

Version 1

Good Work Algorithmic Impact Assessment

An approach for worker involvement



This document provides guidance for employers on how to involve workers in the assessment of algorithmic systems used in the workplace that may have significant effects on access, conditions and quality of work ('Good Work').¹

As a complement to this guidance, we have produced two resources to help improve accessibility and understanding of the ways in which algorithmic systems can impact work.

First, the [Good Work Charter](#) identifies the main *legal and ethical* frameworks that apply to work access, conditions and quality of work. Toolkit 1 can help identify legal and ethical impacts in the workplace.

Second, '[Understanding AI at Work](#)' provides accessible explanations of how human choices in the design, development and deployment of AI at work are determined by human choices. This considers impacts to fairness – including equality – but goes beyond this to consider wider possible impacts on Good Work.

These resources, together with this guidance, will help employers assess the wide range of impacts that AI and other algorithmic systems may have on Good Work.

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The principles of ‘good work’ should be recognised as fundamental values ... to guide development and application of a human-centred AI Strategy. This will ensure that the AI Strategy works to serve the public interest in vision and practice, and that its remit extends to consider the automation of work.

All Party Parliamentary Group on the Future of Work²

INTRODUCTION



AI at work – why guidance is needed

Artificial intelligence (AI) and algorithmic systems are increasingly used in the workplace, and designed, developed and deployed in ways which can transform access to, conditions of, and quality of work.³ When well designed, these technologies offer new opportunities to increase efficiency, augment capacity and drive growth. But this transformation is also driving a wide range of social, psychological and material impacts.⁴ This means that employers face new opportunities and challenges as they try to maximise the positive, and minimise the negative outcomes for their businesses and workers.

Whether it be about how their rights are respected,⁵ how their working conditions are likely to change, or how their interests are balanced with those of the business,⁶ workers need confidence that these systems are being used fairly and transparently. This requires significantly higher levels of transparency and workforce involvement.

Responsible employers increasingly recognise the merits of this approach. Greater transparency about the purpose, remit and likely outcomes of algorithmic systems, and the time, space and process required for evaluation by those affected, underpins effective risk management and trust.⁷

More widely, there is increasing recognition that meaningful stakeholder engagement at work (and in other high stakes environments) is integral to understanding impacts, promoting good work and building a trustworthy and responsible AI ecosystem.⁸

However, a marked absence of guidance hinders employers from delivering this in practical, context-sensitive ways.⁹ In particular, there is no guidance on how to involve workers and their representatives in the assessment of impacts on work and working people. Supported by the United Kingdom Information Commissioner's Office (ICO), the Institute for the Future of Work (IFOW) aims to fill this gap by providing a framework and methods for worker involvement in the assessment of algorithmic systems on good work, with a particular focus on new methods for worker involvement.

The guidance is intended to complement the work of the ICO, including the recent publication of draft guidance 'Monitoring at Work',¹⁰ as part of a forthcoming wider suite of employment practices guidance and an update to the Fairness in AI content of the ICO [Guidance on AI and Data Protection](#). The guidance pays careful attention to data protection principles, rights and responsibilities. With caveats explored below, these materials can be seen as a gateway through which other legal, ethical and social principles of good work come to life to champion human-centred and responsible AI in the workplace.¹¹

Our model – the Good Work Algorithmic Impact Assessment (Good Work AIA) – uses IFOW's Good Work Charter as a framework to combine the technical, legal, social and ethical dimensions of evaluation.¹² Our guide recognises that worker involvement is particularly important to ascertain and respond to the social and ethical impacts of algorithmic systems on good work, but it is also important to understand and anticipate the full range of legal impacts and can help demonstrate legal compliance.

“The Institute for the Future of Work’s Good Work Charter is a useful checklist of AI impacts for risk and impact assessments—for instance, in a workplace context, issues relating to access, fair pay, fair conditions, equality, dignity, autonomy, wellbeing and support”

Lord Clement Jones, Former Chair of the House of Lords AI Committee, 13 July 2022¹³

INTRODUCTION

What is an algorithmic system?

We define an ‘algorithmic system’ as a *data driven software process that uses one or more algorithms designed, developed and deployed by humans, operating in an institutional context. For the purposes of this guidance, an algorithm is defined as a sequence of instructions programmed in a computer, designed to complete a task or solve a problem.*

Within this definition of an algorithmic system, we include computational statistics, complex systems and AI and machine learning (ML) (including knowledge or rule based systems, and supervised and unsupervised machine learning).

The properties of the software and hardware, as well as the institutional choices about how these are designed and implemented within a business, are all relevant to determining the impacts of the system at work, which may also be cumulative in nature.

Recognition that human choices shape technology and determine outcomes reflects a socio-technical approach.

How to use this guidance

This guidance is intended to help employers and engineers involve workers and their representatives effectively in designing, developing and deploying algorithmic systems to:

- anticipate and manage risk
- promote good work
- comply and demonstrate compliance with the law
- unlock innovative approaches
- build trust in technology

When should this guidance be used?

A Good Work AIA should be undertaken where any algorithmic system is designed, procured or deployed to make or inform decisions about access or terms and conditions of work, including pay, promotion, work allocation, evaluation of performance, and discipline. This guidance recommends that a Good Work AIA is also undertaken when there is a risk of significant impact to any other dimension of Good Work.

The guidance is directed at any employer who uses – or is thinking of using – algorithmic systems in the workplace that *may* impact access, conditions or quality of work. The guidance covers all employment and other worker relationships. It may also be useful to engineers, third party contractors, platforms and unions.

This guidance is adaptable for businesses of different sizes, resource capacities and capabilities, operating in different sectors. Similarly, our methods can be adapted to suit different contexts, different points of intervention, and the proximity, severity and likelihood of anticipated impacts.¹⁴

The Institute for the Future of Work intends to support organisations to pilot the Good Work AIA methodology and develop further iterations and refinements to our guidance over time.

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The Good Work AIA at a glance



Context Based Risk Assessment

Identify relevant accountable agents within the organisation, and document key design choices regarding design, development and proposed approach to deployment.

Produce a Key Design Choices Report



Commit to the process

Once the Context Based Risk assessment is completed, the group of accountable agents should make a series of commitments about completing the process of Good Work AIA.



Stage 1

Identifying individuals who may be impacted

- a) Identify total population
- b) Chose sampling approach
 - Representative
 - Elective
 - Direct
 - Purposive

Produce a Stakeholder Engagement Report



Stage 2

Undertake an ex ante risk and impact analysis

- a) Undertake a group exercise for value mapping
- b) Review key design choices and document key risks
- c) Develop scenarios and user journey stories

Produce a Risk Assessment Report



Stage 3

Taking appropriate action in response to the ex ante analysis

- a) Select target risks
- b) Identify mitigations
 - Rights and entitlements
 - Distributed rewards
 - Universal design changes
 - Tailored design changes

Produce an Impact Mitigation Plan



Stage 4

Continuous evaluation to ensure assessment and appropriate action is ongoing and responsive

- a) Establish forum for ongoing dialogue
- b) Consider terms of reference
- c) Identify different sources of feedback

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CHAPTER 1

The case for Good Work AIA

Just as the future of work is not fixed, the outcomes of technology are not pre-determined. Human choices and values determine which technology is made, how technology is designed, deployed and used, and these choices determine outcomes or ‘impacts’ on work and workers. These changes can and should be for the betterment of work.

There is growing consensus that to drive and design-in beneficial outcomes, as well as manage risks, a socio-technical approach is needed.¹⁵ The International Organization for Standardization (ISO)¹⁶ and National Institute of Standards and Technology (NIST)¹⁷ both highlight the importance of recognising how social and technical capabilities relate in practice to effectively govern AI.

Current forms of assessment of algorithmic systems vary, including mandatory (where the processing is likely to result in high risk, Article 35(1)) Data Protection Impact Assessments, more voluntary technical audits, such as those which review the ‘robustness’ of systems, through to more ethical impact assessments, which evaluate the way a system works against values and principles.¹⁸ Our approach integrates these approaches. In particular, we recommend incorporating the Data Protection Impact Assessment (DPIA), for which the ICO has published detailed guidance. As we explain below, we recommend taking a broad approach to the mandatory (as above) DPIA and building out from it so that assessment extends to all good work impacts.

In this chapter, we set out the rationale for an employer to use Good Work AIA with a focus on worker involvement to implement an effective, socio-technical approach.

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Identifying relevant risks and impacts

Established principles in the field of AI ethics include fairness, accountability, sustainability, safety and transparency.¹⁹ However, these frameworks are not designed to consider the full spectrum of intersections between good work and algorithmic systems. In this context, we have conducted a bespoke review of legal, ethical and regulatory bases for good work including those which relate to AI governance.

The Good Work Charter provides an organising framework for aspiration, alignment and action to shape a fairer future of better work. It sets out ten fundamental principles of ‘good work’ – work which promotes dignity, autonomy and equality; work with fair pay and good conditions; work where people are properly supported to develop their talents and maintain a sense of community. The principles are interdependent and interrelated – seeking improvement in one area (e.g. conditions) is likely to support improvement in others (e.g. wellbeing). The Charter aims to encourage dynamic, values-based policy and practice as businesses introduce new technology.²⁰

Importantly, the Charter also captures fundamental rights and interests as they apply in the workplace. We have published a synthesis of AI ethical principles on algorithmic systems which apply to the workplace as a ‘checklist’ against which the impacts on work can be surfaced and evaluated.²¹

Research has also demonstrated that the use of AI at work can impact all good work principles²², such as **fair pay**²³, **terms and conditions**²⁴, **equality**²⁵, **dignity**²⁶, **autonomy**²⁷, **participation**²⁸, **learning**²⁹, and **wellbeing**³⁰. The charter therefore acts as a checklist of social economic and ethical impacts.

Good Work Principles	
For our review of the legal, ethical and regulatory bases of good work principles, follow the links below.	
Access	
Fair Pay	
Fair Conditions	
Equality	
Dignity	
Autonomy	
Wellbeing	
Support	
Participation	
Learning	

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A note on participation

Notably, **participation** is a distinct principle in the charter. This reflects the right and expectation that a person should be involved in decision-making where their interests are affected, including the determination and improvement of working conditions, and should help shape an environment that allows them to flourish. In this guidance, however, participation is elevated to enable the best assessment of risks and impacts across all dimensions of the Charter. This is because the first-hand experience of people who are (or will be) interacting with an algorithmic system is required to ascertain the breadth, nature and severity of actual and likely risks and impacts. Adverse impacts and the practical or ethical concerns of workers cannot be forecast on their behalf³¹ and the impact of iterative use may change, or only be detected, over time. This means that workers and their representatives can be seen as ‘domain experts’, and need to be involved in the context-sensitive and ongoing assessment of impacts experienced across the dimensions of the Good Work Charter. This is particularly important where algorithmic systems increase information asymmetries between employers and workers.³²







Worker involvement is also necessary to ascertain new, invisible or unintended consequences. Examples highlighted in international guidance on AI include impacts on people’s **dignity** where there is a “chilling effect” on behaviour,³³ and on **autonomy**, where worker ability to make decisions can become impeded.³⁴ In many cases, these impacts may not have matured to the point of formal recognition as a health and occupational hazard. Here, worker involvement may unlock important information and interpretations of impacts on Good Work.

A wide range of “hard” and “soft” legal instruments reflect the principle of participation: that the individual or community affected by a decision should be involved in the decision-making process. These instruments range from the UK Information and Consultation Regulations to the requirement to consult data subjects or their representatives as part of a Data Protection Impact Assessment, where the processing is likely to result in high risk to the rights and freedoms of individuals in the UK’s General Data Protection Regime.

For further information, please see ICO’s guidance on DPIAs³⁵, Prospect-IFOW joint guidance³⁶ and IFOW summary of legal and ethical principles relating to the Good Work Charter.

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Table 1: Example risks, impacts and opportunities of algorithmic systems at work

Principle	Example risks and impacts	Example opportunity
Access 	Algorithmic systems can be used to substitute for tasks or jobs, changing overall demand for workers, or track time for task completion to allocate shifts.	Algorithmic systems can be used to create new roles in firms, enable wider participation of those with different abilities, or identify ‘unusual suspects’ as candidates for a role.
Fair Pay 	Algorithms can be used to exploit wage elasticities by dynamic pricing or be introduced as part of new business models which see cost burdens transferred to workers.	Algorithmic systems can be used to improve efficiency of production, creating financial gains which can be shared with workers.
Fair Conditions 	Algorithmic systems can be used to transition a workforce from regularised to predictively scheduled work, with a view to increasing insecure contracts and changing terms of work.	Algorithmic systems can be used to track and reveal working conditions and inform the development of better work.
Equality 	Algorithmic systems can be used to make decisions about workers on the basis of historic patterns commonly reproducing inequalities of history by projecting these into the future.	Algorithmic systems can be used to reveal inequalities, monitor impacts more closely and suggest interventions to promote equality.
Dignity 	Algorithmic systems can be used to monitor workers in ways which lead them to feel they are less trusted, valued or respected.	Algorithmic systems can be redesigned in ways which promote human capabilities and recognise individual differences.
Autonomy 	Algorithmic systems can be used to specify exactly how tasks should be completed, with impacts on workers’ sense of agency.	Algorithmic systems can be used to help promote workers’ discretion around when and where they complete tasks.
Wellbeing 	Algorithmic systems can create power asymmetries which lead to feelings of anxiety and vulnerability, driving psychosocial harms or ‘technostress’ ³⁷ .	Algorithmic systems can be used to tailor experience of work to individual preferences, such as offering different patterns of shift times or types of tasks within the working day.
Support 	Algorithmic systems can be used to eliminate management roles, reducing worker access to redress for incidents at work or support around workload management. ³⁸	Algorithmic systems can be used to enable workers to communicate with peers for support, reducing managerial oversight.
Participation 	Algorithmic systems can be used to detect worker dialogue about membership of unions and reduce space for dialogue or attempts to collectively bargain.	Algorithmic systems can be used to generate insights which can inform understanding around working conditions and support improvements.
Learning 	Algorithmic systems can elicit work methods and storing information about how work is conducted, deployed to reduce the use of independent thought and space for learning.	Algorithmic systems can be used to create roles which require more critical thinking and analysis by workers, complementing their capabilities.

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Compliance with Data Protection Law

Data Protection Impact Assessments

Article 35 of the UK GDPR requires a data protection impact assessment (DPIA) at work whenever “a type of processing, in particular using new technologies...is likely to result in a high risk to the rights and freedoms [of workers].”³⁹ The DPIA is required *before* the data processing. High risk is not defined but recitals expressly require a DPIA where there is systematic profiling (Article 35(3)) on which significant decisions are based and extends to non-physical risks, in particular when performance and behaviour is analysed or predicted (Recital 75).⁴⁰

This means that the use of algorithmic systems at work will trigger the legal requirement for a DPIA in most cases, when the technology or approach is novel or if there are significant elements of automated decision making. A DPIA is certainly required for decisions concerning work, allocation, payment, access to benefits, potential disciplinary matters or any contractual matters. In this sense, the DPIA can act as a window into assessment of other rights and freedoms of workers. In this guide, we therefore propose that it is best practice for employers to conduct assessments not only on impacts on data protection, but for any use of algorithmic systems which may impact access, conditions or quality of work to data subjects, with good work defined by the Good Work Charter.⁴¹

The DPIA must assess the impact of the envisaged processing, the risks it poses to workers’ rights and freedoms, the proportionality of using the algorithmic system and risk mitigation measures. The ICO guidance emphasises that a DPIA should be clear, comprehensive and thorough and must explicitly address the risks that the algorithmic system creates. It also requires consideration about whether the employer’s objectives can be achieved through less intrusive means, and the consultation of data subjects. Disclosure of the DPIA itself is not required by the UK GDPR but is increasingly recognised as best practice. If a DPIA identifies high risk which cannot be mitigated, prior consultation with the ICO is required.

Automated decision-making

The UK GDPR provides additional protection when data processing is “solely automated” and has a “significant or legal” effect on the worker.⁴² Article 22 restricts significant and solely automated decision making and requires “suitable safeguards” to be put in place in the narrow cases where such processing is permitted.⁴³ International guidelines and lawyers have proposed that appropriate safeguards may include worker participation and impact assessments.

Legitimate interests

Employers often rely on the ‘legitimate interests’ basis for processing worker data. This lawful basis requires the employer to identify the legitimate interest, show that the processing is necessary to achieve it, and carefully balance this against the workers interests, rights and freedoms. Again the Good Work Charter serves as a useful checklist to aid this balancing exercise. This assessment overlaps with the DPIA but is a separate obligation on employers. It also requires documentation, adding weight to our policy case for a Good Work AIA.⁴⁴ In summary, a detailed assessment of the impacts of an algorithmic system on workers and ‘good work’ is desirable and – frequently – mandatory. Worker involvement in this assessment is certainly useful and often required.

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Consultation

The UK GDPR specifically requires the data controller (the employer) to seek the views of data subjects (workers) or their representatives on intended data processing “where appropriate” as part of conducting the DPIA. The form, content or timeline for the consultation is not specified, nor are the ‘appropriate’ circumstances for this engagement. The ICO suggests organisations should seek and document the views of individuals (or their representatives) unless there is a good reason not to, providing further support for the Good Work AIA. It is anticipated that the ICO will provide additional guidance on this point as part of its 2023 update.

In summary, worker involvement in the assessment of impacts at work is likely to be necessary to meet binding national and international law and standards.

Best practice

Technology has the potential to improve work and enhance efficiency,⁴⁵ but this outcome is not inevitable and must be consciously designed, with careful consideration of both positive and negative impacts on good work.⁴⁶ IFOW has previously highlighted the business case for promoting good work through technology introduction and shown how this plays out at the level of the individual, of the firm and of society.⁴⁷ Poor job quality is associated with higher absenteeism, greater health problems, more health-related early retirements and increased turnover rates. All these aspects have a direct link to worker productivity and, in turn, firm performance. A good working environment is not only welfare enhancing but also economically efficient.⁴⁸

The introduction of technology presents a unique challenge and opportunity for work redesign and improvement of good work outcomes. It should therefore be treated as a key moment for workforce involvement in decision-making to maximise benefits and minimise risks for both workers and businesses. Empirical evidence has demonstrated that various forms of worker participation can promote organisational performance.⁴⁹ One study cites a 14% higher productivity rate where worker voice and representation is high.⁵⁰ Involvement also helps a firm be an intelligent customer when procuring technology: providing a clearer view of how work is done on the frontline and ensuring systems are compatible.

For example, participatory design of shift-scheduling technology can enable workers to improve their sleep patterns, allowing them to come to work feeling better – translating as higher ‘workability’.⁵¹ More importantly, participation in decision-making can improve worker wellbeing by leading to more intrinsically rewarding work,⁵² and can drive higher levels of satisfaction with pay.⁵³

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People are more likely to embrace systems that are deployed by businesses with their informed consent.⁵⁴ Engagement is also associated with higher levels of trust between workers and employers, which is especially important when algorithmic systems are deployed at work.

Key decisions about how algorithmic systems are designed, and what they are designed to achieve, significantly determine impacts. For choices and trade-offs to adequately reflect shared moral values and socio-legal norms, these decisions must be disclosed so that contextually-sensitive value judgements can be made.

This is especially important given the tendency for algorithmic systems to be designed in ways which centralise control.⁵⁵ Approaches to algorithmic management which drive concentration of power can fail to deliver productivity,⁵⁶ while also undermining legitimacy. Good Work AIA can remedy this through participation. Algorithmic systems encode aspects of our shared reality, about which people may reasonably disagree.⁵⁷ In this context, when considering questions about fairness in AI, it is important to have adequate information to address the question not only of ‘are these decisions fair?’ but also: ‘is it fair to automate these decisions?’⁵⁸

Become an industry leader in responsible innovation

In spite of widespread recognition that novel tools for risk management are needed for the deployment of AI at work, very few practical applications have been developed, or piloted. International legislators are taking action to enforce accountability mechanisms.⁵⁹ Currently, the UK government is taking an approach which centres responsible behaviour by business. This creates an opportunity for businesses to take the lead in demonstrating how effective governance can work, pre-empting regulation.

In this context, undertaking a Good Work AIA, as presented in this guidance, will render organisations trailblazers in the practice of a responsible AI and valuable stakeholders in the emerging, wider ecosystem informing the development of future regulation. This is particularly important as intersections with existing architectures of accountability continue to be worked out.

CHAPTER

2



CHAPTER 2

Getting ready for a Good Work AIA

This chapter sets out the process for a Good Work AIA. Our model for Good Work AIA, based on a review⁶⁰ of existing models of algorithmic impact assessments (AIAs), has four key stages, preempted by a Context Based Risk Assessment. Each of these stages involves documenting decisions made, which is a core tenet of accountable decision making.⁶¹

Context Based Risk Assessment

This is necessary to undertake before any Good Work AIA process can be completed. This should generate a **Key Design Choices Report**, used as a diagnostic and information to inform subsequent stages of the process. This involves mapping decisions, and addressing clearly identifiable risks ahead of any participatory exercise.

Good Work AIA

Stage 1 Identifying individuals who might be impacted

This stage sets out methods for identifying relevant worker stakeholders. How the sample is chosen should reflect organisational size, preferred methods for undertaking risk assessment, and resource commitment. A summary of these choices should be recorded as a **Stakeholder Engagement Report**.

Stage 2

Undertaking an ex ante risk analysis

In this stage risks arising from proposed problem definition, and approach to design and deployment, are identified through participatory exercises involving workers as experts. This should build on the context based risk assessment and may develop proposed mitigations. This should produce a **Risk Assessment Report**.

Stage 3

Taking appropriate action in response to the ex ante analysis

In this stage, risks are ranked and prioritised, new mitigations are identified for any risks which do not have proposed solutions, and appropriate actions are decided. This should produce an **Impact Mitigation Plan**.

Stage 4

Continuous evaluation to ensure assessment and appropriate action is ongoing and responsive

If the system is deemed viable for deployment, ongoing systems should be created to ensure avenues for access to redress, and to enable ongoing monitoring of unforeseen impacts, and evaluation of the success of mitigations in the Impact Mitigation Plan. This is best mediated via a dedicated **forum**.

CHAPTER 2



Context Based Risk Assessment

The Good Work AIA process is designed to identify, preempt, manage and mitigate social, legal and ethical risks, and further, to advance good work. Undertaking a context-based risk assessment should assist an organisation to ensure they are approaching adoption responsibly, and show demonstrable commitment to promoting good work ahead of any involvement of wider stakeholders. This should also promote trust.

What is a risk?

The characteristics or properties of an AI innovation context that could contribute to some outcome (or outcomes) that negatively impact key ethico-legal principles of good work.

Employers should go on to conduct a Good Work AIA where an algorithmic system involves supervised, unsupervised or reinforcement machine learning to make or inform a decision about access or terms and conditions of work, including pay, work allocation, evaluation of performance, or discipline of workers.

Choices made in the design, procurement and deployment of an algorithmic system will determine these impacts. For this reason, context-based risk assessment involves reflecting on and documenting key design choices.

Who completes a Context Based Risk Assessment?

Organisations using AI or algorithmic systems as part of wider workplace transformation increasingly rely on dedicated teams to ensure design is in line with organisational values, and legal requirements for Good Work.

Organisations should establish architectures for responsible innovation which bring together key accountable agents. This should include the Data Protection Officer, Health and Safety Officer, Human Resources, Chief Technology Officer, Internal Audit Officer, Chief Compliance Officer, all of whom may all hold responsibility for potential impacts.

Wherever there is a union representative, they must be involved (see recommended role for unions in guidance on Algorithmic Impact Assessments by the Trades Union Congress). It is also recommended that at least two frontline workers are involved in this process (see 'purposive sampling', on page 30).

As context based risk assessment involves recording key choices about planned design, development and deployment. These together form a record of key design choices.

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Documenting Key Design Choices

Where businesses are procuring technology, they should ensure access to information from providers. This is critical as providers, being data controllers, are responsible for system outcomes.

We recommend that at least two frontline staff are involved in these choices. Full methods for involvement across the following four stages of Good Work AIA are set out from Stage 2.

Key decisions which can determine impacts are made at various points in the process including in particular:

- Design
- Development
- Deployment

All decisions should be consciously planned and recorded. We recommend that any organisation already deploying algorithmic systems at work consider retrospectively creating such an inventory of the design choices made at each of these stages. For further information on the key decisions which can determine impacts to equality from the design of algorithmic systems, please see our Mind the Gap Report.⁶²

Design

Organisations do not always clearly define the problem to be solved ahead of implementing technological solutions.⁶³ A poor approach to problem definition and understanding relationships between technical and social systems is likely to obstruct productivity gains, and increase negative over positive impacts on Good Work.⁶⁴

Where the proposed system involves the processing of personal data, there is also a legal obligation to understand the purpose and objectives of a system to verify it has a lawful basis.⁶⁵ For any balancing of interests, the specific forms of benefit to a business should be known.

When defining the problem, it is important to clearly articulate:

A) The problem to be solved by technology and rationale for this.

Is the technology solving an identified problem in relation to workforce management?

If so, what other solutions were considered?

If workers are not involved in problem definition, are employers confident they understand the workflow?⁶⁶

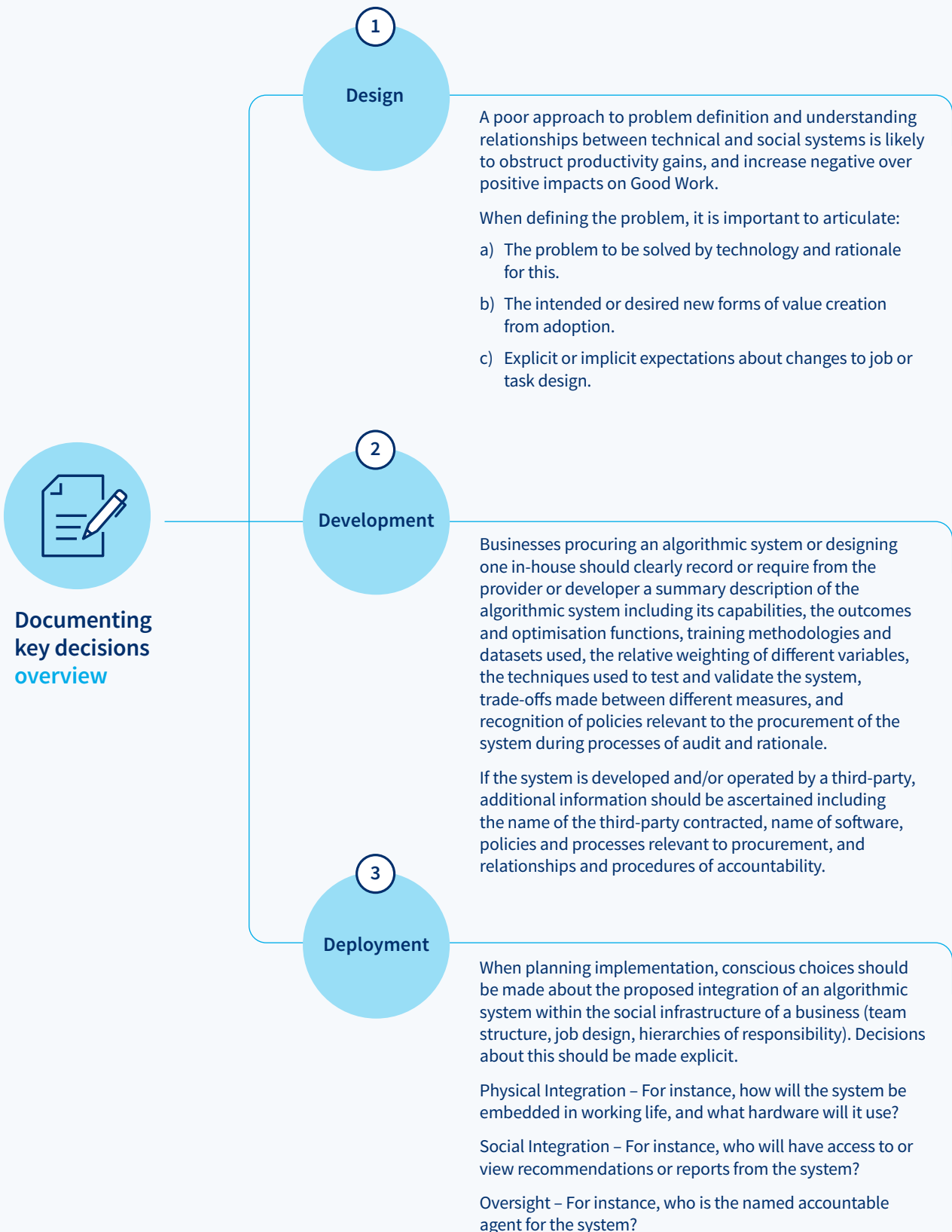
B) The intended or desired new forms of value creation from adoption.

Substitution

Technology conducts tasks previously conducted by people, to generate efficiencies.

This may impact upon Access to work.

CHAPTER 2



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Creation

Technology creates new potential roles. This can come at the same time as substitution and/or drive 'high discretion augmentation'.

This may impact upon Fair Pay, Learning and Access to work.

Telepresence

Algorithmic systems can be used to execute managerial functions, without managerial presence ('algorithmic management'). Systems may be used to make or augment managerial decisions relating to restricting and recommending, recording and rating, replacing and rewarding.⁶⁷ These functions can have myriad effects on good work.

This may impact upon Access, Fair Conditions, Autonomy, Dignity, Support and Learning

High Discretion Augmentation

Workers use technological tools to improve product quality or efficiency.

This may impact upon Fair Pay, Learning and Access to work.

'Low Discretion' Augmentation

AI can be used to reduce the 'cognitive load' of workers, delimiting their choice environment and reducing skill required for work.

This may impact upon Fair Pay, Learning, Dignity, Autonomy and Wellbeing.

Intensification

Algorithms can be used to monitor, track and schedule tasks for workers, reducing 'non-productive time' within the working day.

This may impact upon Fair Pay, Learning, Dignity, Autonomy and Wellbeing.

Wage Matching

There are a range of mechanisms by which algorithmic systems can transform wages, without substituting labour. For instance,

- Dynamic pricing to exploit wage elasticities
- Predictive, flexible scheduling of shifts
- Suppression of collective bargaining⁶⁸

This may impact upon Fair Pay, Learning, Dignity, Autonomy and Wellbeing.

C) Explicit or implicit expectations about changes to job or task design.

- a) Under which forecasts and assumptions is the system meant to save capacity?
- b) Which if any tasks or roles will be substituted or changed?
- c) Which if any tasks or roles will be created?
- d) Which tasks, which workers, in which contexts?

Undertaking this process is important to support review of changes to the 'objective' characteristics of Good Work. Examples are provided in the checklist below. Questions should start open and then narrow in on any specific concerns that have been identified. Please note that the checklist assumes compliance with the law, which should be seen as a minimum requirement. Reviewing with a view to compliance with the law is a minimum.

CHAPTER 2



Development

Businesses procuring an algorithmic system or designing one in-house should clearly record or require from the provider or developer the following aspects of design.⁶⁹ The terms used below are defined in the glossary.

- a) A summary description of the algorithmic system including its capabilities, remit and proposed applications for full or semi-automated decision-making.
- b) The outcomes and optimisation functions (including key constructs used to evaluate and assess, such as those relating to monitoring, evaluating or managing work, recruitment, promotion, dismissal).
- c) The training methodologies and datasets used.
- d) The relative weighting of different variables selected to predict, rank or classify data subjects.
- e) The techniques used to test and validate the system, including outcomes of technical audits verifying robustness, privacy, explicability and fairness in system development.
- f) Trade-offs made between different measures during processes of audit and rationale given in plain language.
- g) Recognition of policies relevant to the procurement of the system,⁷⁰ noting cultural and institutional heritage of the system and possible need to amend these to fit the culture, norms, ethics etc. of the deploying institution and legal location.

If the system is developed and/or operated by a third-party, additional information should be ascertained including:

- a) name of the third-party contracted;
- b) name of the software;
- c) organisational policies and processes relevant to procurement;
- d) the relationships and procedures of accountability; the competence, authority, and accountability of the human persons involved.

Commercially conscious procurement

If these features are not understood by employers, who are accountable agents, the system should not be used to make decisions about or determine access, or terms or conditions of work.⁷¹

The above information is necessary to inform any Good Work AIA and to adequately forecast and understand risk.

CHAPTER 2



Deployment planning

*'In the context of AI systems, ensuring that written policies and procedures address key roles, responsibilities and processes at all stages of the AI model lifecycle is critical to managing and detecting potential overall issues of AI system performance.'*⁷²

Algorithmic systems become embedded within the wider culture and decision-making structures of a firm.

When planning implementation, conscious choices should be made about the proposed integration of an algorithmic system within the social infrastructure of a business (team structure, job design, hierarchies of responsibility). Decisions about this should be made explicit.

Physical Integration

How will the system be embedded in working life, and what hardware will it use?

- a) If collecting data, which hardware will the system draw data from?
- b) Who owns this hardware? Where is it located?
- c) When will data collection capabilities be turned on and off?

Social Integration

- a) Who will have access to or view recommendations or reports from the system?
- b) Who will have access to the data within the organisation? What is their understanding of design choices and their implications for reliability of information?
- c) What decisions will the system be used to make or to inform? Who has oversight of these decisions?

Oversight

- a) Who is the named accountable agent for the system?
- b) How will this be shared?
- c) Has a forum been established to oversee the system in perpetuity? What are the credentials of this team?
 - i) Does the team involve those with frontline experience of the system?
 - ii) How are accountable agents to be represented?
 - iii) Do oversight teams represent the workforce?
 - iv) Do they have adequate knowledge and understanding of the relationship between technical design and potential impacts?
 - v) Is work by this team transparent and accessible to workers?

CHAPTER 2



Produce a Key Design Choices Report

At the end of this process, a statement compiling 'Key Design Choices' should be compiled as part of the Context Based Risk Assessment Report.

This should explain in clear terms how design choices have been reached, strategies identified for compliance with UK GDPR and Equality Laws, identified potential risks to Good Work, and any mitigations already established in technical and bias audits.

Key design choices should be made available to participants in the subsequent process of Good Work AIA.

As best practice this should be published on the organisation's website, and disclosed to research organisations specialising in workplace AI risks for advancing understanding.

Using the context based risk assessment (CBRA) the organisation should make a decision about whether and how to undertake the full Good Work AIA. We note that the extent of participation and methods applied should be proportionate to the likelihood, severity and proximity of risks to the good work principles in the context of the case, as indicated by the CBRA. This should be discussed, agreed and recorded by the CBRA team including chosen worker representatives.

If the initial assessment indicates that access, terms or conditions of work may be affected, then a full Good Work AIA should be undertaken before a system is deployed. This guidance recommends that a Good Work AIA process is undertaken if wider aspects of quality (see our review of legal, regulatory and ethical bases of Good Work) could be impacted.

Impacts of algorithmic systems can be cumulative and develop over time. Therefore we recommend that for all systems even where a full Good Work AIA is not conducted ex ante that a forum similar to that presented in Stage 4 of the Good Work AIA is established for monitoring.

What is proportionate?

A proportionate approach entails that impact assessment, mitigation strategies, risk management, and stakeholder involvement approaches are proportionate to the likelihood, severity and proximity of risks for adverse impacts on good work.

Proportionate approaches to sampling, remit and degree of involvement should be guided by estimated likelihood, severity and proximity of risks identified in the pre-context based risk assessment.

A full Good Work AIA should be completed wherever a system is designed, procured or deployed to make or inform decisions which could impact access, or terms and conditions of work such as pay, work allocation, evaluation of performance, and discipline.

We recommend that a Good Work AIA is also undertaken when there is a risk of significant impacts to any other dimension of Good Work and note that risks to wellbeing, dignity, autonomy, support, learning and participation are best suited to worker-expert identification. Significant risks to these dimensions should ordinarily be considered severe and proximate.

CHAPTER

3



CHAPTER 3



Good Work AIA

Following the Context Based Risk Assessment, and once the organisation has determined a Good Work AIA is necessary, the following commitments should be made.

‘Commitment’ checklist

1. Commitment to good work as organisational priority

For effective engagement, workers need to trust that management is committed to promoting and protecting their interests, including the promotion of good work.⁷³ A **supportive** environment is needed for **participation** to be successful. Employers too need to trust in the benefits of worker involvement in important decisions about work.

2. Commitment of resources ensuring innovation is responsible

An effective impact assessment requires resources to be allocated to the process:

- Time – the time for workers and contractors to be involved.
- Cost – resources may be needed to deliver mitigations or redesign parts of the system.
- Learning – firms may also need to allocate resources, such as time for learning (please see our toolkit) and support, such as ‘mediators’ and ‘translators’.

3. Commitment to mitigations

Workers and employers should make ‘design commitments’ throughout the process. The Good Work AIA does not end with the identification of risks. It requires steps to be taken in response to findings. Ahead of the process, clear commitments should be made to how risks identified will be addressed. This could for instance include:

- committing not to proceed if impacts deemed ‘high risk’ cannot be mitigated
- committing to consider proposed mitigations to risk and impacts deemed medium risk
- committing to establish mitigations which advance good work where there is not a significant associated cost burden.

4. Commitment to dialogue

The process of Good Work AIA forms the basis of agreement regarding the use of an algorithmic system within a business to make or inform decisions about conditions and quality of work. Both workers and management must learn and practice negotiation in order to balance interests, particularly where ethical choices must be made in the absence of bright-line law. Collective agreements hold precedence in providing an infrastructure through which detailed agreements about technology use can be made and monitored.⁷⁴

CHAPTER 3



Stage 1

Identifying individuals who might be impacted

This process should be undertaken to identify and plan the engagement of potentially impacted individuals. Decisions reached should be recorded within a Stakeholder Engagement Report (details at end of section).

Approaches taken should reflect understanding of risk, and comprehensive transformation to work as identified in the preliminary risk assessment.

Identify the total population

Involvement in processes of algorithmic assessment should go beyond “*add diverse stakeholders and stir*”.⁷⁵ Before working out how to recruit workers to participate in the process, it is necessary to identify the ‘total population’. As this guidance focuses specifically on workplace deployments of algorithmic systems, the impacted population is largely known and contained relative to other forms of impact assessment.⁷⁶

As those potentially impacted by the introduction of algorithmic systems is likely to include self-employed workers and independent contractors, for example,⁷⁷ we propose that the ‘total population’ is not generated on the narrow basis of employment/worker status, but is instead comprised of all persons who have an identifiable right, freedom or interest in the system including those who meet the following criteria:

- a) data gathered about them by such systems (purposefully or potentially incidentally);
- b) subject to automated decisions by the algorithmic system;
- c) use the system to inform decisions affecting other persons; and
- d) union representatives and members from across the organisation, where available.

If an organisation is procuring a system, it may be sensible to involve developers of the system as stakeholders in order for their learning and development.

To effectively deduce this, it is necessary to have undertaken the recording of key design choices and understand the intentions of using the system.

We note that customers or service users are often also data subjects in workplace algorithmic systems, and that systems used to monitor customer behaviour can be inversely used to monitor workers.⁷⁸

Methods for recruitment

Once the total population is identified, the sample should be generated. We present four potential approaches to identifying and recruiting workers to take part in the AIA:

1. Representative
2. Elective
3. Direct
4. Purposive

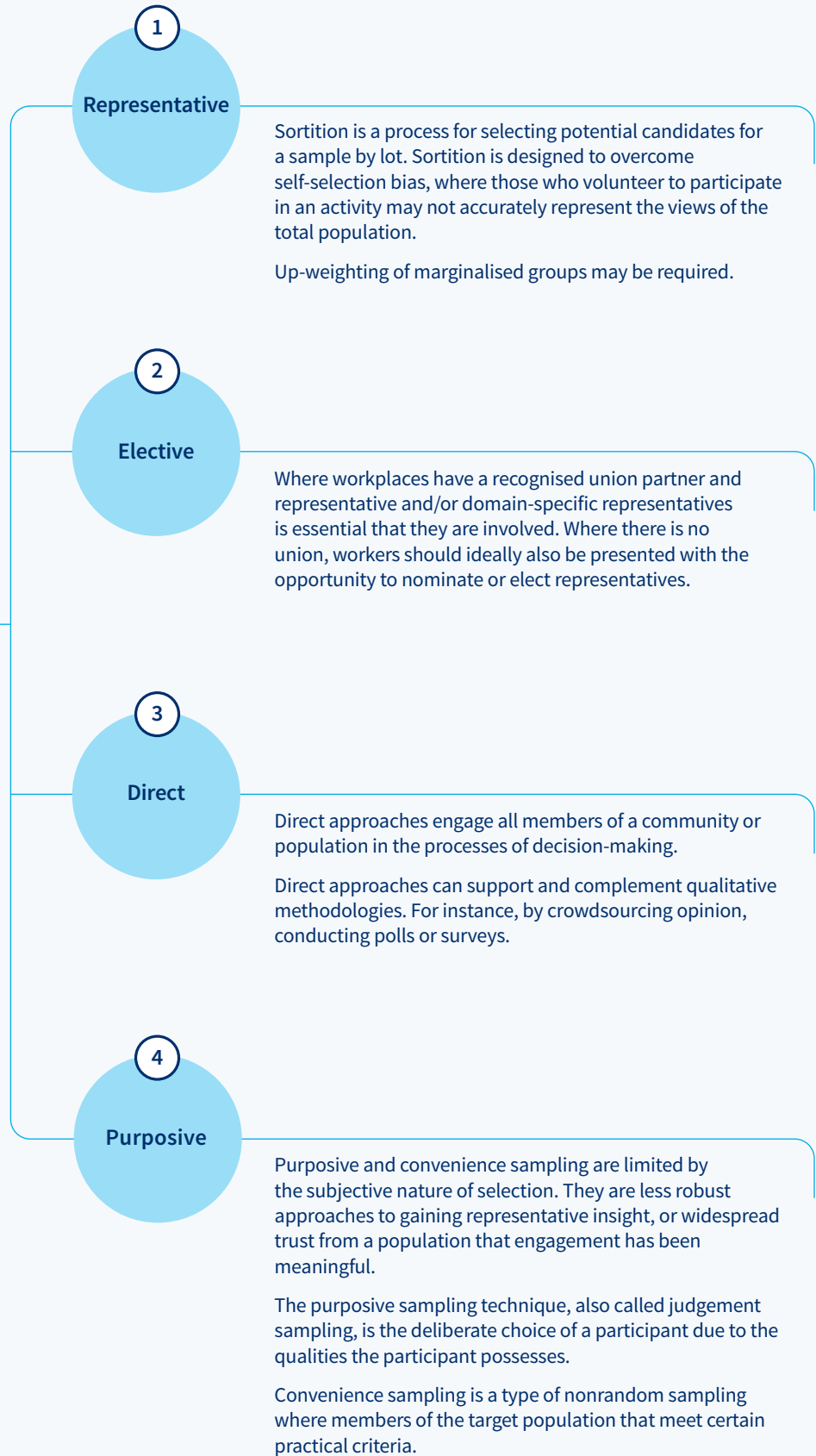
As noted above, approach should be proportionate to risk and reflect organisation and total sample size (see Table 2). Each approach presents its own opportunities and constraints, which we outline in further detail below. The methods can be used in combination.

At each stage of the assessment process, a different sampling approach has different strengths or weaknesses. Therefore, different samples can be used for different stages of the assessment. We have identified the appropriate sampling approach(es) for each stage of the assessment in Table 3.

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Methods for recruitment overview



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1. Representative

Sortition is a process for selecting potential candidates for a sample by lot.

This process involves the following stages:

a) Identify the total population

With the criteria set out above, contact details of the total workforce should be obtained from HR or agencies supplying labour to the firm who will engage with or be affected by the technology.

b) Label all those in the total population with a number using a random-number generator.

Random-number generators are available online. Once a sample is labelled this can be used to select participants.

c) Send invites to a total sample and request appropriate demographic data⁷⁹ in the response from all those who agree to participate.

Not all organisations have good data on workforce demographics, such as ethnicity and disability.⁸⁰ It may therefore be necessary to collect such information, alongside gender and age through the sortition process. Use and storage of this information should be conducted in compliance with the ICO's regulatory guidance on special category data.⁸¹

d) Select a final sample that has appropriate representation of demographic groups

Sortition is designed to overcome self-selection bias, where those who volunteer to participate in an activity may not accurately represent the views of the total population.⁸² However, it is still important that people are not forced to take part in participatory processes.

Marginalised groups may be less likely to speak in participatory processes when the group is biased towards a dominant majority.⁸³ It is therefore helpful to 'upweight' the representation of marginalised groups to help account for this. This is also important due to high risks to equality of algorithmic systems⁸⁴, and communities with experience being best placed to identify risks.⁸⁵

Identification of marginalised groups should go beyond special category data and protected characteristics to consider other forms of vulnerability. For instance, systems are known to reproduce place-based, socio-economic forms of disadvantage.⁸⁶

2. Elective

Collective bargaining provides a useful framework for developing terms of reference around the governance of technology in the workplace.⁸⁷ Therefore, where workplaces have a recognised union partner and representative and/or domain-specific representatives (e.g. Equality or Health and Safety Officers) it is essential that they are involved.

Unions tend to have well-established training infrastructures to support workplace representatives with skills in communication and negotiation and knowledge of relevant issues surrounding technology and their intersection with labour law. Equality officers will also have greater training and understanding in equality issues, and Health and Safety Officers should be trained to have a greater understanding of Health and Safety Law. Workers in these roles are also often protected,⁸⁸ which may improve deliberation.

Where there is no union, workers should ideally also be presented with the opportunity to nominate or elect representatives. Where organisations have forums dedicated to advancing the interests, representation or welfare of specific demographic groups or communities, these should be consulted and involved in processes of a Good Work AIA.⁸⁹

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3. Direct

Direct approaches engage all members of a community or population in the processes of decision-making. Conventionally, this is used for voting and is therefore well suited to survey methods and online engagement. Such an approach is unlikely to be feasible for qualitative processes which require focused, shared discussion of key issues. This is relevant to some of the methods set out in this guidance (see ‘match sampling to method’ below).

However, as part of the Good Work AIA process is about building trust with the impacted community, direct approaches can support and complement qualitative methodologies. For instance, by crowdsourcing opinion, conducting polls or surveys.

4. Purposive

Convenience and purposive sampling are limited by the subjective nature of selection. They are less robust approaches to gaining representative insight, or widespread trust from a population that engagement has been meaningful. However these approaches can have merit when randomization is impossible, or where there are limited resources or time due to perceived low risk or buy-in from senior leadership.

Convenience sampling is a type of nonrandom sampling where members of the target population that meet certain practical criteria, such as easy accessibility, geographical proximity, availability at a given time, or the willingness to participate are included.⁹⁰

The purposive sampling technique, also called judgement sampling, is the deliberate choice of a participant due to the qualities the participant possesses.

Purposive sampling methods include:

- Maximum Variation Sampling: also known as heterogeneous sampling involves selecting candidates on the basis of subjective interpretations of their difference.
- Typical Case Sampling: candidates are chosen on the basis of being perceived to be an average of the sample
- Extreme/Deviant Case Sampling: the opposite of typical case sampling, this involves selecting individuals who are seen to be ‘atypical’.
- Expert Sampling: those perceived to hold expert knowledge are engaged. This will apply to non-user (worker) stakeholders, should they be involved in the full Good Work AIA process.

If an organisation is satisfied with less robust engagement methods which could be subject to scrutiny, less robust selection methods could be adopted such as convenience sampling.

Choosing a sampling approach

Different sampling approaches are better or worse suited to total population size as shown in Table 2.

Table 2: Selecting a sampling approach

Method	Best when the total population is:
Representative	Over 50
Elective	All sizes
Direct	Under 50
Purposive	N/A

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Sampling methods can also be chosen to complement preferred methods used for different stages of a Good Work AIA. This is explained outlined in Table 3.

Table 3: Sampling approaches for Good Work AIA

Stage	Method(s)	Rationale	Optimal sampling approach
Stage 2 Record key design choices	Documenting	It is preferable to engage workers from the outset of a project, particularly for the purposes of problem definition and design scoping. However, full workforce participation can be resource intensive.	Purposive sampling (including union representatives).
Stage 3 Risk and impact analysis	Value Alignment (optional kick off exercise)	This exercise requires dialogue and is therefore best undertaken in groups.	Direct, Elective or Representative (depending on total sample size) in groups of between 10–20.
	Scenario Development	Scenario development requires deliberation and is therefore best suited to small groups, either online or in person.	Direct, Elective or Representative (depending on total sample size) in groups of 10–20.
Stage 4 Decide on appropriate actions	Risk Severity Ranking	Can be conducted as an extension of scenario development. Alternatively scenarios can be shared and reviewed by the total population and voting on severity can be direct.	(as above). Direct
	Identifying mitigations	While mitigations will be identified within the risk and impact assessment process (as design commitments), some risks may require dedicated thought and specific actors (such as the developer) to model solutions.	Purposive
	Preference elicitation	This process is an assessment of individual preferences, potentially allowing for re-programming algorithmic systems to meet individual preferences. ⁹¹ This requires the participation of the total population.	Direct
Stage 5 Ongoing monitoring		A forum involving workers (or/and their representatives) and employers could be established (see more in Stage 4).	Selected cohort join Technology Forum

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Produce a Stakeholder Engagement Report

Establishing and documenting methods and objectives is crucial to avoid the Good Work AIA process being seen or treated like a cosmetic tool or condoning ineffective participatory methods.

The Stakeholder Engagement Report should document information regarding how choices are made around stakeholder engagement.

These choices will reflect:

- assumptions about proportionality reached during the context based risk assessment and recording of key design choices;
- commitment to all stages of the process;
- commitment of resources to the principle of participation.

Now you have the group ready to undertake this process. The next stage is to assess risks and potential impacts on good work.

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Stage 2

Undertaking an ex ante risk analysis

This stage deploys methods to identify risks to good work. With risk ranking and mitigation development it forms the heart of the Good Work AIA.

Kick Off Exercise: Value Mapping

While algorithmic systems are understood to need to be ‘aligned’ with human values, these are not always commonly understood or shared. Ahead of any process of risk and impact assessment, it can be helpful for participants to develop a sense of what good work means to them, and for the group to recognise how it is understood and protected in the organisation.

The Good Work Charter should be used as a normative framework to inform this exercise.

There are various methods through which this can be considered. Most simply, a group could come together and openly discuss principles, using the prompts below. A recommended method is to use post-it notes so that all individuals, including those less likely to speak, are given space to state their thoughts, without being shaped so much by the thinking of others.

For good work principles which do not have common definition or understanding within the organisation, ask the group to write down independently their own answers to the following questions:

- What are the most important indicators of this principle?
- What, if any, existing standards, codes or procedures are in place to promote this?
- What, if any, parameters or baselines should be agreed ahead of changes to job design?

A more advanced method, which could be used to build on and unpack the findings of the exercise above, would be to use ‘deep democracy’. This requires a skilled facilitator and provides a practical method to undertake dialogue for revealing the wisdom of the minority and managing conflict through revealing differences.

Key Design Choices: Preliminary Review of Good Work Risks





An educational component is common in processes of participation.⁹² To overcome power imbalances it is important that information asymmetries are reduced. Therefore, before the group is first convened, all involved should be given time to review the key design choice documentation. This should be supported by our toolkit for Understanding AI at Work.

Organisations may also consider investing in paid support to identify an independent ‘translator’ who can mediate understanding of key design choices and as appropriate, any technical auditing reports (where the toolkit is not adequate). In some regions, this is already a regulatory requirement.⁹³

Once the group has had time to review these materials, they can come together to discuss the implications of the design specification across the four stages. This should inform initial thinking about ‘constructive design commitments’ – alternative strategies to better advance good work. It is also an important baseline ahead of scenario development.






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Table 4: Key design choices and good work risk assessment

Principle	Example considerations
Access 	<p>Are any roles at risk as a result of system adoption, whether wholly or in part? Which roles and how many, by which forecasting methods, on which assumptions? Do estimates about labour saving seem reasonable? Have all tasks within roles been identified and understood? What broader conditions would enable these efficiencies to be realised?</p> <p>Is the system likely to determine access to work in other ways, such as predictive scheduling of shifts and shift allocation? Will access to hours of work be reduced for some staff?</p> <p>Are any new roles being created?</p> <p>What mechanisms are in place to support worker transition to different roles in place if some jobs are to be fully substituted?</p>
Fair Pay 	<p>Could system adoption lead to or enable changes in pay, directly or indirectly?</p> <p>How many and which workers will be affected, in which ways?</p> <p>How will transparency around algorithmically calculated pay be mediated?</p>
Fair conditions 	<p>Will system introduction alter terms and conditions of work, beyond access and pay?</p> <p>Are the variables used to measure, predict or reward performance, productivity or disciplinary matters known, and considered reasonable? Are they relevant to the problem at hand? Has their potential to act as proxies for protected characteristics been considered?</p> <p>Is the relative importance (weighting) of different variables reasonable from the perspective of job design?</p> <p>Is it understood which parties have access to data, both identifiable and non-identifiable, and the purposes for which this will be used? Is there a clear agreement in place with any third-party provider on this?</p>
Equality 	<p>What individual and group equality impacts were identified in bias audit? Which fairness metrics, definitions of bias, and methods were used? Which if any proxies were identified?</p> <p>What key trade-offs were made through the course of technical audits for accuracy and bias? Which groups were impacted?</p> <p>What mitigations were introduced? How were these chosen? Which other options were considered?</p> <p>What are the implications of these choices for equality, company policy and reputation?</p> <p>How might system deployment create indirect forms of discrimination?</p> <p>How will cumulative impacts over time be monitored if the system is deployed? Who will have access to this?</p> <p>Has the technical audit been integrated into a wider equality impact assessment?²⁹⁴</p>
Dignity 	<p>Is the approach to data collection seen as proportionate?</p> <p>How will human oversight be structured to remain accountable? (see Support below)</p> <p>Can people override algorithmic decisions, choices and classifications? Which people in which circumstances?</p> <p>Are there potential impacts on dignity from approach to system integration and deployment?</p> <p>How will candidates access recourse to contest decisions, request human review of decisions, or provide feedback on system functioning? Will workers be involved in ongoing processes of review of the functioning of automated decision making?</p>

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Table 4: Key design choices and good work risk assessment *continued*

Principle	Example considerations
Autonomy 	<p>How could the approach to value capture impact worker autonomy? If this is deemed proportionate on the basis of projected returns, how sufficient is evidence these returns will be secured? On which grounds?</p> <p>Has effort-reward balance within new job design been considered?</p> <p>Does the system allow for individual preferences to be expressed or encoded?</p>
Wellbeing 	<p>How could system deployment present risks to physical safety in the context of broader job design and activity?</p> <p>Is any task scheduling set at a reasonable rate?</p> <p>How might a system present risks to psychological and social wellbeing?</p>
Support 	<p>If management roles will be replaced by the system, are alternative routes to support and redress for workers in place?</p> <p>If management roles will be augmented by the system, is there confidence that those persons understand how recommendations or reports are reached? Blind adherence to algorithmic outputs may constitute a breach of UK GDPR.</p> <p>How will managers using the system to inform decisions be trained to understand the basis of recommendations and system limitations?</p> <p>How could the system impact relationships between workers?</p>
Participation 	<p>Is there a shared sense of the problem to be solved by the system? Could other solutions achieve the same outcomes or better promote good work?</p> <p>Does introduction of the system present opportunities to initiate or deepen workforce participation?</p> <p>Did workers involved in the context based risk assessment see design choices as reasonable?</p> <p>How will information be shared with workers about the data used by the system and how it is processed (global logic)?</p> <p>How explainable are reports on local decisions; will these be understood by the wider non-specialist workforce, can they be edited or capacity be boosted?</p> <p>What are the proposed structures for system monitoring and reporting? Does this involve those who are frontline users of a system? Can resources be allocated to training?</p>
Learning 	<p>How does system design consciously, or could it unconsciously, impact opportunity for use of skill and learning?</p> <p>Have new opportunities for learning been identified?</p> <p>Where low discretion augmentation is to be used, is there evidence that this will support reduced cognitive load in positive ways?</p> <p>Will workers require new skills or capabilities to use the system or conduct their work? Which new skills and capabilities will be required?</p> <p>Does use of the system offer any new opportunity for learning and development?</p> <p>Will the system be used to reduce or promote decision-making and required learning from workers?</p>

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Scenario analysis: Unpacking risk of Good Work impacts

The context-specific risks and impacts of algorithmic systems will vary according to specific workplaces and environments.

Scenarios are manufactured narratives, produced to explore equally plausible future contexts and counterfactuals.⁹⁵

Scenario development – the process whereby a group imagine these alternative futures, and how they would be shaped by different conditions (different design parameters), could extend understanding of possible system impacts and risks and generate new forms of design commitment, improving good work through technological adoption. Scenarios can help to challenge assumptions, identify novel aspects of a future and allow for unexpected questions to emerge.

Table 5: Forecasting Good Work impacts through scenario development

Good Work Principles	Scenario Prompts (Examples)
Problem Definition 	Value Proposition Scenario Development Review ways in which a system is intended to capture value. Develop scenarios to imagine how this would change work, for the better or worse, in practice. Consider: would an intensification of work lead to wellbeing harms? How would rates for delivery impact wider aspects of job quality such as autonomy ? How would low-discretion augmentation impact workers over the long term? How would this impact organisational ethos and brand?
Design and Procurement 	Optimisation Criteria Scenario Development Systems are designed to optimise behaviour. Performance, for instance, may be optimised by measuring a series of variables (customer feedback, completed items) and selecting workers for access or promotion on this basis. Consider: what other variables could be used to monitor performance? What datasets would this require? How could this lead to knock-on changes in experience and meaningfulness of work? Which groups stand to benefit most, or be most disadvantaged? How is this informed by technical audit of the system? Develop scenarios on the basis of different optimisation criteria to reflect on how this would shape access, conditions, equality, dignity in work.
Implementation 	Implementation Scenario Development Consider: chosen approach to system implementation and integration. In what scenarios might there be risks to individuals reporting issues? How could relationships between staff be impacted by approaches to deployment? What could happen to established models of review, such as collective bargaining? Develop a best-case and a worst-case scenario, for promoting support, participation, fair conditions, and dignity .

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The group should have access to the context-based risk assessment. This will forecast some hazards of the system, through documenting Key Design Choices. Once the group has engaged in discussion about these, they will be better placed to undertake scenario planning. This can help to tease out risks in more granular detail and identify alternative routes to managing them. This is important given that systems are being assessed ex ante. Real impacts will be identified through ongoing monitoring (see Stage 4).

These scenarios should be documented as stories or a list of recognised risks. Individuals could also develop ‘user journey’ stories and narratives to represent what work might feel like under the proposed conditions.

Produce a Risk Assessment Report

Scenarios, potential user pathways, scenario narratives, and any constructive design commitments proposed to respond to known risks identified through the review of Key Design Choices, should be documented and compiled. Where issues have been identified in the risk and impact assessment stages:

- the design choice which is the source of the issue should be specified;
- the issues presented should be listed;
- the good work principles impacted should be consciously outlined;
- intersections with relevant legal, ethical regimes should be reviewed. This should refer back to the internal values mapping exercise, and have due regard to the Good Work Charter.

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Stage 3

Taking appropriate action in response to the ex ante analysis

The purpose of any audit should be to act on the information surfaced. As a minimum, this should enable compliance (and demonstration of compliance) with the law. However, best practice should also see businesses take steps to improve good work and promote equality.⁹⁶ Priority areas must be identified. A range of options for mitigation should be developed and considered and trade offs evaluated. Finally, the appropriate mitigation should be selected and implemented with an agreed time frame. Stage 4 covers ongoing evaluation of this action and any further adjustment that may be required. This process and factors to be considered are set out below.

a) Selecting priorities

‘Ongoing risks and harms are a product of the socio-technical gap: the great divide between what we know we must support socially and what we can support technically.’⁹⁷

Potential breaches of the law identified in the course of risk assessment should be responded to directly. Ethical and social risks may intersect with these but may require further mechanisms for the balancing of interests. People have different values⁹⁸ and cannot easily or always rank or compare them.⁹⁹ Because values are qualitative rather than quantitative, they are not easily compared or contrasted.¹⁰⁰

However, humans are able to evaluate differences and make comparisons on the basis of moral judgments about what they ultimately want, need and find to be just and good.

In this context a matrix can help evaluate where action/mitigation is needed in auditing algorithmic systems.¹⁰¹ This should only be used to evaluate severity of risks which go beyond ensuring legal compliance. Where legal risks are identified these should of course be rectified.

Reach and proximity of impacts can be assessed through ranking. This can be participatory, using a direct sampling approach (a survey of the total population), or be undertaken as an extension of smaller group based dialogue following on from the ex ante risk assessment.

Where a system is being procured rather than designed in house it will likely be necessary to engage third party providers.

Table 6 presents an example of how this could be documented.

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Table 6: Example of ranking risk severity

Challenge identified	Good Work Principles Impacted	Stake-holder Group 1 (workers) Impact Ranking 0–10	Stake-holder Group 1 (managers) Impact Ranking 0–10	Difficult to address? (10 easy, 0 hard)
The variables used to measure performance only reflect some aspects of job requirements. This may lead some aspects of work to be valued over others.	Fair Conditions	6	5	3 Change variables/ weightings representing outcomes for performance
	Wellbeing	6	0	
	Equality	10	10	
Workers are not confident of how their data is held by third parties who may access data within the system	Dignity	2	2	1 Employer requests full disclosure on third party data sharing as part of contractual agreement (note controller/processor and controller/controller relationships and ICO Data Sharing Code of Practice)

An alternative approach would be to adhere to the following stages in a more deliberative discussion.

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b) Identifying mitigations

Some mitigations may become obvious through the process of risk and impact assessment and process of developing 'constructive commitments'. Where issues are identified but mitigations are not, employers could use design thinking processes, inviting convergent and divergent thinking.

Table 7 sets out a typical process for design thinking. This is best led by a facilitator. Stage 1 ('discover') should be covered by the risk and impact assessment stage of an AIA, and therefore a group could begin from Stage 2 ('define').

Mitigations: Options and approaches

Mitigations should take reasonable and proportionate steps to mitigate risks, address harms and promote benefits with due regard to the size, resources and capabilities of the organisation and the severity and proximity of the organisation to any adverse impact.

Mitigations could take four forms:

1. New rights and entitlements
2. Distributed rewards
3. Reprogramming: Universal
4. Reprogramming: Tailored

Table 7: Using design thinking to develop mitigations

Stage 1 Discover	The purpose and aim of this stage is to garner deep insights about a set of problems and understand them from different angles and viewpoints.
Stage 2 Define	Participants distil findings into the articulation of a well-defined problem. This process could support extrapolation of specific 'problem statements' from the scenarios.
Stage 3 Design	In the design phase, ideas to find practical solutions are brainstormed. The purpose is to generate ideas and solutions.
Stage 4 Develop	Participants are encouraged to test the feasibility and impact of the different solutions proposed in the design phase. The solutions with the most potential are identified.
Stage 5 Deliver	In this phase, practical applicability and delivery are considered. A visual diagram is provided to help identify the processes and methods to deliver the most promising solution.
Stage 6 Distribute	A framework is developed to identify and scale a solution.

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Mitigations: Options and approaches overview



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1. New rights and entitlements

Processes of mitigation can be established where the needs of workers are balanced with business priorities. In some contexts, this could be bolstering mechanisms by which existing rights at the level of the workplace, such as the ‘right to be informed’ operate to ensure workers know when changes are made to the design of a system, and to be consulted on this.¹⁰² It may also be important to establish a principle of system removal if it does not achieve intended, collectively agreed objectives.

2. Distributed rewards

Distributing rewards may involve improving conditions or quality of work. This includes pay, investment in upskilling,¹⁰³ including training in understanding and being able to negotiate around technology deployment and recognising that where workers are a source of data they should have equal access to it.¹⁰⁴

3. Reprogramming: Universal

Optimisation criteria

Optimisation criteria may be amended or changed and or revised in light of distributed rewards for productivity gains.

Data(set) exclusions

Through evaluating design choices, scenarios and risks regarding the inclusion of certain datasets, workers may decide to exclude some sources of information from decision-making systems or to set parameters around use.

Examples could include:

- Customer reviews and ratings (known to be discriminatory reflecting social biases).
- Restrictions around the collection of data when outside the workplace.

Programming

Identifying problematic proxies which may have potential for discriminatory impact; changing optimisation criteria; modifying system design to accommodate individual differences where protected characteristics are revealed. See below on preference elicitation.

Integration

Reviewing information around implementation planning could lead to requests for different structures of decision-making, disclosures to the workforce, training of those using data to inform decisions, routes to reporting and redress.

4. Reprogramming: Tailored

Preference elicitation offers a methodology to mediate conflicting or varied interests.¹⁰⁵ As data allows for increased tailoring to individual needs, this approach allows people’s personal choices to be integrated into design, from a defined set of options. In this process, the community of users or beneficiaries propose different options (through interviews or surveys) and are given the choice to vote on them, to shape the functioning of a system collectively.

This has been used to support redesign of algorithmic systems used at work to promote wellbeing.¹⁰⁶ This approach works when there are a manageable set of alternatives but is limited by the extent to which individuals can fully express their preferences.¹⁰⁷

Produce an Impact Mitigation Plan

Decisions reached about which risks are prioritised for action (if not all are); how these will be addressed; and ongoing monitoring architectures should be recorded as an Impact Mitigation Plan. This should be shared with the whole workforce as best practice.

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Stage 4

Continuous evaluation to ensure assessment and appropriate action is ongoing and responsive

While risks and potential for improvements can be identified during ex ante forms of system assessment, many impacts and opportunities to improve good work through system deployment will only be detected after deployment. It is therefore important to monitor the ongoing outcomes of a system on individuals and communities for impacts across all good work principles.

What is an impact?

A harm to an individual resulting from the deployment of an algorithmic system.

It is important that ongoing channels of communication are maintained between workers and management, to:

- a) Ensure mitigations are in place and the system is deployed as intended as per the design commitments established through the process.
- b) Evaluate ongoing performance of the algorithmic system, relative to its designed purpose.
- c) Scrutinise changes to the system in accordance with any future updates (for instance new datasets, or changes to organisational approach to deployment within structures of human decision-making).
- d) Scrutinise ongoing bias audits as part of wider technical assessments and agree actions.
- e) Identify novel and cumulative impacts across good work principles.

The documented choices made throughout a Good Work AIA form the template of an agreement about how an algorithmic system will operate within an organisation. Establishing a distinct forum for the purpose of ongoing review of the system can encourage ongoing and credible feedback from the workforce. The forum should be designed to engender constructive dialogue and may be especially advantageous for remote or ‘fissured’ workplaces. Clear terms of reference of the forum should be agreed by all parties.¹⁰⁸

Data can be used to validate, contest or contextualise other forms of reporting.¹⁰⁹ Forums may also review the ongoing results of technical assessments, such as bias audits, which should run through the lifetime of any algorithmic system.

Processes of review may seek to ask:

- Were the benefits and work improvements from the system achieved?
- Were the mitigations delivered?
- Are mechanisms for feedback, decision challenge, and reporting working effectively?
- Have exceptions proven cause for redesign or risk of non-compliance?
- Have developments in business interface and implementation or the addition of new data-driven technologies led to changes in system functionality?
- Are there new, unforeseen impacts on **Good Work**, reviewed against each charter principle?

APPENDICES



APPENDIX 1

Methodology and acknowledgements

This document has been developed drawing on:

- Three literature reviews
- Expert interviews
- Iterative design of the process, with feedback from the Advisory Panel
- A Social Policy Innovation Accelerator (SPIA) convening workers and experts

Literature reviewed to inform this report drew from work in the fields of participatory AI, participatory machine learning, design justice, computer supported collaborative work, human computer interaction, audit and algorithmic impact assessment. Papers reviewed were both conceptual and empirical.

The ICO expert panel is comprised of an interdisciplinary group representing varied expertise. We are grateful to:

Associate Professor Dr Reuben Binns
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Mary Towers
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Professor Jeremy Myerson

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APPENDIX 2

Glossary of terms

Actors

Data Controller

Organisations, persons or other bodies that determine the purposes and means of processing personal data.

Data Subject

A data subject is someone who is or could be identified from personal data.

Engineer

Someone with technical expertise who contributes to the design of an algorithmic system.

Technical Terms

Data

Information that is collected, processed or stored by, and in, digital technologies.

Dataset

Collections of data, typically related to each other.

Algorithm

A sequence of instructions programmed in a computer, designed to complete a task or solve a problem.

Machine Learning

A branch of AI in that learns from collected data how to perform tasks, as defined by humans.

Artificial Intelligence (AI)

Artificial intelligence (AI) is an umbrella term commonly conflated with machine learning which is better understood as a scientific field. The term can be used as a marketing term for a range of technologies.

Algorithmic System

A system that uses one or more algorithms designed, developed and deployed by humans operating in an institutional context

Prediction

Statistical estimations of what is likely to happen in the future, based on data

Classification

Placing people or things into groups through analysing data.

Model

What is saved after running a machine learning algorithm on training data and represents the rules, numbers, and any other algorithm-specific data structures required to make predictions.

APPENDIX 2

Glossary of terms

Variable

Any phenomena that can be measured or counted within an algorithmic system.

Proxy

A variable that is not in itself directly relevant, but that serves in place of an unobservable or immeasurable variable.

Target Variable

The phenomenon which the decision-maker is trying to predict, also called the dependent variable.

Weighting

The chosen significance given to different variables in an algorithmic system.

Optimisation Function

A relationship between a set of variables that achieves the best outcome for a given purpose.

Interpretability

The extent to which cause and effect can be understood in a system, given how it has been designed.

Explainability

The extent to which a model can be explained in human terms and understood by humans.

Accuracy

The ability of a model to predict outcomes on the basis of given datasets.

Robustness

The extent to which a system can be disturbed by changes in the data it processes, or changes in the real world environment that limits its effectiveness.

Fairness

The extent to which a system treats different groups and individuals in a reasonable and morally acceptable way.

Review/Assurance**Construct**

An idea containing conceptual elements, typically considered subjective.

Construct Validity

The extent to which a measurement accurately reflects what it is supposed to measure.

Historical Bias

When the algorithm learns from, and reflects past patterns of behaviour and resource [ref data sets].

Sampling Bias

Occurs when the algorithm has been fed data that does not represent the population accurately.

Algorithmic Design Bias

When the engineer intentionally or unintentionally includes bias in the model.

Audit

A process which evaluates a system against technical standards, commonly used for fairness ('bias audit') robustness, performance and safety.

Assurance

Processes to build confidence or trust in something, for example a system or process, documentation, a product or an organisation.

Validation

The set of activities ensuring that a system is able to accomplish its intended use, goals and objectives in the intended operational environment.

ENDNOTES



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- 1 This might be understood as ‘algorithmic management’: the collection or creation of any information (whether identifiable or not) with a view to monitoring, supervising or evaluating work performance and/or the use of that information to augment or fully automate decisions that affect working conditions, in particular access to work, earnings, occupational safety and health, working time, promotion and contractual status and disciplinary as well as termination procedures.
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- 11 This approach rests on a broad, purposive interpretation of data protection law and is reinforced by other legal and ethical imperatives (see our Good Work Charter review of legal, ethical and regulatory bases).
- 12 As recommended by Lord Clement Jones, former chair of the Lords Committee on AI.
- 13 Lord Clement Jones, debating the Procurement Bill on Wednesday 13 July 2022 in the House of Lords. Full transcript available at: [https://hansard.parliament.uk/Lords/2022-07-13/debates/E4A9A7A3-E3DD-433F-BFE8-FCEA6FE4822B/ProcurementBill\(HL\)#contribution-55B71760-757D-4D82-83D2-49B0183105FB](https://hansard.parliament.uk/Lords/2022-07-13/debates/E4A9A7A3-E3DD-433F-BFE8-FCEA6FE4822B/ProcurementBill(HL)#contribution-55B71760-757D-4D82-83D2-49B0183105FB)
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For specific guidance on Algorithmic Impact Assessment within Collective Agreements, see forthcoming guidance from the IFOW and TUC.
- 88 TULRCA, ss 146 & 152
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- 92 Fishkin, James S., *Democracy when the people are thinking: Revitalizing our politics through public deliberation*. Oxford University Press (2018).
- 93 See Art 9(3) of the Platform Worker Directive: The platform workers' representatives or the platform workers concerned may be assisted by an expert of their choice, in so far as this is necessary for them to examine the matter that is the subject of information and consultation and formulate an opinion. Where a digital labour platform has more than 500 platform workers in a Member State, the expenses for the expert shall be borne by the digital labour platform, provided that they are proportionate.
- 94 See more in: Graham, Logan, Abigail Gilbert, Joshua Simons, Anna Thomas (2020) Artificial Intelligence in Hiring: Assessing Impacts on Equality. Available at: <https://www.ifow.org/publications/artificial-intelligence-in-hiring-assessing-impacts-on-equality>
- 95 Ramirez, Rafael, Malobi Mukherjee, Simona Vezzoli, and Arnoldo Matus Kramer, "Scenarios as a scholarly methodology to produce "interesting research"." *Futures* 71 (2015): 70–87.
- 96 Some have understood this as delivering 'reparations': Davis, Jenny L., Apryl Williams, and Michael W. Yang, "Algorithmic repairation." *Big Data & Society* 8, no. 2 (2021): 20539517211044808.
- 97 Dobbe, Roel, Thomas Krendl Gilbert, and Yonatan Mintz, "Hard Choices in Artificial Intelligence." *arXiv preprint arXiv:2106.11022* (2021).
- 98 Dobbe, Roel, Thomas Krendl Gilbert, and Yonatan Mintz, "Hard Choices in Artificial Intelligence." *arXiv preprint arXiv:2106.11022* (2021).
- 99 'Semantic indeterminism', see: Dobbe, Roel, Thomas Krendl Gilbert, and Yonatan Mintz, "Hard choices in artificial intelligence." *Artificial Intelligence* 300 (2021): 103555.
- 100 'Value pluralism', see: Dobbe, Roel, Thomas Krendl Gilbert, and Yonatan Mintz, "Hard choices in artificial intelligence." *Artificial Intelligence* 300 (2021): 103555.
- 101 Brown, Shea, Jovana Davidovic, and Ali Hasan, "The algorithm audit: Scoring the algorithms that score us." *Big Data & Society* 8, no. 1 (2021): 2053951720983865.
- 102 See, for instance, regarding the US experience: Krege, Lisa, 'Union Collective Bargaining Agreement Strategies in Response to Technology' UC Berkley Labour Centre Working Paper, Technology and Work Programme (November 2020).
- 103 In Sweden, firms and workers have an established model since the 1970s called 'Job Security Councils', whose aim is to ensure a smooth transition from jobs and solve the reskilling and redeployment needs created by the adoption of new technologies in the workplace. They are funded by both workers and employers.
See: <https://www.eurofound.europa.eu/observatories/emcc/erm/support-instrument/job-security-councils>
- 104 Also known as 'data reciprocity'. See: TUC AI Manifesto, Kaosjji, Sheheryar, 'Worker and Community Organizing to Challenge Amazon's Algorithmic Threat'. In *The Cost of Free Shipping: Amazon in the Global Economy*, edited by Alimahomed-Wilson, Jake and Ellen Reese, London: Pluto Press, (2020); and see: A.B. 701, 2021–2022. Warehouse distribution centers (CA), granting certain Californian warehouse workers access to a limited subset of such data.
- 105 Ibid.
- 106 This was piloted to elicit preferences for shift schedules and managerial rules that assign shifts (managerial fairness) in one workplace. Through this review, the team elicited information about interest in tasks, perceived social usefulness, desired amounts of social interaction, stress associated with tasks, opportunities for higher earning and career advancement, job security and opportunities for independent decision-making. This drew upon key metrics of task impact on worker physical and psychological wellbeing. Through the process, it was revealed that different types of workers had different preferences (in terms of shift type, shift time, total hours, weekday vs weekend working) which could be largely accommodated algorithmically through increased worker personalisation. Using the system in this way overcomes the tendency in algorithmic management for workers to lose their ability to express preferences. Meanwhile, managers also benefit through greater ability to create schedules which are responsive to individual characteristics. See more in: Min Kyung Lee, Ishan Nigam, Angie Zhang, Joel Afriyie, Zhizhen Qin, and Sicun Gao, "Participatory Algorithmic Management: Elicitation Methods for Worker Well-Being Models." *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society (AIES '21)* (2021): 715–726.
- 107 Robertson, Samantha, and Niloufar Salehi, "What If I Don't Like Any Of The Choices? The Limits of Preference Elicitation for Participatory Algorithm Design." *arXiv preprint arXiv:2007.06718* (2020).
- 108 Silberman, M. "Operating an employer reputation system: Lessons from Turkopticon, 2008–2015." *Comp. Lab. L. & Pol'y J.* 37 (2015): 505.
- 109 See forthcoming guidance for the TUC to review approaches to developing technology forums.



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