Artificial intelligence, task complexity and uncertainty: analyzing the advantages and disadvantages of using algorithms in public service delivery under public administration theories

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Abstract

Purpose – This article revisits some theories and concepts of public administration, including those related to public value, transaction costs and social equity, to analyze the advantages and disadvantages of using artificial intelligence (AI) algorithms in public service delivery. The author seeks to mobilize theory to guide AI-era public management practitioners and researchers.

Design/methodology/approach – The author uses an existing task classification model to mobilize and juxtapose public management theories against artificial intelligence potential impacts in public service delivery. Theories of social equity and transaction costs as well as some concepts such as red tape, efficiency and economy are used to argue that the discipline of public administration provides a foundation to ensure algorithms are used in a way that improves service delivery.

Findings – After presenting literature on the challenges and promises of using AI in public service, the study shows that while the adoption of algorithms in public service has benefits, some serious challenges still exist when looked at under the lenses of theory. Additionally, the author mobilizes the public administration concepts of agenda setting and coproduction and finds that designing AI-enabled public services should be centered on citizens who are not mere customers. As an implication for public management practice, this study shows that bringing citizens to the forefront of designing and implementing AI-delivered services is key to reducing the reproduction of social biases.

Research limitations/implications – As a fast-growing subject, artificial intelligence research in public management is yet to empirically test some of the theories that the study presented.

Practical implications – The paper vulgarizes some theories of public administration which practitioners can consider in the design and implementation of AI-enabled public services. Additionally, the study shows practitioners that bringing citizens to the forefront of designing and implementing AI-delivered services is key to reducing the reproduction of social biases.

Social implications – The paper informs a broad audience who might not be familiar with public administration theories and how those theories can be taken into consideration when adopting AI systems in service delivery.

Originality/value – This research is original, as, to the best of the author's knowledge, no prior work has combined these concepts in analyzing AI in the public sector.

Keywords Artificial intelligence, Public administration, Algorithms, Digital services, Citizens

Paper type Conceptual paper

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Introduction

The adoption and use of algorithmic support in public service delivery is subject to debate and has recently attracted researchers, particularly because of the inequities that some artificial intelligence systems have brought about. In this article, we appeal to theories of social equity, public value, and transaction costs in public administration to answer the following research question:

> *RQ1.* What are the advantages and disadvantages of using algorithms in public service delivery when tasks are: a) low in complexity and low in uncertainty and b) high in complexity and high in uncertainty (Bullock, 2019)?

After juxtaposing, through the exploration of existing literature, those advantages and disadvantages as related to tasks and their complexity, we mobilize several concepts from the paradigms of New Public Management (NPM) and New Public Service (NSP) to argue that it is possible, for public servants, to minimize the disadvantages such as the reproduction of social biases in the algorithms intended for public service delivery. Our literature review section explores the research problem: Although AI systems are being deployed in the delivery of public services to citizens in many countries around the world, there is a growing scientific literature and evidence that criticize the reliance on algorithmic support for decision-making, arguing that algorithms internalize and reproduce existing social biases. Our methodology section uses an existing task classification model to mobilize and juxtapose public management theories against AI's potential impacts in service delivery. We conclude by showing that designing AI-enabled public services should be centered on citizens, and we propose avenues for future research. We employ the term algorithms to designate the models enabling AI, which, we define using UNESCO (2020) recommendation as "information-processing technologies that embody models and algorithms that produce a capacity to learn and to perform cognitive tasks leading to outcomes such as prediction and decision-making in real and virtual environments" (p. 5). We conclude by proposing avenues through which public service officials can consider contextual particularities to minimize the reproduction of AI inequities in the delivery of citizen-centered services.

Literature review

Artificial intelligence in public management: a bitter-sweet trend

The adoption of artificial intelligence systems in public management is both promising and ominous. In many countries, governments have deployed AI to support decision-making and to better deliver services to citizens. The uses of these systems range from anticorruption robots to relieving workload from public servants and to personalization of service delivery. AI systems are used to improve government efficiency, deliver better services, and ensure accountability. For example, Odilla (2023) shows that "bots" have been deployed as anti-corruption agents to protect public money in Brazil, doing tasks as complex as identifying "suspicious activities related to, for example, bid-rigging, fraud in contracts, cartel practices, the misuse of public money by congressional representatives, and sluggishness in the Supreme Court" (p. 2). Androutsopoulou, Karacapilidis, Loukis, and Charalabidis (2019) have proposed a model for AI enabled communication improvement between citizens and governments. Building on technologies such as machine learning and data mining, these authors show that traditional communication channels between public servants and citizens can significantly be improved by enabling "richer and more expressive interaction of citizens with government in their everyday natural language, for both information seeking and transaction purposes" (p. 365).

In their systematic literature review on AI in public governance, Zuiderwijk, Chen, and Salem (2021) show that some of the potential benefits of AI use in government include efficiency, risk identification, information processing, economic benefits, and improved engagement benefits, among others (pp. 8–10). Wirtz, Weyerer, and Geyer (2019, p. 600) identified 10 potential public sector AI application areas that have been used or tested by governments across the world. These areas include Knowledge Management (KM) applications, complex and non-complex task automation, computer-assisted public virtual agents, advanced data analytics, high-level, self-learning cognitive applications for security and intelligence services, among others. Among other AI-related challenges, Zuiderwijk *et al.* (2021) identified those related to data, privacy, ethics, transparency, responsibility, accountability, and dehumanization of activities (pp. 11–12) and Wirtz *et al.* (2019) proposed grouping AI challenges under four integrated dimensions related to AI implementation, law, ethics, and society. The challenges of implementation include the quality of the systems and factor in the need for financial feasibility. The society-based challenges are those that are related to AI social acceptance and trust. Issues of privacy, safety, responsibility, and accountability fall under the dimension of AI regulation and law while value judgment, AI discrimination and moral questions pertain to the larger topic of AI ethics (Wirtz *et al.*, 2019, p. 607).

Literature has shown the adoption of artificial intelligence systems may encounter a citizens' trust problem because of the inequities they have proven they can create. These include interfering with peoples' rights (Završnik, 2020; Köchling & Wehner, 2020).), creating a digital divide between people and technology Chu *et al.* (2022), predicting crime while profiling and policing the vulnerable, the poor and the marginalized (Yu & Carroll, 2022; Brayne, 2021; Papachristos, 2022) and creating economic inequalities (Eubanks, 2018; Acemoglu & Restrepo, 2017). Beyond public management, trends in AI innovation continue to pose serious challenges that are likely to affect public trust. Studying the impact of recently developed OpenAI's ChatGPT on academic integrity, Susnjak (2022, p. 1) concluded that the powerful chatbot is a "potential threat to the integrity of online exams, particularly in tertiary education settings where such exams are becoming more prevalent."

Gaozhao, Wright, and Gainey (2023) studied citizens' perceptions of decisions made by AI systems and tested them against the perceptions of those decisions when made by humans. They concluded respondents preferred bureaucrats to AI; especially when passive representation was present:

> The results show that all respondents regardless of their race generally prefer a public employee who is an African American female, with 5–6 years of training, to serve as the quality control reviewer. For African American participants, if they cannot choose an African American bureaucrat to be their reviewer, they may regard other bureaucrats and AI the same. In addition, we find that people believe that AI is more efficient than bureaucrats, but less capable of applying equity (Gaozhao *et al.*, 2023, p. 3).

This finding is consistent with conclusions made by Ingrams, Kaufmann, and Jacobs (2022) who used an AI system designed for tax policy and regulation to investigate citizens' perceptions of AI under considerations of red tape and concluded that citizens' trust in decisions were lower when those decisions were made by AI compared to when they were made by a human. Thus, existing literature shows the adoption of artificial intelligence in public management could be bitter-sweet, and a double-edged sword but researchers have also identified an important factor potentially defining the position on the axis of the two potential extremes of AI systems adoption and implantation: task nature and characteristics. Our research builds on the latter to bring AI adoption in public service delivery to test against theories of public management.

Methodology: using artificial intelligence and task classification concepts to mobilize theories of public management

In this article, we use an existing task classification model to mobilize and juxtapose public management theories against artificial intelligence potential impacts in service delivery.

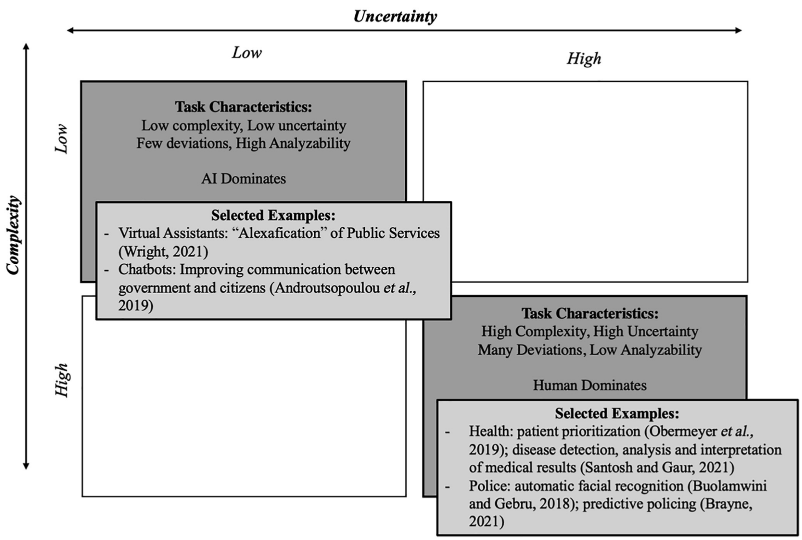
AI promises are often explained through certain capabilities related to the nature of tasks that it can complete. While some tasks such as responding to inquiries using a pre-populated database can be regarded as routine and ordinary, other tasks such as medical diagnosis can be seen as advanced and non-routine. Bullock (2019) uses tasks classification and contextualization insights from Busch and Henriksen (2018) and Perrow (1967) and proposes a classification matrix of tasks based on their complexity and uncertainty. In his 2×2 matrix, the author juxtaposes AI vs human dominance in bureaucratic decisions. While AI dominates in tasks that are less uncertain and less complex, human decisions (should) dominate in those tasks that are regarded as highly complex and very uncertain as shown in Figure 1 below.

In Figure 2, we adapt the main diagonal of Bullock's matrix (Low Complexity, Low Uncertainty and High Complexity, High Uncertainty) by adding common examples of tasks performed by algorithms in the delivery of public services. For each of the two quadrants in our adaptation of Bullock's matrix, we use existing literature to explain real-life examples of algorithms used by governments in service delivery to which we apply selected theories and concepts of public administration to study their advantages and disadvantages. The choice of these two quadrants of the main diagonal is explained by the fact that they both represent the

	Uncertainty	
Complexity	*Low*	*High*
Low Task Characteristics: Relative Strengths of Human and AI	Low Complexity, Low Uncertainty Few Deviations, High Analyzability AI Dominates	Low Complexity, High Uncertainty Few Deviations, Low Analyzability Leaning AI
High Task Characteristics Relative Strengths of Human and AI	High Complexity, Low Uncertainty Many Deviations, High Analyzability Leaning Human	High Complexity, High Uncertainty Many Deviations, Low Analyzability Human Dominates

Source(s): Bullock, 2019, p.757

Figure 1.
Task complexity and uncertainty



Source(s): Figure by author, adapted from Bullock (2019)

Figure 2.
Task classification: low complexity – low uncertainty and high complexity – high uncertainty

two possible extreme pairs, i.e. (Low Complexity, Low Uncertainty) and (High Complexity, High Uncertainty). We do not include the pairs on the antidiagonal (Low Complexity, High Uncertainty) and (High Complexity, Low Uncertainty) to ensure a clear-cut of task characteristics.

Artificial intelligence, task classification and task uncertainty

Quadrant 1: low complexity, low uncertainty

Following the definition provided by Bullock (2019, p. 756) under this quadrant, we propose two examples drawn from existing literature on the use of algorithms in the delivery of services to citizens: virtual assistants and chatbots. Virtual assistants, also called virtual intelligent assistants (VIA), are software capable of performing basic tasks and rendering some simple services. Users can make queries (written commands) or use voice (voice commands) to instruct a system to perform tasks like email and calendar management (Hoy, 2018, pp. 83–84). Common examples of this type of service are those provided by Microsoft (Cortana), Apple (Siri), Google (Google Home) and Amazon (Alexa).

In a study of the adoption of this type of technology in the United Kingdom, Wright (2021) shows that local governments are increasingly implementing chatbots and virtual assistants as practical and inexpensive alternatives in the delivery of adult social care to beneficiaries. The author calls that shift the "*Alexafication* of social assistance for seniors". Chatbots are software intended to conduct online conversations via text or via voice synthesis as a replacement for direct contact with a human agent. They owe their name to a combination of the English words "chat" and "bot" which is the contraction of "robot". Androutsopoulou *et al.* (2019) argue that chatbots have "the potential to dramatically transform and improve communication between citizens and government, which has long been problematic" (p. 366) and Aoki (2020, pp. 2–3) shows that these technologies are used by Japanese local governments to respond to citizen demands.

Advantages of using AI systems for low complexity, low uncertainty tasks: efficiency, economy, and the transaction costs theory

In the following section, we argue that the advantages of adopting AI technologies for low complexity and low uncertainty tasks are related to improved efficiency and economy, two concepts of the transaction costs theory applied to the delivery of public services to citizens. Rooted in the New Public Management (NPM) paradigm which envisioned bureaucrats capable of doing "more with less" (Hood, 1991, p. 5) by "steering and reinventing" government through innovative alternatives (Osborne & Gaebler, 1992, p. 30), cost reduction is at the heart of the delivery of services to citizens. According to this paradigm, citizens are customers and public administrators are entrepreneurs who must optimize resources, which Hood and Dixon (2015, p. 4) called the "efficiency agenda". In the study of organizations, the theory of transaction costs is associated with the postulates of this NPM by advancing that the economic analysis of organizations must consider the total costs of a transaction, including the costs relating to decision, planning, negotiation, and delivery. Transaction cost theory owes its popularity to the work of Williamson (1979) who published *Transaction - Cost Economics: The Governance of Contractual Relations* in which he studied the role of contracts and transactions in the governance of organizations. He proposed a matrix of the specificity of costs and argued that different types of governance (which he called structures) generate different types of costs (pp. 247–254). Thus, the economy criteria should not be assessed in terms of production costs only, but also in consideration of total costs, including transaction costs. Public contractors are assessed by audits using criteria of efficiency and economy, which assume rational public sector agents must aim to obtain results with the least possible resources, just as in the private sector. At the dawn of this NPM paradigm, automation had made it into academic essays, prompting Hood (1991, p. 4) to place the automation of service delivery among the four "administrative megatrends" to which he linked the advent of NPM.

The use of algorithms in routine and less complex tasks can help public officials achieve efficiency gains while optimizing performance. Although empirical literature on monetary gains by algorithms is scarce, Golding and Nicola (2019) and the Deloitte audit firm have projected a promising look at the potential benefits of AI-enabled cost reduction in public administration. Eggers, Schatsky, and Viechnicki (2017) showed that by automating routine tasks, the US public federal government could free up millions of work hours and save billions of dollars, while not compromising the quality of services:

> Today, the typical government worker allocates her labor among a "basket" of tasks. By breaking jobs into individual activities and analyzing how susceptible each is to automation, we can project the number of labor hours that could be freed up or eliminated. Our analysis found that millions of working hours each year (out of some 4.3 billion worked total) could be freed up today by automating tasks that computers already routinely do. At the low end of the spectrum, we estimate, automation could save 96.7 million federal hours annually, with potential savings of $3.3 billion; at the high end, this rises to 1.2 billion hours and potential annual savings of $41.1 billion (Eggers *et al.*, 2017, pp. 2–3)

In the years that followed the NPM, this paradigm was highly criticized and its assumptions of an entrepreneurial government that only cares about 'steering' *rather* than serving was questioned. Many researchers have argued the postulates of the NPM do not work, and some empirical studies have shown its promises might have been overstated (Hood & Dixon, 2015, pp. 178–183). Nevertheless, despite those criticisms, the criteria of resource optimization and the potential for efficiency have transcended criticisms and schools of thought and remain at the heart of modern theories of public administration. In this sense, justifying the adoption of services using algorithms by the promises of cost reduction constitutes a rather solid argument in favor of its advantages.

Disadvantages of using AI systems for low complexity, low uncertainty tasks: the theory of social equity

Bullock (2019, p. 756) argues that algorithms should dominate in cases where tasks rarely deviate from normal procedures and are less complex and more routine. Under the lens of social equity theory, we show that even in such cases of low complexity and low uncertainty, AI systems can present serious drawbacks in service delivery. The theory of social equity in public administration is often attributed to the work of Frederickson (1990) who proposed equity as a third pillar of public administration, alongside efficiency and economy and many scholars view him as "the father" of social equity in public administration (Walton, 2018; Davis, Moldavanova, & Stazyk, 2020). It is, however, worth noting that the concept of fairness predates him and was present in earlier works. For example, when arguing that efficiency must be "socially and humanly interpreted" and that "true democracy and true efficiency are reconcilable", Waldo (1948/2017, p. 197 and 207) proposed great foundations for the notion of equity which would become a benchmark theory in public administration years later. In fact, in his theory of social equity, Frederickson himself drew on the works of the philosopher John Rawls on social justice (Frederickson, 2010, pp. 42–45). Moreover, Frederickson's writings on social equity followed his attendance of a conference that came to be known as the First Minnowbrook Conference which he co-organized under Waldo's patronage in 1968. After this conference, attendees published a collection of works under the title *Toward a New Public Administration: The Minnowbrook Perspective,* which became the foundation of the New Public Administration paradigm (Frederickson, 2010, pp. 3–6). In subsequent decades, Frederickson would take the lead on social equity, one of the themes that was dear to this new public administration. At the heart of a renewed public administration and at a time when governments were content with the principles of effectiveness and efficiency inherited from the so-called classical public administration, advocates of social equity pledged to add the pillar to the principles of administration. It was no longer enough, they argued, to ask questions about effectiveness and efficiency in the delivery of services to citizens: it was also necessary to ensure that these services improve equity for all.

To define social equity in public administration, Svara and Brunet (2005, p. 254) noted two key principles, namely fairness and equitable distribution. Norman-Major (2011, p. 237) argues that of all the available definitions of social equity, the one provided by the American Academy of Public Administration is the most accepted. This academy defines social equity as the equitable management of institutions whose mandate is to serve the public. It is a commitment to promote justice in the processes leading to public service delivery. As Frederickson wrote in his 2010 book "designed to be the definitive statement on the theory and practice of social equity in public administration", social equity has, over time, become a third pillar of public administration because efficiency and effectiveness alone were no longer enough:

> Gradually, beginning in the 1960s, it became apparent that the implementation of many public programs was much more efficient and effective for some than for others. Indeed, it came to be understood that public administration could not logically claim to be without responsibility for some practices that resulted in obvious unfairness or injustice. Based upon this understanding, there emerged an argument for a social equity ethics in public administration, an ethic of importance equaling our ethics of efficiency and economy. Social equity took its place with efficiency and economy as the third pillar of public administration (Frederickson, 2010, p. 52).

We use this theory to argue, in the following sections, that AI systems can pose challenges to equity, even for the so-called less complex and less uncertain technologies. In our adaptation of the task complexity and uncertainty classification matrix from Bullock (2019), we have proposed the example of Wright (2021) which explores the systems enabling virtual assistance used in the delivery of services by British public administrations and chatbots like those proposed by Androutsopoulou *et al.* (2019) to improve communication between governments and citizens. As Wright (2021, p. 2) shows, researchers are beginning to look at the delivery of services to the elderly through intelligent tools such as virtual assistants. However, ageism is becoming digital (Chu *et al.*, 2022). Ageism is defined by Iversen, Larsen, and Solem (2009, p. 15) as stereotypes, prejudices against people based on their age. Chu *et al.* (2022, p. 2) have introduced the concept of *digital* ageism which they define as technology-enabled prejudice and discrimination against people based on their age. They show that this creates a physical-digital divide which excludes the elderly who, not only are generally not represented in the design and creation of such technologies, but sometimes do not understand how they work. This fracture excludes this category of service beneficiaries and alienates them from the rest of an increasingly inter-connected society. Similarly, studying carers' experience of using virtual assistive technologies for home-based dementia care in the UK, Sriram, Jenkinson, and Peters (2020, p. 9) found that caregivers faced challenges in teaching sick and elderly people the basic functions of certain electronic devices such as mobile phones. These examples show that the delivery of some services to some categories of citizens may miss the call from Frederickson (1990, 2010) for whom social equity requires responsiveness to the needs of citizens rather than to those of public organizations. Social equity requires there to be an active commitment to justice and equity throughout the processes leading to the delivery of services (Johnson & Svara, 2011). Furthermore, Lee (2021, pp. 6–7) shows that the promotion of social equity is essential in maintaining the trust that citizens have in their governments.

Quadrant 2: high complexity, high uncertainty

On Figure 1, the bottom-right part of the main diagonal of our adaptation of the task classification matrix looks at the characteristics of tasks and their levels of complexity as explained by Bullock (2019, pp. 756–757). We have added some examples from the medical and law enforcement literature on the use of algorithms in the field of public administration that we believe meet the criteria of complex tasks with high uncertainty. Bullock (2019, p. 756) argues that complex tasks are those with large deviations from normal procedures and with higher uncertainty. The author posits that the discretion of civil servants should dominate in this category of tasks. We draw our examples from the fields of health care and law enforcement. In doing so, we assume that these fields present high complexity and that there is high uncertainty in the performance of the related tasks and can thus be classified on the bottom right side of the main diagonal (more complex, with high uncertainty).

Advantages of service algorithms for high complexity, high uncertainty tasks: concepts of administrative burden and "red tape"

Among other examples of this category of algorithmic applications in complex, highly uncertain tasks, Alugubelli (2016) notes the CDSS system (Clinical Decision Support System) which is used to inform medical decisions by comparing a patient's data which is matched to a set of other pre-existing medical data (p. 2), the Brain-Computer Interface application which allows measurement of the activity around the central nervous system and the Arterial Spin Labeling imaging (ASL) system which is used to monitor brain flow (p. 3). Another type of complex algorithms is found in law enforcement. For example, DARLENE (Deep *AR* Law ENforcement Ecostystem), is a project funded by the European Union that combines the use of algorithms and augmented reality to help law enforcement officers deliver services in complex and stressful situations. Apostolakis *et al.* (2022) provides the following description of this system:

> DARLENE incorporates the advantages offered by both AR [augmented reality] and AI to realize technology-assisted policing in ways that have previously only been imagined in science fiction. Police officers will patrol and respond to incidents using wearable gear that will utilize AI in the form of ML [*Machine Learning]* and DL [*Deep Learning]* routines to enable rapid scene analysis and interpretation to capture, outline and single-out interesting findings and threats requiring the attention of the smart glasses wearer. AR will then be used to superimpose such mission-critical information directly on top of the real world, catering to the officer's unique point of view, and ensuring a functional visualization experience, meant to enhance the officer's capacity to respond to incidents (p. 4).

Other applications of algorithms for complex policing tasks include object classification and recognition, including face and voice recognition, gunshot recognition, digital forensics as well as DNA analysis (Dupont, Stevens, Westermann, & Joyce, 2018, pp. 68–86).

Cumbersome rules and procedures and the necessary compliance with excessive, rigid, or redundant formal standards, have been at the center of public administration research since it existed as a field of study (Blom, Borst, & Voorn, 2020, p. 2). The concept of red tape, which brings together all the finicky rules and the administrative burden, has become one of the most studied concepts and one on which vast literature has been produced. For example, using the keywords "red tape," "compliance burden," "administrative burden," "unnecessary rules," and "ineffective rules," Blom *et al.* (2020, p. 6) identify a total of 8,886 studies on the concept of administrative burden. Red tape has been studied alongside other key concepts and theories such as those related to leadership (Campbell, 2017), job satisfaction, satisfaction (Cantarelli, Belardinelli, & Belle, 2015; Kaufmann & Tummers, 2017) and organizational performance (Jacobsen & Jakobsen, 2018), among others. Blom *et al.* (2020, p. 3) note that the generally accepted definition of administrative burden was proposed by Bozeman (1993) who defined the concept of red tape as the set of “rules, regulations, and procedures that remain in force and entail a compliance burden for the organization but have no efficacy for the rules’ functional object” (p. 283). In the sections that follow, we argue that one benefit of relying on algorithms for complex and high uncertainty is the potential of red tape reduction for bureaucrats. We recognize that there may be some difference between the concepts “red tape” and “administrative burden”, nevertheless, we use them together in our argument as do most authors (for example, see Bozeman & Youtie, 2019; Carrigan, Pandey, & Van Ryzin, 2019).

Aung, Wong, and Ting (2021, p. 5) noted that the application of AI systems in the medical field dates to the year 1976 when an algorithm was first employed in identifying the causes of acute abdominal pain. Today, the use of artificial intelligence in healthcare is helping to ease administrative burden on physicians by performing less sophisticated and more routine tasks such as booking appointments and managing communications with patients and even in some sophisticated and less routine tasks such as the detection of diseases including cancer, the detection of sources of pain, chest X-ray analyses, medical imaging and the identification of brain tumors, among others (Santosh & Gaur, 2021, p. 25). In making the case for the benefits of adopting algorithms for complex and high-uncertainty tasks, the use of algorithms in the medical field is an example of the applicability of these systems in relieving administrative burden from medical professionals to whom this type of burden is rather common (Javanmardian & Lingampally, 2018).

Disadvantages of service algorithms for high complexity, high uncertainty tasks examined under public value theory

While the benefits of reducing the administrative burden that we discussed earlier are eloquent in favor of adopting AI technologies to perform complex and high-uncertainty tasks such as those in the fields of health and law enforcement, literature shows that the promises of these systems could be overstated. We show, in the following sections, that the value created by public initiatives seeking the delivery of services by this type of technology is not always guaranteed. Public value theory has often been attributed to the works of Moore (1995), although Fukumoto and Bozeman (2018, p. 636) note that public values are rooted in the concepts of public interest theory that has dominated the political science and public administration for a long time. In his book *Creating Public Value: Strategic Management in Government,* Moore (1995) laid the foundations of a theory that would become the reference in the analysis and evaluation of administrative decisions by practitioners throughout the world (Benington & Moore, 2011, p. 2). Emerging from the context where public administrators put forward the virtues of the business world (business-like government) such as productivity and efficiency indicators, the author observed that the pressures faced by managers of public organizations was sometimes misguided:

> They [managers of public organizations] are also expected to be administratively competent – to be skilled in devising the organizational structures and arrangements that can guide the organization to perform efficiently and effectively and in accounting for the financial and human resources entrusted to them so that it can be proven that public resources are not being stolen, wasted, or misused (Moore, 1995, p. 17).

This theory maintains that in the public sector, the relevant customer is not an individual consumer who makes personal and selfish choices as the proponents of the NPM paradigm would have liked, but a whole community acting through imperfect processes. Thus, the role of public administrators goes beyond the production of services and outputs: they must concretize the values of an entire society (Osborne, Nasi, & Powell, 2021, p. 5) and above all they must consider the principles according to which these services are created (Bozeman, 2007, p. 13).

There are two streams of thought on public value theory: the "public value" stream and the "public values" stream (Fukumoto & Bozeman, 2018, p. 636). Nabatchi (2012, p. 699) notes that the "public value" stream concerns the evaluation of what is produced by public administrations as having value in the eyes of the public. The "public values" stream seeks to identify and activate the so-called public values, which are principles on which governments and public policies should be based (Bozeman, 2007, p. 13). We argue that these streams are complementary, because to assess the value that the public places on a service, public officials have a duty to understand the values of the public they serve. Furthermore, Nabatchi (2012, p. 700) notes that the creation of that public value requires an understanding of the values of citizens. Therefore, Public servants must be able to identify and name these values, to reconcile conflicting values and to create a so-called global public value. To this end, Moore (1995) suggests that managers ask themselves three key questions about the goals they set out to achieve: whether the goal is useful in the eyes of the public (publicly valuable), whether it will be politically and legally supported, and whether it is administratively and operationally feasible (p. 22).

In examining the role of innovation in the creation of public value, Hartley (2011, p. 175) offers four pairs of possible outcomes of the relationship between innovation and public value: (1) improvement without innovation, (2) no improvement and no innovation, (3) innovation and improvement and (4) innovation but no improvement. In the world of algorithmic inequities such as the case of highly complex and highly uncertain tasks, it is possible to produce innovation that is not valued by the public and recipients of services and that falls under the fourth pair "innovation but no improvement". Several studies have shown some serious drawbacks of algorithms in various contexts. For example, Obermeyer, Powers, Vogeli, and Mullainathan (2019) showed how algorithms can discriminate patients based on their race in healthcare priority decisions. Many types of facial recognition technologies used by law enforcement have proven to unfair to some groups of people, especially those of darker skin (Garvie & Frankle, 2016; National Institute of Standards and Technology, 2021; Buolamwini & Gebru, 2018) and citizens have raised concerns of their use, especially by law enforcement officers (Nzobonimpa, 2022). In Moore's theory of public value, there is value creation if and only if citizens find that value in the services delivered to them and, as shown by Nabatchi (2012, pp. 699–700), what is delivered to citizens must be consistent with their own values for them to attach value to it. When that is not the case, the use of innovation such as AI in public service delivery results in valueless and costly innovation.

Adapting public service delivery to contextual particularities to minimize algorithmic bias: agenda setting and Co-production

Theories of public administration provide a solid foundation of the ways that AI-enabled public services can be adapted to minimize bias by tailoring innovation to contextual particularities. We propose two conditions for this adaptation to be possible: on the one hand, issues related to algorithmic inequities must find their place on the political agenda. Since citizen services reflect public policies (McNulty, 2003; Osborne & Brown, 2011), the latter must guide the former. On the other hand, the involvement of citizen-beneficiaries in the design and (co)creation of the services provided to them is essential to ensure the representativeness of the data on which the algorithms are based and to counter bias.

Bernier and Lachapelle (2010, p. 24) show that the public policy emergence models popularized by Kingdon (1995/2011) allow the study of the policy cycle in 5 phases starting with the setting of the agenda and ending with the evaluation. Kingdon (2011, p. 1) uses the phrase "an idea whose time has come" and argues that for an issue to be put on the agenda, it must first be recognized as a problem. He defines the political agenda as a list of issues that command the attention of governments (p. 3). As some issues may attract more attention than others, the role of actors outside of government, including researchers, the media and even public opinion, is critical. In fact, Kingdon (2011, pp. 45–67) shows that there are bridges between those inside governments and those outside, such that once a problem is identified from the outside, it also gets known inside (of governments). Bernier and Lachapelle (2010, p. 26) call these bridges "a window of opportunity" that opens in the emergence and formulation of public policies. When such a window is opened, it creates flows whose convergence leads to the setting of the agenda (pp. 25–26). To complete the process of public policy emergence Majone (2006, p. 228) proposed the "feasibility criterion" and argued that once problems have found an interest and placed on the agenda, the proposed solutions must also be feasible.

To adapt public services to specific situations and minimize the reproduction of algorithmic biases, the existence of these biases must be seen as a problem and placed the political agenda. Concerns related to algorithmic issues have been widely discussed, both in academic literature and in the press such that they should be known as problems. Moreover, the literature of AI in Government has been very fruitful in recent years. For example, in a literature review on the adoption of AI in the public sector by municipal, state, and federal governments, Sousa, Melo, Bermejo, Farias, and Gomes (2019, p. 3) identify 1682 publications made between 2000 and 2018 on the theme, while Garvey and Maskal (2020, p. 3) find that no less than 12,376 press articles were published on artificial intelligence between 1956 and 2018. Among the concerns that should trigger and shift the political agenda researchers have shown the occurrence of socio-economic inequalities (Eubanks, 2018), the reinforcement of racism and sexism (Noble, 2018; Benjamin, 2019), misguided technochauvinism (Broussard, 2019), profiling, including racial profiling (Brayne, 2021) as well as a threat to democracy (O'Neil, 2016), among others.

The concept of co-production in public administration means that citizens are involved in the creation of public services. Like public value theory, this concept is related to the writings of the New Public Service paradigm (Denhardt & Denhardt, 2000, 2015) which argue that citizens, who are not mere customers, should be more actively engaged in their governance. If the goal of public administration is the public interest, citizens should be included in the processes leading to shaping the services delivered to them. They therefore share, with governments, the responsibility for the (co) creation of value which is translated into public services (Denhardt & Denhardt, 2000, p. 552). By involving citizens in the design of services using algorithms, public administrators would ensure representativeness and contextual appreciation. This may involve consultations such as when labeling data of a specific group before using it in systems training. The study by Obermeyer *et al.* (2019) that we referenced earlier demonstrated that discrimination against Black patients in the American context was the result of data that only considered monetary expenditures, rather than the severity of patients' conditions, in determining their priority. The authors concluded that the choice of labels on which the algorithms were trained explained the biases they found. By resorting to a better co-production that involves citizens in the collection and validation of these types of data and labels, biases can significantly be reduced in specific contexts. For example, instead of relying on data from their majority White clientele, the US health care facilities surveyed by Obermeyer *et al.* (2019) could have ensured that the data they provided to the various systems also reflected their minority patients.

Conclusion

The use of algorithms in decision-making, particularly those intended to improve the delivery of services to citizens, is a reality across public administrations. Literature has shown that this type of technology is far from being the *crème de la crème* of the public service: biases causing discrimination, exclusion, profiling and threatening the democratic principles on which modern societies are based, greatly question the promises of this innovation, often hailed as revolutionary. Through this paper, we have shown that the advantages and disadvantages of the use of algorithms exist when examined under the lens of certain theories of public administration. We have also argued that public administration theories provide a foundation to ensure algorithms are used in a way that improves service delivery. From agenda setting to coproduction, designing AI-enabled services should be centered to citizens who, as the NPS paradigm reminds us, are not just customers. We believe the exercise of juxtaposing existing public administration theories to AI adoption and usage is essential to understanding where the deployment of AI technology stands on the long line of public management paradigms, theories and concepts ranging from traditional theories of bureaucracy to modern paradigms of public service delivery. This theoretical overview will help partitioners and researchers of AI and public policy situate algorithmic technology adoption in the public service, its promises and potential impact when looked from a public administration lens. This paper has one limitation worth mentioning. As a fast-growing subject, artificial intelligence research in public management is yet to empirically test some of the theories that we presented. This is an avenue for future research that should seek to empirically explore AI transaction costs, AI equity, AI and public policy agenda setting and AI's potential in reducing public service burden and red tape, among other concepts. We believe our study opens the door for testing these theories and concepts.

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