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Research Article

Ten simple guidelines for decolonising algorithmic systems

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ABSTRACT

As the scope and prevalence of algorithmic systems and artificial intelligence for decision making expand, there is a growing understanding of the need for approaches to help with anticipating adverse consequences and to support the development and deployment of algorithmic systems that are socially responsible and ethically aware. This has led to increasing interest in "decolonising" algorithmic systems as a method of managing and mitigating harms and biases from algorithms and for supporting social benefits from algorithmic decision making for Indigenous peoples.

This article presents ten simple guidelines for giving practical effect to foundational Māori (the Indigenous people of Aotearoa New Zealand) principles in the design, deployment, and operation of algorithmic systems. The guidelines are based on previously established literature regarding ethical use of Māori data. Where possible we have related these guidelines and recommendations to other development practices, for example, to open-source software.

While not intended to be exhaustive or extensive, we hope that these guidelines are able to facilitate and encourage those who work with Māori data in algorithmic systems to engage with processes and practices that support culturally appropriate and ethical approaches for algorithmic systems.

1. Introduction

There is a growing body of research on how minoritised peoples, such as Indigenous populations, are often those most affected by biases and unanticipated effects of algorithmic systems. This has led to increasing interest in "decolonising" or "indigenising" algorithmic systems as a method of anticipating and avoiding harms and biases, supporting social benefits from algorithmic decision making, and to empower those impacted by algorithmic systems (Gartner et al., 2023; Krakouer et al., 2021; Arora et al., 2023; Baker & Hawn, 2022; Gasparotto, 2016; Caliskan et al., 2017; Eaglin, 2017; Eubanks, 2018; Oswald et al., 2018).

In this practice paper, we offer 10 practical and easy-to-follow guidelines to provide some assistance in the creation of responsible, ethical, culturally inclusive, and accountable algorithms. These guidelines are intended not as a checklist, but as a starting point to facilitate and focus practitioners in considering how indigenous perspectives might be compatible with, and contribute to, better algorithmic systems. These guidelines are intended to be adapted by practitioners to their particular context.

The content of this article very much stands on the shoulders of giants: it builds off of the work of many established Aotearoa New Zealand scholars in the fields of Māori Data Sovereignty (MDS) and Māori Algorithmic Sovereignty (MAS), as well as others internationally. MAS (Brown et al., 2024) and MDS (Te Mana Raraunga, 2018) principles recognise that algorithms that use Māori data, or that are applied to

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Māori individuals or collectives (including groups or organisations), or environments that Māori have rights and interests in, are subject to laws and governance structures of Māori. These principles of MAS and MDS articulate what it means to decolonise algorithmic systems.[1] However, there is currently an urgent need to bridge the gap between these high-level principles and implementation. In this paper, we specify 10 practical guidelines to guide those working with Māori data in algorithmic systems in the development, deployment, and use of ethical, effective, and culturally inclusive algorithmic systems. We also believe that these guidelines could be of benefit to a broader range of data practitioners. While our focus is on Māori in Aotearoa New Zealand, elements may also be applicable to other Indigenous nations.

When we discuss algorithms, we are referring not only to software and code, but also to the wider socio-technical system that surrounds those algorithms. Because of the huge range of types of algorithms each with different contexts and applications, the paper does not attempt to provide technical guidance in relation to implementing each guideline. Rather it provides decision-making advice, focusing on the 'human-in-the-loop' as part of the development and deployment of algorithmic systems.

The article begins from the assumption that algorithmic systems are going to continue to be commissioned. It does not engage with the question of whether certain algorithms *should* be developed in the first place or the wider effects such as environmental impact from manufacturing and operating the technological infrastructure that algorithms may require. Such considerations are clearly important and should be considered as part of the wider context of ethical considerations for algorithmic systems and artificial intelligence (Bolte et al., 2022).

The list of ten guidelines is:

1. Articulate a set of foundational principles
2. Identify and engage meaningfully with key partners
3. Consider, and articulate, the different scopes of the algorithm as a socio-technical system
4. Make use of the fact that algorithmic transparency is often compatible with and facilitated by open-source software methods
5. Don't expect indigenous developers or practitioners to "donate" existing processes, technology or resource
6. Incorporate methods for identifying, reporting, and tracking issues as part of designing and implementing the algorithmic system
7. Consider the implications of the algorithm for both individual and collective privacy
8. Determine baselines; write tests and checks. Use them; share them
9. Document your code; state your assumptions; show your working
10. Build capacity of individuals and collectives.

This list is intended to be a starting point for you, the reader. The guidelines here are not exhaustive, nor are they likely to all be applicable in every possible context: they are simply a way to point you in the right direction and to provide some tangible steps to follow on your journey towards effective and appropriate algorithmic creation and governance. For guidelines 2–10 we have indicated the relevant MDS and MAS principles from foundational texts (Brown et al., 2024) and (Te Mana Raraunga, 2018). While we have tried to give a brief contextualisation for these principles within the relevant guidelines, we ***highly recommend that readers also consult these MDS and MAS references to gain a deeper understanding of the principles***.

[1] A good understanding of MDS and MAS requires not just familiarity with the principles but also an understanding of the relevant concepts within te ao Māori (the Māori world view). This involves understanding them within their sociocultural and intellectual history. For broader reading and deeper cultural context, see Linda Tuhiwai Smith, *Decolonizing Methodologies* and *Tikanga Maori: Living by Maori Values* by Hirini Moko-Mead.

2. The guidelines

2.1. Articulate a set of foundational principles

Establishing a well-articulated set of principles is important for guiding the rest of the steps you might take in creating algorithms in ways that are responsible and accountable to relevant partners (see guideline 2). This underpins the following guidelines in the article. Having explicit principles will allow those involved in algorithm development and deployment to refer to and check that actions and objectives align with the shared vision of developing culturally responsible socio-technical systems. While it may be possible to address the remaining guidelines in the absence of articulated principles, in their absence it is more likely that any actions may be misaligned with what they are trying to achieve.

Moreover, articulating your foundational principles is an opportunity to ground the team in the guidance that has been established by others – particularly by Māori or other Indigenous researchers – as important, or essential, to enhancing inclusive practises.

In almost all cases you won't want to be starting from scratch with developing these principles, as you will be able to look to those that have already been developed, debated, and tested by indigenous scholars for use in a variety of contexts. Good starting points for considering the foundational principles you might adopt include references (Brown et al., 2024; Te Mana Raraunga, 2018; Statistics New Zealand, 2020).

Many of these resources come from a starting point of data ethics and indigenous data sovereignty – an important aspect of algorithmic socio-technical systems, but not the only one. A good set of foundational principles should be easily accessible and interpretable for those looking to use (or scrutinise) the algorithm you have created.

2.2. Identify and engage meaningfully with key partners. Kotahitanga; rangatiratanga

Do this as early as possible in the process of algorithm development. There will be a wide range of people who might be partners, stakeholders, end-users, interested parties, or affected groups. Without engagement it will be unlikely that algorithm development will foster kotahitanga (collective benefit). This benefit could be derived directly from the algorithm but equally could be derived from capacity building as part of the engagement. Similarly, engagement is necessary to support the MAS principle of rangatiratanga (authority or self-determination) as without engagement to allow for meaningful input, Māori control and jurisdiction over algorithmic systems and their outcomes will be curtailed.

As much as it might be desirable, it's probably not going to be feasible to engage meaningfully with all of these. One useful rule-of-thumb for who might be most important to engage with is to ask who is going to be impacted by the algorithmic system, and how (see also guideline 3). In particular, consider engagement with Indigenous communities who are likely to be underserved by traditional approaches to algorithmic systems which can tacitly encode systemic biases from social systems resulting in inequitable outcomes.

Think also about the *nature* of the engagement of the relationship that you envisage. What are the benefits, and the costs, for the different parties that could be involved? What is the capacity to resource, or to cover, those costs of engagement? Part of engagement can be building capacity (Guideline 10).

2.3. Consider and articulate the different scopes of the algorithm as a socio-technical system. Whanaungatanga; rangatiratanga

Algorithms and their associated socio-technical systems will have different types of, and different degrees of, impact and relevance for different groups. Articulating both the intended and the potential scope of an algorithmic system can help with establishing who you should be engaging with (guideline 2), where you might hope to build capacity (guideline 10), and implications for privacy (guideline 7).

The MAS principle of whanaungatanga (obligations) requires practitioners to consider balancing rights – both individual and collective – along with enabling redress for the outcomes of an algorithm and supporting accountability of individuals and institutions to those who the algorithm affects. Considering the scope of an algorithmic system means considering to who those obligations hold. It also involves considering with whom rangatiratanga (authority) should lie.

Comparing intended and potential scope can be a useful way of identifying and hopefully mitigating possible unintended consequences of the algorithmic system. Similar to the foundational principles (guideline 1), information recorded here can be a useful reference point as development and deployment of the algorithmic system progresses.

Some questions that can facilitate considering scope are:

- How and by whom has the algorithm been commissioned?
- Who is involved in the design and development?
- What input data could it operate on, where will that data come from? How is it collected/stored/updated?
- Who is intended to be the main users of the algorithm? Who else could use it?
- What is the level of familiarity with the algorithm design & implementation is expected for users once the algorithm is deployed?
- If the algorithmic system is making decisions that affect people, who is directly (or indirectly) impacted?
- Is there potential for algorithm outputs to be stored and re-used in contexts beyond the main purpose?
- How does scope or impact potentially change if assumptions that the algorithmic system makes no longer hold? For example, if inputs are no longer collected in the same way, with the same biases; if things don't work as intended, are consequences likely to fall disproportionally in one area or for one group of people?

2.4. Make use of the fact that algorithmic transparency is often compatible with and facilitated by open-source software methods. Whakapapa

Algorithmic transparency is an important factor for fostering MAS. The MAS principle of whakapapa (relationships) requires transparency of not only data and its provenance but also of who is involved in algorithm development, management, and maintenance.

Open-source software tools and methods are frequently well suited to enabling transparency by requiring code to be made accessible and examinable. For example, by using an open Git repository for an algorithm, not only do the code and assumptions become visible but the repository also maintains a record of who has contributed to an algorithm and how that algorithm has changed over time – a technological whakapapa or genealogy.

Following such practices not only has the potential to improve accountability but also to share potential benefits more widely. However, openness by itself is not the same as accessible or interpretable. Explanation and *documentation* (guideline 8) and *capacity building* (guideline 10) can also be necessary to make algorithms fully transparent. The wider dialogue that is necessary to be transparent will be fostered by engagement with appropriate audiences (guidelines 2 and 3).

2.5. Don't expect indigenous developers or practitioners to "donate" existing processes, technology, or resources. Kotahitanga, manaakitanga

There may be conflict between the expectations of open-source best-practice and in doing what is right for Māori communities: while the former may promote as much transparency and accessibility as possible, the latter might require some restrictions to ensure that sovereignty is appropriately respected.

The MAS principle of kotahitanga (collective benefit) implies Māori should derive both individual and collective benefit from algorithmic systems, including through capacity building in relation to supporting development of algorithms, which may not be best supported through making all knowledge completely open. Limiting use or access can also address the MAS principle of manaakitanga (reciprocity) by supporting privacy of data and outputs related to an algorithmic system and upholding the mana (respect) and dignity of Māori individuals and communities.

While many of the principles of open-source software are well aligned with the principles of MAS, it won't always be desirable to make algorithms developed by, or for, indigenous entities open-source and freely available for reuse or redevelopment. In particular, it may be desirable to *not allow* free access for colonial, or non-indigenous, institutions to Indigenous algorithms and resources.

MAS emphasises 'beneficence', or the idea that algorithms that impact Māori should also benefit Māori. As a result, and to protect such benefits for the future, when an indigenous community has contributed to an algorithm (including data or design elements) it may be appropriate for that community to maintain a degree of *kaitiakitanga* (guardianship) and *tino rangatiratanga* (sovereignty) over that algorithmic system. This could include restricting access to some or all the algorithmic system or ensuring Indigenous governance over who can use an algorithm and for what purposes it can be used. The Kaitiakitanga Licence employed by Te Hiku Media is a good example of how this concept can be applied (Te Hiku Media, 2023).

2.6. Incorporate methods or processes for identifying, reporting, and tracking issues as part of designing and implementing the algorithmic system. Whanaungatanga; rangatiratanga; whakapapa

Transparency (Guideline 4) is most useful when the visibility of, and access to, an algorithm also come with an opportunity to raise and seek resolution of issues that might be identified. Such issues could range from technical faults in an algorithm, to noting where assumptions in an algorithm might lead to different impacts for different groups, through to higher level issues such as where outputs or metrics from an algorithm might be mis-interpreted by others using them as part of a socio-technical system.

Incorporating methods of raising and tracking issues related to algorithms supports the MAS principles of whanaungatanga (obligations), rangatiratanga (authority), and whakapapa (relationships) through creating processes whereby individuals and institutions that are responsible for algorithm development can be visibly accountable to Māori individuals and collectives in relation to specific issues. This can also help to foster Māori control over the development and use of the algorithm.

This goal can be well supported by existing open-source tools such as the issue tracking features of version control platforms such as GitHub (GitHub, 2025) and GitLab (GitLab, 2025). While traditionally used mostly with respect to technical details in code, issue tracking allows a way of recording and discussing issues related to an algorithmic system more broadly – as long as there is an openness to receiving and responding to feedback.

While other methods of seeking and responding to feedback, such as through wānanga (workshops), will also be important - and may serve different purposes - using approaches such as version control and issue trackers can be an alternative (and asynchronous) way of fostering accountability and allowing for wider or better redress of issues with an algorithm.

2.7. Consider the implications of the algorithm for both individual and collective privacy. Kaitiakitanga; manaakitanga

There are often strong reasons for trying to work with data that is detailed at the individual record level and highly linked or contextualised, as outlined in Arora et al. (2023). However, such detailed micro-data carries with it increased risk of disclosure, re-identification, and not upholding individual or collective rights to privacy. The MAS principle of manaakitanga (reciprocity) means that individual and collective privacy must be considered for data collection, storage, and use while the principle of kaitiakitanga (guardianship) requires consideration of appropriate protections for inputs, outputs, and computational components of an algorithm underpinned by ethics informed by kawa (protocols) and mātauranga (knowledge).

While methods like aggregation and working with summary data are commonly used to mitigate individual privacy risks, it can remain difficult to address issues of collective privacy using such approaches. Furthermore, excessive aggregation can risk undermining the value of an algorithm by potentially making its outputs generic and of less relevance to the communities it might otherwise help. Because issues of privacy always involve balancing the risk and reward from a given level of information disclosure, it is important to consider here *who information is being disclosed to* and *to whom the benefits of the related algorithmic system are going* (i.e. the reward that motivates the privacy risk).

Consider also that while an algorithmic system might be developed with beneficent intentions, there is the potential for other agents to use the algorithm or its outputs to unanticipated ends that might be more maleficent.

In creating your algorithm, ensure that the possible risks are considered alongside the likely benefits of using personal data. Be aware that in an Indigenous context, personal data may not just relate to people – it can relate to flora, fauna, and the natural landscape more broadly. Conducting genuine engagement (guideline 2) is a key method through which you can identify the likelihood of benefits being realised and of any potential harm being fully understood prior to the development of your algorithm.

2.8. Determine baselines; write tests and checks. Use them; share them. Rangatiratanga; whanaungatanga

Determining baselines and tests provides a way of articulating how you think things should look and for determining when things have changed. This includes dealing with situations such as working with a machine learning model or an artificial intelligence approach that may have a degree of "black-box" inexplicability. In such situations, tests and benchmarks are a way of codifying what expected algorithm outcomes look like. This helps with identifying any unanticipated changes or issues, when they occur.

Similarly, tracking summary statistics and features of input data can warn of situations where issues such as data pipelines or processes may have changed unexpectedly or where other factors of the system, including social or policy factors, may have led to changes in what input data arrives at an algorithm.

Being transparent (see Guideline 4) about the results of tests will create better opportunities for redress (and possibly also for identifying issues earlier) but will also involve careful consideration of the trade-offs regarding individual and collective privacy and the benefits that can come from information sharing (guideline 7).

In the absence of tests that codify expected behaviour of an algorithm, and which can identify when this behaviour is missing, it is difficult to give effect to the accountability and opportunity for redress that are essential to whanaungatanga (obligation). Well-developed baselines, test, and checks also support rangatiratanga (authority) - which requires that Māori have control of the development and use of an algorithm – by allowing better assessment of an algorithm's performance and potential impacts.

Baselines and tests need not be restricted to the data and algorithm at the centre of an algorithmic socio-technical system. They can also include things like articulating expectations about how it is expected that an algorithmic system will be used, or who will be involved in it. Articulating and sharing such expectation can also support building capacity (guideline 10).

2.9. Document your code; state your assumptions; show your working. Whakapapa; kaitiakitanga

Not only do documentation and explanation support the transparency (Guideline 4) and partnership (Guideline 2) guidelines, they also form part of the whakapapa (ancestry or relationships) of an algorithm or socio-technical system.

Good documentation and explanation, including stating any assumptions, will improve the interpretability and understandability of algorithms - an essential precursor to being accountable, fostering kaitiakitanga (guardianship) and moving towards rangatiratanga (authority or sovereignty). Almost all algorithms and models require simplifying assumptions and heuristics in order to be effective and make real-world complexity tractable as part of a codified process or system. These same assumptions and heuristics that can make an algorithmic system effective in some situation can make it inappropriate in others.

Once an algorithmic system is in place it is often difficult to tell where any assumptions or simplifications have been made and how they might now be influencing the behaviour of an algorithmic system in its final form. By documenting assumptions and "showing the working" involved in algorithm development, not only is the resulting algorithmic system more maintainable, it also improves accountability for the algorithmic system by detailing where it has come from. This can in turn suggest how different assumptions or choices could be part of a potential different algorithmic system in future, supporting kotahitanga (collective benefits).

2.10. Build capacity of individuals and collectives. Kotahitanga; manaakitanga

Several of these guidelines (engaging with partners - guideline 2; algorithmic transparency - guideline 4; incorporating issue tracking and redress - guideline 6) can only be as effective as the capacity of partners to meaningfully engage with them.

Building capacity of both individuals and collectives will help to give effect to these and other guidelines and will help to move towards a future with more indigenous led algorithm development and operation.

The nature of capacity building will depend on the context (Are you the algorithm sponsor? The commissioning client? The developer or consultant? Who are the partners in this work?) and other constraints such as timeframes and resourcing. By building capacity of, for example, indigenous data scientists, with relation to your algorithmic system, there is an opportunity for better algorithmic system sustainability and more meaningful partnerships.

3. Summary

The guidelines above have attempted to strike a balance between MDS and MAS principles and specific, actionable advice that can be used to develop and deploy responsible, ethical, culturally inclusive, and accountable algorithmics as part of a socio-technical system. The intent of the guidelines is to support the decolonising of algorithmic systems to address the risks of algorithms codifying (likely opaquely and unintentionally) systemic biases that often led to indigenous communities being underserved by traditional approaches.

It is the authors' hope that following such an approach will result in better algorithmic systems, not just for indigenous communities, but more generally – resulting in algorithms that are more transparent, and accountable.

A common thread that runs through many of these guidelines is one of engagement and collaboration with communities - particularly indigenous communities – including seeking and incorporating their knowledge and understanding to improve the development and deployment of algorithmic systems. However, it is important that this should not turn into indirectly devolving accountability or divesting responsibility for consequences of the algorithmic system to those communities.

CRediT authorship contribution statement

Dion R.J. O'Neale: Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization. **Daniel Wilson:** Writing – review & editing, Conceptualization. **Paul T. Brown:** Writing – review & editing, Conceptualization. **Pascarn Dickinson:** Writing – review & editing. **Manakore Rikus-Graham:** Writing – review & editing. **Asia Ropeti:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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