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THE MACHINES OF MUDDLING THROUGH AND POLICY SCIENCE

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According to Lindblom, public policy relies on limited analysis, is formulated under conditions of bounded rationality, and operates with little or no explicit programme theory. Policies are shaped by trial and error and achieve only incremental results. Machine learning algorithms have been adopted in the public sector under the expectation that they would strengthen the evidentiary foundations of policymaking, fulfilling Harold Lasswell's vision of a scientifically grounded policy enterprise. Yet documented cases of algorithmic deployment in social protection, policing, and benefit administration across multiple countries reveal that these systems reproduce, rather than resolve, the condition of bounded rationality. This article asks how the incorporation of predictive machine learning into the policy process alters the epistemic foundations of policy science and what implications this transformation carries for evidence-based policymaking. Drawing on an analytical review of the literature on machine learning and public policy, complemented by empirical cases from Australia, Brazil, and India, we argue that the industrial character of these algorithms and their uncritical adoption do not support a policy process founded on scientific knowledge. Machine learning algorithms carry significant implications for the epistemology and practice of policy science. Their outputs are shaped not by scientific evidence but by processes of trial and error and experimentation conducted within opaque design processes. The design of algorithms converges with the design of public policies, generating new practical dilemmas for policymaking. We conclude that the incorporation of machine learning into the policy process produces what we call machines of muddling through: systems that alter the epistemic foundations of policy work without resolving its fundamental uncertainties.

Keywords: machine learning; predictive artificial intelligence; evidence; epistemic change; knowledge; policymaking.

As máquinas do muddling through e a ciência das políticas

Segundo Lindblom, as políticas públicas se baseiam em análises limitadas, são formuladas sob condições de racionalidade limitada e operam com pouca ou nenhuma teoria explícita de programa. As políticas são moldadas por processos de tentativa e erro e alcançam apenas resultados incrementais. Algoritmos de aprendizado de máquina têm sido adotados no setor público sob a expectativa de fortalecer as bases empíricas da formulação de políticas, concretizando a visão de Harold Lasswell de uma ciência das políticas fundamentada no conhecimento científico. Entretanto, casos documentados de aplicação desses algoritmos em proteção social, policiamento e administração de benefícios em diversos países revelam que tais sistemas reproduzem, em vez de superar, a condição de racionalidade limitada. Este artigo investiga como a incorporação do aprendizado de máquina preditivo ao processo de políticas públicas altera os fundamentos epistemológicos da ciência das políticas e quais implicações essa transformação traz para a formulação de políticas baseada em evidências. Com base em uma revisão analítica da literatura sobre aprendizado de máquina e políticas públicas, com-

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plementada por casos empíricos da Austrália, do Brasil e da Índia, argumentamos que o caráter industrial desses algoritmos e sua adoção acrítica não sustentam um processo de políticas fundamentado no conhecimento científico. Os algoritmos de aprendizado de máquina têm implicações significativas para a epistemologia e a prática da ciência das políticas. Seus resultados são moldados não por evidências científicas, mas por processos de tentativa e erro e de experimentação conduzidos em processos de desenvolvimento opacos. O desenvolvimento de algoritmos converge com a formulação de políticas públicas, gerando novos dilemas práticos para o processo de formulação de políticas. Concluímos que a incorporação do aprendizado de máquina ao processo de políticas públicas produz o que denominamos *machines of muddling through*: sistemas que alteram os fundamentos epistemológicos da atividade de formulação de políticas sem resolver suas incertezas fundamentais.

Palavras-chave: aprendizado de máquina; inteligência artificial preditiva; evidências; mudança epistemológica; conhecimento; formulação de políticas públicas.

Las máquinas del muddling through y la ciencia de las políticas

Según Lindblom, las políticas públicas se basan en análisis limitados, se formulan bajo condiciones de racionalidad limitada y operan con escasa o ninguna teoría explícita del programa. Las políticas se configuran mediante procesos de prueba y error y solo alcanzan resultados incrementales. Los algoritmos de aprendizaje automático han sido adoptados en el sector público con la expectativa de fortalecer las bases empíricas de la formulación de políticas, materializando la visión de Harold Lasswell de una ciencia de las políticas sustentada en el conocimiento científico. Sin embargo, casos documentados de implementación de estos algoritmos en la protección social, la actividad policial y la administración de prestaciones en diversos países muestran que estos sistemas reproducen, en lugar de superar, la condición de racionalidad limitada. Este artículo examina cómo la incorporación del aprendizaje automático predictivo al proceso de las políticas públicas transforma los fundamentos epistemológicos de la ciencia de las políticas y qué implicaciones tiene esta transformación para la formulación de políticas basada en evidencias. A partir de una revisión analítica de la literatura sobre aprendizaje automático y políticas públicas, complementada con casos empíricos de Australia, Brasil e India, sostenemos que el carácter industrial de estos algoritmos y su adopción acrítica no respaldan un proceso de formulación de políticas basado en el conocimiento científico. Los algoritmos de aprendizaje automático tienen importantes implicaciones para la epistemología y la práctica de la ciencia de las políticas. Sus resultados están determinados no por evidencias científicas, sino por procesos de prueba y error y experimentación desarrollados en procesos de diseño opacos. El diseño de algoritmos converge con el diseño de políticas públicas, generando nuevos dilemas prácticos para la formulación de políticas. Concluimos que la incorporación del aprendizaje automático al proceso de las políticas públicas produce lo que denominamos machines of muddling through: sistemas que transforman los fundamentos epistemológicos de la actividad de formulación de políticas sin resolver sus incertidumbres fundamentales.

Palabras-clave: aprendizaje automático; inteligencia artificial predictiva; evidencias; cambio epistemológico; conocimiento; formulación de políticas públicas.

1. INTRODUCTION

Public policy, as Lindblom (1959) argued, is formulated through trial and error within processes of bounded rationality. Policymakers navigate uncertainty by making incremental adjustments rather than pursuing comprehensive solutions, in a process Lindblom termed muddling through. In response to these constraints, a scientific conception of policy analysis has sought to rationalize the selection of alternatives through the systematic use of evidence (Head, 2016; Howlett, 2009). This movement rests on the premise, traceable to Lasswell (1970), that policy work guided by scientific knowledge and supported by computational technologies can overcome the limitations of incremental reasoning. The emergence of machine learning algorithms has given new impetus to this aspiration, as governments have adopted these systems under the expectation that they would strengthen the evidentiary foundations of policymaking.

In practice, however, the deployment of machine learning in the public sector has produced outcomes that contradict this expectation. Automated welfare systems have denied benefits to eligible citizens without transparent justification, predictive policing tools have reproduced and amplified existing social biases, and algorithmic risk assessments have generated classifications whose epistemic status remains opaque to the policymakers who rely on them (Eubanks, 2018; Benjamin, 2019; United Nations, 2019). The core problem that this article addresses is that these systems are adopted with the expectation that they will rationalize the policy process, yet they reproduce and, in some cases, deepen the very condition of bounded rationality and incremental adjustment that Lindblom identified decades ago.

This article addresses the following research question: how does the incorporation of machine learning algorithms into the policy process alter the epistemic foundations of policy science, and what are the implications of this transformation for evidence-based policymaking? The analysis draws on a review of the existing literature on machine learning and public policy. In this article, we illustrate the practical consequences of algorithmic deployment in governance. The argument is organized around three conceptual dimensions. In the first section, we conceptualize machine learning algorithms and situate them within the broader landscape of artificial intelligence. In the second section, we analyse the challenges that emerge when these algorithms are incorporated into the policy process, with particular attention to the relationship between implementation failures and the assumptions embedded in policy formulation. In the third section, we examine the epistemic changes that machine learning introduces into the knowledge base of policy science. We argue that machine learning algorithms, rather than fulfilling the aspiration of a scientifically grounded policy enterprise, function as what we call machines of muddling through: systems that alter the epistemic foundations of policy work without resolving its fundamental uncertainties.

PUTTING THE PROBLEM OF MACHINES OF MUDDLING THROUGH IN POLICY SCIENCES

Artificial intelligence encompasses a broad family of computational methods, and it is necessary to distinguish among its principal modalities before examining their implications for policy science. Predictive AI refers to systems that employ machine learning algorithms to identify patterns in existing data and generate probabilistic estimates about future states or classifications. These systems, which include supervised learning models, unsupervised clustering techniques, and reinforcement learning architectures, constitute the predominant form of AI currently deployed in public sector operations such as fraud detection, risk assessment, predictive policing, and benefit eligibility determination (Russell & Norvig, 2010). Generative AI, by contrast, designates a more recent class of large-scale models, including large language models such as GPT and Claude and multimodal systems capable of producing text, images, code, and synthetic data. While generative AI is built upon the same foundational machine learning techniques, particularly deep learning and transformer architectures, its distinctive feature is the capacity to produce novel outputs rather than to classify or predict from structured inputs (Okadome, 2025). A third and still emergent category, agentic AI, refers to systems designed to operate with a degree of autonomous decision-making, executing sequences of actions in pursuit of specified objectives with minimal human intervention. Agentic systems combine elements of both predictive and generative models, but their defining characteristic is operational autonomy within complex task environments (Bornet *et al.*, 2025).

All three modalities are grounded in machine learning as a methodological foundation. Predictive AI relies on supervised, unsupervised, and reinforcement learning to extract patterns from data. Generative AI extends these techniques through neural network architectures trained on large corpora to produce probabilistic outputs. Agentic AI integrates learning with planning and tool use to pursue goals across multiple steps. This article focuses primarily on predictive AI and its associated machine learning algorithms, because these are the systems most extensively deployed in public policy operations and most directly implicated in the epistemic and governance challenges examined here. The cases discussed throughout the article, from automated welfare systems to predictive policing, involve predictive models that classify, score, and rank individuals and situations on the basis of historical data. While generative and agentic AI raise important and partly distinct questions for policy science, particularly regarding the production of synthetic evidence, the automation of advisory functions, and the delegation of decisional authority, a systematic examination of these modalities falls beyond the scope of the present analysis. Where relevant, the article signals how the arguments developed here may extend to or require qualification in light of generative and agentic systems.

According to Lindblom (1959), public policies do not consistently achieve optimal outcomes because they are formulated through trial and error within processes of bounded rationality. The policy process is characterized by what Lindblom termed muddling through. In this perspective, policymakers navigate uncertainty by making incremental adjustments rather than pursuing comprehensive solutions. In response to these limitations, a scientific conception of public policy has sought to rationalize the selection of policy alternatives. Central to this effort is the growing reliance on evidence as an instrument of policy analysis. As Head (2016) observes, the quality of public decision-making depends substantially on the quality of analysis and advice that public organizations produce. Policy studies have thus developed along a conceptual divide between muddling through and a more scientifically oriented vision of policy work.

The incorporation of machine learning algorithms into this landscape has introduced a specific practical problem that this article seeks to address. Governments have adopted these algorithms under the expectation that they would strengthen the evidentiary foundations of policymaking. In practice, however, the deployment of machine learning in public policy has produced outcomes that contradict this expectation. Automated welfare systems have denied benefits to eligible citizens without transparent justification. Predictive policing tools have reproduced and amplified existing social biases. Algorithmic risk assessments have generated classifications whose epistemic status remains opaque to the policymakers who rely on them. The core problem, therefore, is not simply that machine learning may produce unjust outcomes, although it frequently does, nor that it is accompanied by a technocratic discourse of neutrality and impartiality, although this discourse is pervasive. The problem is that these systems are adopted with the expectation that they will rationalize the policy process, yet they reproduce and, in some cases, deepen the very condition of bounded rationality and incremental adjustment that Lindblom identified decades ago.

At the center of this debate lie the evidentiary and analytical capacities of policymakers. The ability of governments to address public problems, including those that qualify as wicked problems (Rittel & Webber, 1973), improves when policymakers draw on evidence to inform their decisions. Evidence-based policy enables responses that are better aligned with identified problems, facilitating anticipation, simulation, and improvement of the decision-making process. Analytical capacities, in turn, strengthen broader state capacities, allowing governments to construct more robust responses to complex challenges (Howlett, 2009; Koga *et al.*, 2023; Carney, 2017). However, these analytical capacities require that policymakers possess the skills to work systematically with evidence.

Evidence-based public policy reflects a broader movement emphasizing the importance of data and information across the policy cycle. This movement rests on an assumption of instrumental rationality, according to which evidence serves as a neutral input for decision-making. Critics have pointed out that this conception is reductive, as it overlooks the political processes embedded in the selection of which evidence is used, under which interpretive framework, and in service of which narrative (Carney, 2019; Parkhurst, 2017; Jasanoff, 2012).

There is, therefore, a positivist premise in which the use of evidence is considered essential for policymakers to understand different action situations and to design interventions capable of addressing societal problems. Popper (2002) frames evidence as an instrument that enables policymakers to act as social engineers, understanding social reality and introducing incremental changes. As social engineers, policymakers use evidence and experimental methods to build informed perspectives on institutional reform.

The assumption underlying this instrumental conception is that evidence allows policymakers to construct what Lasswell envisioned as a scientific epistemology of policy analysis. Knowledge in public policy, under this view, treats evidence as the product of scientific inquiry, grounded in a purportedly neutral method for formulating more effective government actions. Lasswell's (1970) vision involved building a professional discipline of public policy mobilized by scientific knowledge, in which problems and evidence guide the work of analysts and can be supported by computational technologies. In Lasswell's argument, policy work guided by "computerized" information is essential to maintaining the scientific character of the discipline and to cultivating a technical identity among its professionals.

The relationship between artificial intelligence and the policy process, however, extends beyond the mere optimization of evidence production. As Filgueiras (2025) argues, artificial intelligence constitutes an epistemic instrument that disrupts the foundations of policy science by transforming how knowledge is constructed and applied within government. In this account, AI does not simply augment existing analytical capacities. It introduces a sociotechnical reengineering of the policy process that alters the dynamics of formulation, implementation, and advisory practices, as well as the behavior of actors and the institutional structures through which policy responses are developed. The premise that policy science rests on applied, contextual, and interdisciplinary knowledge, as originally formulated by Lasswell, is reconfigured when algorithmic systems mediate the relationship between problems and solutions, creating new instrument constituencies and reshaping the conditions under which policymakers exercise epistemic agency (Filgueiras, 2025). This disruption demands not only new governance mechanisms but also a reassessment of the theoretical foundations of policy science itself.

A more politically informed perspective, rooted in broader processes of rationalization, considers that policy analysis uses evidence in a wider sense, drawing on diverse sources and purposes that extend beyond instrumental rationality. Evidence, from this standpoint, encompasses not only quantitative data but also texts, deliberative discourse, images, administrative records, and legal interpretations (Koga *et al.*, 2022). This conception emerges from a pragmatic policy tradition in which the resolution of public problems is guided by engagement, discourse, and exchange among the various actors in the policy process (Koga *et al.*, 2022; Zittoun, 2014). From this perspective, these exchanges and the construction of shared meanings are central to policy analysis because they inform how problems are defined and solutions are proposed (Zittoun, 2014). Policymakers learn from epistemic communities and continuously construct and reconstruct problems and solutions based on shared knowledge (Dunlop, 2012; Haas, 1992).

The concept of evidence thus remains contested within the field of policy knowledge. There is no consensus on how evidence shapes the work of policymakers or on their capacity to address public problems effectively. Despite this dissent, the discussion surrounding evidence-based policy has acquired a new dimension with the emergence of big data and the increasing use of artificial intelligence, particularly machine learning algorithms. These technologies are designed to identify problems and support data-driven decision-making (El-Taliawi, Goyal, & Howlett, 2021). The deployment of data-intensive systems creates an epistemology that potentially amplifies the analytical capacities of the public sector and, consequently, supports evidence-informed governance (Dunleavy & Margetts, 2013).

With their work oriented toward policy formulation, policymakers operating within a positivist framework function as social engineers, designing interventions informed by knowledge systems sustained by machine learning algorithms. Governments have increasingly turned to these algorithms to confront the challenges posed by expanding uncertainties arising from economic, social, environmental, climatic, and cultural crises. The responses that policymakers have begun to develop in the face of these expanding uncertainties reflect a new policy epistemology: one based on propositions of plausible, rather than definitive, alternatives for societal intervention. Interventions in society are thus sustained by new knowledge systems that do not present correct solutions but satisfactory perspectives (Hartley & Kuecker, 2022; Simon, 1955).

Machine learning algorithms serve a distinctive function in this context. They can process numbers, texts, discourse, and images as data and address a wide range of problems. Even from a pragmatic policy perspective, these algorithms are capable of treating texts, speeches, and images as inputs, transforming them into analytical vectors for understanding problems and proposing data-driven solutions. The growing use of machine learning in the policy process thus represents an instrument of rationalization without precedent in the history of government, establishing new parameters of learning that influence the behavior of policymakers.

This article addresses the following research question: how does the incorporation of machine learning algorithms into the policy process alter the epistemic foundations of policy science, and what are the implications of this transformation for evidence-based policymaking? The scope of the analysis is circumscribed to predictive machine learning systems deployed in public sector operations, with particular attention to cases in which these systems have been adopted to support or automate decisions in social protection, policing, and benefit administration. The article draws on an analytical review of the existing literature on machine learning and public policy, complemented by documented empirical cases from Australia, Brazil, and India that illustrate the practical consequences of algorithmic deployment in governance. The analysis is organized around three conceptual dimensions: the technical characteristics of machine learning and their relationship to evidence production, the governance challenges that arise when these algorithms are incorporated into the policy cycle, and the epistemic changes that machine learning introduces into the knowledge base of policy science. The justification for focusing on predictive machine learning, rather than on the broader field of artificial intelligence, rests on the observation that these are the systems most widely deployed in government operations and most directly responsible for the governance failures documented in the empirical literature.

The article proceeds as follows. In the first section, we conceptualize machine learning algorithms and situate them within the broader landscape of artificial intelligence, including the distinction between predictive, generative, and agentic modalities. In the second section, we analyse the challenges that emerge when these algorithms are incorporated into the policy process, with particular attention to the relationship between implementation failures and policy formulation. In the third section, we examine the epistemic changes that machine learning introduces into the knowledge base of policy science. In the conclusion, we discuss the implications of these findings for the theory and practice of evidence-based policymaking.

MACHINE LEARNING FUNDAMENTALS AND THEIR REACH IN SOCIETY

Algorithms are a foundational concept in computer science (Knuth, 1968). They are finite sets of well-defined instructions designed to solve a given problem, perform a task, or execute a calculation. Computer scientists and engineers focus on designing and analyzing algorithms, assessing their efficiency, correctness, and optimization from a technical standpoint (Kearns & Roth, 2020).

In recent years, algorithms have advanced considerably (Russell & Norvig, 2010). The development of sophisticated algorithms is closely associated with increases in computational capacity and the proliferation of big data. Big data refers to the large volumes of data collected from diverse sources, including numerical records, images, speech, and text, which are stored and processed rapidly owing to the expansion of digital infrastructure. Although big data is a contemporary topic, no consensus exists regarding its precise concept, scope, or defining properties (Ekbia *et al.*, 2014). In general terms, big data is the field concerned with methods for analyzing and managing extensive datasets collected from multiple sources at high speed and with considerable complexity. Among its defining features, big data requires methodologies and technologies for collecting, storing, processing, and sharing data from heterogeneous sources to create an expanded informational domain and to deploy a range of computational technologies (Kitchin, 2013; Mayer-Schönberger & Cukier, 2013).

The emergence of big data made it possible to revitalize the field of artificial intelligence and to expand the application of machine learning algorithms to a wide array of problems. Unlike traditional algorithms, which follow specified rules and predetermined procedures, machine learning algorithms are programmes that learn from examples, data, and experience (Samuel, 1959). These algorithms compute learning functions and can derive solutions from data. Machine learning algorithms belong to a broader family of artificial intelligence methods that includes deep learning and reinforcement learning (Kelleher, 2019). Such algorithms drive modern applications embedded in virtual personal assistants, autonomous vehicles, recommendation engines, image and voice recognition tools, and language translation services.

In essence, a machine learning algorithm takes data as input and produces a model that represents the patterns it has identified within that data (Samuel, 1962). Grounded in statistics and probability theory, machine learning algorithms generate results that carry a degree of uncertainty about what is practical or ideal, thereby creating conditions for performing a variety of tasks. These algorithms identify recurring patterns in datasets and, beyond static learning from historical data, offer dynamic adaptation through feedback collection. Such feedback improves the accuracy of reinforcement learning processes and, consequently, the overall performance of algorithmic systems in addressing transactional and interactive demands of connected populations (Kelleher, 2019).

Machine learning encompasses two principal stages: training and inference. The training process is organized into three main approaches. In supervised machine learning, a system is trained on data that has been previously labelled, and the system subsequently uses this information to predict the categories of new, unlabeled data (Kelleher, 2019). In unsupervised learning, no labeled data is available, and the algorithm seeks to detect functions that map similar examples into clusters. Reinforcement learning occupies a position between supervised and unsupervised learning, operating through feedback generated from the interaction between humans and machines. Deep learning algorithms, a subfield of machine learning, are artificial neural networks inspired by findings from physiology and neuroscience. Once a model is trained, the second stage of machine learning, inference, involves applying the trained model to generate outputs for new cases (Kelleher, 2019).

Algorithms are being incorporated into virtually every dimension of contemporary life and provide governments with an unprecedented opportunity to collect transactional and relational data, expanding the knowledge base derived from administrative records. The collection of diverse data broadens the possibilities for applying algorithms in real-time decision-making, creating agency conditions for policymakers in both policy formulation and societal intervention (Filgueiras, 2022a). These agency conditions arise from the transformation of human knowledge through machine learning algorithms (Coeckelbergh, 2022). Algorithms function, in this sense, as general-purpose technologies that affect a wide range of societal domains (Aradau & Blanke, 2022).

Computer science recognizes that algorithmic systems are agents, and in many cases multi-agent systems, that perform various coordinated actions. Russell (2019) defines artificial intelligence systems as agents that perceive a stream of inputs and produce a stream of outputs to accomplish a given human goal. This condition of agency is attributed to algorithms through the rules and procedures embedded in their complex code. Algorithms are not fully autonomous agents; they are artefacts, or artificial entities, shaped within specific contexts that encode rules capable of influencing human behaviour. According to Issar and Aneesh (2022), the use of algorithmic systems in policy governance creates new agency conditions, as sociotechnical systems carry out decision-making and implementation tasks through massive volumes of data processed by algorithms.

Recommendation algorithms, image identification systems, search engines, routing algorithms, and digital agents are examples of algorithmic systems that reduce or eliminate the need for human involvement in certain tasks. For instance, algorithms are deployed at border facilities to supplement human decisions in security operations (Amoore, 2021). Credit score algorithms assess the suitability of applicants for loans and other financial operations and serve as instruments of social control by the state (Dai, 2020). Algorithms, and machine learning in particular, are instruments of power shaped by political and social conceptions that have come to function as new institutional frameworks (Almeida, Filgueiras, and Mendonça, 2023).

In what Wagner *et al.* (2021) describe as algorithmically infused societies, the social fabric is co-constituted by algorithmic and human behavior. It becomes necessary, therefore, to examine the potentially harmful and sometimes unforeseen consequences of algorithmic systems, particularly for the functioning of democratic institutions. Artificial intelligence algorithms are at the center of contemporary social transformations, with far-reaching consequences for society and democracy (Aradau & Blanke, 2022; Amoore, 2022; Frischmann & Selinger, 2018). Algorithms define situations, scripts, and frames for social action, thereby instrumentalizing new logics that emerge from human-machine interaction. This process is associated with epistemic changes in the social dimension, as new dynamics of knowledge construction and new forms of mediation arise with the application of algorithms across different areas of collective life (Coeckelbergh, 2023).

Machine learning algorithms can serve diverse applications and potentially enhance analytical capacities related to knowledge construction and the use of evidence in public policy. However, significant limitations and unintended consequences continue to arise from an uncritical acceptance of machine learning in the policy process. In many circumstances, machine learning algorithms can introduce processes that resemble alchemy rather than rigorous science in the construction of policy knowledge, with significant repercussions for society. The following section analyses these emerging limitations and the criticisms they have generated.

SCIENCE OR ALCHEMY?

A positivist perspective on policy analysis assumes that public policy design involves knowledge of a problem, a solution, and the construction of government interventions in society, implemented through institutions to achieve a specified objective. A more pragmatic perspective, by contrast, recognises that relational elements and the sharing of meanings are essential to policy analysis. This perspective calls for a broader evidentiary framework (Pinheiro, 2022). The formulation and implementation of public policy depend on a knowledge system in which evidence contributes to all phases of the policy cycle (Freeman, Griggs, & Boaz, 2011). Within this framework, the analytical capacities of policymakers are fundamental to understanding problems and navigating the policy process (Koga *et al.*, 2023).

Machine learning algorithms can enhance these analytical capacities and may be incorporated across all phases of the policy cycle (Valle-Cruz *et al.*, 2020; Porciello *et al.*, 2020). In problem identification and agenda-setting, for example, machine learning algorithms enable governments to analyze data from social media and to develop perspectives on citizen attention (Giest, 2017). In policy design, they can perform a range of analytical tasks and support decision-making. In policy implementation, machine learning algorithms can automate tasks related to the welfare state (Coles-Kemp *et al.*, 2020) and carry out predictive policing and various security operations (Meijer & Wessels, 2019).

Machine learning algorithms enhance analytical capacities primarily because they incorporate an automated, data-driven system of knowledge and learning. They deliver data-based analytical activities with greater speed and efficiency (Giest, 2017), potentially optimising the entire policy cycle and reinforcing a scientific policy perspective that echoes Lasswell's vision. Furthermore, machine learning algorithms produce new institutional frameworks that shape the conditions under which policymakers act. In other words, machine learning algorithms potentially create an epistemological shift in policy analysis and practice, altering the entire framework of knowledge and learning available to policymakers and implementers (El-Taliawi, Goyal, & Howlett, 2021). Algorithms are transforming various organizational dimensions of the state, generating what Meijer, Lorenz, and Wessels (2021) describe as the algorithmization of bureaucracy.

This epistemological shift warrants scrutiny. The adoption of artificial intelligence in the public sector may facilitate the efficiency and effectiveness of public services through the accelerated production of information. However, this potential must be weighed against fundamental concerns about the scientific status of machine learning itself. Ali Rahimi, an artificial intelligence researcher at Google, stated at a prominent conference that machine learning algorithms represent not a scientific activity but a form of alchemy. According to Rahimi, researchers and designers of machine learning systems lack strict criteria for selecting one algorithmic architecture over another, operate without consistent standards for choosing input data, and face reproducibility problems that prevent independent verification by other researchers or regulators (Hutson, 2018). These concerns echo broader debates in the philosophy of science about the distinction between reliable knowledge production and ad hoc technical practice (Gillies, 1993).

In addition to reproducibility problems, machine learning algorithms are not transparent about how they process data and construct information. Machine learning algorithms are opaque with respect to the procedures they adopt, thereby preventing effective oversight of their operations across various fields of society (Pasquale, 2015). Without transparency, machine learning algorithms applied in governance cannot be held accountable to citizens (Binns, 2018). Moreover, they do not readily permit forms of learning that allow policymakers to modify their procedures, because machine learning algorithms incorporate entire knowledge systems and produce their own forms of learning, whether supervised or unsupervised, without enabling policymakers to construct feedback mechanisms beyond those already embedded in the data.

Machine learning algorithms thus resemble a practice of alchemy more than rigorous scientific work. When applied to policy analysis, it is difficult to maintain that the evidentiary environment is genuinely improved or that it can meaningfully influence policy formulation. The claim that machine learning algorithms facilitate the production of evidence and thereby strengthen analytical capacities risks producing a contradiction. First, data are not neutral objects. As objects of knowledge that classify or rank things and people, data can introduce analytical biases, reproduce social hierarchies, and distort the understanding of contexts (Gitelman & Jackson, 2013; Issar & Aneesh, 2022; Crawford, 2021).

When applied within artificial intelligence systems, biased datasets can generate algorithmic injustice across multiple dimensions, causing the resulting knowledge structures to reflect prevailing racial (Benjamin, 2019; Noble, 2018), gender (Joyce *et al.*, 2021), and socioeconomic inequalities. Eubanks (2018) identifies the emergence of what she terms digital poorhouses, as algorithmic systems establish new mechanisms of exclusion and punishment directed at the most disadvantaged populations. Philip Alston's report to the UN General Assembly documents how governments around the world have silently transformed the dynamics of access to social rights and protection through machine learning algorithms, creating the need for a new body of digital rights to protect the most vulnerable populations (United Nations, 2019).

Several empirical cases illustrate these concerns. In Australia, the federal government created Robodebt, an algorithmic system designed to calculate and collect overpayments of social welfare benefits automatically. Launched in July 2016, the system's automated recommendations caused considerable harm to citizens and employees of social assistance agencies. Robodebt's mode of operation was found to be illegal by Australian courts and was investigated by the Commonwealth Ombudsman and three Senate committees. The system improperly charged 470,000 beneficiaries, negatively affecting their physical and mental health, and ultimately compelled the Australian government to return AUS$1.8 billion following multiple lawsuits (Rinta-Kahila *et al.*, 2022).

Similar cases have emerged in Brazil. According to ruling 514/2023 of the Federal Court of Accounts (Tribunal de Contas da União), an algorithm implemented by the National Institute of Social Security (INSS) to analyze applications for benefits and pensions rejects approximately 60 per cent of requests on grounds that lack transparency for citizens. According to Minister Aroldo Cedraz, rapporteur of the case, this algorithm has created a condition of social deprotection, with broad implications for Brazilian society, including the expansion of queues for social security applications, the erosion of settled judicial precedent, and the reduction of transparency in INSS activities.

Algorithmic systems make decisions that directly affect citizens' lives, generating diverse implications arising from the concentration of technocratic power. The Aadhaar unique identification system implemented in India, for example, manages the allocation of social benefits through a single platform that employs facial recognition algorithms to identify citizens and determine eligibility. Failures in the Aadhaar system have, in documented cases, denied individuals access to food and disaster relief. Each person must possess this identification number to access social benefits linked to biometric data used in various social protection operations (Ratcliffe, 2019).

These cases illustrate a pattern that extends beyond implementation failures in isolation. The problems documented in Australia, Brazil, and India are not merely operational malfunctions within existing policy frameworks. They reveal a structural relationship between algorithmic deployment in implementation and the assumptions embedded in policy formulation. The Robodebt system was designed on the basis of a policy premise—namely, that welfare fraud is widespread and detectable through automated income averaging—that was itself never subjected to rigorous evidentiary scrutiny. The INSS algorithm in Brazil reflects a formulation choice to prioritize administrative efficiency over substantive assessment of individual claims. The Aadhaar system embeds a policy design assumption that biometric identification can serve as a universal gateway to social protection without accounting for the material conditions of access. In each case, the machine learning system does not merely execute a policy. It encodes and amplifies the epistemic limitations present at the formulation stage. The connection between these implementation outcomes and the broader debate on evidence-based policymaking is therefore direct.

When machine learning algorithms are adopted as instruments of policy implementation, their design choices constitute de facto formulation decisions, because they determine which criteria govern the allocation of public goods, who is included or excluded from protection, and what counts as a relevant input for decision-making. The distinction between formulation and implementation, already contested in the policy literature, becomes further blurred when algorithmic systems mediate both stages simultaneously.

The automation of the welfare state in several countries through machine learning algorithms creates a situation in which social change is driven not by social engineers but, to extend the metaphor, by social alchemists. The scientific dimension of algorithms lies in the mathematical models at the core of their programming procedures and rules, not in their application to solve real-world problems. Biased databases, inappropriate choices of algorithmic architectures, reproducibility problems, lack of transparency and accountability, and the industrial process of deploying artificial intelligence produce a condition of imbalance in policy formulation. Policy steered by such processes is built on trial and error rather than on scientific epistemology. Machine learning algorithms do not fundamentally change how policymakers identify and address problems; instead, they reproduce longstanding difficulties under the guise of novel solutions. Machine learning algorithms are, in this sense, machines of muddling through.

The absence of transparency and explainability (Pasquale, 2015), the use of unqualified databases (Joyce *et al.*, 2021), and design choices regarding algorithmic architectures combine to make machine learning algorithms instruments that reinforce a technocratic and, at times, authoritarian conception of public policy. In addition to these factors intrinsic to the technology, solutions based on artificial intelligence for public policy tend to prioritize a calculated logic of cost and benefit rather than considerations of public values and social justice (Filgueiras, 2022a). Furthermore, the production of these technologies follows industrial processes designed to maximize accuracy and commercial potential rather than to produce contextually appropriate solutions (Issar & Aneesh, 2022).

These examples point to important considerations for the use of machine learning algorithms in the policy cycle as instruments of evidence production. The capacity of these technologies to process large volumes of data is not a sufficient condition for claiming that machine learning expands the availability of evidence for policy decision-making. While the volume and diversity of data can accelerate the capture and processing of information, design flaws, choices made by system designers regarding datasets, data quality and its implications, and the analytical architecture of algorithms blur the boundary between science and alchemy. These factors demand governance mechanisms for artificial intelligence and for controlling its effects on society (Issar & Aneesh, 2022). Without transparency, reproducibility, and accountability, machine learning algorithms function as a form of alchemy in pursuit of the elixir of bureaucratic efficiency, sustained by a technocratic framework and driven by the image of policymakers, whether human or machine, as neutral agents that amplify policy capacity by calculating governmental courses of action from data.

MACHINE LEARNING AND POLICY LEARNING: EPISTEMIC CHANGES

Machine learning algorithms applied to public problems carry far-reaching policy implications. As Amoore (2022, p. 21) argues, they represent a way of gathering and ordering knowledge that fundamentally transforms how the state and society come to understand each other. The result is the emergence of programmable and codified institutions that reshape the behavior of policymakers within broader organizational and political contexts.

According to Amoore (2014), working with artificial intelligence, and with machine learning algorithms in particular, demands a different type of capacity from designers: one that is more imaginative and intuitive. This argument, informed by Wittgenstein's critique of Alan Turing, rests on the observation that, in many situations, algorithmic systems are tasked with calculating what is fundamentally incalculable. Such tasks demand more than the automation of computation; they require imagination in the routinization of procedures that directly affect the real world. Algorithms, therefore, carry a form of mathematical intuition that produces a range of political effects, demanding from system designers a capacity that extends beyond technical proficiency to encompass judgement and foresight.

Sociotechnical systems based on machine learning are produced on an industrial scale, built upon ready-made algorithms that are shared or marketed through cloud platforms with standardized architectures adaptable to different problems in both the public and private sectors. Designers select algorithmic architectures through trial and error with respect to the problem at hand, choosing the solution that offers the best accuracy and optimization (Amoore, 2022). Machine learning algorithms thus function as solutions in search of problems within broader organizational processes (Filgueiras, 2022a; Cohen, March & Olsen, 1972). Although technical measurements of algorithmic accuracy exist, they do not permit assessment of the degree of relevance, coherence, and consistency of an algorithm when it is applied within the policy process. Technical accuracy does not account for policy objectives, public values, criteria of justice, or the effectiveness of the solution. System designers evaluate the accuracy of outputs, not the epistemological status of the knowledge that arises from the confrontation between algorithmic outputs and social reality.

In policy design and in the selection of algorithmic architectures, decisions are made through trial and error. Uncertainties are inherent to policy formulation. The policy process is not a cycle of rationality. In the definition of problems, in the selection of alternatives, and in policy formulation, broader political values and practices shape the resulting institutional design (Lindblom, 1959). The policy process is not linear and unidirectional but incremental, involving sequential adjustments through trial and error. According to Lindblom, policymaking is a continuous process of incremental adjustment through institutional design. Policymakers select among alternatives in contexts of bounded rationality and in the absence of a formal programme theory. Trial and error constitute a common mode of decision-making in both policy design and the configuration of machine learning algorithms. The adoption of machine learning to address policy problems is subject to the same difficulties that characterize the choice of policy design (Filgueiras, 2022a). These choices are made under conditions of uncertainty and can produce ambiguous responses to policy problems.

What is distinctive about algorithmic governance is the convergence between policy design and system design that occurs when artificial intelligence is applied in the policy cycle (Filgueiras, 2022a). However, this convergence is based on practices that differ substantially from one another, and this divergence amplifies the challenges that machine learning introduces. Machine learning will not, by itself, produce evidence. Rather, it constructs accurate factual propositions derived from data. Policymakers identify a problem to be solved. System designers, through trial and error, select an algorithmic architecture optimized for accuracy in calculating a solution and for the organizational tasks to be performed. This new epistemology of policy work is fundamentally distinct from evidence-based policymaking.

Machine learning systems do not operate as, or increase the reliance on, evidence in public policy, even though they are clothed in mathematical calculations and organizational rationalization. Machine learning applied to the production of evidence in public policy carries diverse political effects that need to be mapped as risks to the functioning of systems that support decision-making and the execution of tasks. The reliance on imagination and intuition as capacities of policymakers does not warrant the claim that a scientific conception of policy analysis is being constructed. What emerges, instead, is the coexistence of a political system that incorporates sociotechnical systems capable of transforming various aspects of society through human-machine interaction. These sociotechnical systems rupture the epistemological structure of public policy, displacing the status of evidence and replacing it with accurate factual propositions that are not, in themselves, evidence.

This new epistemology of policy analysis based on machine learning algorithms resonates with Wittgenstein's philosophical critique of Turing. According to Wittgenstein, propositions about the world are contingent. They configure the facts and create a discursive figuration whose truth values depend on confrontation with reality. Machine learning algorithms, by producing mathematically accurate factual propositions, generate a form of knowledge grounded in intuition rather than in the prior description of problems and realities. These algorithms support decision-making and task execution not on the basis of evidence but through the figuration of a reality calculated from data, with material consequences for society. As Amoore (2014) argues, such systems demand more imagination and intuition than certainty and evidence.

The case of Robodebt in Australia illustrates this dynamic. The system was not designed in response to a well-defined problem grounded in evidence. The problem was imagined by policymakers within the Australian welfare system who operated under a neoliberal orientation favoring the restriction of social assistance. The algorithm embedded in the Robodebt system was selected not because it aligned with a particular conception of well-being but because it was the most accurate and efficient at detecting fraud. Policymakers already presupposed, through intuition rather than evidence, that social protection policies are subject to widespread fraud. The system was therefore deemed better to the extent that it was more efficient at detecting fraud, with the selection of its parameters driven by trial and error. In this way, machine learning systems reproduce bounded rationality in policy decision-making. According to Amoore (2014), they reinforce the centrality of intuition and imagination while functioning as solutions that, in each context, find windows of opportunity to be implemented in opaque ways within governance systems (Filgueiras, 2022a).

Recognizing this shift toward an imaginative and intuitive capacity among policymakers represents a significant change that artificial intelligence systems introduce into the knowledge base of policy analysis. Machine learning algorithms applied in the policy process operate between evidence, broadly conceived, and the search for what might be compared to the philosopher's stone, as sociotechnical systems accelerate transformations and practices within the public sector. Machine learning algorithms produce profound changes in the epistemology of policy analysis, demanding from policymakers more imagination and creativity than a systematic and positivist use of evidence (Filgueiras, 2025). They incorporate a more pragmatic conception of exchanges, discourses, and frameworks that draw on factual propositions, in the Wittgensteinian sense, when confronted with reality. These factual propositions reshape the epistemology of policymakers and their capacity for learning within public policy practice.

Learning in public policy has traditionally been understood as the process by which policymakers understand public problems through comparison with other jurisdictions and experiences (Freeman, 2009). Policymakers learn from other experiences to develop diverse perspectives and solutions to public problems. Policy practice involves the construction of knowledge informed by evidence on various issues that affect society (Freeman, Griggs & Boaz, 2011). The form of learning inscribed in policy practice depends on knowledge networks based on information that policymakers produce and absorb in the daily work of governance. The epistemic basis of public policy has thus been grounded in practical action shaped by diverse information disseminated through these networks.

Machine learning algorithms, when applied to public policy, disrupt this epistemic basis. In a world shaped by uncertainties that permeate economic, social, and environmental domains, policymakers are increasingly inclined to rely on algorithmic systems as repositories for their forms of learning. These technologies can transform numbers, texts, speeches, images, and sentiments into data. Such data, collected in real time, provide intuitive means of engaging with different action situations and frames for public problems. Furthermore, when incorporated into interfaces that perform implementation tasks, these algorithms collect feedback and accelerate the forms of learning available to policymakers. Systems based on machine learning thus provide new ways of constructing knowledge, transforming the epistemologies previously employed by policymakers and implementers.

Machine learning systems have produced both epistemological and practical changes related to the policy process (Filgueiras, 2025). Changes in how knowledge about public policy is constructed suggest the emergence of a new epistemic paradigm in policy science, driven by the advent of new technologies and correlated crises. This new paradigm is characterized by both theoretical and practical dimensions. From a theoretical standpoint, epistemic changes render positivist legacies more situational or marginal, fostering a critical perspective grounded in pragmatism. From the standpoint of practice, comprehensive solutions to public problems become increasingly unthinkable or impractical. Within this paradigm, policy work focuses on proposing plausible alternatives rather than on the definitive resolution of complex problems (Hartley & Kuecker, 2022).

The large volumes of data that governments collect and store daily create diverse possibilities for applications that directly affect the policy process. Nevertheless, the diversity of algorithms and possible applications based on machine learning does not necessarily strengthen evidence-based policymaking. Having more data available does not automatically produce more evidence. Evidence requires rigorous procedures of collection, processing, and interpretation in order to produce information that can be tested, falsified, and evaluated against a knowledge objective.

Machine learning dispenses with these collection and processing procedures and with an explicit theory of the policy process. Instead, algorithms learn from training datasets and produce various effects on society, guided by recommendations that are more political and intuitive than scientific. The incalculable, following Amoore (2014), renders intuition essential, presented as a new capability when machine learning algorithms are deployed in the public sector as solutions in search of problems. Machine learning offers plausible perspectives for predicting or simulating alternatives, but it does not necessarily produce evidence, particularly when viewed in the context of the epistemic crises shaped by disruptive technologies (Hartley & Kuecker, 2022; Benkler, Faris & Roberts, 2018).

Lasswell argued that high-speed computing had been a revolutionizing tool, allowing a contextual, multi-valued point of view to pass from aspiration to practice (Lasswell, 1971). Lasswell's positivist vision did not anticipate that changes in policy science would derive from a more unpredictable, critical, and complex world, or that computers equipped with machine learning algorithms could fail precisely when data do not necessarily produce reliable information. Contrary to Lasswell's vision, machine learning algorithms disrupt the epistemology of policy science by introducing a new form of knowledge based on trial and error, craftsmanship with data, and mathematical intuition.

This insight carries critical implications for digital transformation processes. The expansion of machine learning algorithms in the public sector demands a new capacity from policymakers: the development of intuition and a sense of justice that cannot be delegated to the machine. In the foreseeable future of the public sector, machine learning will be essential for optimizing administrative, managerial, and policy capacities. However, public policy demands the recognition that more data do not produce more evidence. What machine learning offers, instead, is a set of plausible alternatives for addressing problems, provided that policymakers develop intuition and judgement as integral components of their practice.

Policymakers must develop sensitivity and judgement regarding the effects of artificial intelligence on society and democracy. Contrary to the proposition that more data produce more evidence, these algorithms require imagination and intuition from policymakers to address the different problems, critical junctures, and challenges that arise in a new policy science emerging amid epistemic crises. Recent disruptions in public policy call for more experimentation, trial and error, and governance processes for emerging technologies that are not yet fully defined or standardized (Filgueiras & Raymond, 2023). Disruptive technologies such as artificial intelligence challenge not only administrative, managerial, and relational capacities but, more fundamentally, the imagination and judgement of policymakers to produce plausible, inclusive, fair, and democratic solutions.

CONCLUSION: CONSTRUCTING MACHINES OF MUDDLING THROUGH

The use of machine learning algorithms is expanding the scope of the policy process. These algorithms function as both detectors and effectors in the construction of policy knowledge, enabling the automation and optimization of activities related to formulation and implementation. They disrupt and transform the agency conditions of the public sector, introducing practical changes in how public policies are designed and deployed to address identified problems. Nevertheless, as we have argued, the industrial architecture of these algorithms and their uncritical adoption do not fulfil Lasswell's aspiration of a policy process grounded in scientific knowledge. Machine learning algorithms carry significant implications for the epistemology and practice of policy science. Their outputs are shaped not by scientific evidence but by processes of trial and error and experimentation, conducted within the opacity of algorithmic design. Although they process extensive volumes and diverse types of data, machine learning algorithms engage in what Amoore (2014) terms the calculation of the incalculable.

In the various contexts where machine learning algorithms are deployed in the policy process, they do not produce evidence about problems and solutions in the conventional sense. Rather, they generate contingent propositions that may offer useful perspectives but that must be continually confronted with reality. The epistemic crisis that follows from this shift is that public problems expand in complexity and become resistant to definitive resolution, demanding from policymakers responses that are more assertive around plausible and provisional solutions. These epistemological changes emerge from a new policy practice shaped by machine learning algorithms, a practice coated in technical imagination and sustained by computerized information. Yet this technical imagination is grounded not in a scientific conception of public policy but in a process in which institutional choices are uncertain, contested, and shaped by trial and error.

Trial and error make public policies more experimental, grounded in industrial processes that are difficult for policymakers to comprehend, and thereby increase uncertainties regarding the design process. These uncertainties are not overcome through evidence and public deliberation but through a process of mathematical accuracy sustained by sociotechnical systems. In this context, values of social justice and policy effectiveness risk being subordinated to the optimization and efficiency of algorithmic systems deployed to address uncertain public problems. In this new epistemology of public policy, uncertainties and ambiguities do not disappear from the horizon. What is required of policymakers is the development of intuition and judgement, a development that runs counter to the core premises of the evidence-based policy movement.

Following Lindblom's perspective, machine learning algorithms applied in the policy process function as machines of muddling through. They are industrially designed to compare the accuracy of systems in solving a problem and reaching a goal by trial and error. The selection of machine learning algorithmic architectures is driven by choice biases and is oriented toward achieving operational objectives rather than producing evidence to support policymaking, in view of frames shaped by discourses of efficiency and efficacy. The convergence of algorithmic design and policy design does not resolve the fundamental condition of bounded rationality. Rather, it reproduces that condition within new technological arrangements. The challenge for policy science is not to reject machine learning but to develop governance frameworks capable of situating these technologies within a broader epistemological and democratic practice.

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