet consumption was above 36 million gigabytes. The same statistic was 42 million minutes per episode for the TV series "Aghazadeh" and 105 million minutes for the film "The Singer". Filimo created an option for targeting people based on their favorites. This feature of the algorithm was created to decide who can see what. Figure 6 analyzes the above processes using the cybernetic analysis framework of social machines. This diagram shows that the production of TV series influences the design of Filimo, causing it to adapt its algorithmic structure accordingly. Now, if the big data of cyberspace, in addition to the user action on the Filimo platform, is incorporated into the decision-making model of the Filimo platform, those who are targeted will change. From the cybernetic perspective, the above interactions reach an equilibrium in which the media production pattern in Iran can change the media consumption pattern and use the platform of these services in different ways.

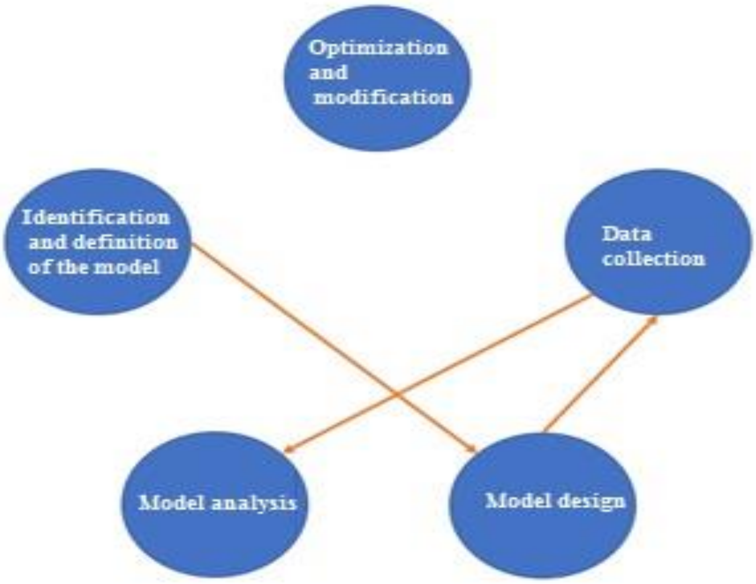



**Figure 6**. Analyzing the behavioral influence of Filimo on the media consumption pattern

| Targeting | Modeling process | Action in the modeling process | The expected output of the action | Cybernetic impact |
|---|---|---|---|---|
| Welcoming foreign TV series | Change of model definition | Production of continuous TV series | Change of the model design | Feedback loop |
| | | | | |
| Production of continuous TV series | Change of the model design | Change of targeting algorithm | Change of algorithms | Feedback loop |
| Change of targeting algorithm | Change of algorithms | Using algorithms to target those interested in series | Model analysis | Feedback loop |

**Table 3**. Analysis of the Filimo platform

- **Knowledge extraction and framework potential**

The above examples show how modeling processes are in social machines. This framework serves as a tool to evaluate such interactions in a more structured way. Processes can be classified based on modeling processes, and their effects can be connected to other categories, reducing the complexity of systems and tracing direct and indirect relationships. In a study on social machines from the perspective of political studies, it was attempted to define concepts based on power, and all categories were defined in relation to the phenomenon of influence and power-finding. So, in the first two case studies, it was tried to indicate how people's thoughts and behavior can be used for the benefit of political powers (Papakyriakopoulos 2022a). But the present research addresses the category of social empowerment and socialization and indicates that this level of entering social data at different levels causes us to experience new concepts in the field of social science studies that cannot be interpreted only in the discussion of political power. For example, the three case studies investigated indicate that how algorithms influence users on social platforms depends on the design decisions of platform owners and changes in model design. Such evidence can be used as an argument to support accountability claims related to unfair and problematic algorithmic inferences. Of course, it is necessary to complement any knowledge extracted using more scientific theories that can transform the evidence into structured arguments.

The social machine framework may be used not only to evaluate the complex influence processes in social machines but also for the purposes of social machine design and policy making. By intervening in a system, and keeping everything equal, scientists can discover how a single change in a social machine influences multiple processes, leading to influence evaluation and quantification. Scientists can evaluate how a new social machine feature might affect political behavior, or how a new regulation causes changes in the structure of a social machine. This is greatly important in an era where socio-algorithmic ecosystems are largely unregulated. Designers maintain a high degree of transparency around their systems, which translates into a lower degree of accountability. The same can be seen exactly in the platforms discussed today under the title of transparency, and the reasons for their success or failure should be examined with the social machine approach. Social machines, as a framework, can support researchers in answering questions such as the above and unveiling and understanding countless influence processes in ecosystems.

- **Implications, limitations, and future work**

The presented framework successfully answers the first research question: by adopting a systemic perspective, it provides a way to analyze and classify influence processes in social machines. In this way, it bridges an important scientific gap, because no significant effort has been made to analyze influence processes in socio-algorithmic ecosystems. This was achieved in this framework by examining the interplay of influence processes in social machines that are not usually analyzed or thought to belong together. The framework does this by separating humans and technology from their materiality and focusing on what each does, which was carried out by modeling based on cybernetics research.

This study also answers the second research question: this framework provides a structure that can guide researchers in understanding, designing, and intervening in socio-algorithmic ecosystems. Using case studies, it was shown that the framework can successfully evaluate the influence processes occurring, even in cases where the systems are highly complex and a change can have unpredictable effects. The analyzed case studies explain how inputs change the equilibria of social machines and can be used as a tool to complement scientific theories in knowledge extraction. Moreover, since socio-algorithmic ecosystems constantly experience important ethical and policy challenges, this framework can be used to semantically plan how potential interventions, both in regulations and in the social machine itself, might alter the dynamics of the systems.
Since this framework is used for the conceptual understanding of politics in socio-algorithmic ecosystems, it also faces specific limitations. First, there is a need for a systemic analysis of existing social machines and their internal social

processes to trace regularities of influence. In this way, specific events can be connected to each set of modeling processes, creating additional and comprehensible knowledge about the nature of society for each type of social machine. Second, although this study used the framework to understand past interactions in social machines, it is required to carry out further empirical work, that uses the framework in ongoing interventions, to verify its capability to anticipate and guide researchers, policymakers, and platform designers in their work.

Despite the above limitations, even in the short examples abovementioned, additional knowledge on social processes was generated in socio-algorithmic ecosystems. In most cases of social machines, there is a social equilibrium in which platform owners and algorithmic designers have the most control over the function of the systems. This systemic feature initiates a discussion of how social machines should be and how they should be designed. Nowadays, most algorithmic implementations are part of the economic approach, states have marginal control over them, and legislators face serious challenges. Furthermore, individuals and social groups are the most passive participants in the system, meaning that they usually either take the role of consumers or are assumed to be datafied artifacts. From a normative perspective, society needs to think about the meaning of these roles and reimagine the future of socio-algorithmic ecosystems.

Focusing on the public interests and the idea that technology should serve individuals and society in a way that ensures equality, justice, freedom, and social inclusiveness, the study of social machines should be expanded. Researchers must not only describe how social machines work but also define the principles, frameworks, and constraints that can generate social-algorithmic ecosystems that serve the public interest. Designing social machines prevails as a necessity in a setting where technological and algorithmic implementations influence society in unexpected ways, transforming the essence of society. By defining social machines and introducing a framework for analyzing society in socio-algorithmic ecosystems, this study took a first step in this direction and there is a wide space for addressing and investigating this issue from different dimensions by researchers. It is an endless space for scientific research to generate and use new knowledge to create social machines, used by society and for society.

**References**

1) .(2( 61Tijdschrift Voor Filosofie .«. «Die gesellschaft der gesellschaft1999Niklas. ،Luhmann
2) . «The Nerves of Government: Models of Political Communication and 1965Karl W. Deutsch. و ،.H. M ،McLuhan Control .«The University of Toronto Law Journal 16(1): 226. https://doi.org/.10.2307/825125
3) Khalili, Azizollah, Aliasghar Pourezzat, and Mohammadhassan Jafari."The application of the "Inferential-analytical" method in management research". Islam and Management Research. 16 (7): 93-12
4) Ahlers, Dirk, Patrick Driscoll, Erica Löfström, John Krogstie, and Annemie Wyckmans. 2016. “Understanding Smart Cities as Social Machines.” In , 759-64. ACM Press. https://doi.org/10.1145/2872518.2890594.
5) Ajunwa, Ifeoma, Sorelle Friedler, Carlos E. Scheidegger, and Suresh Venkatasubramanian. 2016. “Hiring by algorithm: predicting and preventing disparate impact.” Available at SSRN 2746078.
6) Ashby, W. Ross. 1957. “An introduction to cybernetics.”
7) Bakshy, Eytan, Solomon Messing, and Lada A. Adamic. 2015. “Exposure to ideologically diverse news and opinion on Facebook.” Science 348 (6239): 1130-32.
8) Barberá, Pablo, John T. Jost, Jonathan Nagler, Joshua A. Tucker, and Richard Bonneau. 2015. “Tweeting from left to right: Is online political communication more than an echo chamber?” Psychological science 26 (10): 1531-42.
9) Barocas, Solon, Moritz Hardt, and Arvind Narayanan. 2017. “Fairness in machine learning.” Nips tutorial 1: 2.
10) Bateson, Gregory. 1972. “A theory of play and fantasy.” Semiotics: An Introductory Anthology, 131-44.
11) Beer, David. 2017. The social power of algorithms. Vol. 20. Taylor & Francis.
12) Bennett, W. Lance. 2012. “The personalization of politics: Political identity, social media, and changing patterns of participation.” The annals of the American academy of political and social science 644 (1): 20-39.
13) Benyon, David, Turner Phil, and Susan Turner. 2010. Designing interactive systems: A comprehensive guide to HCI and interaction design. Vol. 2. Addison Wesley Harlow.
14) Berners-Lee, Tim. 1999. Weaving the Web: The original design and ultimate destiny of the World Wide Web by its inventor. Harper San Francisco.
15) Bird, Sarah, Krishnaram Kenthapadi, Emre Kiciman, and Margaret Mitchell. 2019. “Fairness-aware machine learning: Practical challenges and lessons learned.” In Proceedings of the twelfth ACM international conference on web search and data mining, 834-35.
16) Bolukbasi, Tolga, Kai-Wei Chang, James Y. Zou, Venkatesh Saligrama, and Adam T. Kalai. 2016. “Man is to computer programmer as woman is to homemaker? debiasing word embeddings.” Advances in neural information processing systems 29.
17) Bozdag, Engin. 2013. “Bias in algorithmic filtering and personalization.” Ethics and information technology 15 (3): 209-27.

18) Buntain, Cody, Richard Bonneau, Jonathan Nagler, and Joshua A. Tucker. 2021. "YouTube recommendations and effects on sharing across online social platforms." Proceedings of the ACM on Human-Computer Interaction 5 (CSCW1): 1-26.
19) Buolamwini, Joy, and Timnit Gebru. 2018. "Gender shades: Intersectional accuracy disparities in commercial gender classification." In Conference on fairness, accountability and transparency, 77-91. PMLR.
20) Burégio, Vanilson, Silvio Meira, and Nelson Rosa. 2013. "Social machines: A unified paradigm to describe social web-oriented systems." In Proceedings of the 22nd international conference on World Wide Web, 885-90.
21) Chouldechova, Alexandra, and Aaron Roth. 2018. "The frontiers of fairness in machine learning." arXiv preprint arXiv:1810.08810.
22) Cristianini, Nello, and Teresa Scantamburlo. 2020. "On social machines for algorithmic regulation." AI & SOCIETY 35 (3): 645-62.
23) Dalton, Craig M., Linnet Taylor, and Jim Thatcher. 2016. "Critical data studies: A dialog on data and space." Big Data & Society 3 (1): 2053951716648346.
24) De Roure, David, Clare Hooper, Kevin Page, Ségolène Tarte, and Pip Willcox. 2015. "Observing social machines part 2: How to observe?" In Proceedings of the ACM Web Science Conference, 1-5.
25) De Saussure, Ferdinand. 2011. Course in general linguistics. Columbia University Press.
26) Del Vicario, Michela, Alessandro Bessi, Fabiana Zollo, Fabio Petroni, Antonio Scala, Guido Caldarelli, H. Eugene Stanley, and Walter Quattrociocchi. 2016. "The spreading of misinformation online." Proceedings of the National Academy of Sciences 113 (3): 554-59.
27) Dressel, Julia, and Hany Farid. 2018. "The accuracy, fairness, and limits of predicting recidivism." Science advances 4 (1): eaao5580.
28) Effing, Robin, Jos van Hillegersberg, and Theo Huibers. 2011. "Social media and political participation: are Facebook, Twitter and YouTube democratizing our political systems?" In International conference on electronic participation, 25-35. Springer.
29) Endres, Kyle. 2016. "The accuracy of microtargeted policy positions." PS: Political Science & Politics 49 (4): 771-74.
30) Engelmann, Severin, Jens Grossklags, and Orestis Papakyriakopoulos. 2018. "A democracy called Facebook? Participation as a privacy strategy on social media." In Annual Privacy Forum, 91-108. Springer.
31) Ensign, Danielle, Sorelle A. Friedler, Scott Neville, Carlos Scheidegger, and Suresh Venkatasubramanian. 2018. "Runaway feedback loops in predictive policing." In Conference on Fairness, Accountability and Transparency, 160-71. PMLR.
32) Erickson, Bradley J., Panagiotis Korfiatis, Zeynettin Akkus, and Timothy L. Kline. 2017. "Machine learning for medical imaging." Radiographics 37 (2): 505.
33) Faris, Robert, Hal Roberts, Bruce Etling, Nikki Bourassa, Ethan Zuckerman, and Yochai Benkler. 2017. "Partisanship, propaganda, and disinformation: Online media and the 2016 US presidential election." Berkman Klein Center Research Publication 6.
34) Ferrara, Emilio, Onur Varol, Clayton Davis, Filippo Menczer, and Alessandro Flammini. 2016. "The rise of social bots." Communications of the ACM 59 (7): 96-104.
35) Gorham, Ashley E. 2020. "Anonymous's Glory." International Journal of Communication 14: 19.
36) Gustafsson, Nils. 2012. "The subtle nature of Facebook politics: Swedish social network site users and political participation." New Media & Society 14 (7): 1111-27.
37) Hendler, James A., and Alice M. Mulvehill. 2016. Social machines: The coming collision of artificial intelligence, social networking, and humanity. New York: Apress.
38) Hendler, Jim, and Tim Berners-Lee. 2010. "From the Semantic Web to social machines: A research challenge for AI on the World Wide Web." Artificial intelligence 174 (2): 156-61.
39) Hersh, Eitan D. 2015. Hacking the electorate: How campaigns perceive voters. Cambridge University Press.
40) Iliadis, Andrew, and Federica Russo. 2016. "Critical data studies: An introduction." Big Data & Society 3 (2): 2053951716674238.
41) Just, Natascha, and Michael Latzer. 2017. "Governance by algorithms: reality construction by algorithmic selection on the Internet." Media, culture & society 39 (2): 238-58.
42) King, Rochelle, Elizabeth F. Churchill, and Caitlin Tan. 2017. Designing with data: Improving the user experience with A/B testing. O'Reilly Media, Inc.
43) Kreiss, Daniel. 2016. Prototype politics: Technology-intensive campaigning and the data of democracy. Oxford University Press.
44) Kruikemeier, Sanne, Minem Sezgin, and Sophie C. Boerman. 2016. "Political microtargeting: relationship between personalized advertising on Facebook and voters' responses." Cyberpsychology, Behavior, and Social Networking 19 (6): 367-72.

45) Larus, James, Chris Hankin, Siri Granum Carson, Markus Christen, Silvia Crafa, Oliver Grau, Claude Kirchner, Bran Knowles, Andrew McGettrick, and Damian Andrew Tamburri. 2018. When computers decide: European recommendations on machine-learned automated decision making. ACM.
46) Latour, Bruno. 2005a. An introduction to actor-network-theory. Reassembling the Social. Oxford University Press Nova York.
47) ———. 2005b. Reassembling the social: An introduction to actor-network-theory. Clarendon lectures in management studies. Oxford ; New York: Oxford University Press.
48) Lazer, David. 2015. “The rise of the social algorithm.” Science 348 (6239): 1090-91.
49) Leskovec, Jure, Daniel Huttenlocher, and Jon Kleinberg. 2010. “Governance in social media: A case study of the Wikipedia promotion process.” In Fourth international AAAI conference on weblogs and social media.
50) Martin, Ursula, and Alison Pease. 2013. “Mathematical practice, crowdsourcing, and social machines.” In International Conference on Intelligent Computer Mathematics, 98-119. Springer.
51) Mead, Margaret. 1968. Cybernetics of cybernetics. éditeur non identifié.
52) Mehrabi, Ninareh, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. 2021. “A survey on bias and fairness in machine learning.” ACM Computing Surveys (CSUR) 54 (6): 1-35.
53) Meira, Silvio RL, Vanilson AA Buregio, Leandro M. Nascimento, Elaine Figueiredo, Misael Neto, Bruno Encarnação, and Vinícius Cardoso Garcia. 2011. “The emerging web of social machines.” In 2011 IEEE 35th Annual Computer Software and Applications Conference, 26-27. IEEE.
54) Mol, Annemarie. 2010. “Actor-network theory: Sensitive terms and enduring tensions.” Kölner Zeitschrift für Soziologie und Sozialpsychologie 50 (1): 253-69.
55) Mosier, Kathleen L., and Linda J. Skitka. 2018. “Human decision makers and automated decision aids: Made for each other?” In Automation and human performance: Theory and applications, 201-20. CRC Press.
56) Murray-Rust, Dave, Alan Davoust, Petros Papapanagiotou, Areti Manataki, Max Van Kleek, Nigel Shadbolt, and Dave Robertson. 2018. “Towards executable representations of social machines.” In International conference on theory and application of diagrams, 765-69. Springer.
57) Norman, Donald A., and Pieter Jan Stappers. 2015. “DesignX: complex sociotechnical systems.” She Ji: The Journal of Design, Economics, and Innovation 1 (2): 83-106.
58) Novikov, D. A. 2016. “Cybernetics: From Past to Future.” книга.
59) Palermos, Spyridon Orestis. 2017. “Social machines: A philosophical engineering.” Phenomenology and the Cognitive Sciences 16 (5): 953-78.
60) Papakyriakopoulos, Orestis. 2022a. “Political machines: A framework for studying politics in social machines.” AI & SOCIETY, 1-18.
61) ———. 2022b. “Political machines: A framework for studying politics in social machines.” AI & SOCIETY 37 (1): 113-30.
62) Papakyriakopoulos, Orestis, Juan Carlos Medina Serrano, and Simon Hegelich. 2020. “The spread of COVID-19 conspiracy theories on social media and the effect of content moderation.” The Harvard Kennedy School (HKS) Misinformation Review 18.
63) Papapanagiotou, Petros, Alan Davoust, Dave Murray-Rust, Areti Manataki, Max Van Kleek, Nigel Shadbolt, and Dave Robertson. 2018. “Social machines for all.” In Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems, 1208-12.
64) Pariser, Eli. 2011. The filter bubble: How the new personalized web is changing what we read and how we think. Penguin.
65) Rahwan, Iyad, Manuel Cebrian, Nick Obradovich, Josh Bongard, Jean-François Bonnefon, Cynthia Breazeal, Jacob W. Crandall, Nicholas A. Christakis, Iain D. Couzin, and Matthew O. Jackson. 2019. “Machine behaviour.” Nature 568 (7753): 477-86.
66) Rainie, Lee, Aaron Smith, Kay Lehman Schlozman, Henry Brady, and Sidney Verba. 2012. “Social media and political engagement.” Pew Internet & American Life Project 19 (1): 2-13.
67) Ribeiro, Manoel Horta, Raphael Ottoni, Robert West, Virgílio AF Almeida, and Wagner Meira Jr. 2020. “Auditing radicalization pathways on YouTube.” In Proceedings of the 2020 conference on fairness, accountability, and transparency, 131-41.
68) Rosenblueth, Arturo, Norbert Wiener, and Julian Bigelow. 1943. “Behavior, purpose and teleology.” Philosophy of science 10 (1): 18-24.
69) Ruesch, Jurgen, Gregory Bateson, Eve C. Pinsker, and Gene Combs. 2017. Communication: The social matrix of psychiatry. Routledge.
70) Ruppert, Evelyn, Engin Isin, and Didier Bigo. 2017. “Data politics.” Big data & society 4 (2): 2053951717717749.
71) Schipper, Burkhard C., and Hee Woo. 2018. “Political awareness, microtargeting of voters, and negative electoral campaigning.” Microtargeting of Voters, and Negative Electoral Campaigning (September 17, 2018).

72) Seaver, Nick. 2019. Knowing algorithms. In digitalSTS—A field guide for Science & Technology Studies, Hrsg. Janet Vertsi und David Ribes, 412–422. Princeton: Princeton University Press.
73) Selbst, Andrew D., Danah Boyd, Sorelle A. Friedler, Suresh Venkatasubramanian, and Janet Vertesi. 2019. “Fairness and abstraction in sociotechnical systems.” In Proceedings of the conference on fairness, accountability, and transparency, 59-68.
74) Shadbolt, Nigel, Kieron O’Hara, David De Roure, and Wendy Hall. 2019. The Theory and Practice of Social Machines. Lecture Notes in Social Networks. Cham: Springer International Publishing.
75) Shahrezaye, Morteza, Orestis Papakyriakopoulos, Juan Carlos Medina Serrano, and Simon Hegelich. 2019. “Measuring the ease of communication in bipartite social endorsement networks: A proxy to study the dynamics of political polarization.” In Proceedings of the 10th International Conference on Social Media and Society, 158-65.
76) Shneiderman, Ben, Catherine Plaisant, Maxine S. Cohen, Steven Jacobs, Niklas Elmqvist, and Nicholas Diakopoulos. 2016. Designing the user interface: strategies for effective human-computer interaction. Pearson.
77) Smart, Paul, Elena Simperl, and Nigel Shadbolt. 2014. “A taxonomic framework for social machines.” In Social collective intelligence, 51-85. Springer.
78) Stieglitz, Stefan, and Linh Dang-Xuan. 2013. “Social media and political communication: A social media analytics framework.” Social network analysis and mining 3 (4): 1277-91.
79) Taylor, Linnet. 2017. “What is data justice? The case for connecting digital rights and freedoms globally.” Big Data & Society 4 (2): 2053951717736335.
80) Tufekci, Zeynep, and Christopher Wilson. 2012. “Social media and the decision to participate in political protest: Observations from Tahrir Square.” Journal of communication 62 (2): 363-79.
81) Von Foerster, Heinz. 2007. Understanding understanding: Essays on cybernetics and cognition. Springer Science & Business Media.
82) Vosoughi, Soroush, Deb Roy, and Sinan Aral. 2018. “The spread of true and false news online.” science 359 (6380): 1146-51.
83) Wachter, Sandra, Brent Mittelstadt, and Chris Russell. 2017. “Counterfactual explanations without opening the black box: Automated decisions and the GDPR.” Harv. JL & Tech. 31: 841.
84) Wiener, Norbert. 1961. “Cybernetics: Control and Communication in the Animal and the Machine--2nd.”
85) Yang, JungAe. 2016. “Effects of popularity-based news recommendations (‘most-viewed’) on users’ exposure to online news.” Media Psychology 19 (2): 243-71.
86) Zuckerman, E. 2014. New media, new civics? Policy & Internet, 6 (2), 151–168.