Uncovering Areas for AI Governance Tools Refinement through Real-World Use Case Analysis from Canada, Chile and Singapore

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Governments and organizations around the world in most jurisdictions have begun to operationalize principles establishing goals for fair, explainable, robust and trustworthy AI systems through AI governance tools. AI governance tools, socio-technical tools for assessing AI systems and their risks, are used to implement AI governance laws and policies. Understanding the types of measurements and analytical methods embedded within them and evaluating how these tools are implemented in various contexts helps to ensure they effectuate legal and policy goals. The research presented in this paper compares and analyzes the implementation of AI governance tools from Canada, Chile and Singapore. The analysis articulates commonalities among the tools and their implementations and illuminates areas for further analysis and potential refinement in relation to application and interpretation of the metrics and measures used by the tools, implementation of the tools themselves, as well as interests and motivations of tool end users. A key conclusion suggests that although AI governance tools require adequate assessment before they are made available, in some cases, it may be necessary to put some of these tools to use in context in order to articulate otherwise unknown or obscured shortcomings and areas of opportunity for adjustment, refinement, and improvement.

Keywords: AI governance, AI policy, algorithmic accountability, algorithmic fairness, automated decision-making, explanations, explainability, fairness, human-ai interaction, human-in-the-loop, measurement, metrics

Reference Format:
Kate Kaye. 2025. EWAF'25 Anonymous Submission. In *Proceedings of the Fourth European Workshop on Algorithmic Fairness (EWAF'25)*. Proceedings of Machine Learning Research, 13 pages.

1 Introduction and Background

The research presented in this paper seeks to compare and analyze early applications of select AI governance tools from national governments. It advances analysis of a wider spectrum of AI governance tools from governments and NGOs surveyed and evaluated in prior work from the author of this paper and other co-authors. That prior work, *Risky Analysis: Assessing and Improving AI Governance Tools* [1], defines AI governance tools as socio-technical tools for mapping, measuring, or managing AI systems and their risks in a manner that operationalizes or implements trustworthy AI.

This paper also complements prior work presenting critical analysis of the growing landscape of practical guidance, self-assessment questionnaires, auditing and evaluation frameworks, process frameworks, technical frameworks, technical code, and software interfaces, benchmarks, and other types of tools used for AI assessment [2,3,4,5,6]. For instance, related work defines AI Audit Tools as software, interfaces, code, benchmarks, frameworks, and other artifacts used by auditors in the AI audit process. This prior work suggests audit tools include resources that support algorithmic analysis and inspection (e.g., benchmarks/datasets, documentation templates) as well as resources that support the assessment of internal and external expectations for institutions across stages of design and development [2].

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EWAF'25, June 30–July 02, 2025, Eindhoven, NL

This research takes a step beyond this author's prior work by selecting three specific AI governance tools and addressing their use in real world implementation contexts. The research is based on two key types of information gathering: 1.) empirical data derived through qualitative interviews conducted solely by this paper's author with twelve sources in Canada, Chile, and Singapore who have developed, implemented or used the three tools and 2.) original analysis of publicly-available information including technical information and guidance related to the three tools. Additional details about this paper's interview sources and the subject matter discussed during interviews with them, including sample interview questions, are included in Appendix A of this paper.

Table 1. AI Governance Tools definition developed for *Risky Analysis: Assessing and Improving AI Governance Tools, An International Review of AI Governance Tools and Suggestions for Pathways Forward*, World Privacy Forum 2023 [1].

AI Governance Tools	Socio-technical tools for mapping, measuring, or managing AI systems and their risks in a manner that operationalizes or implements trustworthy AI

This paper is structured in a way that first familiarizes readers with the three tools by providing an overview of each tool, its origins, and what it is intended to do. Next, it articulates and analyzes four categories of observed commonalities and how those commonalities were present in real-world use cases involving each tool. The articulation and analysis of these commonalities are key outputs of both the interviews conducted for this research as well as the supplementary investigation of the makeup and technical design of the tools. The commonalities address tool measurement, metrics and methods incorporated in the tools – particularly in relation to fairness and explainability, as well as implementation of the tools, experiences of and impacts on tool end users, and refinements and expansion of the tools.

Lastly, the tools were selected for deeper analysis for additional socio-technical reasons. The selected tools represent a variety of tool types and they have been created for and applied in a diverse array of geographical regions. Additionally and critically, each tool has been implemented in real-world situations. Because this research aimed to incorporate interviews with people who have designed or used the tools, availability of appropriate sources was a necessary component. Appropriate sources including sources in government were available to be interviewed regarding the three tools in focus here.

2 Analyzing Use of AI Governance Tools from Canada, Chile, and Singapore

This research analyzes three AI governance tools which are key exemplars of AI governance tools. These tools reflect a spectrum of approaches to tool design and represent three distinct geographical regions. All three tools have been available since at least 2022, creating a suitable foundation for early observation and analysis. Canada's Algorithmic Impact Assessment allows for varying levels of public access to documentation indicating how the tool has been used in real world applications. Chile's template for procurement of AI by government agencies is an example of an updated approach to a common, practical government process, one that offers an especially educational use case. Singapore's AI evaluation software is a technically complex and prescriptive-yet-flexible set of tools offering its own valuable use cases and considerations. The tools represent different tool types, categorized according to an AI governance tools lexicon created based on evidence from a 2023 survey of the international landscape of AI governance tools published by multilateral organizations and by governments [1], in addition to early evidentiary documentation regarding multiple aspects of those tools, in-depth case studies and a review of related scholarly literature. The full lexicon of tool types, described in more detail here in Appendix B, includes practical guidance, self-assessment questionnaires, process frameworks, technical frameworks, technical code, and software, and hybrids of these types.

2.1 Canada's Algorithmic Impact Assessment

Canada's Algorithmic Impact Assessment or AIA [7] has been required for assessment of automated decision systems used by federal institutions since the country's Directive on Automated Decision-Making [8] went into effect in April 2019. The AIA process was designed by representatives of Canada's Treasury Bureau. It is comprised of several questions intended to determine risk and reduce potential negative impacts of automated systems. To measure the risk level of the system evaluated, the assessment process produces a numerical score based on answers to criteria-oriented questions related to a system's design, algorithm, decision type, impact and data. Impact levels are classified from "little to no impact" to "very high impact" in relation to individual rights, health and well-being of individuals or communities, economic interests, and sustainability of an ecosystem. The value of each question is weighted based on the level of risk it introduces or mitigates in the automation project. To determine the number of points assigned to a particular question, the Treasury Bureau has determined its significance in relation to other questions. For instance, the use of personal data in a system increases points attributed, potentially resulting in a higher overall risk level. Depending on impact level, the AIA process requires peer review, data bias and quality testing, data governance implementation, analysis using Canada's "Gender-based Analysis Plus" analysis method [9], human intervention during the decision-making process, and meaningful explanation of decision results. Canada's Directive on Automated Decision-Making requires federal agencies to publish the results of its AIAs. As of March 12, 2025, agencies including those overseeing employment, immigration, police, public services and procurement, transportation, and veterans affairs published a total of 25 AIAs and related documents in Canada's Open Government Portal [10]. The tool type assigned to Canada's AIA is a hybrid incorporating two types, Practical Guidance with Self-assessment Questions and Scoring Output.

2.2 Chile's Standard Bidding Terms for Data Science and AI Projects

Chile's purchasing and public procurement directorate, ChileCompra, established the country's Standard Bidding Terms for Data Science and AI Projects (Formato Tipo de Bases Administrativas Para la Adquisición de Proyectos de Ciencia de Datos e Inteligencia Artificial) in December 2022 [11, 12] to guide government agency purchase of algorithmic systems. The template for vendor bids on data science and AI projects was mandatory for about one year and was integrated as part of ChileCompra's broader procurement platform. During that time, procurement of AI related projects required application of the standard bidding terms process, which incorporated guidance, and suggested methods for statistical equity and risk analysis to assist in detecting bias in training data in AI models procured by government agencies, as well as to facilitate explainability. The bidding process also included traditional government procurement vendor cost and competition criteria. As an update on the common and sometimes mundane process of government procurement, Chile's Standard Bidding Terms for Data Science and AI Projects is an exemplary illustration of a practical AI governance tool incorporated into already-ingrained government policy procedures. The procurement template was part of the country's work with the Ethical Algorithms Project (Proyecto Algoritmos Éticos) [13] at GobLab UAI, the public innovation laboratory of Chile's Universidad Adolfo Ibáñez's School of Government. The tool type assigned to Chile's Standard Bidding Terms for Data Science and AI Projects is Practical Guidance.

2.3 Singapore's AI Verify

Singapore's Infocomm Media Development Authority launched AI Verify in 2022 [14]. As of 2023, AI Verify testing frameworks, codebase, standards, and best practices development are overseen by IMDA's not-for-profit subsidiary, AI Verify Foundation. The standardized self-testing AI Verify tool incorporates process guidance and checklists, as well as open-source software and testable criteria addressing AI robustness, fairness, and explainability. The software is designed for companies to download and use by importing their AI models and running technical tests in their own localized testing environments. The technical tests feature several testable criteria including for fairness classification, explainability, robustness, and image corruption. For instance, the tool evaluates fairness of ground truth datasets used in AI model training. It incorporates several technical plugins intended to assess model fairness, robustness and explainability. One technical plugin uses an algorithm to compute and display a list of fairness metrics to measure how correctly a model predicts among a given set of sensitive features — such as how it allocates job opportunities, loans, or medical assistance among demographic groups reflected in the data. Another technical plugin intentionally inserts unwanted "noise" into a dataset to test the robustness of the model. A technical plugin for explainability aims to explain how AI system features affect overall predictions. The tool also helps create reports based on results of the AI Verify technical and process tests and checks, which also offer suggestions for improving and fine-tuning AI models. The inclusion of specifically designed and piloted software in AI Verify, and continued technical updates are relatively rare among AI governance tools from other national governments, multilateral organizations and NGOs. The tool type assigned to Singapore's AI Verify in its original form is a hybrid of two types, Practical Guidance and Technical Framework and Software. Since AI Verify first launched, it has evolved into a Catalog of tools through several iterative expansions and updates in scope and tool types, as described in more detail below in the *AI Governance Tool Iteration, Evolution and Expansion* section.

3 Analysis of Early AI Governance Tool Use Cases

Implementation of AI governance tools is nascent and those designing, deploying and applying them have only just begun to experience and learn about the practical impacts of these tools. There will be a great deal of research and analysis to come about actual use of AI governance tools and their effects as they are implemented. However, this analysis of early use cases involving implementation of these three AI governance tools has helped to reveal and articulate some emerging commonalities among them. In particular, this research articulates and analyzes four categories of observed commonalities: 1.) AI Governance Tool Metrics and Interpretation of Tool Measurement Results 2.) AI Governance Tool Implementation 3.) AI Governance Tool End User Expertise, Interests and Motivations, and 4.) AI Governance Tools Iteration, Evolution, and Expansion. As these three tools reflect a wide spectrum of AI governance tool formats and approaches, it is possible that the emerging commonalities observed here are experienced among those applying other AI governance tools. This early analysis suggests that in some cases, refinement and improvement of AI governance tools may be enhanced as a result of real-world use outside the often-closed environment of the metaphorical policy lab.

3.1 AI Governance Tool Metrics and Interpretation of Tool Measurement Results

Like so many measurement tools that are utilized for an array of purposes — from assessing economic impacts to gauging rainfall — the choice of metrics used to conduct those measurements matters immensely. Ongoing review and analysis of AI governance tools [1] indicates that the measurements and metrics used to understand and improve AI fairness [6], explainability [15, 16], privacy [17], and other aspects of AI systems are imperfect and could benefit from assessment themselves. For instance, some governments and other organizations seeking to put AI principles into practice through use of AI governance tools aim to quantify AI risk and analysis measures in the form of fairness scores or ratings [3, 7, 18]. But the impulse to quantify AI risks through one-size-fits-all assessments, encoded technical tools, or other quick technical fixes carries with it its own pitfalls. Reliance on AI governance tool ratings or scores can lead to errors or misinterpretations, and abstraction from relevant context [4, 19], especially if there is a lack of documentation and guidance for implementation of the tool or interpretation of its measurements. Also, research evaluating methods and metrics used to score or predict AI risk levels indicates the distribution of true risks may differ among different groups of people and may not be proportional to one another [1]; this could lead to unfair allocation or access to resources, among other potentially negative outcomes [20].

Some AI governance tools already have recognized the need for metrics assessment. For example, in addition to emphasizing the importance of evaluating a system's impacts on equity, Chile's Standard Bidding Terms for Data Science and AI Projects [11] called on public sector agencies acquiring AI-related products to themselves determine appropriate metrics for evaluation, rather than rely on the technology vendor to choose metrics; the goal was for both parties to collaborate to determine the most appropriate metrics.

There is a robust body of scholarly research and standard practices addressing assessment of measurements [21, 22, 23, 24]. For instance, researchers who have analyzed the limits of traditional government procurement and the policy choices embedded in machine learning systems acquired and used by governments have concluded that traditional procurement methods need to be updated for the impacts of AI and digitalization [21]. And more recently, an emerging body of work addressing assessment of the measures used in AI governance tools continues to grow and deepen [22, 23, 24]. In the past decade, research has highlighted the potential problems that could result from use of automated AI governance tools that promise to create systems that are more fair. Scholars from around the world have raised alarms about application of metrics that do not align with specific AI fairness-related tasks, such as measuring bias in a dataset used to train an AI model or assessing the risk of unfair decisions made by an AI system [1, 6, 14, 20].

Research suggests that the most appropriate fairness metrics "will always be application-dependent" [20, 25]. Complementary work spotlights inappropriate use in AI governance tools of methods and metrics intended to automatically alleviate bias of AI systems by simplifying and decontextualizing complex legal fairness-related concepts [1] such as specific quantified disparate impact thresholds that may not be useful for judging algorithmic bias [3, 33, 35]. Prior work also discusses inappropriate use of metrics [36, 38] intended to explain how AI systems produce outputs or decisions which have attracted scrutiny among computer science researchers [39] and indicates that standards and guidance for quality assessment and assurance of AI governance tools do not appear to be consistent across the AI ecosystem [1].

3.1.1 Canada: AI Governance Tool Measurement Application and Transparency

As of 2023, Canada's AIA requires that agencies evaluate the impacts of algorithmic systems according to Canada's intersectional Gender-Based Analysis Plus (GBA+) [9] assessment which evaluates the impacts of algorithmic systems on populations and considers gender and age factors. However, although the assessment is required, publication of the GBA+ assessment reports is not required. In part because publication of the GBA+ assessments is only voluntary, their availability has been inconsistent. Multiple AIAs included in Canada's publicly-available repository [10] reviewed for this research state that the agency applied a GBA+ of the data associated with the system under review, but did not make the GBA+ itself public. When a lawyer discovered that documents associated with a particular AIA published in the repository from Canada's immigration agency — Immigration, Refugees and Citizenship Canada (IRCC) — also included the full GBA+ report, he called it "unheard of in terms of public disclosure." The lawyer noted that his previous attempts to obtain GBA+ reports through Access to Information and Privacy requests had resulted in access only to "heavily redacted" documents. He called publication of the report "very positive for transparency." Still, he questioned why other AIAs did not publish GBA+ reports, and why the GBA+ reports he had obtained through Access to Information and Privacy requests were redacted if the AIA-related report was not [26]. The GBA+ is a set of measures intended to gauge gender and age-related impacts; however, as a supplement to the AIA process, it becomes more than that. The assessment takes on additional meaning as a tool of AI governance, one whose impacts and efficacy is partially contingent on its very level of transparency. Also, in some ways, by itself serving as an online repository enabling public access to AIAs and related documents including GBA+ reports, the country's open government repository is itself an AI governance transparency tool.

3.1.2 Chile: AI Governance Tool Fairness Measurement Interpretations

Use of Chile's short-lived mandatory AI governance tool offered important takeaways related to the appropriate use and interpretation of AI fairness and explainability metrics with potentially long-lasting impact. For about a year following its establishment in 2022, use of the country's template for vendor bids on government data science and AI projects was mandatory. In December 2023, the template was revoked to allow for adjustments to be made in relation to a new public procurement law. While it was mandatory, the template required evaluation of AI models supplied by potential vendors bidding on AI projects according to criteria including model accuracy, transparency, explainability mechanisms, bias, and equity; and it required assessment documentation in project deliverables. But ChileCompra's procurement template left room for interpretation of the results of fairness measurements, leading to confusion and disagreement among staff at Chile's Department of Social Security Superintendence (SUSESO) — a division of the country's Ministry of Labor. SUSESO manages Chile's social security and healthcare system.

Interpretation of measures required by the procurement template influenced debates inside SUSESO about human autonomy amid use of AI. The key question: whether the human medical claims processors working at the social security agency would decide to approve or deny medical claims, or whether a machine learning model would entirely automate those potentially life-changing decisions. SUSESO medical claims processors, many of whom have medical expertise, are responsible for determining whether the agency covers the costs of employee wages during medical leave or work-related mental health related costs. In 2023, around 80 claims processors were responsible for approximately 200,000 medical claims, the majority of which were made by people of lower income who may have needed the medical leave wages to afford other expenses. The claims typically take around 60 days to resolve, and the agency had struggled to respond to the high volume of claims. In an effort to ease the heavy workload and speed up the claim decision process, SUSESO sought out an external vendor to build a predictive machine learning model for medical claims [27].

In compliance with ChileCompra's then-mandatory procurement process and vendor bidding template, auditors conducted fairness assessments of the machine learning model. Auditors evaluated fairness, bias and equity using metrics including statistical parity difference and disparate impact ratio [30, 34, 35]. The measurements indicated some minor likelihood or risk of inaccurate or biased model decisions. But SUSESO staff debated how to interpret and apply those fairness measurement results. Some SUSESO staff suggested that the results proved the model should be deployed to entirely automate the claims decision process. Other SUSESO staff disagreed, interpreting the fairness measurement results as indication that the model did pose risk of bias, and therefore concluding that the model should be used solely to inform or support medical claim decisions made by human experts [28, 29]. However, although the bidding terms required successful bidders to provide information regarding how human intervention was anticipated, a SUSESO project manager said ChileCompra's procurement template did not provide relevant guidance to address the issue. And although the project manager valued the ChileCompra AI procurement and governance tool's required assessments, he experienced frustration as a result of this disagreement over how to apply some of the fairness measurement outputs derived through use of the tool.

3.1.3 Chile: AI Governance Tool Fairness and Explainability Metrics

The ChileCompra template required fairness and explainability assessments, and suggested use of specific measurement methods, including a bias measurement tool [30] that incorporates a metric for gauging disparate impact [34, 35] that has been found to introduce new problems if applied without care and in inappropriate circumstances — the Four-Fifths or 80% rule. The Four-Fifths Rule [31], detailed in the US Equal Employment Opportunity Commission Uniform Guidelines on Employee Selection Procedures of 1978, is commonly used by employers, lawyers, and social scientists to measure adverse impact and fairness in hiring selection practices in the US labor recruitment field. The Four-Fifths Rule is based on the concept that a selection rate for any race, sex or ethnic group that is less than four-fifths — or 80% — of the rate reflecting the group with the highest selection rate is evidence of adverse impact on the groups with lower selection rates. Despite its widespread use, employment, legal, and technical scholars have cautioned against use of the rule as a singular gauge of disparate impact, and experts have cautioned against simplistic applications of the rule's 80% threshold, both within its historical use in US labor contexts as well as for its use in AI contexts [1, 3, 32, 33, 34, 35]. An auditor of SUSESO's medical claims model said disparate impact measures were used to assess the model, but she noted that the rule's 80% threshold, sometimes considered arbitrary including when used in conjunction with AI disparate impact measurements [3], was not applied. However, the bidding template did not offer detail on how fairness metrics or tools gauging disparate impact should be applied or interpreted.

The ChileCompra template also suggested use of an AI explainability tool called the What-if Tool [36]; the open-source tool attempts to assess the behavior of trained machine learning models, and documentation associated with the tool features use of a widely-used but often misunderstood metric for model explainability called SHAP [37] to reveal feature importance to analyze model fairness. Today, SHAP is often repurposed in an attempt to reveal and quantify machine learning model feature importance, or the importance of factors that contribute to model predictions [38]. However, research shows that SHAP has limited applicability and efficacy when used to explain how factors affect the outputs of complex AI systems such as deep learning models and neural networks, which are difficult to interpret [1, 39].

Despite the abundance of scholarly literature showing problems with use of the 80% rule for measuring fairness and SHAP for explainability, several AI governance tools from national governments reference use of both methods [1]. In the case of the SUSESO medical claims model, SHAP has been used to assist SUSESO claim processors to understand how the model makes decisions. To address potential misunderstanding regarding how to interpret SHAP explainability measurements, one auditor said that SUSESO claim processors have been educated about how to interpret those measurement results when assessing medical claim model outputs. However, the procurement template itself did not provide this level of guidance, and it is unclear how or whether such educational information will be accessible to future SUSESO staff. The SUSESO manager overseeing the bidding and assessment process associated with the medical claims model said he appreciated the inclusion of suggested measurement methods and metrics despite their caveats, and suggested these intricate issues could be addressed through future evaluation or updates of the template and assessment process. Ultimately, this analysis suggests that use of these metrics to measure the medical claims model illustrates nuances in application and interpretation of AI governance tools and their metrics, even when tools include some specified guidance.

3.2 AI Governance Tool Implementation

Analysis of emerging AI governance tool use cases reveals some real-world commonalities of tool application and applicability which may have been hidden during the design and development phases and only apparent as a result of actual tool use.

3.2.1 Canada: AI Governance Tool Implementation Quality

Canada's Treasury Bureau staff overseeing AIA implementation suggested that AIAs have varied in quality depending on factors such as how public sector agencies conduct their assessments, and the roles and experiences of the people conducting them [3]. Bureau staff said they found that when agencies collaborated with and sought out the expertise of bureau staff, assessments improved; as a result, bureau staff recommended that all agencies should engage with Treasury Bureau staff to facilitate higher quality assessments. However, some agencies in Canada have not collaborated with Treasury Bureau staff when conducting their assessments. Treasury Bureau staff also said some public sector agencies have relied mainly on their internal IT or technology staff to conduct assessments rather than involving agency staff with legal or sector-specific knowledge and expertise. Treasury Bureau staff suggested that computer science and tech experts may lack backgrounds in social and human rights impacts or legal concepts, and may be ill-equipped to complete assessments comprehensively. Bureau staff also said they saw first-hand how a more multidisciplinary approach helped improve AIAs from Canada's immigration agency, which has published a large portion of all AIAs published by federal agencies in the country. To improve the caliber of AIAs, Bureau staff suggested agencies should include multidisciplinary agency staff in conducting assessments, helping ensure that a variety of perspectives through varied expertise and experiences are considered. But this sort of engagement is not required.

3.2.2 Singapore: AI Governance Tool Relevance and Applicability

In some early use cases, companies implementing Singapore's AI Verify software tools reported a lack of clarity regarding relevance of the tools to their specific use cases. For example, a transportation and mobility analytics company reported a lack of compatibility of AI Verify with some computer code libraries they employed [41]. In addition, a source from a large, multinational company suggested that AI Verify tools were not applicable in use cases involving unstructured data or for assessing machine learning models and software that were developed by third parties rather than internally. Complications in assessment of AI systems, AI software and hardware, and data components developed or controlled by external third parties have been well-documented [42]. And despite goals of AI governance tools like AI Verify, they may not be able to penetrate the inner workings of opaque third-party AI systems. They also could be blockaded technically or as a result of trade secret related access limitations.

Cultural distinctions and context have also been barriers to AI governance tool applicability. An expansion of Singapore’s initial set of AI Verify tools, its Generative AI Evaluation Catalogue [43], recommended Large Language Model evaluation techniques such as evaluation frameworks and benchmarks. But the document acknowledges the limits of their applicability to AI systems intended for use outside of Western contexts or regions, explaining that concepts such as toxicity, bias, and demographic considerations are often addressed by the evaluation methods through Western-centric framings; the AI Verify Generative AI Evaluation Catalogue also emphasized that the impact of bias in LLMs varies across cultural and social groupings. And it noted that most benchmark datasets and tools are developed in English and may not apply to multilingual and multicultural settings, datasets and frameworks, or may not recognize distinctions among languages and linguistic structures. Use of Singapore’s AI governance tools will be important to watch as they continue to be piloted and used by a variety of organizations and thus can be expected to provide early indicators of AI governance tool relevance and applicability.

3.3 AI Governance Tool End User Expertise, Interests, and Motivations

The end users of AI Governance Tools hold distinct roles and have differing or sometimes conflicting interests, goals and motivations in relation to their use of the tools. However, some tools were not necessarily designed with the array of people who have emerged as real-world tool end users in mind.

3.3.1 Canada: AI Governance Tool End User Interests and Motivations

Canada’s AIAs are employed for multiple purposes by a variety of end users. For example, federal agencies conducting the assessments have used AIA results gauging risk impact levels as evidence that authorities should approve use of the systems under evaluation. But a different set of end users also rely on AIAs: Immigration lawyers who have analyzed AIAs published by Canada’s immigration agency, IRCC. The lawyers have used them in several ways: to learn about the automated systems used in relation to decisions affecting their clients, to help educate their clients about those systems, to help educate the court about those systems, and as exhibits to affidavits. Canadian immigration lawyers suggest that the automated systems used by the country’s immigration agency have created profound shifts in their day-to-day work defending immigrants and refugees, adding a possibly unexpected layer to understanding of how AI governance tools might affect future-of-work related issues. Despite their criticisms of the AIA process and levels of transparency of AIA documentation, the lawyers say the assessments offer a glimpse into the inner workings of the automated systems that affect the lives of their clients, sometimes influencing decisions about immigration case risk, whether immigrants or refugees can legally work, and even whether people must separate from their spouses or children.

3.3.2 Chile: AI Governance Tool End User Expertise

Results of assessments required by Chile’s procurement template have been employed by a variety of end users including vendors conducting assessments of their products, other external auditing partners, as well as government agency staff inside SUSESO. Understanding of the assessment results, what they mean and how they should be applied may vary widely depending on purpose and expertise. For instance, while vendors and experienced AI auditors likely have detailed knowledge to properly interpret metrics used to gauge fairness, bias, explainability and other aspects of AI systems, government staff such as SUSESO medical claims processors may not – despite their medical expertise. This distinction was addressed above in the *Chile: AI Governance Tool Fairness and Explainability Metrics* section. In the case of the SUSESO medical claims model assessment, auditors found that the model produced biased results in relation to claims involving mental health related pathologies. One auditor suggested that current SUSESO staff were aware of this risk and were expected to avoid using the model in relation to mental health related claims. However, as is the case with aforementioned use of model explainability measures by SUSESO claims processors, it is unclear how that important information might be disseminated to future users of the model.

3.4 AI Governance Tool Iteration, Evolution and Expansion

Not all AI governance tools have been reviewed or altered after their initial publication or deployment; however all three tools analyzed in this research have gone through their own versions of metamorphosis.

3.4.1 Canada: AI Governance Tool Reviews and Algorithmic Updates

Multiple components of the AIA have morphed since the tool was first established, in part as a result of regular reviews of the Directive on Automated Decision-Making required every two years. For instance, Canada's Treasury Board of Canada Secretariat has added questions to the AIA questionnaire including inquiries assessing the role of personally-identifiable information in systems under evaluation, and addressing issues related to deidentified data. Additional questions also were added in 2024 to address potential impacts on persons with disabilities [44]. The AIA's scoring algorithm, which assigns points to each questionnaire answer to determine the risk level of a system under evaluation, also has been adjusted as new questions have been added. To determine the number of points assigned to a particular question, Canada's Treasury Bureau has determined its significance in relation to other questions. For instance, the use of personal data in a system increases points attributed, potentially resulting in a higher overall risk level. The aforementioned GBA+ assessment was added in a 2023 AIA update, requiring agencies to evaluate the impacts of algorithmic systems on particular populations and according to gender and age considerations based on Canada's intersectional Gender-Based Analysis Plus (GBA+) analysis. Later in 2024, new amendments added a requirement of public access to AIAs and to findings of peer reviews before AI systems are launched. A fourth review of the directorate was underway when this research was completed. Proposed modifications would clarify obligations and enhance impact assessment of human rights, strengthen protections and assessment of impacts for persons with disabilities, and identify unacceptable AI risks [45]. Canada's continued iteration of the AIA tool is noteworthy as it has often been the result of its built-in regular AIA review process and has led to actual changes affecting measurement, transparency and its algorithmic risk scoring process.

3.4.2 Chile: AI Governance Tool Mandate Shift

The evolution of Chile's standard procurement bidding terms template has come, not through changes to its internal components, but through changes to its mandate. For about a year following its establishment in 2022, the use of the template for vendor bids on government data science and AI projects was mandatory. In that time, it was integrated as part of ChileCompra's broader procurement platform and used by the country's government agencies such as SUSESO.

However, ChileCompra, the country's procurement agency, revoked the bidding terms and template along with other procurement templates in December 2023 to allow for adjustments to be made in relation to a new law modernizing the public procurement system. In the meantime, a related Procurement Directorate for AI and Data Science published in December 2023 [46] offers similar guidance for all types of purchases but is not mandatory. No further updates were available at the time this research was completed. A goal of ChileCompra's short-lived mandatory bidding template was to incentivize companies to build AI systems with trustworthy AI considerations in order to win government contracts. But its mandatory requirements had the additional effects of convincing some staff within SUSESO of the value of the assessment process, and of helping to convey the importance of bias assessment, transparency, and data protection criteria to people in other units within the agency who may not have emphasized or considered those criteria otherwise.

3.4.3 Singapore: AI Governance Tool Iteration and Expansion

Since it was first piloted in 2022, AI Verify has evolved into a Catalog of tools through several iterative expansions and updates in scope tool types. The AI Verify Foundation has regularly updated its original set of AI Verify governance and testing tools. For instance, in 2024, it made its original toolkit more modular and customizable and allowed for more flexibility in use of testing algorithms [47]. It has also expanded its AI Verify tool set to respond to technical AI advancements. In 2023, the AI Verify Foundation and Singapore's Infocomm Media Development Authority were among the first government entities to recommend specific approaches to evaluating generative AI systems. They introduced a Generative AI (Gen AI) Evaluation Sandbox [43], featuring an Evaluation Catalogue including baseline methods, specific benchmarks, and recommendations for Large Language Models. In 2024, AI Verify launched Project Moonshot, an open-source evaluation toolkit for assessing performance of Large Language Models. Then in 2025, the Foundation launched its Global AI Assurance Pilot to help standardize and codify approaches to testing Gen AI systems. Singapore's AI Verify efforts reflect a willingness to test, learn and revise its AI governance tools at a speedier rate than some other government policymaking processes.

4 Discussion

Use of the three AI governance tools analyzed for this paper indicates a variety of commonalities and areas for potential refinement in relation to application and interpretation of the metrics and measures used by the tools, implementation and applicability of the tools themselves, and consideration of end users of those tools. Policymaking, including design and development of AI governance tools, is typically a slow and deliberative process for good reason: government policies can affect people's lives in profound and serious ways, and poor or hasty policies can have significant and potentially negative consequences. However, perhaps the most poignant finding of this research relates to the very use of these three AI governance tools. When it comes to the still relatively nascent policy area of AI governance tools, in some cases it may be worthwhile and even necessary to put the tool to use in order to begin to articulate its more elusive shortcomings. Indeed, truly beneficial refinement and improvement of AI governance tools may require real-world use outside the policy laboratory. For instance, it is questionable whether the drafters of ChileCompra's procurement template could have foreseen that staff in the country's social security agency would have drastically different interpretations of the same fairness and bias risk assessment results. It was only after the tool was used to guide assessment of the medical claims model that considerations regarding how the fairness measures should be interpreted and how they should influence the appropriate approach to deploying the model became apparent. This use revealed opportunities for adjustment of the tool to provide additional guidance regarding measurement interpretation, human agency, and model automation. In Canada, it was only through actual implementation of the AIA, and crucially, the public availability of those assessment documents, that their use by immigration lawyers eager for insights into the use of government AI systems affecting their clients could have occurred. This constituency of policy tool end users quite possibly was unexpected and is comprised of people with different interests and motivations from AIA end users inside government. This observation of real-world AIA use offers opportunities for adjusted approaches to AIA transparency and access as well as presentation and formatting. Meanwhile, had they not actually applied AI Verify tools, organizations would not have recognized some use related challenges or areas of possible improvement. Actual use of AI Verify software tools has helped reveal ways to make them more directly applicable to end users and also helped to define the contours of tool applicability.

5 Conclusion

Efforts invested in designing and implementing AI governance tools to evaluate the impacts of AI systems could be for naught if the tools themselves do not assess and measure as intended. AI governance tools require adequate assessment before they are made available, and an evaluation period should be a deliberate component of tool development. However, in the AI governance tool use cases addressed, practical implementation of the tools served to expose important assessment factors that may have been obscured otherwise. These factors provide helpful information and insights that can lead to more meaningful evaluation of tool impacts and effectiveness. Indeed, this analysis does more than reaffirm the need for continuous evaluation of AI governance tools throughout their lifecycles, both before and after deployment. It also suggests in some cases, a component of the AI governance tool lifecycle might involve a limited and methodologically observed pilot or applied demonstration stage intended to glean relevant real-world assessment criteria. In one other example, researchers who applied the European Commission's own Assessment List for Trustworthy Artificial Intelligence [48] implemented the tool in conjunction with a process involving case-specific audit planning that was "subject to further audit iterations" [49].

There exists a body of evaluation and measurement methods and standards that designers and developers of AI governance tools as well as other stakeholders might reference for consistent assessment of tool quality. Possible approaches include use of ISO 9001, a group of international standards that include flexible criteria for a quality management system [50]. Measurement Modeling [22], meta-evaluations [51] and the growing body of work more directly aimed at addressing evaluation of AI evaluations might also be considered [23]. Research on improving impact assessment frameworks and processes [52] as well as approaches for involving stakeholders in development of methods for assessing algorithmic impacts [53] will also be helpful.

No matter what measurement and assessment approaches are chosen, those evaluating AI governance tools should consider existing regulatory policy and legal contexts when it comes to addressing impacts of data use and data processing in relation to AI. For instance, there are several types of impact assessments that might assist in evaluating AI governance tools, such as Ethical Impact Assessments [54], Fundamental Rights Impact Assessments [55], and Safety Impact Assessments [56]. Also, the European Union's General Data Protection Regulation [57] requires Data Protection Impact Assessments [58, 59, 60] to assess the impacts of high-risk data processing and has been adopted around the world [61]. In addition, the more recent EU AI Act calls for development of tools, templates, questionnaires, and methodologies for evaluating capabilities of general-purpose and high-risk AI models and systems [62], and these types of tools are also helpful for evaluating AI governance tools.

Acknowledgements

The author would like to thank Pam Dixon and the EWAF ’25 paper reviewers for their thoughtful reviews and comments which aided immensely in improvement of this paper. Thanks also to some research interview sources who agreed to be named: Benoit Deshaies, Dawn Hall, Maria Paz Hermosilla Cornejo Mariana German, Rodrigo Moya, Reinel Tabares Soto, and William Tao.

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