

AI Ethics Principles in Practice: Perspectives of Designers and Developers

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Abstract—As consensus across the various published AI ethics principles is approached, a gap remains between high-level principles and practical techniques that can be readily adopted to design and develop responsible AI systems. We examine the practices and experiences of researchers and engineers from Australia’s national scientific research agency (CSIRO), who are involved in designing and developing AI systems for a range of purposes. Semi-structured interviews were used to examine how the practices of the participants relate to and align with a set of high-level AI ethics principles that are proposed by the Australian Government. The principles comprise: Privacy Protection & Security, Reliability & Safety, Transparency & Explainability, Fairness, Contestability, Accountability, Human-centred Values, and Human, Social & Environmental Wellbeing. The insights of the researchers and engineers as well as the challenges that arose for them in the practical application of the principles are examined. Finally, a set of organisational responses are provided to support the implementation of high-level AI ethics principles into practice.

Index Terms—AI ethics, ethics principles, responsible AI, responsible design, system design, artificial intelligence, machine learning.

I. INTRODUCTION

The use of artificial intelligence (AI), which includes machine learning (ML), is rapidly increasing throughout society and has already produced significant benefits across a variety of fields, with promise to deliver more in the future [1], [2]. As AI becomes more ubiquitous there are rising concerns regarding the way it is used and developed [3]. AI may be used in applications that reinforce existing biases and historical disadvantage in society, infringe individual privacy, and make opaque decisions that affect people’s lives [4]–[6]. Responses to these concerns are well underway in many countries, including Australia. A recent review of international principles and guidelines for AI ethics included 84 such documents [7]. Out of the numerous ethics frameworks and guidelines produced by governments and organisations, a broad consensus is emerging around what the major principles of AI ethics should be [8].

Governments and organisations are beginning to develop mechanisms to make high-level AI ethics frameworks more actionable in practice. Governance, regulation, and legal frameworks concerning the development and use of AI systems and associated technologies are emerging in many countries [9], [10]. The EU has recently proposed a legal framework for AI for its member states [11]. A recent report by

the Australian Human Rights Commission has recommended introducing legal accountability for both government and public sector uses of AI, as well as establishing an independent AI Safety Commissioner [12]. However, there is still a large gap between high-level AI principles and practical techniques that can be readily used in the design and development of responsible AI systems [13], [14]. Furthermore, ethics principles are just one of a range of governance mechanisms and policy tools necessary to promote ethical development and use of AI technologies.

The work presented here forms part of an organisational response by Australia’s national science agency, the Commonwealth Scientific and Industrial Research Organisation (CSIRO), to initially examine and ultimately improve the implementation of AI ethics in practice. CSIRO is the Australian Government corporate entity responsible for delivering scientific research across a diverse research portfolio, which includes a growing focus on the implementation of AI into various research and application contexts (i.e. for health, agricultural, environmental and other industry applications). In this context, we first seek to better understand the existing practices and perspectives of designers and developers of AI systems, to determine how they align with high-level AI ethics principles, identify gaps and trade-offs, and what forms of organisational support would be useful.

We conducted semi-structured interviews with 21 CSIRO scientists and engineers that develop and/or use AI/ML technologies across a wide range of projects. We used the Australian Government’s voluntary 8 high-level AI ethics principles [15] as a framing structure for the interviews and their analysis. The resulting implications and recommendations are focused on building organisational support for the implementation of high-level ethical principles in practice.

The paper continues as follows. Section II overviews related work. Section III summarises the AI ethics principles proposed by the Australian Government. Section IV describes the methods used to conduct the interviews and the subsequent thematic analyses. Section V examines the practices and challenges of scientists and engineers surrounding each of the 8 high-level ethics principles. Section VI provides recommendations that support the implementation of the principles at an organisational level and across the principles. Concluding statements are presented in Section VII.

II. RELATED WORK

The development and deployment of responsible AI requires users to adopt a largely implicit set of high-level ethics principles into explicit practices. Yet the availability of useful ethical design specifications for AI designers and developers is currently lacking [14], with a recent review highlighting various limitations [16]. Such limitations include the lack of methods that support the proactive design of transparent, explainable and accountable systems, in contrast to the less useful post-hoc explanations of system outputs. The focus of existing methods is also skewed to assessing the impact of an AI system on individuals rather than on society or groups. Finally, the examined methods were found to be difficult to implement and typically positioned as discourse aids to document design decisions [16].

The limited support for tools available for designers and developers demonstrates a gap in what is available and what is useful for adopting responsible, or ethical, design approaches [14]. The implementation of ethics principles in practice requires an improved understanding of the practices of designers and developers of AI systems, and how they relate to high-level ethics principles. By building this understanding, organisations can better position themselves develop the support required to produce and use AI systems responsibly.

The operationalisation of AI ethics can be framed as a design process rather than an end goal [17], [18]. Fostering an understanding of the complexities and challenges of implementing responsible AI provides the foundation for iterative and adaptive approaches rather than as the completion of activity checklists. The implementation of responsible, or ethical, design has been characterised across three complimentary design approaches [19], summarised as:

- **Ethics *in* Design:** requires designers and developers of AI systems to consider the purpose of the AI system under development, and the likely consequences of its use [19]. Part of this involves considering the values (or motivating principles) reflected in the design and purpose of the AI system [20]. This has parallels with efforts to incorporate human values in software engineering [21], [22].
- **Ethics *by* Design:** concerns the behaviour of AI systems in deployment. The functions of systems should reflect ethical principles, such as minimising harm. This also covers constraints imposed on permissible actions and decisions the AI system may make [19]. This is particularly significant for autonomous systems that may come into contact with humans or animals during their operation, and for AI systems that may be used to recommend decisions that affect people’s lives.
- **Ethics *for* Designers:** refers to the ethics that motivate and govern the developers of AI systems, and may include professional codes of conduct, ethical principles, and regulatory requirements [19]. These design approaches characterise the complex and dynamic task of developing responsible AI. In turn, the infrastructure required from organisations and

governing bodies to effectively support responsible AI must be responsive to those complexities and the evolving nature of the field.

Various mechanisms are required to implement these design approaches in practice, and support the responsible design and development of AI systems across organisations.

III. AUSTRALIAN AI ETHICS PRINCIPLES

The Australian Government recently proposed a set of eight high-level principles [15], based on an earlier AI ethics framework discussion paper [23]. The principles are intended to be voluntarily applied while designing, developing, integrating, or using AI systems. An adapted summary of the principles is given in Table I.

Overall, the high-level principles aim to promote positive societal outcomes while minimising negative outcomes from the use and development of AI technologies. These principles join a global effort towards the responsible AI use and development, and share a high level of convergence with the principles published by other organisations [8]. In examining the current practices and experiences of researchers and engineers from Australia’s national scientific research agency, these principles were used as a framework for interviews and subsequent analysis.

IV. METHODS

Semi-structured interviews were conducted with 21 CSIRO scientists and engineers that use AI technologies (such as machine learning) within their projects. The ‘use’ of AI technologies in this context was defined as design, development or implementation of systems with AI/ML components. The participants were initially recruited via a “call for participation” distributed across the organisation. This was followed by a snowballing technique where additional participants were sought via recommendations made by preceding participants, until a saturation of perspectives from across the organisation was reached [24], [25]. The main selection criterion for participants was self-reported involvement with research and/or development work that substantially included the use of AI methods and/or technologies. We note that the selection and availability of interviewees may have constrained the nature and span of perspectives and outcomes of the study.

The interviews were conducted between February and April 2021. Participants represented a cross-section of experience and responsibility; the job positions of the interviewees included: Postgraduate Student (1), Research Scientist (1), Senior Research Scientist (4), Principal Research Scientist (2), Principal Research Engineer (1), Team Leader (8), Group Leader (4). The gender split was approximately 24% female and 76% male. Prior to each interview, each participant was provided with a summary of the Voluntary High-Level Ethics Principles for AI (see Table I). Informed consent was collected from all participants. The interviews were conducted both in person and via video teleconferencing. The interviews ranged

TABLE I
AN ADAPTED SUMMARY OF THE 8 VOLUNTARY HIGH-LEVEL ETHICS PRINCIPLES FOR AI,
AS PROMULGATED BY THE AUSTRALIAN GOVERNMENT DEPARTMENT OF INDUSTRY, SCIENCE, ENERGY AND RESOURCES [15].

Principle	Summary
Privacy Protection & Security	AI systems should respect and uphold privacy rights and data protection, and ensure the security of data.
Reliability & Safety	AI systems should reliably operate in accordance with their intended purpose throughout their lifecycle.
Transparency & Explainability	There should be transparency and responsible disclosure to ensure people know when they are being significantly impacted by an AI system, and can find out when an AI system is engaging with them. Explainability includes what the AI system is doing and why, and may include the system's processes and input data.
Fairness	AI systems should be inclusive and accessible, and should not involve or result in unfair discrimination against individuals, communities, or groups.
Contestability	When an AI system significantly impacts a person, community, group or environment, there should be a timely process to allow people to challenge the use or output of the system.
Accountability	Those responsible for the various phases of the AI system lifecycle should be identifiable and accountable for the outcomes of the system, and human oversight of AI systems should be enabled.
Human-centred Values	AI systems should respect human rights, diversity, and the autonomy of individuals.
Human, Social & Environmental Wellbeing	AI systems should benefit individuals, society, and the environment.

from approximately 22 to 59 minutes in length, with a median length of approximately 37 minutes.

An interview protocol was used for each interview to initially elicit a subset of the high-level principles that was most relevant to each participant, as experienced through their work. The top 3-4 principles, as selected by the participant, were then explored via questions such as: (i) how each selected principle manifested itself in their work, (ii) how each selected principle was addressed (using tools and/or processes), (iii) what tools/processes would be useful in addressing each selected principle. Follow-up questions aimed to cover relevant intersections with the following areas: machine learning, software development, and ethics in AI. Finally, participants were also invited to reflect on other ethical considerations or dilemmas not covered by the high-level principles but encountered and possibly addressed in their work.

The transcripts of the interviews were analysed using thematic analysis, which used a theoretical approach to coding the interview data by using the high-level principles as themes [26]. Concepts identified in discussions of specific principles were recorded as subthemes related to applicable principles. The analysis was performed at a semantic level, meaning that the analysis focused on describing and interpreting patterns identified in the interview data rather than searching for any underlying assumptions or concepts within

it [26]. The thematic analyses derived from the interview transcripts were cross-checked independently by three reviewers to ensure inter-rater reliability and consensus.

V. RESULTS

In this section we present a summary of the thematic analysis of the interviews, noting salient practices and insights of participants relating to each of the 8 high-levels principles shown in Table I.

A. Privacy Protection & Security

This principle was largely interpreted by participants as the protection of sensitive data and privacy across the lifespan of a system, both during the development and deployment. The use of impact assessments was raised as a mechanism to identify and develop responses to privacy concerns. Privacy impact assessments are a well-established tool that can be used to understand and respond to the privacy risks of a project. Under the EU's General Data Protection Regulation (GDPR), the use of impact assessments is now mandatory for high-risk applications [27].

Participants also noted the importance of appropriate security methods to protect both the data and the AI system using the data. Participants suggested methods such as federated

machine learning, aggregation of data, and differential privacy. Minimisation of data and avoiding the use of personal data were seen as design goals. However, participants also noted that methods required for protecting sensitive data in ML model training data can negatively affect the usefulness of the model. In general, the richer the data is, more accurate and/or reliable ML models can be built [28]. Managing the trade-off between accuracy and privacy protection was commonly encountered by the participants. There were also challenges and tensions with protecting privacy and responding to accountability and explainability principles.

B. Reliability & Safety

Participants interpreted this principle as meaning that the AI system should produce accurate and reproducible recommendations. The ability to produce reliable AI systems is dependent on the volume and quality of training data that is available [28]. Challenges arose for the participants when the time and financial costs of obtaining data samples was high. Moreover, the complexity of ‘noisy’ real world environments may force developers to specify a range of conditions in which the systems can reliably operate.

Participants reported that the lack of continued oversight of AI systems after deployment was a challenge to the practical application of this principle. Examples were given where an AI system is used in contexts that differ from the one which it was developed for. Participants also reported the need for collaboration with domain experts in the design and development of AI systems. Ensuring the reliability and safety of a system requires domain knowledge and input from various stakeholders (including end users) to ensure that the system is operating according to norms, expectations and within the legal and regulatory bounds of the domain. This was seen as especially critical when AI systems are used to replace an existing process or model.

A lack of governance and regulation of AI technologies made the practical application of this principle difficult. In the context of autonomous systems this deficit was identified as a potential safety issue. This raised concerns for developers around ensuring the safety and reliability of the technologies they produce. Where AI is used in robotic systems, the quality of the hardware used in the system is an important safety consideration for developers. Industry standards and certifications were suggested as mechanisms to ensure the safety and reliability of robotic AI systems. Implementation of this principle may involve adopting safety measures that are proportionate to the magnitude of potential risks.

C. Transparency & Explainability

Participants largely focused on the explainability domain of this principle throughout the interviews. Interpretability of the outputs of AI systems was reported as critical to building human trust in AI. Although critical to engendering trust in AI systems, participants noted that explainability is dependent

on the form of AI used [29]. The degree of explainability required by AI systems was also seen in relation to the risk they pose. High-level explanations may be sufficient for some users and contexts, while others may require more detailed explanations of the AI system’s decision. Explainability is not a homogeneous concept and relates to the objectives and parameters of individual projects [30]. One participant expressed that in some instances trade-offs between accuracy and explainability may be necessary: “there have been instances where we’ve chosen an explainable model which has slightly lowered performance to a non-explainable model which has higher performance but would be harder to convey the reasoning behind the prediction”.

The use of proprietary datasets and the complexity of machine learning models were identified as challenges to explainability. Releasing the source code for AI applications was reported as a means of transparency, especially as part of publishing research. However, practical concerns often prevent this from occurring, as expressed by one participant: “often it doesn’t happen because it costs money to do, you have to spend time to clean it up, to maintain it, to publish it and so on. Second, you decrease the commercial value of it usually”. This insight illustrates the broader tension between openness and transparency with preserving commercial incentives. A set of standards and official guidance concerning the requirements for publishing AI systems’ source code was identified as a potential solution for developers publishing their research.

D. Fairness

The application of fairness in AI systems was expressed by participants as addressing bias in various ways. Adjustments to AI/ML models to promote fairness may occur in the input data for the model (pre-processing), in the processing performed by the model, or in the output of the model (post-processing) [31]. Participants spoke of the need for transparency around specific approaches employed for mitigation of various biases (e.g. data selection, data weighting). The ability to assess the methods and processing used to develop AI systems was seen as crucial for the principle of fairness.

Even with the use of mitigation approaches, biases in the data used to train AI systems were seen as inevitable to some extent. User judgement when using AI systems by including a ‘human-in-the-loop’ was suggested as a potential response. Participants also recognised the importance of the explainability of AI systems in relation to fairness. This means a user’s understanding of the context as well as the limitations of predictions and outcomes made by the system is important to ensuring the AI system is used in a way that supports fair outcomes. However, participants observed that there are multiple definitions and measures of fairness, and choosing between them was considered both a technical problem and a question of values [32]. The role of fairness was unclear to participants in contexts where the AI system is not used to make decisions that directly impact individuals, communities, or groups.

E. Contestability

Participants interpreted contestability as providing users with the ability to overrule decisions recommended by AI systems. Contestability was reported as critical for building trust in AI. One participant suggested that it is hard to get people to trust an AI system that simply provides a recommended action without an option to disagree with the recommendation.

Participants linked the principle of contestability to explainability and transparency. The explainability of an AI system was considered important for understanding the system output being contested. The complexity an AI system's decision making and the inability to clearly explain the process was raised as a potential issue to addressing the principle of contestability. In complex systems it becomes difficult to critically evaluate the AI systems outputs. Participants also noted that in many complex systems the ability to revise the decisions with a new set of assumptions is not possible. In these cases, the ability of users to opt out of using the system becomes important.

F. Accountability

Participants interpreted this principle as accountability for the methods and data used by an AI system, as well as the outputs of the system. There were differences in opinion over accountability for the outcomes of decisions based on an AI system's recommendations. Some participants reported that both the developers and users of AI technology are equally responsible for its actions. Other participants felt that developers' lack of control over the way technology is used challenges their ability to remain accountable for those applications post-deployment. This complexity was emphasised in AI systems that continue to learn post-deployment, using, for example, data provided by users. The practical application of this principle is challenging and likely to require a dynamic approach and clear frameworks that elucidate requirements and lines of responsibility across stakeholders [33]. The need for such a framework was raised by several participants.

This principle was perceived to intersect with other AI ethics principles. For example, there is a requirement for transparency and explainability in AI systems that are used in ways that have a significant impact on human lives [34], [35]. Moreover, AI systems that lack explainability may attribute greater levels of accountability towards the designers and developers of the systems when users have little input over the outcome of the systems' decisions [36]. Participants reported that transparency and explainability were seen as important for accountability; giving an explanation of an AI system's outputs/actions was seen as a requirement for being accountable for it. Further, accountability was also associated with the *Reliability & Safety* principle, and was seen as important for

the acceptance and adoption of autonomous systems, including self-driving vehicles.

G. Human-Centred Values

Participants believed that the implicit nature of human values and how they might be differentially interpreted by individuals complicates the application of this principle in practice. The ability to explicitly identify the presence of human-centred values in their AI systems was difficult for the participants. The challenge in translating abstract human values into software and technologies is well recognised [21], [22], [37]. Social science theories, such as Schwartz's model of universal values, have previously been used to frame human values for software development [22], [38]. Similarly, human-centred design approaches seek to understand and respond to the impact and interaction that a technology will have on users and the wider environment throughout design and development process [39].

The application of this principle was mainly raised by participants involved in projects collaborating with Indigenous Australians, and the issues raised were centred around addressing cultural complexities. Co-design of AI systems to ensure the incorporation of Indigenous knowledge, perspective and lived experience was presented as a possible method for addressing such issues that had been trialled effectively. Frameworks, such as the CARE principles developed by the Global Indigenous Data Alliance, provide guidance to support Indigenous innovation and self-determination through data governance [40].

H. Human, Social & Environmental Wellbeing

Participants reported that there were still significant uncertainties regarding the positive or negative impact of existing and future applications of AI on human, social and environmental wellbeing. This insight is reflected by Makridakis [41], where the major challenge for society is posed as the ability to utilise the benefits of AI technologies while avoiding the dangers to society.

In response to this principle, some participants raised concerns about data analyses and recommendations that may have uneven benefits and reinforce disadvantage in society. This reinforces the need for diverse perspectives and collaborative teams in the design, development and use of AI technologies [42]. Participants were also concerned about applications of AI systems that they regarded as having contested impacts on human and social wellbeing, such as facial recognition, dual-use applications, and non-civilian applications. In Australia, the Australian Human Rights Commission has recommended privacy law reform to protect human rights against applications such as facial recognition as one response to these issues [12].

VI. BUILDING ORGANISATIONAL SUPPORT FOR THE APPLICATION OF AI ETHICS PRINCIPLES

In this interview study, the unique requirements, constraints and objectives of the diverse range of projects that participants have been involved in provide valuable insight into the complexities of designing and developing responsible, or ethical, AI systems. Framing these discussions around the 8 high-level principles provided insight into how ethics principles were interpreted in the context of the professional experience of the participants.

A notable challenge that emerged was balancing the trade-offs and tensions that were inherent to using the principles. Tensions were highlighted between the practical approaches used for implementing privacy and security, transparency and explainability, as well as accuracy. For example, ML techniques may be used to develop a system that provides highly accurate outputs with the caveat that those outputs are not explicitly explainable. Similarly, the development of a highly explainable AI system may be vulnerable to privacy risks. In these cases, a choice must be made to prioritise one set of values over another [43]. Weighing the risks and benefits of such decisions requires the implementation of supportive mechanisms and should not fall to the designers and developers of AI systems alone. The ability to assess risk was also presented as critical across the interviews as a way to gauge the degree of oversight, accountability, reliability and explainability required for an AI system.

The interviews and discussions that arose during this research highlighted key areas where proactive support is sought by developers and designers through training, education and organisational policies. Below we provide a set of high-level recommendations that target and support building the capacity to operationalise the principles at the organisational level, which may be useful to organisations that are considering an AI transformation.

A. Learning

The development of a digital academy to provide capability and skills uplift through education and training programs. The provision of organisation-wide training and processes to increase awareness and understanding of ethics principles and their application, followed by the adoption and implementation of such principles across all projects involving AI systems. Developing and supporting proactive education and training in responsible AI can position an organisation as a leader both in practice and thought. In turn, this has the potential to positively affect the culture within other organisations using and developing AI technologies.

B. Process

The implementation and organisation-wide use of a Research Data Planner (RDP) at the start of every project that involves AI technologies or systems. RDPs are widely used across research and academic institutions to enable developers to consider the research data that will be created, as well as how data will be shared and preserved [44]. The RDP may also incorporate functions that identify applicable ethics principles within the context of each project, and promote planning actions for addressing/implementing principles. The RDP may provide links to useful material that raises awareness of ethics in practice and building vignettes that facilitate how ethics can be operationalised. As a useful side effect, use of the RDP may lead to an increase in the organisational knowledge of a broad range of relevant ethics principles and increase the pool of methods and approaches for operationalising these principles.

C. Practice

The operationalisation of high-level principles into a range of practices through mapping between the present principles and a set of design notes aimed at developers of AI systems. The design notes may include suggestions and specific attributes to consider while designing and implementing AI systems. Another possible avenue is the application of reusable design methods, where the design and implementation of system components, as well as their integration, follows known patterns that are aligned with high-level AI ethics principles [45].

D. Strategy

The adoption of responsible AI as a fundamental aspect of the organisation's digital strategy. Within organisations or departments devoted to scientific research, a digital strategy can include investment in the responsible development and use of AI to accelerate scientific discovery through the use of current and future digital technologies (e.g. digital assistants, automation and robotics).

E. Policy

The development and adoption of an organisational policy on the permissible uses of AI systems (e.g. guidelines for projects involving dual-use applications and/or non-civilian focus). Active guidance on an organisational level manages the risks involved with powerful technologies that could be used in harmful ways that violate human rights and accepted norms. Providing clear boundaries around permissible AI development builds trust with the public and within the organisation.

VII. CONCLUSION

Governments and organisations are beginning to respond to calls to manage and govern the development and adoption of AI systems in society. Building an understanding of the practical aspects relevant to the application of AI ethical principles is a critical step towards devising an implementation process for such principles. This work provides insight into the links between current practices of scientists and engineers at Australia’s national scientific organisation (CSIRO) and the Australian Government’s eight high-level AI ethics principles. The presented observations and discussions contribute to a greater understanding of the practical aspects and challenges relevant to the implementation of each AI ethics principle, and are forming the basis for the development of a suite of organisational-scale responses to support the operationalisation of AI ethics principles.

AI technologies will continue to shape and impact what humankind can achieve, and how we interact with each other and the world [46]. The significant opportunities and benefits presented by AI are balanced with opposing risks. The advancement of responsible AI practices mitigates risk and provides the opportunity to develop and use technologies in ways that benefit individuals, organisations and society as whole [46]. Furthermore, organisations that take the lead in implementing practices that support the ethical development of AI technologies are well positioned to benefit from opportunities, such as gained trust leading to competitive advantage, retention of highly skilled staff, avoidance of reputational damage, as well as being responsive and ready for regulatory requirements.

We note that the existence of the principles alone does not guarantee ethical AI [13]. Further infrastructure, beyond the organisational level, may be required to build the capability and capacity of AI developers and designers to create responsible AI. High-level support and governance of AI development to support the practice of implementing principles is required. Such support could be in the form of professional codes and regulatory frameworks, as well as legal and professional accountability mechanisms to uphold professional standards and provide users with redress for negligent behaviour [13].

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