Exploring the Complexity of AI Applications in the Public Sector: The Interplay of Visibility, Autonomy, and Self-Learning

Zong-Xian Huang[1], J. Ramon Gil-Garcia[1, 2] and Mila Gascó-Hernández[1]

[1] *University at Albany, State University of New York, 1400 Washington Ave, Albany, NY 12222, USA*
[2] *Universidad de las Americas Puebla, Ex-Hacienda Santa Catarina Mártir S/N Ex-Hacienda Santa Catarina Martir Ex-Hacienda Santa Catarina Mártir, 72810 San Andrés Cholula, Pue., Mexico*

Abstract
Artificial intelligence (AI) has been deployed in many government contexts and with very different results in countries around the world. There seems to be a distinct transformational power when compared with previous technologies. However, it is not clear how different characteristics of AI systems affect their purpose and outputs. Therefore, by understanding some of the unique characteristics of self-learning systems in the context of a proposed typology consisting of two dimensions—visibility and autonomy—this study explores the interplay of visibility, autonomy, and self-learning in government AI systems. Based on the analysis of four distinct AI cases across diverse U.S. federal agencies, this ongoing research paper aims to uncover some of the opportunities and challenges posed by AI and specifically self-learning as one of its main features. Our preliminary results underscore the necessity of contextual analysis in deploying AI systems, thereby contributing to previous research on different characteristics and types of AI.

Keywords
AI typology, AI visibility, AI autonomy, self-learning, self-improvement

1. Introduction

The proliferation of artificial intelligence (AI) and machine learning algorithms in government has significantly transformed the practices of public administration. Some scholars have begun using the terms 'algorithmic bureaucracy' or 'algorithmic governance' to describe this new phase of public administration, referring to a new era where AI and advanced computational algorithms play an integral role in public governance [22, 37]. This approach of using machine learning techniques in the public sector can not only automate relatively simple tasks but also augment complex decision-making [36]. Along with potential benefits for government and society, however, concerns are raised as well, such

Proceedings EGOV-CeDEM-ePart conference, September 1-5, 2024, Ghent University and KU Leuven, Ghent/Leuven, Belgium
zhuang7@albany.edu (Z.-X. Huang); jgil-garcia@albany.edu (J. R. Gil-Garcia); mgasco@albany.edu (M. Gascó-Hernández)
0000-0002-3751-6583 (Z.-X. Huang); 0000-0002-1033-4974 (J. R. Gil-Garcia); 0000-0002-6308-8519 (M. Gascó-Hernández)

as issues surrounding privacy intrusions [5, 16], transparency and accountability [6, 15], and inequality and discrimination [16, 20, 34].

Depending on the complex contexts in which AI is deployed, researchers have devoted significant effort to the development of multiple taxonomies to navigate the intricacies of AI in the public sector. Some studies have sought to describe and compare different AI systems based on a single dimension, such as technology, application, function, or level of bureaucratic discretion [1, 3, 30, 38]. Others, although relatively rare, have constructed more complex taxonomies based on multiple dimensions, reflecting intersections of different theoretical attributes [22, 35]. These existing studies constitute the foundation for understanding the various core characteristics of AI when applied in the public sector, as well as underscoring the challenges and risks associated with different AI applications.

Nevertheless, we argue that existing typologies do not specifically address one crucial characteristic of AI — the self-learning attributes. Self-learning algorithms, systems that are capable of adjusting parameters and weights in machine learning models, have gradually garnered attention from scholars for their potential to produce not only positive outcomes but also risky policy solutions to public problems [15, 28, 38]. As self-learning algorithms increasingly become the foundation for AI innovations, incorporating this specific characteristic into current typologies is becoming crucial. Specifically, by considering the feature of self-learning algorithms, researchers and practitioners can move beyond static descriptions to compare the effects and risks of different AI applications in a more sophisticated manner.

Given that current studies have developed several typologies focusing on varying degrees of discretion and transparency in AI applications, this study aims to incorporate the self-learning characteristic of AI into existing typologies. By explicitly considering self-learning attributes in current typologies, we could not only refine our understanding of AI typologies but also provide nuanced guidance for public managers in tailoring their AI deployment strategies to fit specific contexts. Accordingly, the research questions in this paper are (1) how do visibility and autonomy interplay in a typology that represents different types of AI, and (2) when taking self-learning characteristics into account, what challenges and opportunities are associated with the deployment of different types of AI systems?

From a practical perspective, the interplay among these three dimensions—visibility, autonomy, and self-learning attributes—can benefit the discussion and understanding of AI applications in the public sector in different ways. First, a clear taxonomy of AI, supported by real-world cases, can enable meaningful comparisons of the effects and risks of AI, thus overcoming the obstacles of overly abstract and general arguments currently available. Second, with a more detailed and nuanced delineation of different AI systems, this study offers guidance for public officials in tailoring their AI deployment strategies according to specific contexts, thereby mitigating potential risks and maximizing the benefits of AI applications in public administration. In other words, the formation of a more comprehensive typology can facilitate better-informed decisions and more effective governance.

The remainder of this ongoing research study is structured as follows. In section two, drawing on prior literature related to AI, we develop and define a proposed typology that categorizes different AI systems based on their visibility and autonomy. Section three outlines self-learning as one of the most important characteristics of AI systems. Section four introduces the method use in this study, including the selection of cases. In section five, we discuss preliminary findings based on the cases including implications for theory and concrete policy recommendations for public managers when deploying AI systems. Finally, we provide some final comments and briefly describe the next steps.

2. Visibility and Autonomy of AI

Visibility and autonomy form two core attributes of AI systems. Existing studies have used similar dimensions, such as transparency and alignment of operations, as the foundation for a conceptual framework to evaluate the impacts of algorithmic systems [22, 35]. For instance, with this two-dimensional framework, Katzenbach & Ulbricht differentiated four types of algorithmic governance systems based on low/high degree of transparency and low/high degree of automation, namely, autonomy-friendly systems, trust-based systems, licensed systems, and out-of-control systems. These two dimensions, we argue, offer distinct perspectives on understanding the risks and opportunities of AI. As these two dimensions are more closely tied to societal elements rather than technological elements, they provide a basis for assessing how AI applications align with or challenge societal norms and values.

AI visibility can be defined as the extent to which users are aware of the presence and operation of AI when interacting with it. This dimension is strongly associated with elements instrumental in building trustworthy AI, such as transparency, interpretability, and accountability. Drawing on concepts from information systems integration [19] and e-government integration [21, 24], we argue that AI visibility will decrease as AI systems become more seamlessly integrated into other systems. The reasoning is that as these AI systems blend or become incorporated into larger information systems, the components unique to AI systems become less visible and more challenging for users to identify. For example, in AI-powered traffic management systems, where AI technologies are deeply integrated into larger information systems such as routing and transportation systems, it may become difficult for most users to recognize or trace the use of AI.

AI autonomy, additionally, can be defined as the level of human control and oversight present when the AI system is executing or operating. This dimension closely relates to the concepts of 'human-algorithm interactions' [13, 14] and 'human-in-loops' [32], indicating the inverse relationship between the degree of human intervention and the degree of AI autonomy. Given the rising ethical risks and unforeseen impacts associated with machine learning algorithms, countries and supranational organizations have started to promote regulatory frameworks and guidance aimed at overseeing algorithmic systems and initiating intervention when necessary [13, 18, 28]. Green, for instance, collected and summarized various practical guidelines for human oversight of algorithms use in the public sector, identifying three key elements for human oversight of algorithmic systems [13]: restricting solely automated decisions, emphasizing the importance of human discretion, and requiring meaningful human input.

Based on the degree of visibility and autonomy of AI systems, Table 1 lists some prevalent AI-powered applications that exhibit varying levels of these attributes. Chatbots, which have high visibility and autonomy, usually directly interact with users at the forefront and make autonomous decisions within their programmed capabilities. In most situations, users are clearly aware that the agents they interact with are powered by AI technologies, while the content produced by those agents might not be fully determined by humans. On the other hand, recommendation systems also exhibit high AI visibility, despite their lower autonomy. These systems guide users or promote content based on predefined algorithms and data sets, yet they do not function entirely autonomously. Taking recommendation systems used by social media platforms as an example, most companies employ human review teams to ensure sensitive content is detected and, if applicable, rescinded swiftly.

On the other end of the spectrum, facial recognition systems, while highly autonomous in their operation, tend to have low visibility in terms of direct user interaction. As these systems frequently work behind the scenes in security and monitoring applications, users may not easily notice that they are being screened by an AI application. Predictive policing systems are also less visible to the public, as they are typically integrated into broader law enforcement systems to support decision-making for police agencies. Furthermore, since the results generated by predictive policing systems usually require examination and approval by police officers, the degree of autonomy in these systems could be considered low.

Table 1
Examples of classifying AI systems based on visibility and autonomy

	High AI Visibility	**Low AI Visibility**
High AI Autonomy	Chatbots	Facial recognition systems
Low AI Autonomy	Recommendation systems	Predictive policing systems

Rooted in previous studies, we build a basic typology of AI applications based on their visibility and autonomy. This basic typology offers three-fold advantages in making sense of the complexities of AI systems. First, as mentioned above, these two dimensions are highly associated with critical issues such as explainability, responsibility, accountability, and discretion in the decision-making process, linking AI to important theoretical debates. Second, it provides a coherent classification for understanding a variety of AI use cases in the public sector, covering a wide range of use cases. Third, rather than merely focusing on technological elements, these two dimensions offer an intricate societal perspective on understanding the interaction between users (e.g., citizens) and service providers (e.g., government agencies), as these interactions can be shaped by the level of visibility and autonomy in AI applications.

In addition, this initial typology can be further developed to provide a deeper understanding of the complexity of AI. One crucial difference between AI applications and other information technologies is that most AI systems include learning attributes and the outputs of AI systems are not purely restricted by rules designed by humans. This means that the adoption of AI systems in the public sector introduces a new thread of uncertainty in the decision-making process. To account for this new uncertainty, we argue that the current typology could be better understood when incorporating the unique self-learning element of AI technologies. The next section will briefly outline the characteristic of self-learning attributes of AI, as well as how this self-learning characteristic impacts the operations of AI systems.

3. Self-learning as the main characteristic of AI

The discussion about the self-learning characteristic of AI is far from new. Tracing back to the 1950s, one critical aspect of AI is its self-improvement attribute, which implies that machines are capable of learning, inferencing, and forming concepts [17, 27]. While current AI applications do not meet the acceptable standard of an unboundedly self-improving machine or artificial general intelligence, the concept of self-learning AI opens up important possibilities for AI [2, 17]. For example, self-adaptive software is designed to modify its behaviors in response to changes in its operating environment, enabling systems to autonomously adjust themselves based on feedback from their current performance [26, 31]. This approach allows designers to initially program AI systems and then let the systems learn the rest for themselves based on the data fed to them.

The self-learning characteristic highlights at least two positive opportunities for deploying AI systems. First, AI systems with self-learning capabilities can enhance their model performance to respond to evolving environments. For instance, reinforcement learning models have shown their potential in assisting health professionals with pandemic control measures [23, 25]. Second, based on large amounts of training data, self-learning algorithms can modify parameters or weights in their models to make optimal predictions about input-output relationships. Given this capability, most self-learning algorithms can leverage these predicted input-output relationships to forecast results on 'as-yet-unseen' data [6]. This characteristic has led to the proliferation of AI systems in areas that can utilize specific input-output relationships to optimize their decisions, such as recommendation systems or risk assessment systems.

These opportunities, however, come with associated challenges. Since the unique self-learning characteristic has influenced the extent of public discretion within public organizations, a primary concern when implementing AI in the public sector is the potential generation of fault scenarios in which bureaucrats lack prior experience [3, 4]. That is, the probability of encountering unexpected consequences and applying different standards in the same process increases due to the self-learning characteristic. Furthermore, the self-learning feature complicates the 'black-box' issue, which is already widely discussed by scholars and practitioners [e.g., 6, 7, 23, 31]. As Busuioc clearly states, the issue of algorithm complexity could exacerbate traditional information asymmetry problems and diminish users' capability to conduct reasonable assessments [6]. Last, but not least, this self-learning characteristic could potentially lead to a runaway feedback loop that reinforces and pronounces existing social injustices [9, 11]. For instance, based on the case of predictive policing systems, research found that the systems would continually direct police to the same neighborhoods, irrespective of the actual crime rates [9].

Given this unique and crucial aspect of AI systems, we argue that researchers should play closer attention to the self-learning characteristic and explore its intersections with other important features of AI systems. As mentioned before, when public organizations deploy AI systems, which normally includes the self-learning characteristic, they could face situations that intersect with profound issues in the public sector, such as discretionary power, transparency, accountability, or administrative discrimination. Therefore, this study aims to take the self-learning characteristic into account, integrating it with two other critical dimensions used to classify different AI systems. In doing so, we expect to produce a more holistic and dynamic picture of the opportunities and challenges of different AI systems, based on the illustration of real-world cases. In the next section, we briefly outline our case selection process.

4. Case selection process

To identify real-world cases, this study focuses on AI cases within the federal government of the United States. Based on Executive Order No. 13960 issued in 2020, titled 'Promoting the Use of Trustworthy Artificial Intelligence in the Federal Government,' the U.S. federal government has established a website to compile all AI use cases across federal agencies [12]. The website has documented 710 AI cases deployed in federal agencies, containing basic information for each case, such as the deploying agency, summary of AI projects, techniques used, and source code. Given this rich dataset, we identified four cases that exhibit different degrees of AI visibility and autonomy.

Specifically, we reviewed the summaries of each AI project to identify four cases we used for further analysis. We conducted three steps to select the appropriate cases. First, as many AI projects are designed for internal tasks or managerial purposes, such as automatically scanning barcodes in documents or detecting spam emails, we excluded those cases that are not related to services or interactions with citizens. Second, we prioritized cases that could be clearly categorized by our proposed typology based on AI visibility and autonomy. To select the cases that are more appropriate for further analysis, we used the aforementioned definitions of AI visibility and autonomy (the level of integration with other systems and the level of human intervention) to evaluate the description of each AI project. Therefore, projects whose description is primarily technical are excluded due to the lack of sufficient information to categorize them into the current typology. Third, while some federal agencies, such as the Social Security Administration, might have multiple cases that meet our criteria due to the nature of their tasks, we decided to select cases from different federal agencies to ensure more variability and broader potential impacts of our results.

Through the case selection process, four cases across different federal agencies were identified. These include the Aidan Chatbot deployed by the Department of Education [10], the Medication Safety Clinical Decision Support system deployed by the Department of Veterans Affairs [29], the Person-Centric Identity Services system deployed by the Department of Homeland Security [8], and the Quick Disability Determinations system deployed by the Social Security Administration [33]. In the next section, we illustrate the attributes of visibility, autonomy, and self-learning for each case, and discuss specific opportunities and challenges.

5. Preliminary results

This section outlines the content of the four selected AI cases. Opportunities and challenges associated with the self-learning characteristic of AI are also discussed.

5.1. High visibility and high autonomy: Aidan Chatbot

Deployed by the Department of Education, a virtual assistant named Aidan is designed with the aim of responding to common questions about federal student aid. Powered by natural language processing technology, the Aidan Chatbot helps users figure out their current loan account balance, grants information, or the contact information for loan servicers. Similar to other chatbot applications, the interface of the Aidan Chatbot is straightforward and easily recognizable as being powered by AI-related technologies. In fact, on the StudentAid.gov website, where Aidan services are offered, the Department of Education explicitly points out that this virtual assistant is powered by AI technologies. Furthermore, most responses from the Aidan Chatbot are not reviewed by human agents before being sent to users. Therefore, it can be categorized as a classic application with a high degree of visibility and autonomy.

Taking the self-learning feature into account, this type of AI application can generate customized responses by learning from users' feedback and input. Specifically, Aidan will keep a record of users' conversations and request logs to improve the quality of future interactions. Given this, the self-learning characteristic provides greater opportunities for human-machine collaboration, since it enables the system to adapt and improve over time based on real-world interactions. On the other hand, the self-learning characteristic might introduce specific challenges to the Aidan Chatbot. As there is no clear checking point between AI systems and users, the risk of reproducing large-scale inaccurate and biased responses might increase if the original data is biased or contains errors. As a result, establishing certain processes for human intervention in certain situations or at some regular time intervals could be helpful to prevent these potential issues.

5.2. High visibility and low autonomy: Medication Safety Clinical Decision Support

The Medication Safety Clinical Decision Support system, deployed by the Department of Veterans Affairs, features evidence-based recommendations for primary care providers. Incorporating various electronic clinical data, such as laboratory test results and history of adverse drug events, the system automatically offers patient-specific recommendations to care providers. By doing so, this AI application assists veterans and their care providers in managing chronic and other types of diseases. This AI project is highly visible to its users as it is not integrated into a complex decision-making structure. Users can easily identify that the system is making the recommendations. Additionally, the recommendations provided by the system does not directly make the decision regarding medicine use or other health-related treatments, which reflects a relatively low degree of AI autonomy in this case.

Considering the self-learning characteristic of this decision support system, one crucial opportunity is to enhance the precision and personalization of the recommendations over time. Since users can perceive the iterative learning processes that provide better alignment between patients' needs and treatments, it creates a sense of trustworthiness and a positive experience in using this AI application. Nevertheless, the results recommended by the system might not always lead to final decisions, and algorithms are designed to learn from interventions made by humans, such as tagging invalid recommendations or offering alternative responses. Specific challenges might emerge when these learning processes, intentionally or unintentionally, incorporate human biases, thereby limiting the system's effectiveness.

5.3. Low visibility and high autonomy: Person-Centric Identity Services

The goal of the Person-Centric Identity Services system is to become a trusted source that profiles an individual's comprehensive immigration history and status. Deployed by the Department of Homeland Security, this system aims to establish an identity profile by compiling and aggregating various biographic and biometric information with the assistance of machine learning algorithms. Since this system is highly intertwined with other operational systems in the Department of Homeland Security, the visibility of this AI application appears to be low. Moreover, the algorithms used to match individuals' different immigration records are highly autonomous, and explicit human intervention is limited due to the high complexity of the data structure.

The characteristic of self-learning presents both opportunities and challenges to this highly autonomous but less visible AI system. On the upside, the self-learning attribute could cover more data sources having immigration records and streamline the matching procedures from various data sources, which can significantly reduce routine tasks and increase the operational efficiency of agencies. On the downside, however, the self-learning characteristic in this system might entail higher risks and challenges in rectifying or detecting potential administrative errors. As public managers or experts might lose sufficient control during the system's iterative learning processes, the concerns about the 'black-box' effect would be exacerbated.

5.4. Low visibility and low autonomy: Quick Disability Determinations

The Quick Disability Determinations system, deployed by the Social Security Administration, utilizes an AI-powered model to initially screen applications submitted for disability benefits. Building on historical data from completed claims, the system identifies claimants with the most severe disabilities. Subsequently, public employees in the Social Security Administration prioritize cases where a favorable disability determination is highly likely and medical evidence is readily available, thereby expediting the application process for those who are the most vulnerable and in high need. Given that this system is integrated into the complex structure of the social security benefits system, its visibility could be considered low. Furthermore, since public employees in social security agencies can control the final decisions of benefit claims, the autonomy of this system is also deemed low.

Factoring in the self-learning aspect, the Quick Disability Determinations system could encounter distinct opportunities and challenges. In terms of opportunities, the self-learning characteristic can assist human workers to a more manageable decision-making process. The frequent human intervention could also help to consider very specific characteristics of certain difficult or unique cases. On the other hand, given the high degree of human intervention and the high degree of system integrations, the challenges might be centered on issues related to accountability and evaluating the performance of the models. That is, the decisions of approving or rejecting disability applications might result from several factors, such as employees' prejudice or decision structures in social security benefit applications, rather than from the AI system itself. Given the ambiguous feedback loops between inputs and outputs, the system might not achieve its full potential from the self-learning characteristic.

Based on the cases we illustrated, Table 2 summarizes our preliminary results in terms of tailored opportunities and challenges of different types of AI applications, when taking the self-learning characteristic into account. Generally, we underscore that the self-learning feature can be an important factor contributing to the complexities of benefits and other consequences. By explicitly recognizing the interplay of visibility, autonomy, and self-learning in government AI systems, practitioners and researchers can analyze AI applications under the analytical lens of specific contexts and types. We will conclude our research findings and outline further steps in the next section.

Table 2

Considering the self-learning characteristics in different types of AI systems

AI system type	Opportunities	Challenges
High Visibility and High Autonomy	• Enhances human-machine collaboration by adapting over time.	• Risks of generating inaccurate or biased responses on a large scale
High Visibility and Low Autonomy	• Improving precision and personalization of recommendations. • Fostering trustworthiness with a controllable improvement.	• Potential incorporation of human biases in learning processes
Low Visibility and High Autonomy	• Increasing operational efficiency by streamlining	• Hard to correct or detect administrative errors due to compounded

AI system type	Opportunities	Challenges
	complex and onerous tasks.	complexity resulted from self-learning.
Low Visibility and Low Autonomy	• Assisting human workers to a more manageable decision-making process.	• Ambiguity in evaluating model performance due to human intervention and complex system integrations, causing issues related to accountability. • The self-learning characteristic might be limited and not necessary in some situations.

6. Final comments and next steps

With four AI cases deployed in U.S. federal agencies, this ongoing research study contributes to previous research by exploring the advantages and implications of a more complex categorization of AI systems [22, 35]. Our preliminary findings suggest that the self-learning characteristic might introduce different opportunities and challenges for different types of AI systems. Considering the interplay of visibility, autonomy, and self-learning in government AI systems, AI systems distinguish themselves from previous technology issues regarding the complexities and challenges. Thus, it might be fair to argue that the proposed typology consisting of two dimensions—visibility and autonomy—shows the importance of understanding complex AI systems in the public sector due to the unique self-learning nature of AI technologies. Given that these two dimensions highlight essential aspects for the public sector, future research can utilize these dimensions as key contextual differentiators among AI systems.

For future directions, a deeper analysis of the cases would be beneficial. The current analysis is based on official case documents available on government websites, but the descriptions of cases in these documents provides limited information. As a result, conducting interviews with public employees who actively engage with these AI systems, as well as with citizens and stakeholders affected by the decisions, could yield richer insights in future studies. Furthermore, incorporating additional cases for comparison within the same category could be beneficial. The comparison might illuminate the subtle distinctions among AI cases, teasing out the critical factors that merit closer examination in AI systems even when they are in the same category.

References

[1] Benbya, H. et al. 2020. Artificial Intelligence in Organizations: Current State and Future Opportunities. MIS Quarterly Executive. 19, 4 (Dec. 2020).

[2] Brynjolfsson, E. and Mitchell, T. 2017. What can machine learning do? Workforce implications. Science. 358, 6370 (Dec. 2017), 1530–1534.

[3] Bullock, J. et al. 2020. Artificial intelligence, bureaucratic form, and discretion in public service. Information Polity. 25, 4 (Jan. 2020), 491–506.

[4] Bullock, J. 2019. Artificial Intelligence, Discretion, and Bureaucracy. The American Review of Public Administration. 49, 7 (Oct. 2019), 751–761.

[5] Burrell, J. 2016. How the machine 'thinks': Understanding opacity in machine learning algorithms. Big Data & Society. 3, 1 (Jun. 2016), 205395171562251.

[6] Busuioc, M. 2021. Accountable Artificial Intelligence: Holding Algorithms to Account. Public Administration Review. 81, 5 (2021), 825–836.

[7] Chen, Y.-C. et al. 2023. Artificial Intelligence and Public Values: Value Impacts and Governance in the Public Sector. Sustainability. 15, 6 (Jan. 2023), 4796.

[8] DHS/USCIS/PIA-087 Person Centric Identity Services Initiative: 2022. https://www.dhs.gov/publication/dhsuscispia-087-person-centric-identity-services-initiative. Accessed: 2024-03-07.

[9] Ensign, D. et al. 2018. Runaway Feedback Loops in Predictive Policing. Proceedings of the 1st Conference on Fairness, Accountability and Transparency (Jan. 2018), 160–171.

[10] Federal Student Aid: 2024. https://studentaid.gov/h/aidan. Accessed: 2024-03-07.

[11] Ferrara, E. 2024. The Butterfly Effect in artificial intelligence systems: Implications for AI bias and fairness. Machine Learning with Applications. 15, (Mar. 2024), 100525.

[12] Government Use of AI: 2024. https://ai.gov/ai-use-cases/. Accessed: 2024-03-07.

[13] Green, B. 2022. The flaws of policies requiring human oversight of government algorithms. Computer Law & Security Review. 45, (Jul. 2022), 105681.

[14] Green, B. and Chen, Y. 2019. The Principles and Limits of Algorithm-in-the-Loop Decision Making. Proceedings of the ACM on Human-Computer Interaction. 3, CSCW (7 2019), 50:1-50:24.

[15] Grimmelikhuijsen, S. 2023. Explaining Why the Computer Says No: Algorithmic Transparency Affects the Perceived Trustworthiness of Automated Decision-Making. Public Administration Review. 83, 2 (2023), 241–262.

[16] Grimmelikhuijsen, S. and Meijer, A. 2022. Legitimacy of Algorithmic Decision-Making: Six Threats and the Need for a Calibrated Institutional Response. Perspectives on Public Management and Governance. 5, 3 (Sep. 2022), 232–242.

[17] Hall, J.S. 2007. Self-improving AI: an Analysis. Minds and Machines. 17, 3 (Oct. 2007), 249–259.

[18] Harrison, T.M. and Luna-Reyes, L.F. 2022. Cultivating Trustworthy Artificial Intelligence in Digital Government. Social Science Computer Review. 40, 2 (Apr. 2022), 494–511.

[19] Hasselbring, W. 2000. Information system integration. Communications of the ACM. 43, 6 (Jun. 2000), 32–38.

[20] Heinrichs, B. 2022. Discrimination in the age of artificial intelligence. AI & SOCIETY. 37, 1 (Mar. 2022), 143–154.
[21] Jochen Scholl, H.J. and Klischewski, R. 2007. E-Government Integration and Interoperability: Framing the Research Agenda. International Journal of Public Administration. 30, 8–9 (Jul. 2007), 889–920.
[22] Katzenbach, C. and Ulbricht, L. 2019. Algorithmic governance. Internet Policy Review. 8, 4 (Nov. 2019), 1–18.
[23] Kwak, G.H. et al. 2021. Deep reinforcement learning approaches for global public health strategies for COVID-19 pandemic. PLoS ONE. 16, 5 (May 2021), e0251550.
[24] Lam, W. 2005. Barriers to e-government integration. Journal of Enterprise Information Management. 18, 5/6 (2005), 511–530.
[25] Libin, P.J.K. et al. 2021. Deep Reinforcement Learning for Large-Scale Epidemic Control. Machine Learning and Knowledge Discovery in Databases. Applied Data Science and Demo Track (Cham, 2021), 155–170.
[26] Macías-Escrivá, F.D. et al. 2013. Self-adaptive systems: A survey of current approaches, research challenges and applications. Expert Systems with Applications. 40, 18 (Dec. 2013), 7267–7279.
[27] McCarthy, J. et al. 2006. A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, August 31, 1955. AI Magazine. 27, 4 (Dec. 2006), 12–12.
[28] Medaglia, R. et al. 2023. Artificial Intelligence in Government: Taking Stock and Moving Forward. Social Science Computer Review. 41, 1 (Feb. 2023), 123–140.
[29] Medication Safety (MedSafe) Clinical Decision Support (CDS): 2024. https://www.actiac.org/et-use-case/medication-safety-medsafe-clinical-decision-support-cds. Accessed: 2024-03-07.
[30] OECD 2022. OECD Framework for the classification of AI systems.
[31] Oreizy, P. et al. 1999. An architecture-based approach to self-adaptive software. IEEE Intelligent Systems and their Applications. 14, 3 (May 1999), 54–62.
[32] Peeters, R. 2020. The agency of algorithms: Understanding human-algorithm interaction in administrative decision-making. Information Polity. 25, 4 (Jan. 2020), 507–522.
[33] Quick Disability Determinations (QDD): 2024. https://www.ssa.gov/disabilityresearch/qdd.htm. Accessed: 2024-03-07.
[34] Ruijer, E. et al. 2023. Social equity in the data era: A systematic literature review of data-driven public service research. Public Administration Review. 83, 2 (Mar. 2023), 316–332.
[35] Straub, V.J. et al. 2023. Artificial intelligence in government: Concepts, standards, and a unified framework. Government Information Quarterly. 40, 4 (Oct. 2023), 101881.
[36] Veale, M. and Brass, I. 2019. Administration by Algorithm? Public Management Meets Public Sector Machine Learning.
[37] Vogl, T.M. et al. 2020. Smart Technology and the Emergence of Algorithmic Bureaucracy: Artificial Intelligence in UK Local Authorities. Public Administration Review. 80, 6 (2020), 946–961.
[38] Wirtz, B.W. et al. 2019. Artificial Intelligence and the Public Sector—Applications and Challenges. International Journal of Public Administration. 42, 7 (May 2019), 596–615.