Algorithm Auditing Policies Rest on Flawed Assumptions About Public Sector Systems

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Acknowledging that automated decision-making systems can generate significant societal harms, policymakers have proposed regulations that require audits of algorithms. However, although these policies are popular, scholars have warned that algorithm audits can provide a veneer of accountability without meaningful impact. In this paper, we evaluate the emerging landscape of algorithm auditing policies. First, we analyze 25 United States policies that require audits of public sector algorithms to distill their core assumptions. Second, we test those assumptions against a representative case of public sector algorithms gone wrong: the Michigan Integrated Data Automated System (MiDAS). We find that auditing policies rely on flawed assumptions that limit their ability to identify and address algorithmic harms. While audit policies conceptualize harm as discriminatory bias, government algorithms can produce a much broader range of issues, including misallocation of public resources and violations of due process. While audit policies investigate algorithms as static and isolated pieces of software, these systems are dynamic and embedded in complex relationships with other technical systems and human practices. While audit policies envision that problems uncovered by audits will be corrected, many public agencies lack the capacity to fix or replace automated systems. In light of these flawed assumptions, we provide recommendations to improve audit policies and the broader governance of public sector algorithms.

CCS Concepts: • **Social and professional topics** → **Government technology policy**; **Governmental regulations**; **Technology audits**; • **Applied computing** → *Computing in government*.

Additional Key Words and Phrases: algorithm audits, algorithmic governance, AI regulation, accountability, MiDAS

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1 Introduction

Acknowledging that automated decision-making systems can generate significant societal harms, computer scientists and policymakers have sought to rein in these issues through auditing—independent evaluations of algorithmic systems. Advocates of audits argue that these evaluations promote transparency, accountability, and harm reduction by providing external oversight of algorithmic systems [5, 14, 63, 72]. There is some evidence that audits can uncover problems and spur reform: for instance, after an audit revealed discriminatory patterns in a welfare fraud prediction algorithm used by the Dutch city of Rotterdam, the city stopped using it [11, 23]. Thus, in recent years, policymakers have proposed and passed numerous bills that require algorithm audits [10, 60].

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However, recent scholarship questions the efficacy of algorithm audits, highlighting how they can function as box-ticking exercises that legitimize flawed systems. Researchers have pointed out several limitations that prevent audits from providing genuine oversight and accountability, including a lack of clear definitions and standards [9, 10, 24, 117, 126, 128]. Empirical assessments focus on a New York City law that requires bias audits of automated employment decision tools, finding that the audits are narrow, inconsistent, and incomplete [41, 50, 128].

With audits emerging as a popular policy intervention for finding and addressing algorithmic harms, it is vital to understand their strengths and limitations. If policies meant to curb algorithmic harms are ineffective in practice, they can provide a false sense of security that enables harms to perpetuate [47]. Currently, there is a lack of empirical evidence about whether audit policies are effective, particularly in the public sector. This is in part because most policies are merely proposed rather than passed, making post-hoc assessment impossible.

In this paper, we evaluate the efficacy of algorithm auditing policies in the public sector. Rather than focus on a single policy, we zoom out to consider the broad landscape of algorithm audit policies. We use a comparative qualitative approach that analyzes the assumptions of audit policies and then tests those assumptions against a representative case of public sector algorithms gone wrong. By analyzing a single system, we provide detailed insights about the complex ways in which technical systems, organizational processes, and people interact in practice—insights that are essential to understanding the practical strengths and limits of audits.

We set out to answer two research questions:

RQ1: What are common assumptions of policies that require audits of public sector algorithms?
RQ2: Do the assumptions of audit policies hold for a real system in the public sector?

To answer RQ1, we surveyed 25 proposed and passed policies in the United States that require audits of public sector algorithms. Our goal was to examine how these policies envision audits conceptualizing, identifying, and remedying algorithmic harms (Section 3). Through thematic analysis, we distilled key assumptions underpinning these policies. First, a majority of policies frame harm in terms of discriminatory bias. Second, policies assume that it is sufficient to audit algorithms by running technical assessments of discrete technical systems. Third, most policies assume that if a harm is identified, the algorithm will be fixed or replaced.

To answer RQ2, we evaluated these assumptions against a case study of the Michigan Integrated Data Automated System (MiDAS), which has administered Michigan's unemployment insurance program since 2013 (Section 4). MiDAS has a long history of problems, from issuing false accusations of fraud [17] to illegally clawing back benefits paid out during the COVID-19 pandemic [110]. In response to these issues, MiDAS has been thoroughly audited. Although MiDAS is representative of other public sector algorithms [16, 47, 69], these audits provide a unique richness of detail about what went wrong. A detailed case study of MiDAS allows us to determine whether policy assumptions hold true in practice and whether these assumptions undermine the efficacy of audits.

By analyzing the MiDAS case, we found extensive evidence that challenges the assumptions embedded in auditing policies. First, MiDAS manifests a much broader range of harms than policies contemplate, such as inadequate security and constitutional rights violations. Second, the MiDAS case demonstrates that certain harms cannot be identified unless auditors adopt systems-level and sociotechnical approaches. Third, MiDAS has had persistent problems even after multiple rounds of audits, revealing that simply detecting harm is insufficient to guarantee remediation. These gaps between audit policies and public sector algorithms significantly undercut the ability of audits to address algorithmic harms. As a result, audit policies provide a false sense of security, producing a misleading image of robust oversight and protection that legitimizes inappropriate and careless applications of public sector algorithms.

In light of these limitations, we provide recommendations to reconcile auditing policies with the realities of public sector algorithms (Section 5). First, audit policies should expand their conceptualization of harm to incorporate a wide array of negative outcomes. Second, audit policies should broaden their scope to include

social and organizational factors, such as system changes over time and human use of algorithms. Third, audit policies should provide resources for remediation and enforce penalties for noncompliance. Because only a few of the analyzed audit policies are finalized legislation, we highlight the promising opportunity to translate our recommendations into revised bills. Nonetheless, despite these opportunities, stronger audit policies alone will not guarantee efficacy and accountability. More systemic changes, such as investing in the capacity of governments to develop technology in-house, are also essential.

2 Related Work

2.1 Audits of Algorithmic Systems

Researchers propose algorithm audits to address a wide range of harms, including discrimination, security breaches, and rights violations [5, 14, 63, 72]. Acting on these proposals, local, state, national, and international policy bodies have promoted algorithm auditing as a mechanism to promote algorithmic accountability [10, 60].

Here, we borrow an expansive definition of algorithm auditing as "a process through which an automated decision system or algorithmic product, tool, or platform is evaluated" [24]. This definition encompasses a range of auditing methods and applications. Mökander [87] taxonomizes two conceptions of auditing: narrow/technical audits and broad/performance audits. Narrow audits probe the behavior and outputs of algorithmic systems via technical experiments. These audits are frequently employed to identify discriminatory bias based on protected characteristics such as race, age, and gender [5, 72]. Meanwhile, broad audits zoom out to also consider processes related to the design, use, and monitoring of algorithmic systems. Many scholars advocate for broad audits, noting the importance of a sociotechnical orientation that accounts for organizational practices and human behavior [34, 70, 88, 126]. They argue that broad audits allow evaluators to not only uncover harms, but also uncover why those issues arise [87]. Such insights can then inform recommendations about how to improve both the technical system and the governance procedures for that system.

Researchers typically propose external, rather than internal, algorithm audits. External audits—also called third-party or independent audits—are conducted by parties whose interests are independent from the audited entity [68]. In contrast, internal audits are performed by parties who have a financial relationship with algorithm developers, raising questions about their objectivity and usefulness as mechanisms for accountability [45, 68, 102, 103].

2.2 Effectiveness of Auditing Frameworks

External audits of public sector algorithms have helped expose and correct problematic behaviors in public sector algorithms tasked with important functions. In one successful case, an audit revealed discriminatory patterns in the algorithm a Dutch city used to flag suspicious welfare claimants for investigation [11, 23]. Facing criticisms that certain model variables served as a proxy for race, the city stopped using the algorithm. In another instance, an audit revealed that a government tool in Pennsylvania provided incorrect advice about who was eligible for subsidized childcare [35]; following this audit, the state updated the tool to fix this issue [42].

However, scholars warn that algorithm audits are not a cure-all. Audits do not completely eliminate harms or guarantee accountability [9, 24, 87, 128]. The lack of clear and stringent standards means that algorithm audits may function as a toothless exercise that legitimizes harmful systems [10, 24, 117]. A further issue is that external audits may not be sufficiently independent and rigorous if they depend on the audited entity providing access to the technical system [129]. More broadly, legal scholars point out that governance mechanisms like audits are designed in ways that limit democratic accountability and enable co-optation, creating a mere veneer of compliance and oversight [20]. These mechanisms typically are conducted by a narrow band of experts who operate outside of public view and rely on technocratic procedures shaped by the audited entities themselves.

Empirical studies have begun to reveal how audit policies can fall short of providing meaningful oversight and reform. This literature focuses on New York City's Local Law 144, which requires bias audits for automated

employment decision tools (and is one of the only audit policies actually in effect in the US). Although media reports initially hailed the law for ensuring that hiring software is free of bias, research found that it is inadequate for addressing algorithmic harms [41, 50, 54, 68, 128]. The required audits are narrow, testing only whether algorithmic systems violate mathematical definitions of discrimination. In addition, employer compliance is low [128], a lack of clear standards enables superficial audits [50], and audits are often uninterpretable [41].

This paper expands on the literature about audit efficacy by comparing the foundational assumptions of audit policies against the realities of how government algorithms are implemented and managed in practice. We focus on policies pertaining to the public sector, where the stakes of algorithmic behavior are often particularly high. Through this analysis, we uncover significant disconnects between assumption and reality, adding empirical evidence to concerns about algorithm audits as an appealing—yet ultimately insufficient—form of governance.

3 RQ1: What are common assumptions of policies that require audits of public sector algorithms?

Our first step in assessing algorithm audit policies is understanding what these policies say and how they function.

3.1 Methods: Survey of Algorithm Auditing Policies

To answer RQ1, we surveyed how policies intend for audits to conceptualize, identify, and remedy harms. We compiled policy documents from proposed bills, enacted legislation, and government-issued guidance for implementing audits. To discover relevant documents, we searched for laws that mentioned audits of computational systems, reviewed academic articles about legal auditing frameworks, and consulted legislation trackers.[1] This process yielded 61 candidate policies.

We filtered the candidate policies based on the following criteria: policies should (1) require third-party evaluation, (2) cover public sector systems, and (3) be introduced in the United States. First, we reviewed each document to determine whether it required third-party evaluation of computational systems. We excluded documents that merely require the development of audit standards (e.g., [51, 98]). Since terminology is still evolving, we included policies that explicitly mention "audits" or discuss related concepts like "independent evaluation" [93, 124, 125]. Second, we removed policies that exclude the public sector. All the policies we included apply to some public sector algorithms—that is, algorithms used by public sector institutions, whether inward-facing or outward/public-facing. These policies obligate either agencies who use algorithms or private vendors who develop algorithms for agencies to conduct audits.

After applying the first two filters, we had a set of 29 policies requiring third-party audits of public sector systems, 25 of which (86%) were from the United States. To avoid making overgeneralized claims about global policy trends, we scoped the analysis to the United States. Our final set of 25 policies encompasses local, state, and federal levels (all policies are listed in Table A.1 and are cited at least once in this section).

These policies cover a range of sectors and systems. Six policies apply only to the public sector, while 19 apply to both public and private sectors. Some apply to a narrow set of algorithmic systems, such as employment decision-making tools, while others apply expansively, such as to any decision-support tool that could lead to residents being "treated differently" [52]. Despite these differences in scope, concepts and definitions circulate across policies. For example, the definition of "automated employment decision tool" in New York City's Local Law 144 was excerpted verbatim to define "automated decision system" in a California bill, even though the latter covers a broad spectrum of sectors beyond employment, including education, housing, and criminal justice. In addition, we note that a narrow scope is often the product of lobbying efforts to whittle down regulation rather than upfront legislative intent [50, 97]. Ultimately, while their scopes vary, all the policies in our final set structure audits of some algorithmic systems involved in high-stakes public sector decisions.

[1]We drew proposed and enacted state legislation from the EPIC [130], IAPP [115] and NCSL [90] trackers; federal legislation from the Brennan Center [13] and American Action Forum trackers [3]; and global legislation from the IAPP tracker [57].

We conducted thematic analysis [12] on our policy documents to determine how they expect audits to conceptualize, identify, and fix harms. We used inductive coding, paying particular attention to descriptions of targeted harms, dimensions of computational systems under examination, and any required corrections. By focusing on these aspects, we aimed to describe what harms the policies addressed, how they scoped investigations, and what actions they envisioned following audits. The first author reviewed our set of 25 policies and compiled relevant excerpts to ground discussions about these three high-level categories of interest. All authors met weekly to discuss, refine, and consolidate emerging themes. Although many policies cover both public and private sector uses of algorithms, we considered their implications only for the public sector. Through that process, we settled on a final set of themes; we retained a theme only if it was followed by a majority of policies (or, conversely, was contradicted by a minority of policies). In a final pass, the first author, who holds a Juris Doctor (JD) degree, classified whether each policy supports, challenges, or does not speak to each identified theme.

3.2 Results: Common Assumptions of Policies That Require Audits of Public Sector Algorithms

We identified seven common assumptions embedded in auditing policies related to conceptualizing, identifying, and fixing algorithmic harms. First, we discuss how most policies frame harm around discriminatory bias. Next, we present how many policies focus audits on discrete computational systems and presume easy access to system internals. Finally, we describe how many policies suppose that problems in computational systems will be fixed.

3.2.1 Conceptualizing Harm.

Harms Manifest as Discriminatory Bias. The majority of audit policies (16 of 25) frame harm as discriminatory bias, calling for audits to assess whether system outputs have differential impacts for protected groups. While race and sex are the most commonly specified characteristics, some policies consider additional attributes like religion or disability [113, 121, 127]. Other policies present a range of criteria for audits, typically by offering high-level goals such as ensuring that systems are "accurate, effective, and fair" [18] or are "complian[t] with legal and ethical standards" [1].

3.2.2 Identifying Harm.

Agencies Have Easy Access to System Internals. Most policies assume that algorithms are transparent and accessible (only 3 of 25 acknowledge potential difficulties in gaining access to technical systems). Audits typically require access to the models, code, and/or data associated with a system. Policies often suppose this information is readily available to agencies, even when they procure technology from private vendors [2, 18, 93, 101].

Annual Audits Are Sufficient. Most audit policies (23 of 25) recognize that technical systems can be updated, so call for periodic re-assessments, typically on an annual basis [22, 52, 93, 127, 132]. However, only five of the 25 policies require maintaining historical versions of algorithmic systems [2, 55, 56, 121, 127]. As a result, most audit policies leave the algorithm unexamined in the intervening periods between annual snapshots.

Audited Systems Are Discrete. Most policies frame their targets as discrete computational models (only 3 of 25 policies recommend evaluating system components that operate in combination with the targeted model). For instance, a California bill takes individual, standalone models as the appropriate unit for review: it defines its targets as "a computational process [. . .] that issues simplified output" [6]. By design, this bill does not consider whether these tools are integrated into larger technical systems. This focus on well-bounded systems assumes that harms can be identified by examining the operation of tools in isolation from their broader technical environment.

Software Can Be Audited in Isolation from Practice. Many policies (13 of 25) limit the scope of audits to technical analyses of algorithm outputs, assuming that algorithms can be evaluated independently of the contexts in which they operate. For example, regulations governing bias audits of automated employment tools require auditors

to calculate selection rates by race and sex, with no requirement to consider how employers actually use and interpret these scores [58, 91, 92, 120, 131]. Only five policies suggest evaluating algorithmic systems in real-world contexts [26, 93, 94, 101, 119]; the others do not require any assessment of how human operators interact with these systems in practice.

3.2.3 *Fixing Harm.*

Agencies Have Capacity to Address Negative Audit Results. Audit policies assume that government agencies can easily acquire the staff and resources required to address negative audit results (only 2 of 25 policies recognize that resource constraints could restrict responses). For example, an Office of Management and Budget Memo requires agencies recruit an "AI-ready workforce" and ensure that operators of algorithmic systems can "manage associated risks" [95]. Similarly, proposed legislation from New York State would require internal reviewers to vet automated decisions manually by interpreting outputs in context with audit results [55]. Despite outlining new agency functions, these policies do not provide funding to fulfill the specified goals and requirements.

Agencies Will Repair or Retire Harmful Algorithms. Policies contemplate two responses following an audit that uncovers harms: the noncompliant system will be fixed or decommissioned. Several policies assert that agencies should correct issues raised by audits, for example by "implement[ing] protocols to address identified deficiencies, including [. . .] recalibration of systems" [1]. Other policies suggest decommissioning algorithms [93, 122, 124]. For instance, a 2020 Executive Order mandates that agencies "supersede, disengage, or deactivate existing applications of AI that demonstrate performance or outcomes that are inconsistent with their intended use" [122]. Despite these mandates, no policy specifies any mechanisms for penalizing public sector noncompliance.

4 RQ2: Do the assumptions of audit policies hold for a real system in the public sector?

Our analysis for RQ1 documented the widespread assumptions embedded in public sector algorithm auditing policies. Our goal now is to assess whether these assumptions accord with the realities of public sector algorithms.

4.1 Methods: Qualitative Analysis of the MiDAS Case

To evaluate algorithm audit policies, we compare their assumptions against an empirical case study. We chose the case study approach because it allowed us to analyze, in-depth, how a particular government algorithm was implemented and governed [39]. The case study approach is especially valuable for its ability to provide a detailed narrative about an algorithm's use and governance. To comprehend the gaps of existing policies and identify opportunities for reform, it is essential to understand what a real system looks like in practice and why attempts at remediation fall short.

Our case study focuses on the Michigan Integrated Data Automated System (MiDAS)—a paradigmatic example of a government algorithm that led to widespread social harm [16, 33, 62, 104, 105]. Researchers and journalists have exposed errors within numerous government algorithms across a wide range of policy domains, leading to harms such as violating human rights, denying government benefits, and keeping inmates in prison beyond their release date [16, 53, 59, 69]. MiDAS is akin to these other public sector software systems in terms of its extensive automated ruleset, its integration of code with internal administrative data and organizational practices, and its persistent problems leading to high-stakes impacts on individual rights [16, 46, 53].

We chose to focus on MiDAS because it has been the subject of extensive audits. In response to public outcries about MiDAS, the Michigan Office of the Auditor General (OAG) and Deloitte have conducted numerous audits of the Michigan Unemployment Insurance Agency (the agency that implemented and uses MiDAS) over the last decade (Table 1; Appendix B). It is important to note that the audits of the Unemployment Insurance Agency (UIA) were not mandated or governed by an algorithm auditing policy akin to those described in Section 3. Instead, the audits of the UIA were conducted under policies that long predate discussions of algorithms; since 1964,

the Michigan Constitution has required the OAG to conduct audits of all state agencies [80]. The audits focus broadly on the UIA's actions and performance in relation to MiDAS, rather than MiDAS alone. Thus, our goal in this section is not to evaluate the UIA audits as algorithm audits per se. Instead, our goal is to use the extensive evidence uncovered by the UIA audits to gain a detailed understanding of why MiDAS's failures occurred and why the issues have been so difficult to resolve.

We note that the policies described in Section 3 are from other states and levels of government that do not cover State of Michigan algorithms. Our intention is not to assert that the OAG should follow the mandates of policies from other jurisdictions. Instead, our intention is to leverage our understanding of MiDAS to assess whether those policies are likely to be effective within the bounds of their own jurisdiction. We aim to compare the granular details of MiDAS—as a representative public sector algorithm—against the widespread assumptions that guide algorithm audit policies.

We compiled the case study narrative of MiDAS from media reports, press releases, and audits of the UIA. Our case study is also informed by the first author's ten months of experience consulting for a law firm that represents people injured by MiDAS. This firm has pursued class-action cases against the Michigan Unemployment Insurance Agency for over a decade, securing millions of dollars of relief for its clients. The first author filed expert witness reports in court that evaluated the technical performance and software development workflow of MiDAS. To prepare these reports, the author conducted extensive reviews of internal UIA documents and data. Although this paper is based only on public documents, the author's experience informs our construction of the case study. In addition, attorneys who have been involved in MiDAS litigation for over a decade reviewed the case narrative to confirm accuracy and thoroughness.

4.2 MiDAS Background and Timeline

In August 2011, the State of Michigan paid the company FAST Enterprises $47 million to modernize the software used by the state's Unemployment Insurance Agency (UIA) [76]. MiDAS is a customized version of a FAST Enterprises product (FastUI for Unemployment Insurance and Paid Leave) that incorporates Michigan's program rules. MiDAS provides the technical infrastructure for key tasks in administering unemployment insurance, such as processing benefits applications. The UIA's objectives for MiDAS were to better detect fraud, raise revenue, increase operational efficiency, and reduce the workforce (in 2012, the UIA laid off one-third of its staff) [17, 104].

4.2.1 Robofraud problems. After MiDAS launched in October 2013, fraud cases skyrocketed. In 2014, the number of applicants accused of committing fraud was five times the typical number [116]. In April 2015, a class action lawsuit alleged that MiDAS accused thousands of committing unemployment fraud based on automated judgments, without human review [133]. The lawsuit described how MiDAS processed benefits records from claimants and flagged individuals if any discrepancy was found in their files. Once a claim was flagged, MiDAS mailed confusing questionnaires and notices to benefits recipients. Failure to respond within ten days led MiDAS to automatically determine fraud had occurred. MiDAS then assessed claimants a statutory penalty for fraud: they had to pay back four times the benefits received. Despite lacking evidence that claimants intentionally misled the UIA, the system initiated collection efforts against these claimants, garnishing their wages and seizing their tax returns.

In 2016, the Michigan Office of the Auditor General (OAG) published two audits finding that the UIA's processes for finding fraud were inadequate [77]. The UIA had determined 60,324 claims were fraudulent, but lacked basis for many of these claims [77]. When people appealed the fraud decisions, only 8% of these accusations were upheld. Following these audits, the UIA reversed 85% of the automated fraud accusations [73].

Rather than scrapping MiDAS, the UIA extended its contract with FAST Enterprises and paid tens of millions for updates [76]. However, despite these efforts, the UIA never fully resolved the problems with MiDAS. In February 2020, the OAG reviewed the UIA's corrective actions taken in response to the 2016 audits; it found that four of the five issues persisted, since the UIA did not comply with the OAG's recommendations [79].

Table 1. Summary of the audits performed on MiDAS. See Appendix B for more information about audit context and methods.

Audit Series	Auditor	Publication Dates	Audited Periods	Audits in Series	Primary Objectives
Robofraud Audits	OAG	Feb. 2016–April 2016	Oct. 2012–Sept. 2015	[77, 78]	Evaluate MiDAS along several dimensions, including its claims processing practices, security protocols, and claimant communications.
Robofraud Follow-up Report	OAG	Feb. 2020	July 2018–June 2019	[79]	Review the UIA's corrective actions to address the Robofraud Audits' findings.
Pandemic Audits	OAG	Nov. 2021–Dec. 2023	Oct. 2019–Dec. 2022	[80–84]	Evaluate the UIA's operations during the COVID-19 pandemic. Assess MiDAS claims processing practices, change controls, and data integrity.
Pandemic Reports	Deloitte	Nov. 2020–Dec. 2021	March 2020–Sept. 2021	[28, 29]	Describe the UIA's fraud management processes during the pandemic and estimate the potential fraud.

4.2.2 Pandemic problems. When the COVID-19 pandemic struck, the UIA confronted an enormous spike in unemployment claims and shifting program rules. The state's unemployment rate reached 23.6% in April 2020 [80], compared to 3.6% in April 2019 [8]. New federal programs expanded unemployment insurance, increasing payment amounts and expanding eligibility to new workers [25, 80]. As the UIA attempted to manage these shifts, many desperate families seeking benefits reported agonizing delays and frustrating roadblocks [96].

A class-action lawsuit filed in January 2022 detailed widespread harms that MiDAS had inflicted on unemployed people [108, 114]. The UIA paid out benefits through pandemic unemployment programs; a year later, the UIA reassessed 54,000 recipients as ineligible and clawed back their benefits (totaling $783 million) without giving them a chance to protest or appeal—a violation of due process [106, 114]. There are lawsuits still pending related to other pandemic-era violations, such as placing over a million applications on an indefinite hold [64]. Due to data integrity issues with MiDAS [67], it is likely impossible to determine the true number of people impacted or the extent of damages.

The Office of the Auditor General released five audits between November 2021 and December 2023 explaining the source of these issues. Because MiDAS was not updated to account for the new pandemic programs, the UIA resorted to workarounds, attempting to follow new rules by re-using old software functions [83]. As time went on, the UIA incrementally changed aspects of MiDAS, such as updating language on applications to conform with new program requirements. However, these changes overwrote existing records, making it appear that jobless people had incorrectly completed applications or failed to answer required questions. Based on this mangled and inaccurate data, the UIA decided that people had been overpaid and attempted to claw back benefits.

4.2.3 Court proceedings and current status. Financial compensation for MiDAS's errors has come slowly and has not reached everyone affected. Class action lawsuits related to the robofraud accusations made in 2013–2015 have inched through the court system. One case settled in 2022 for $20 million, but only 8,000 (less than one-fifth) of the wrongfully accused people received payments [109, 111]. In 2024, the UIA paid $55 million to settle a class

action lawsuit and reimburse claimants subject to improper collection during the pandemic [7]. There is ongoing litigation related to other pandemic-era violations, such as failing to process over a million applications [64].

In 2022, Michigan hired Deloitte to build a replacement system [74]. However, that project has been delayed by more than year past the contracted launch date, costing the state an additional, unanticipated $20 million [32, 112]. At the time of publication, MiDAS still administers Michigan's unemployment benefits.

4.3 Results: Algorithm Audit Policy Assumptions Do Not Hold for MiDAS

Here, we compare the MiDAS case against the assumptions of the algorithm audit policies described in Section 3.2.

4.3.1 Conceptualizing Harm.

MiDAS Afflicted by Many Types of Algorithmic Harms. Though most policies frame algorithmic harm as bias, the MiDAS case reveals a wide range of harms stemming from algorithmic systems. There can be harms from constitutional rights violations. For instance, the Michigan Office of the Auditor General (OAG) questioned the adequacy of the due process afforded to claimants accused of fraud after finding that the UIA could have provided clearer communications about fraud concerns [77]. In addition, for more than a decade, a technical bug misdated incoming protests from claimants who had been denied benefits or believed they were being underpaid, recording those protests as received one day later than actually filed [65]. Because the system wrongly flagged protests submitted on the final day of the appeal window as late, many claimants were prevented from challenging their denials or underpayments and were therefore deprived of procedural due process rights. The OAG also found persistent shortcomings in system security, exposing sensitive personal information to risk [78, 81, 82]. Another major concern involved the waste of taxpayer funds, as errors and inefficiencies in MiDAS led to the misallocation and loss of public resources [80, 84]. Additionally, MiDAS repeatedly issued determinations based on incorrect records, leading to outcomes that had no basis in fact [83].

4.3.2 Identifying Harm.

UIA Struggles to Export Data from MiDAS. Though policies assume that audited entities can easily access data and code, the UIA struggled to extract information from MiDAS. The first pandemic-era audit was hobbled by the UIA's failure to provide multiple datasets requested by the Office of the Auditor General [80]. As a result, the OAG had to release its report absent the relevant data analysis [80]. It took over a year, and three more audits, before the OAG completed its reporting on the delayed data [83]. The UIA claimed to be "hamstrung by the limitations and support of [their] current database" and that "system limitations [...] continue to plague the agency's ability to respond in a timely manner" [83]. From the UIA's perspective, MiDAS is a black-box system; the UIA is reliant on developers employed by FAST Enterprises to fulfill any new data requests [66]. Routing requests across this public-private divide is slow. Moreover, because FAST Enterprises often does not quickly update MiDAS to reflect changes in UIA practices, the data that supposedly documents UIA actions may be incomplete or corrupted. For instance, the UIA director asserted that pandemic-era data features are "inconsistent" and "cannot be used with any level of reliability because they've been bastardized from their initial intent by MiDAS" [66]. Audits will be impeded when an entity cannot provide accurate and timely data about its software systems.

MiDAS Has Thousands of Updates Each Year. Though most policies require algorithms to be audited annually, MiDAS is dynamic, with a steady stream of upgrades and modifications [81]. These amount to thousands of changes each year: the robofraud-era audits record 5,201 change requests initiated by the UIA between October 2013 and July 2015 [78]; the pandemic-era audits record 2,982 changes between October 2019 and June 2021. These changes are not batched together [28], meaning that system operations can vary day-to-day. Even if software bugs are quickly corrected, there can be serious harms for claims that were processed according to defective

logic [28]. Taking a single snapshot of MiDAS would overlook these constant shifts and make it difficult to piece together how and why certain decisions were made.

MiDAS Is Composed of Complex Subsystems. Though policies often frame their targets as discrete computational models, MiDAS involves numerous subsystems working in concert. To process claims, it must synthesize data from many sources and produce many intermediate or final outcomes; the OAG reports that "MiDAS has more than 100 inbound and outbound interfaces" [81]. Often, problems are not attributable to a discrete component of MiDAS, but to the interactions between components. For instance, Fraud Manager is a MiDAS subsystem that applies fraud detection methods and flags certain claims for additional human review [28]. Prior to the pandemic, claims were processed by Fraud Manager and then paid out if no issues existed. During the pandemic, a system developer accidentally changed the order of subsystems to pay claims, then run Fraud Manager. As a result of this sequencing error, the UIA made payments on obviously fraudulent claims [28]. While the Fraud Manager subsystem itself was working as the UIA intended, it was rendered moot due to the timing of when it ran in relation to other subsystems. Auditing subsystem components in isolation would miss problems that result from the operation of these components in concert.

UIA Employees Co-Construct Outcomes with MiDAS. Though policies assume that algorithms can be audited in isolation from practices, harms can result from the interactions between people and technology. During the pandemic, for instance, the Unemployment Insurance Agency began administering new unemployment programs before MiDAS could be updated [83]. These programs had distinct eligibility requirements, so UIA staff had to process claims manually. Because MiDAS did not have a way to signal which claims needed special eligibility review, the UIA simply re-used an existing software flag that required a different form of manual review. However, the UIA failed to train their staff on how to interpret the re-used flags; as a result, some incorrectly followed the original procedures while others applied the new requirements. There was no way to determine which set of procedures had been followed in each case, resulting in incorrect decisions regarding eligibility [67]. These problems were not due to changes in the MiDAS source code, but to a messy collision of software, policies, and human behavior. Audits focused solely on technical components would overlook these interactions.

4.3.3 Fixing Harm.

UIA Lacks Technical Staff and Resources to Correct MiDAS. Though policies assume that agencies have technical competence and adequate resources to address audit findings, the UIA struggled to implement proposed improvements to MiDAS. The OAG has repeatedly admonished the UIA's inconsistent implementation of recommended changes. The UIA cited "resource constraints" to explain its lack of corrective action [84]. Some of these constraints are technical: the UIA could not directly change MiDAS or inspect the source code, meaning that it must issue requests to FAST Enterprises and hope FAST implements those changes correctly [66]. Some of these constraints concern human resources: the UIA attributed its failures to personnel turnover that replaced "a once experienced team" with "novices" [83], depleting institutional knowledge in an agency that already had very limited technical expertise to specify or verify software changes [66]. Some of these constraints are financial: the UIA must balance multiple governance objectives on a limited budget [78, 80, 83]. As a result of these technical, financial, and human resource constraints, the UIA did not have the capacity to address all audit findings.

MiDAS Remains Broken Despite Audits. Though policies typically assume that noncompliant algorithms will be fixed or replaced, MiDAS limps along in a broken state. In each audit, the OAG listed recommendations to remedy identified deficiencies. The UIA frequently neglected these recommendations for years on end [81]. Failure to address audit findings is a recurring problem with the UIA. Eight of the fourteen problems from the January 2023 audit were still unresolved in May 2025 [75]. The unaddressed issues included major procedural overhauls, such as reconfiguring MiDAS messages that the OAG deemed "confusing" and "contradictory" [75, 83]. One reason for

the UIA's failure to resolve these issues is that "[t]he OAG has no enforcement authority for corrective action" [85]. The OAG publishes reports; it is up to Michigan's executive and legislative branches to enforce changes.

The UIA has used MiDAS for over a decade while knowing it to be flawed. Even though its leadership accused FAST Enterprises of mistranslating policies and misrepresenting system reliability [66], the UIA repeatedly renewed its contract and paid the company millions of dollars for system support [76]. The UIA has contracted with Deloitte for a replacement system, but the launch has been plagued by delays and cost overruns [32].

4.4 Contextualizing Findings Within Broader Public Sector Algorithms and Audits

MiDAS is emblematic of public sector automation efforts. Algorithmic systems frequently manifest a wider range of harms than bias, including violations of constitutional due process [16, 19] and erroneous decisions causing thousands to lose critical services [99, 100]. Public sector algorithms are rarely static; they undergo frequent updates to keep pace with evolving policies and organizational objectives [69]. Technical architectures are complex, often consisting of integrated platforms that include a rules or inference engine, a portal for workers, and an interface for the public [40]. In addition, outcomes are co-produced by software and agency employees [47]. The governance of public sector algorithms is further complicated by the fact that many are developed and operated by private vendors, impeding efforts to ensure transparency and achieve robust oversight [69].

In addition, the ongoing challenges with MiDAS are indicative of widespread obstacles to remediating failures in public sector algorithms. Fiscal and technical resource constraints frequently limit the ability of agencies to address problematic software [34]. Consequently, tools often continue to operate in a faulty state for years, even after audits have flagged severe deficiencies [21].

5 Discussion

Our work suggests that algorithm auditing policies risk providing a veneer of accountability that masks, rather than mitigates, the ongoing failures of government software. We build on past work that has examined individual pieces of legislation by surveying the wider landscape of auditing policies. Our analysis reveals that the shortcomings scholars have identified in specific mandates, such as NYC's Local Law 144 [41, 68, 128], are characteristic of a systemic trend: current policies are not equipped to provide robust oversight. We further enrich this scholarship with a longitudinal perspective; we present a case study that follows how a series of audits spanning over a decade failed to prevent extensive, repeated harms. We also provide a grounded focus on the public sector, demonstrating the inability of audit policies to address complex failures in public sector software. While there are opportunities to improve algorithm audit policies, policymakers must also look beyond audits to ensure that public sector technology empowers the public.

5.1 Recommendations to Improve Algorithm Auditing Policies

In this section, we recommend reforms for strengthening algorithm audit policies (Table 2). Overall, we emphasize the need to ground audit policies in the sociotechnical and political realities of public sector algorithms. Rarely do these algorithms exist as simple technical artifacts that can be assessed in straightforward terms of right or wrong outputs. Instead, public sector algorithms are components of complex sociotechnical systems: they are part of larger technical systems used by practitioners who face significant constraints and pressures. To provide valid evidence about the quality of automated tools and guide effective remediation, algorithm audit policies must account for these realities of implementation and use.

We note that the majority of policies we assessed (including every state-level policy) is a proposed bill rather than finalized legislation. This highlights both the opportunity and urgency to act: there is still time to create more robust algorithm auditing policies. Rather than simply lamenting the inadequacy of existing laws, we hope to inform subsequent drafting and debate on these emerging bills.

Table 2. Summary of policy assumptions, conflicting evidence from our case study, and suggestions to enhance audit policies.

Common Audit Policy Assumption	**Case Study Finding**	**Recommendation to Enhance Audit Policy Efficacy**
Harms Manifest as Discriminatory Bias	MiDAS Afflicted by Many Types of Algorithmic Harms	Support Participatory Mechanisms for Discovering Suspected Harms
Agencies Have Easy Access to System Internals	UIA Struggles to Export Data from MiDAS	Mandate Access to Audited Systems
Annual Audits Are Sufficient	MiDAS Has Thousands of Updates Each Year	Enforce Version Preservation Requirements
Audited Systems Are Discrete	MiDAS Is Composed of Complex Subsystems	Test the Interoperability of Components
Software Can Be Audited in Isolation from Practice	UIA Employees Co-Construct Outcomes with MiDAS	Evaluate Human Uses and Downstream Impacts of Algorithms
Agencies Have Capacity to Address Negative Audit Results	UIA Lacks Technical Staff and Resources to Correct MiDAS	Provide Resources and Technical Talent for Remediation
Agencies Will Repair or Retire Harmful Algorithms	MiDAS Remains Broken Despite Audits	Specify Penalties If Agencies Fail to Address Negative Audit Results

5.1.1 Conceptualizing Harm.

Support Participatory Mechanisms for Discovering Suspected Harms. While it is important for audits to address discriminatory bias, this alone is insufficient. Effectively addressing algorithmic harms requires a wider scope.

To ensure that audits focus on the most pressing impacts, policies should support participatory mechanisms for discovering suspected harms that require investigation. Rather than specifying a narrow and rigid set of outcomes to measure, audit policies should require a process for collecting concerns from diverse sources. This approach would require an upstream phase in the auditing process dedicated to soliciting input from a broad range of stakeholders, such as frontline staff, legal advocates, and the impacted public. To facilitate this discovery and prioritization process, agencies or auditors could set up post-deployment incident reporting mechanisms, providing a unified forum for anyone to share concerns. In the MiDAS case, for instance, the audits pursued harms by investigating issues first raised in internal staff emails or flagged by the US Department of Labor [80].

5.1.2 Identifying Harm.

Mandate Access to Audited Systems. Though many policies assume agencies have access to algorithmic systems and data, there can be substantial barriers. Policies must ensure auditors have sufficient access to audited systems.

Policies should require vendors to provide auditors with full access to system data and code. For instance, recent federal guidance states, "[c]ontracts must require vendors to provide agencies with sufficient access and time to conduct any required testing in a real-world context" [94]. To ensure compliance, contracts should empower agencies to impose financial penalties or withhold payments from vendors that fail to provide auditors with the necessary technical access within a mandated timeframe. Even after system access is secured, auditors should treat vendor data as potentially unreliable. If conflicting records or reports surface, auditors should conduct independent verification or adopt methodologies that do not rely on vendor-furnished information.

Enforce Version Preservation Requirements. Though many policies call for periodic audits, few consider oversight in the intervals between assessments. Policies should account for the possibility of constantly changing systems.

To strengthen oversight of dynamic algorithmic systems, policies should incorporate the version preservation requirements that already appear in some proposals. For instance, a New York State bill mandates keeping "a historical record of versions of the tool" that captures "the nature and specifications of the tool as it was used at the time of [rendering a] decision" [55]. Such records are essential for enabling automated decisions to be contestable, as they allow individuals to reconstruct the logic applied to their specific case even after a technical system has been updated. In addition, auditors could enforce process-based oversight, comparing software update procedures against best practices. In Michigan, the Office of the Auditor General found that the Unemployment Insurance Agency's documentation and testing practices deviated from state technical standards [81].

Test the Interoperability of Components. Policies often take a limited view of algorithmic systems, treating them as discrete, well-bounded computational models. However, auditing policies should take a systems-aware approach that examines the interactions between components.

By expanding how audits scope the technical object of the investigation, systems-aware audits can better identify harms that emerge from integrated software subsystems. A few policies have begun to mandate broader evaluations, directing agencies to "ensure the AI, as well as components that rely on it, will work in its intended real-world context" [93]. To operationalize this requirement, auditors should follow the precedent set by the Michigan OAG, which specifically tested the interoperability of MiDAS components. This involved reviewing a sample of 10 out of 94 distinct system interfaces to ensure that the data exchanged between subsystems was correctly retrieved and loaded [81].

Evaluate Human Uses and Downstream Impacts of Algorithms. Many policies scope audits to analysis of technical components, ignoring operational context. Policies must require sociotechnical audits because some algorithmic harms emerge not from technical tools alone, but from the complex interactions between tools and people.

To enable more holistic assessments of algorithm performance, policies should require audits to evaluate automated systems within their contexts of use, taking into account how algorithms are embedded and operated within organizations [49]. One method for sociotechnical audits is to analyze data about the actions that human operators take when interacting with an algorithm [27, 48]. Auditors could also conduct qualitative assessments, such as interviewing system users and observing workflows [61]. These sociotechnical inquiries would shed light on how organizational pressures and human interventions can mitigate or exacerbate technical failures.

Policies should also require audits to connect the algorithm's use with the downstream impacts on individuals. Audits could incorporate causal studies that measure the algorithm's impacts on outcomes of interest. For instance, if a school district deployed an algorithm to help prevent students from dropping out of high school, an audit could test whether the algorithm actually improves graduation rates. Audits could also include interviews with the subjects of algorithmically-informed decisions to understand their experiences (e.g., asking students within that school district whether they feel that the use of the algorithm has been respectful and helpful). These impact-focused studies would not only uncover harms—they would also test whether algorithms are even effective at achieving their intended purposes.

5.1.3 Fixing Harm.

Provide Resources and Technical Talent for Remediation. Although policies assume that agencies will follow audit recommendations, resource constraints can hamper corrective actions. For audits to function as catalysts for change rather than mere documentation of failure, policies should allocate resources to remedying problems.

Addressing resource deficits requires a two-pronged approach: providing remediation funding and cultivating internal technical talent. Financial issues are pervasive in government, where funding priorities are set by political processes that are outside agency control [34]. To address this barrier against improvement, auditing policies

should allocate additional funds to support remediation. The provision of funds will be effective only if paired with a workforce capable of implementing them; this necessitates a dual commitment to recruiting technical talent or upskilling the existing workforce. Attracting technical experts to government jobs remains an open issue, given the prospect of lucrative private sector employment [118]. It may be possible to expand upon models like the US Digital Service and the US Digital Corps, which recruit technologists for stints in the public sector.

Specify Penalties If Agencies Fail to Address Negative Audit Results. Policies assume that algorithms identified as deficient by audits will be repaired or decommissioned. Policy should pair a commitment to remediation with a sober recognition that not all issues will be resolved.

Ideally, audit policies would include stronger requirements for agencies to promptly address issues. However, a significant challenge is that auditing agencies generally lack enforcement powers. In Michigan, it is left to the Governor and Legislature to act in response to Office of the Auditor General reports. If those groups do not act, other groups must seek accountability—for instance, journalists who broadcast problems to the public and lawyers who pursue class-action lawsuits. One way around this gap would be for algorithm audit policies to explicitly describe penalties or next steps if an agency fails to achieve sufficient remedies after an audit uncovers technical flaws or social harms. Examples include requiring agency leaders to testify about the issues to a legislative body or removing the department head from their post. By automatically triggering responses to audits, such provisions would help ensure that audits lead to action.

In addition, to dull the impacts of flawed algorithms that cannot be repaired or replaced, auditing policies should prohibit government entities from relying on any technical system found to be unreliable. Audit findings could trigger a rebuttable presumption of invalidity for adverse actions based on that system's output. Procedural rules should be amended to require that agencies corroborate determinations from faulty algorithms with independent evidence, such as manual calculations or administrator affidavits.

5.2 Reinvigorating and Going Beyond Audits

Our study suggests that many algorithm auditing policies follow a rather hollow conception of auditing. We find a stark disparity between the narrow mandates found in recent policy proposals and the robust, longitudinal investigations conducted in the MiDAS case. The Michigan Office of the Auditor General was established in 1836; its approach to auditing draws on a centuries-old vision of public accountability. (The Colorado Office of the State Auditor, established in 1876, has also uncovered issues with state benefits management software [21].) In contrast, algorithm auditing policies all originated this decade and mandate audits as a technocratic knowledge practice, emphasizing metrics over substantive investigations. As legal scholars observe, this modern regulatory mode often adopts "words like inclusion, accountability, and transparency [...], but the mechanisms touted as effectuating those values are often more performative than real" [20]. While contemporary auditing policies are pitched as accountability mechanisms, the practices they mandate are too restricted to address the harms of public sector systems. To reinvigorate auditing, policymakers should not only expand procedural requirements, but also embrace regulatory modes that build and sustain public power.

Policymakers could borrow from historical and international models by situating algorithm audits within existing oversight bodies. Within the US, longstanding auditing bodies offer a more robust and accountable form of oversight than algorithm audit policies tend to envision. Rather than leaving audits to third parties such as consulting companies [9], policymakers could bolster state audit organizations with the financial and technical resources to conduct algorithm audits. The UK's Information Commissioner's Office (ICO) offers a model for how a regulatory body can use algorithm audits to demand change at scale. New legislation, such as the Online Safety Act, has expanded the ICO's powers: its auditors can inspect workplaces, review documents, observe operational practices, and issue fines if systems do not comply with statutory requirements [123]. The ICO has conducted many impactful audits and wielded its enforcement powers against operators of harmful algorithms [9].

Although there are many opportunities to improve auditing policies, even strong audits cannot be the sole approach to treating algorithmic harm, nor should audits be seen as a guarantor of effective algorithms. The audits of MiDAS and the Michigan Unemployment Insurance Agency were thorough and uncovered numerous harms, but they did not lead to a functional system. Indeed, many algorithm audits fail to achieve impactful outcomes [9].

To achieve more reliable algorithms, policymakers and agencies should intervene at earlier stages of algorithm development and implementation. Procurement offers an opportune focal point for enforcing higher standards on government algorithms [89]. Contracts with vendors could require many of the practices we recommended in Section 5.1, such as providing auditors with access to data and storing records of every system state. Contracts could also include performance-based incentives, such that agencies can withhold funds if an audit finds that a procured tool is deficient or if a vendor fails to make prompt repairs in response to an audit. Collectively, these changes could help ensure that government software works more effectively, that audits run more smoothly, and that repairs are made more quickly.

However, a significant challenge in achieving more effective procurement is that there often is a dearth of vendors, limiting the government's bargaining power. As a result, contracts ping-pong between badly-performing vendors. Notably, while Michigan is shifting from FAST Enterprises's MiDAS system to one built by Deloitte [107], Massachusetts is shifting from its flawed unemployment insurance system built by Deloitte to one built by FAST Enterprises [44, 71].

One way to unsettle this cycle would be to invest in the capacity of government agencies to develop software in-house. Translating public policy into software is an interpretive act; errors and breakdowns in communication are common [36]. If agencies enhance their technical ability to create and verify software, engineers and domain experts could work together in a more integrated fashion, making it more likely that algorithmic systems reflect policy goals. Internal technology teams would also streamline the process of adapting software in response to policy changes by enabling engineers, policymakers, and staff to more quickly create new software functionalities and train staff on revised operational protocols. An additional reason to expand in-house technical capacity is that when systems are proprietary and implemented differently across states, lessons learned about failure modes do not travel well. In the unemployment context, the US Department of Labor could develop open-source base models, which states could then adapt for their own purposes. This approach would allow states to serve as laboratories, with their experimentation and experiences driving collective improvements.

Achieving this shift toward robust, publicly-developed software requires governments to adopt new priorities for algorithms, grounded in expanded capacity rather than in austerity. Policymakers are frequently motivated to adopt automated systems such as MiDAS by an explicit desire to cut costs (e.g., by reducing the number of people on benefits and allowing the government to lay off workers) [17, 37]. Ironically, though, the shoddy quality of these algorithms not only generates severe human suffering, but also imposes exorbitant expenses. In Michigan, MiDAS's flaws cost the state hundreds of millions of dollars through legal fees, payouts to harmed individuals, providing mistaken benefits to fraudsters, paying FAST Enterprises to make repairs, and paying Deloitte to build a replacement system. More broadly, across the United States, governments pay billions of dollars to vendors who provide flawed software [38, 69]. Investing in government technical capacity and reducing reliance on vendors could have the dual benefit of generating more functional software while also reducing administrative costs.

Policy-driven audits can be an important tool for identifying and remedying algorithmic harms, especially if strengthened through our recommendations in Section 5.1. But audits are far from a failsafe. Many flaws of government algorithms, and the challenges of remediating those flaws, stem from systemic dynamics of governance that go beyond the ambit of audits. To ensure that algorithms empower rather than injure the public, policymakers must not only strengthen algorithm auditing policies—they must also reimagine their vision for how the public sector should develop and use algorithms.

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Generative AI Usage Statement

The authors used generative AI to improve fluency and readability of the manuscript. We accessed two models (GPT-4.1 and Gemini 3 Flash) through a university AI platform to support grammar and style editing.

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A Summary of Algorithm Audit Policies Analyzed

Table A.1. Algorithm audit policies that we reviewed in Section 3. To avoid redundancy, we consolidated policies that had substantial overlap with other bills (e.g., bills that were reintroduced in several legislative sessions with superficial changes). Thus, the multiple bills from New Jersey and New York originated from different sponsors and/or contained distinct legal language. Policies are grouped based on local, state, and federal jurisdiction.

Jurisdiction / Author	**Title**	**Year**	**Document Type**	**Sector Scope**
District of Columbia	Stop Discrimination by Algorithms Act of 2023	2023	Proposed Bill	Public + Private
New York City	LL 144	2021	Passed Bill	Public + Private
California	AB 1018	2025	Proposed Bill	Public + Private

Hawaii	HB 1607 / SB 2524	2024	Proposed Bill	Public + Private
Michigan	HB 4439	2021	Proposed Bill	Public
New Jersey	AB 4909 / SB 1926	2022	Proposed Bill	Public + Private
New Jersey	AB 4030 / SB 1588	2024	Proposed Bill	Public + Private
New Jersey	AB 3854	2024	Proposed Bill	Public + Private
New Jersey	AB 3855	2024	Proposed Bill	Public + Private
New Jersey	SB 2964	2024	Proposed Bill	Public + Private
New York State	AB 680B	2021	Proposed Bill	Public + Private
New York State	AB 3308 / SB 2277	2023	Proposed Bill	Public + Private
New York State	AB 8129 / SB 8209	2023	Proposed Bill	Public + Private
New York State	AB 8328 / SB 7623	2023	Proposed Bill	Public + Private
New York State	AB 9315B	2023	Proposed Bill	Public + Private
New York State	AB 8884 / SB 1169	2025	Proposed Bill	Public + Private
New York State	SB 185A	2025	Proposed Bill	Public + Private
Oklahoma	HB 1916	2025	Proposed Bill	Public + Private
Pennsylvania	HB 1729	2023	Proposed Bill	Public + Private
Vermont	HB 340	2025	Proposed Bill	Public + Private
Washington	SB 5356	2023	Proposed Bill	Public
US Office of Management and Budget	Memo: Advancing Governance, Innovation, and Risk Management for Agency Use of Artificial Intelligence	2024	Guidance Document	Public
US Office of Management and Budget	Memo: Advancing the Responsible Acquisition of Artificial Intelligence in Government	2024	Guidance Document	Public
US Office of Management and Budget	Memo: Accelerating Federal Use of AI through Innovation, Governance, and Public Trust	2025	Guidance Document	Public
President Donald Trump	Executive Order 13960 / Promoting the Use of Trustworthy Artificial Intelligence in the Federal Government	2020	Executive Order	Public

B Audits of the Unemployment Insurance Agency

The use of MiDAS by the Unemployment Insurance Agency (UIA) has been the target of various evaluations. In this appendix, we present further details on the context and methods of these audits, which are summarized in Table 1.

B.1 Audits Performed by the Michigan Office of the Auditor General

The most comprehensive UIA audits come from the Michigan Office of the Auditor General (OAG). The Michigan Constitution has required the OAG to conduct audits of all state agencies since 1964 (Article IV, Section 53 of the Michigan Constitution) [80]. However, the OAG does not have resources to oversee all agency actions all of the time, so they employ a "risk-based approach when selecting activities to be audited" [86]. The OAG has conducted two series of audits on the Unemployment Insurance Agency since MiDAS was installed—one regarding the robofraud scandal and one regarding pandemic programs. (The OAG also conducts annual financial audits of the UIA, but these primarily concern accounting practices.)

These audits are thorough and adhere to professional auditing standards. The OAG follows two sets of federal auditing requirements: Government Auditing Standards issued by the Comptroller General of the United States; and Title 2, US Code of Federal Regulations Part 200, Uniform Administrative Requirements, Cost Principles, and Audit Requirements for Federal Awards [86]. These audits compare UIA performance against well-defined standards and best practices, such as National Institute of Standards and Technology (NIST) publications [82], State of Michigan Technical Standards [81, 82], federal regulations [77, 82, 83], and practices of other states [77, 82].

The OAG wrote the UIA audits in a standardized format. All the audit reports explicitly state their objectives. Then, they list findings related to the objectives and make recommendations to address those findings. The audit includes the UIA responses to each of the recommendations. For instance, the January 2023 audit listed an objective to assess the UIA's efforts to satisfy state and federal requirements for processing unemployment claims during the pandemic [83]. Finding 7 said the UIA violated Title 20, Part 602B of the Code of Federal Regulations—requiring the Agency to preserve records used in making decisions—when it retroactively altered people's original application forms in MiDAS [83]. The OAG recommended the UIA preserve original applications in MiDAS, and the Agency agreed to improve document maintenance.

The OAG uses a range of broad and narrow auditing methods to evaluate the staff practices and technical operations of MiDAS, which produces longer reports than audits using only narrow approaches. To decide the scope and objectives of the audit, the OAG conducts a preliminary survey; they typically interview UIA staff, review relevant state and federal laws, and review internal documents and policies. Then, they assess each audit objective with a tailored set of methods. Some objectives are related to the technical components of MiDAS; these are assessed with methods like evaluating server configurations, administrative access rights, and security documentation. Some objectives concern practices; these are assessed by reviewing elements such as communications, claimant comments, and random samples of case records (sizes ranging 25–100). The OAG often requests datasets and performs data analysis to evaluate technical systems and practices (e.g., reviewing system records to calculate how long it takes the UIA to deactivate access for former employees, or totaling the number of payments improperly sent to incarcerated people). Chronicling such diverse approaches, these audits range in length from 36 to 126 pages, averaging 55 pages. In comparison, many of the bias audits produced to satisfy Local Law 144 are less than ten pages [4].

B.1.1 Robofraud Audits. The OAG released this pair of audits in 2016 after broad media coverage of MiDAS's automated unemployment fraud accusations. The primary audit objectives were to review MiDAS claims processing practices, security controls, and communications with claimants [77, 78]. The audits found the UIA's fraud identification practices were insufficient and did not comply with federal and state law [77]. To find fraud,

MiDAS sent questionnaires to claimants [77]. If claimants did not return the questionnaire, MiDAS automatically determined they had committed fraud without further factual basis [77]. In the sample of cases reviewed by the OAG, the questionnaire nonresponse rate was 76.7%. The audits found MiDAS's logic for processing questionnaire responses "did not provide sufficient proof of intentional misrepresentation" and recommended additional efforts to ensure "adequate due process" [77]. Further, the audit found the questionnaire itself violated federal regulations, as it failed to inform claimants of the facts that led the UIA to suspect fraud [77]. In addition to the faulty fraud identification practices, the audits found several other deficiencies related to MiDAS's security management program [78] and the UIA's slowness in paying benefits [77].

B.1.2 Robofraud Follow-up Report. The OAG followed up on the Robofraud audits in February 2020, finding limited improvements. This report evaluated the UIA's efforts to remedy five detected issues. It found that the UIA had fixed its fraud identification practices. However, the other four issues persisted, such as lagging behind federal timeliness standards for paying benefits.

B.1.3 Pandemic Audits. The OAG released this series of five audits between 2021 and 2023 to evaluate the operation of new unemployment programs introduced during the COVID-19 pandemic. The pandemic period was challenging, because the UIA had to implement new programs while transitioning to remote work, fielding record numbers of claims, and combatting novel criminal efforts [80]. The audits found that the UIA incorrectly implemented the new unemployment programs, leading to improper payments and then improper recovery actions [80, 83]. Many problems involved MiDAS. The UIA made changes to MiDAS without following proper authorization or documentation procedures [81]. System changes had unforeseen results, as the UIA's post-implementation testing processes missed major problems [83] and were often skipped altogether [81]. For instance, some MiDAS system updates overwrote claimant records [83]. This overwriting jeopardized the UIA's administration of unemployment benefits, since they based decisions on the corrupted records [83]. In addition to these issues, the audits found that the UIA had insufficiently pursued potential fraud [84], sent confusing messages to claimants [83], and inadequately trained new staff [82].

B.2 Reports Prepared by Deloitte

Alongside the OAG investigations, the UIA hired Deloitte to investigate fraudulent activity during the pandemic [15, 28]. This yielded two documents which Deloitte labeled "reports" [28], but several media outlets called "audits" [30, 31, 43]. Deloitte has a financial interest in the outcome of these reports, as it offers a competitor product to MiDAS (which the UIA subsequently selected as MiDAS's successor [32]). We discuss these documents because the OAG audits relied upon findings from these Deloitte reports and because they fall within popular understandings of audits.

The first report constructed a timeline of UIA efforts to identify unemployment fraud during the pandemic [28]. Deloitte's methods included conducting interviews with UIA staff and reviewing internal documents and data. This report listed organizational, policy, and technical aspects that impacted the UIA's ability to combat fraud. For instance, MiDAS had automatically flagged over 640,000 claims for human review, but manually adjudicating these issues was projected to take twelve months at the current pace. Thus, the UIA removed some of the automated features that generated fraud flags in order to expedite payments. The modifications to the Fraud Manager subsystem resulted in a sequencing error; for months, rather than screening claims for fraud and then paying them out, claims were paid first and then screened. The report traces how UIA practices and systems led to problematic outcomes.

The second report aimed to estimate the amount of money the UIA lost to fraud during the pandemic [29]. Deloitte's methods included a stratified random sampling methodology. This report estimated that the UIA paid out a total of $34.5 billion in the first 18 months of the pandemic, with $8.5 billion to potentially fraudulent claims.